RIETI Discussion Paper Series 24-E-082

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RIETI Discussion Paper Series 24-E-082

December 2024

U.S. Export Controls and the Restructuring of Global Values Chains: An Analysis of Japanese Multinationals' Exits from China*

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Abstract

The increased export controls on advanced technologies like semiconductors imposed by the U.S. and aligned countries targeting primarily China are accelerating technological decoupling. What are consequences of this process on global value chains (GVCs) dominated by the activities of multinational enterprises (MNEs)? To answer this question, we use Japanese microdata for the period 2017–2021. We find an increase in the exit of Japanese MNEs from China. Building on this observation, we hypothesize that this increase in exits may have been triggered by an increase in production costs brought about by a decline in the variety of imported intermediate inputs as a direct consequence of the increased export controls. We offer a simple theoretical framework to rationalize this mechanism, which guided us in creating an export controls index using a detailed review of U.S. Federal Register documents and input-output tables. Our empirical analysis of the probability of exit confirms that the reduction in imported intermediate inputs plays an important role in the behavior of Japanese MNEs.

Keywords: Japanese multinationals, FDI exit, export controls, technological decoupling, United States, China

JEL classification: F10; F14; F23

* This study is conducted as a part of the "East Asia Industrial Productivity" project under the "Raising Industrial and Firm Productivity Program" by the Research Institute of Economy, Trade and Industry (RIETI). The draft of this paper was presented at the RIETI DP seminar for the paper. We would like to thank participants of the RIETI DP Seminar for their helpful comments.
We are also grateful for helpful comments and suggestions by Bo Meng (IDE-JETRO), Eiichi Tomiura (RIETI), Konstantin Kucheryavyy (City University of New York), Richard Mansfield (University of Colorado - Boulder), and participants of the 2024 Western Economic Association International Annual Conference. This study utilizes the micro data of the questionnaire information based on "the Basic Survey on Overseas Business Activities," "Basic Survey of Japanese Business Structure and Activities", "Quarterly Survey of Overseas Subsidiaries" which are conducted by the Ministry of Economy, Trade and Industry (METI). The access to micro data was obtained via the Joint Usage and Research Center, Institute of Economic Research, Hitotsubashi University. Ivan Deseatnicov gratefully acknowledges financial support from the Japan Society for the Promotion of Science (JSPS) in the form of an Invitational Fellowship for Research in Japan (S23022) and from the Faculty of World Economy and International Affairs at HSE University. Ivan Deseatnicov and Kyoji Fukao also gratefully acknowledge financial support from the Joint Usage and Research Center, Institute of Economic Research, Hitotsubashi University (Grant ID: IERPK2432). A part of this research was conducted when Kyoji Fukao was President of IDE-JETRO. Ivan Deseatnicov would further like to thank Bogdan Balanda, Veronika Livintseva, and Meilis Orazov for their excellent research assistance. All remaining errors are our own.

1. Introduction

Not only have the U.S. and China been engaged in a tariff war, since 2018 the U.S. has also strengthened its export controls to prevent U.S. technology from leaking to China and other countries. What is the effect of the increased export controls by U.S. and aligned countries on global value chains (GVCs), which are largely dominated by the activities of multinational enterprises (MNEs)?[1] The aim of this study is to examine the role that such increased U.S. export controls have played in the decision of Japanese MNEs to exit from China.

The U.S. export controls consist of policies imposed by U.S. authorities to restrict the trade in products or technologies originating in the U.S. The export control policies are extensively described in the Export Administration Regulations. The U.S. Department of Commerce Bureau of Industrial Security (BIS) is responsible for maintaining the Export Administration Regulations and for enforcing compliance with them. The Export Administration Regulations contain a detailed list of products and technologies that may need a license to be exported from the U.S. This list is organized using Export Control Classification Numbers, which categorize and describe the controlled items. Another element of U.S. export controls is the Foreign-Direct Product Rule within the Export Administration Regulations, which applies to products that are produced outside the U.S. but use U.S. components and/or technologies. When such products are exported to a third country, a license from the U.S. BIS may be needed.

Preceding studies focusing on the impact of U.S. export controls on international trade (see Deseatnicov et al., 2024; Hayakawa et al., 2023) struggle to find clear evidence of decreased trade with China in the controlled products even at the most disaggregated HS 10-digit level. This is likely because export controls focus on chokepoints,[2] which is a strategy targeting only products with certain advanced technological properties and characteristics.

We argue that due to the limited substitutability of imported intermediate goods from different countries, reduced access to technologically advanced products could significantly impact production in China. In the case of Japanese MNEs, such impact may be large, as they probably depend on imports of goods containing advanced technology from the U.S. and aligned countries. MNEs from Japan and other aligned countries of the U.S. have the option to relocate or reshore their activities from China. Therefore, the economic impact on MNEs' activities is potentially much larger than just the impact on trade in regulated products. Moreover, changes in MNEs' behavior will also substantially change GVCs, as GVCs are formed to a large extent by MNEs (Alfaro et al., 2019). For instance, in 2023, the total sales of Japanese manufacturing affiliates in China amounted to 36 trillion yen (Basic Survey on Overseas Business Activities), which was much larger than Japan's total exports to China of 18 trillion yen (Ministry of Finance, Customs Statistics).

Figure 1 shows the number of exits as a share of the total number of affiliates in a particular country or region for Japanese MNEs' manufacturing affiliates. The figure indicates that the exit share for China between 2014 and 2020 surpassed that of other regions.[3] Several

1 We use term "the U.S. and aligned countries" to refer to the countries that have aligned their export control policies with the U.S. export control policies. The full list of countries is given in footnote 19.

2 National Security Advisor Jake Sullivan described this as a "small yard, high fence" approach. See slide 10 of the following BIS document: https://www.bis.doc.gov/index.php/documents/compliance-training/3472-china-brief-2024-03-14-update-china-brief-final-rpd-knv-v2-w-occ/file (accessed June 22, 2024).

3 According to a recent note by Nicholas R. Lardy from the Peterson Institute for International Economics, official Chinese statistics show that net inward FDI turned negative in 2022-2023. Inward FDI in China was much larger than outward FDI for several decades, since about 2000. However, recently, net inward FDI

factors may have played a role in the exit of Japanese MNEs from China. One factor may be increased competition from local producers, as illustrated by the growing market share of Chinese domestic competitors. Another factor may be Covid-19. In 2021, a surge of exits of Japanese MNEs not only from China but from countries worldwide was observed. Because of Covid-19, Japanese firms were unable to make decisions in 2020, as managers were unable to move between countries. Therefore, the decision to exit may have been postponed and implemented in 2021 instead. Finally, the U.S. export control policies may be another factor explaining the high share of exits of Japanese MNEs from China. Against this background, the purpose of this paper is to examine how U.S. export controls affected Japanese MNEs, with a particular focus on microdata related to their exit from China.

Figure 1. Exit shares: Manufacturing sector, 2010-2021

Note: The figure shows the percentage of Japanese affiliates exiting from the regions shown in the total number of affiliates in a region or country. Exit is defined at the country level and then aggregated to the region level as the sum of all exits. For China, this is the total number of exits from China divided by the total number of affiliates.
Source: Authors' calculations using the Basic Survey on Overseas Business Activities.

However, analyzing this issue poses several difficulties. The first one concerns measurement. To examine the impact of export controls we use trade data based on export product codes at the U.S. HS 10-digit level. The U.S. export controls are based on Export Control Classification Numbers (ECCN), which are accompanied by descriptions of products and their characteristics in the Export Administration Regulations. The two classification systems – i.e., the export product codes and the ECCN – are quite different, so that we need to use the correspondence between U.S. export codes and export controls provided in Deseatnicov et al. (2024). Then, to measure the reduction in intermediate input variety in China due to U.S. export controls, we manually examine all Federal Register documents that address changes in the Export Administration Regulations in the period 2017–2021. We count the number of

turned negative. This observation suggests that there has been an important pattern of disinvestment in China by firms from the U.S. and other countries. See: https://www.piie.com/blogs/realtime-economics/foreign-direct-investment-exiting-china-new-data-show (accessed June 22, 2024).

mentions of each ECCN and also classify each mention in terms of whether it signifies a strengthening or weakening of controls or has no effect. Matching the mentioned ECCNs to the HS 10-digit product level classification, we identify items at the HS 10-digit product level that are subject to changes in export controls. This allows us to construct a variety index that measures the variety of imported intermediate inputs available. The index indicates that U.S. export controls have been strengthening since 2018, and especially since 2020.

The second issue complicating examination of the impact of U.S. export controls on Japanese MNEs operating in China is indirect effects. Export controls restricting access to intermediate inputs using advanced U.S. technology affect production costs at the industry level in China not only directly but also indirectly through the input-output network. Therefore, we take the input-output (IO) table into account and introduce a push-cost IO model that allows us to capture direct and indirect linkages between industries. Using this model, we derive the intermediate input cost vector at the industry level which is induced by the decrease in the variety of intermediate inputs as measured by the variety index explained above. In this approach, we introduce two models: the *China domestic model* and the *GVC model.* The first, the *China domestic model*, exploits the benefits of the detailed industry classification available in the China IO table, and is constructed specifically to analyze domestic input-output relationships in China. The second, the *GVC model*, considers the global transmission mechanism of export controls induced by global direct and indirect linkages between countries and industries. For this analysis, we use the World Input-Output Table (WIOT) provided by the University of Groningen World Input-Output Database (WIOD), the industry classification of which is more aggregated than that of the China IO table. We use the two models to obtain the intermediate input cost vector at the industry level, which captures the effect of U.S. export controls.

Third, we conjecture that intermediate inputs variety affects production costs. As explained above, we obtain our variety index using the count of ECCN mentions in the Federal Register documents and the corresponding HS 10-digit level products. However, the detailed HS 10-digit level classification is not sufficiently granular to elucidate the economic impact of export controls because they are based on a "small yard, high fence" approach. For example, even at the HS 10-digit product level, U.S. exports of semiconductors to China have not declined substantially because export controls focus only on certain types of semiconductors. To reconcile our IO framework, which takes direct and indirect effects into account, and our variety index, we conjecture that when new products or technologies are added to U.S. export controls for a certain HS 10-digit level product (measured by the variety index), this will increase the production costs of importers in China. We offer a simple theoretical model. A representative firm faces production costs that are determined by its total factor productivity (TFP), labor costs, capital service costs, and intermediate inputs costs. A feature that we introduce in the model is that the representative firm sources intermediate inputs from both the domestic and foreign markets. Thus, an increase in U.S. export controls that reduces the variety of foreign intermediate inputs increases production cost in China.

Using our variety index measuring the evolution of export controls for a number of products at HS10-digit level, as well as the push-cost IO model and the theoretical model, we construct an export controls index. The export controls index aims to measure the economic impact of the U.S. export controls taking into account the industry-level effects on production cost in China of the change in access to the variety of imported intermediate inputs via input-output linkages. We refer to this index as the "China IO export controls index" when it is calculated using the China domestic model and the "GVC model export controls index" when it is calculated using the GVC model.

The China IO export controls index we construct shows that the top five industries that saw an increase in export controls in 2017-2021 were electronic computers and related equipment; communication equipment and related equipment, video and audio equipment; electronic equipment; office, service and entertainment equipment; and optical instruments and lenses. Moreover, these five industries are also the industries that experienced the greatest strengthening of regulations between 2019 and 2021.

Our empirical analysis relies on Japanese micro-level data such as the Basic Survey on Overseas Business Activities for 2017–2021. We run a regression where the probability of exit of Japanese MNEs is the dependent variable and the export control index is the key explanatory variable. Controlling for other factors, we obtain robust results showing that an increase in U.S. export controls is associated with a higher probability of Japanese MNEs exiting from China. For example, we find that a one standard deviation increase in the China IO export controls index leads to an increase in the probability of exit by 0.79 percentage point. Specifically, the China IO export controls index for the communication equipment and related equipment, video and audio equipment industry increased by about four standard deviations between 2019 and 2021, which was associated with an increase in the probability that Japanese MNEs in that industry exited from China by 2.63 percentage points.

Moreover, when we use the GVC model export controls index, we find that an increase in this index by one standard deviation is associated with an increase in the likelihood of Japanese MNEs' affiliates exiting from China by 2.52 percentage points. We conduct a number of robustness checks, which overall provide support in favor of the theoretical mechanism we propose as an explanation of Japanese MNEs' exit from China. We therefore conclude that intermediate input imports play an important role in MNEs' decision whether to exit a market, and that the increased U.S. export controls played a role in Japanese MNEs' exit from China.

Our analysis shows that U.S. export controls potentially have important implications for the (re)configuration of GVCs. That is, the export controls may create incentives for global MNEs to restructure their production chains. Specifically, it might lead MNEs to reconsider the location of production activities based on the possibility that a location might become subject to U.S. export restrictions.

Our study is related to various strands in the literature. The first is that on MNEs' choice of production location. An extensive summary of the main theoretical approaches to MNEs' decisions is provided by Antràs and Yeaple (2014). Studies examining the determinants of Japanese MNEs' choice of FDI location include those by Belderbos et al. (2013), Deseatnicov et al. (2021), Hayakawa and Matsuura (2011), Kimura and Kiyota (2006), and Kiyota and Urata (2008). However, while these studies mainly examine the decision to enter foreign markets via FDI, the focus of our study is to examine the FDI exit decision.

To the best of our knowledge, the literature on FDI exit is relatively scarce. Notable exceptions include the study by Gonchar and Greve (2022), who examine the effect of political risk on MNEs' exit from Russia. Deseatnicov and Klochko (2023) show that the propensity of exit of German firms from Russia increased considerably after 2014 (the start of the Russia-Ukraine conflict). One recent study that examines the exit of Japanese MNEs from China using the same microdata as we do in this study is that by Luo et al. (2022). They show that affiliate size, profitability, labor productivity, trade with Japan, parent size, and experience in China, as well as geopolitical tensions, are important determinants of whether Japanese MNEs' affiliates exited from China. Our study differs from those mentioned here in that we focus on the role of GVCs and intermediate input imports as an important determinant of firms' exit decision.

Another strand of literature related to our study is that on the gains from trade and the role of the love of variety, a concept introduced by Krugman (1980). Broda and Weinstein (2006), for example, quantified the elasticities of substitution between product varieties and estimated the gains from trade. A recent work of Gouel and Jean (2023) incorporate the love-of-variety elasticity into households' final demand function to examine the role of love of variety in welfare using various theoretical trade models. In contrast, endogenous growth literature incorporates elasticity parameter in the production function, characterizing degree of returns to specialization given by number of intermediate goods (Ethier 1982, Benassy 1998). Our theoretical model is built in the latter spirit. It focuses on the behavior of a representative firm and its production function, which features elasticity parameter with regard to number of imported intermediate inputs.

Our paper is also related to another strand of literature, namely studies examining the structure and formation of GVCs. Antràs and Chor (2022) provide an extensive summary of this literature. An important aspect of GVC participation relevant to our study is countries' vulnerability to foreign supply shocks. Baldwin et al. (2022) discuss GVC participation measures that capture such vulnerability. In this context, MNEs' decisions about their production and sales locations play an important role in GVCs (Alfaro et al., 2019) as they may influence countries' exposure to GVCs and foreign supply shocks. Against this background, we examine a specific aspect of this dynamic: MNEs' decision to exit foreign markets in response to U.S. export controls, leading to GVC restructuring. To capture the GVC context in our analysis, we construct the export controls index using input-output tables.

The final strand of literature related to our study is the burgeoning literature examining the effect of the export controls of the U.S. and aligned countries on their trade with China. A number of recent studies have explored this process for Asia and Japan (Ando et al., 2024, 2023; Hayakawa, 2024; Hayakawa et al., 2023). Deseatnicov et al. (2024) investigated the impact of export controls on U.S. trade with China. Our study differs from these preceding studies in that we examine the effect of export controls at the firm level using microdata. Our study therefore offers a different but complementary perspective on this issue.

In sum, our contribution is three-fold. First, to the best of our knowledge, this is the first study to examine the effect of U.S. controls on China's economy at the micro level. Second, we offer a novel index, the variety index, to capture the change over time in the severity of U.S. export controls at the HS 10-digit product level and the corresponding industry level. Third and finally, we incorporate an elasticity parameter characterizing degree of returns to specialization given by number of foreign intermediate goods in the production function to derive an export controls index. We test empirically whether the export controls index is correlated with Japanese MNE affiliates' probability of exit from China. We confirm that the decrease in intermediate input imports due to U.S. export controls provides a plausible explanation of the increase in the likelihood of Japanese MNE affiliates' exit from China.

The remainder of the study is organized as follows. Section 2 explains the construction of our variety index based on an examination of Federal Register documents. Section 3 then provides our theoretical framework, derives the export controls index using input-output tables, and presents developments in the export controls index. Next, Section 4 describes our firm-level data and variables used in the analysis, while Section 5 presents our econometric approach and discusses the results and findings. Finally, Section 6 provides concluding remarks.

2. U.S. export controls and the variety index

Tensions between the U.S. and China have not been limited to the tariff war.[4] Concerned over the leakage of technological knowledge to China, U.S. authorities started to tighten export controls on products containing U.S. technology. One example is the inclusion of Huawei in the Entity List in May 2019, which limits Huawei's ability to purchase advanced communications equipment developed in the U.S. or outside the U.S. but using U.S. technology.

The implementation of U.S. export controls can be summarized as follows.[5] The government body in charge of the administration, implementation, and enforcement of the Export Administration Regulations is the BIS. As part of this, the BIS maintains a list of Export Control Classification Numbers (ECCN). Each ECCN encompasses products that may require a license to be exported out of the U.S depending on the nature of the product and the export destination. ECCNs consist of five alphanumeric characters followed by more detailed classification identifiers of varying length.[6]

In this study, we examine how announcements regarding changes in the ECCN descriptions affected the business of Japanese MNEs in China. In order to do so, we take the following four steps.

Step 1. Identification of export controls mentioned in the Federal Register documents

We examine 61 Federal Register documents published by the BIS in the period 2017–2021.[7] The Federal Register documents present changes in the Export Administration Regulations. The goal of our analysis is to identify ECCNs at the five-digit level that were mentioned in the documents. The scope of Federal Register documents varies, so that ECCNs may be mentioned for several reasons. For example, the document titled "Wassenaar Arrangement 2018 Plenary Decisions Implementation" details ECCNs that were revised as well as the specific changes decided at the Wassenar Arrangement 2018 Plenary meeting.[8] We classify mentions in these documents into three categories: the strengthening of controls, the weakening of controls, and revisions with a neutral effect on controls. Take, for example, the case where control over a more sophisticated technology used for producing a product within a particular ECCN is added in the description of that ECCN.[9] We classify this as a strengthening

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[4] During the tariff war, both China and the U.S. have increased tariffs on imports of certain products at the HS8 digit import code level in the case of China and the HS10 digit import code level in the case of the U.S. However, what we want to examine is not the impact of the product level tariff war but the effect of export controls at the industry level.

[5] For a more detailed outline, see Hayakawa et al. (2023).

[6] An example is "3A001.b.2," which refers to monolithic microwave integrated circuit amplifiers. The first alphanumeric character, 3, indicates that the product falls into the category of electronics. The second alphanumeric character, A, indicates that the product falls under the group end items, equipment, accessories, attachments, parts, components, and systems. The remaining alphanumeric characters identify the specific item.

[7] We collected information for the period 2017–2023. However, because the Japanese micro-data we use is available only until 2021, our analysis covers the period 2017–2021.

[8] The Wassenaar Arrangement 2018 Plenary Decisions implemented certain new controls on emerging technologies such as equipment for the manufacturing of semiconductor devices, optical sensors and equipment, and gas turbine engine parts. The Decisions came into effect on September 11, 2020. Forty-nine ECCNs at the 5-digit level were affected by this change. In our data, we excluded one Federal Register document mentioning ECCNs (titled "Elimination of License Exception Civil End Users (CIV) Final Rule," effective June 29, 2020), since it covered almost all ECCNs.

[9] For instance, Federal Register Vol. 85, No. 177, titled *Wassenaar Arrangement 2018 Plenary Decisions Implementation; and Other Revisions Related to National Security Controls*, released on September 11, 2020, outlines a revision to Supplement No. 6 to Part 774, the 'Sensitive List.' The revision adds new paragraph (3)(i) 3A001.b.2—'Monolithic Microwave Integrated Circuit' (MMIC) amplifiers—and new paragraph

of controls, since such a change usually means that the number of licenses for that ECCN will increase. We hypothesize that this, in turn, increases uncertainty for Japanese MNEs in China when importing the specified intermediate good. On the other hand, if a Federal Register document indicates a relaxation of controls over a product under an ECCN, we classify this as a weakening of controls, since it is likely that the number of export license applications for products falling under the ECCN will decrease.[10] Finally, if a mention simply reflects an editorial change, a wording change, or some other insignificant change, we classify the mention as neutral. Overall, we conjecture that the mention of an ECCN may be a signal for firms that the item is subject to more careful control.

A particularly useful feature of the procedure we employ is that it allows us to examine changes in controls over time. While the items under a specific ECCN and the ECCN classifications do not change much over time, the ECCN mentions indicate the evolution of U.S. authorities' attitude to controls with regard to those ECCNs over time. For example, certain semiconductors may be subject to controls for the entire period. However, they may be mentioned several times in the documents, indicating that firms need to carefully consider what technologies they use in the production of those semiconductors if exported so as not to fall foul of export restrictions. This provides BIS with an additional tool to control exports of certain advanced technologies. In particular, if BIS is concerned about exports of U.S. advanced technology to China, it may limit the number of export licenses for such products to China. Given our approach, we can track these changes in the BIS regulations over time at the five-digit ECCN level.

Step 2. Identification of products at the HS 10-digit level mentioned in the Federal Register documents

In Step 1 we focused on ECCNs at the five-digit level and recorded the date on which a change mentioned in the Federal Register documents became effective. In Step 2, we use the correspondence between ECCNs and HS 10-digit tariff codes to identify HS 10-digit level products that were subject to export controls by the U.S. authorities.[11] As a result, we obtained a list of HS 10-digit level codes and the corresponding effective dates of changes mentioned in the Federal Register documents. Figure 2 shows the share of mentioned HS 10-digit level products in the total number of HS-10 digit level products mapped to the ECCNs.[12] The figure shows two peaks in the share of mentions that represent a strengthening of regulations, namely, in 2018 and 2020. This suggests that U.S. authorities strengthened export controls in these years.

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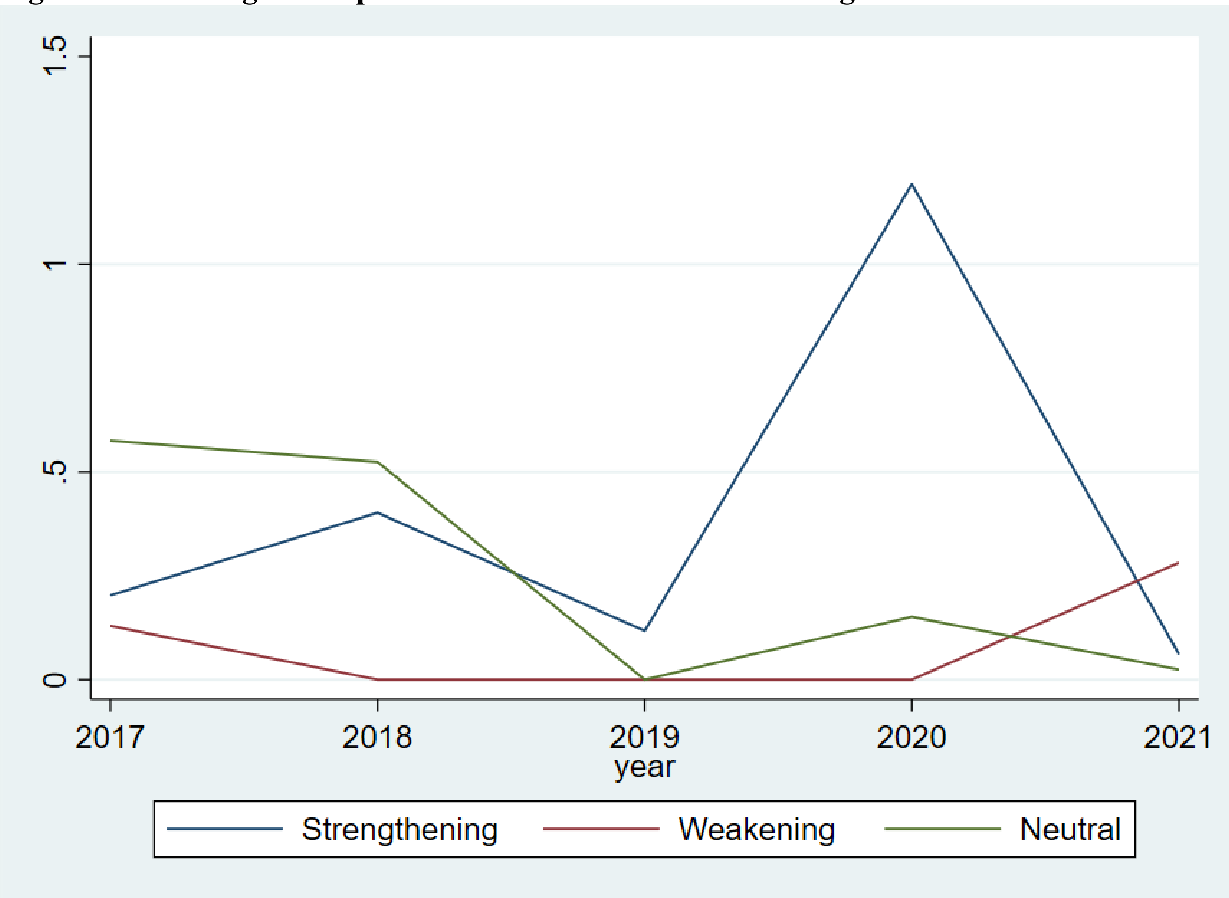
(3)(ii) 3A001.b.3—discrete microwave transistors, citing that these items require heightened levels of control and monitoring. We interpret this as an increase in U.S. export control for these items. In our analysis, we map ECCN code 3A001.b.2 to HS 10-digit code 8517700000, which pertains to 'Parts for apparatus for transmission or reception of voice, images, or other data, including apparatus for communication in a wired or wireless network.'

[10] For example, Federal Register Vol. 83, No. 206, titled *Wassenaar Arrangement 2017 Plenary Agreements Implementation*, released on October 24, 2018, states that "Linear Variable Differential Transformer (LVDT) systems, formerly under 2B006.b.1.b, are moved to 2B206.d and no longer carry a national security control." We interpret this change as a decrease in U.S. export control for the specified item. In our mapping, we associate ECCN code 2B006.b.1.b with HS 10-digit code 9031100000, which pertains to 'Machines for balancing mechanical parts.'

[11] We obtained the correspondence between the ECCNs and HS 10-digit tariff codes from Deseatnicov et al. (2024). They obtained the correspondence using various methods including manual mapping and machine learning methods. In the current analysis, we rely on manual mapping restricted to one best match using machine learning tools (see the description of Dataset 4 in Deseatnicov et al., 2024).

[12] The total number of controlled HS 10-digit level products in our dataset is 956. The total number of HS 10-digit level products is 9,383.

Figure 2. HS10-digit level product mentions in the Federal Register



Note: Share of mentions in the Federal Register documents of HS10 digit level products in the total number of controlled items over the period 2017–2021. Strengthening refers to the share of the number of HS10 product mentions representing a strengthening of regulations in the total number of controlled products. Weakening refers to the share of the number of HS10 product mentions representing a weakening of regulations in the total number of controlled products. Neutral refers to the share of the number of HS10 product mentions that are neutral in the total number of controlled products.

Step 3. Construction of the industry-level index of mentions of export controls to China

We use the mentions of HS 10-digit level codes to construct our industry-level index of mentions of export controls to China. Assuming that affiliates of Japanese MNEs use intermediate inputs containing U.S. technology in their production, an increase in export controls potentially raises their production costs due to limited access to intermediate inputs within their supply chain.[13]

In order to construct the index at the industry level, we use the mapping of industries in the input-output (IO) tables for China to HS 8-digit level codes provided by Chen et al. (2023).[14] The mapping is provided for 1997, 2002, 2007, 2012 and 2017. We use the mapping for 2017, which covers 99 industries, 83 of which are manufacturing industries. The total number of industries in the 2017 China IO tables is 149. The remaining 50 industries are non-manufacturing industries, and we assume that they do not directly import foreign intermediate inputs. Using the mapping of HS codes and China IO table industries, we can calculate the

13 According to Nikkei Asia, many Asian producers with plants in China, such as Sony, rely on American technology in chip design and chipmaking equipment, and therefore are affected by U.S. export controls. See, e.g.: https://asia.nikkei.com/Spotlight/Most-read-in-2021/US-China-tech-war-Beijing-s-secret-chipmaking-champions, accessed on February 23, 2024.

14 The mapping is available at https://github.com/abumazan/Interprovincial-IO-database/tree/main.

extent to which each industry is exposed to the U.S. export controls. To do so, we use the HS 6-digit classification, which is identical for the U.S. and China, to map our dataset of export controls and the China IO industries. We use two approaches to compute the index of China export controls mention. The first is given by the following formula:

$$Export\ controls\ mentions\ index\ (Trade\ weighted)_{i,\tau} = \frac{\sum_{k\in I_i} n_{k,\tau} x_{k,2017}}{\sum_{p\in I_i} x_{p,2017}}$$

where the index of China export controls mentions for industry i is computed as a trade weighted index. $n_{k,\tau}$ is the number of mentions in year τ of product i at the HS 10-digit level that falls under industry i. $n_{k,\tau}$ for each product k is computed as the difference between the number of mentions representing a strengthening of export controls and the number of mentions representing a weakening of export controls. This allows us to track the evolution in U.S. authorities' policy with respect to each HS 10-digit level product. $x_{k,2017}$ represents the amount of exports of controlled product k from the U.S. to China in 2017.[15, 16] We use trade data for 2017 to compute the index in order to avoid endogeneity bias in the index and the regression analysis that follows.[17] $x_{p,2017}$ represents exports from the U.S. to China in 2017 of product p in industry i. The numerator is computed using the subset of industry i products that are controlled and are mentioned in the Federal Register documents in each period. The denominator is computed for all products that belong to industry i.[18] We compute the index for the period 2017–2021.

The second approach to computing the index is based on the number of mentions only:

$$Export\ controls\ mentions\ index\ (Frequency)_{i,\tau} = \frac{\sum_{k\in I_i} n_{k,\tau}}{\sum_{p\in I_i} n_p}$$

where $n_{k,\tau}$ is the number of mentions of product k at that HS 10-digit level in industry i in year τ , and is computed as explained above. The denominator is the total number of HS10 digit level products in industry i.

Step 4. Construction of the industry-level variety index for China

Finally, to measure the decline in product variety over time as a result of U.S. export controls, we assume that the variety of imported industry i products in year t - $N_{i.t}$, is expressed by the following equation:

$$N_{i.t} = N_{i.t}^{*} \times \exp\left(-\alpha \sum_{\tau=-\infty}^{t} Index_{i,\tau}\right)$$

where $N_{i.t}^{*}$ denotes the variety of imported industry i products in year t that are not subject to

15 The U.S. export data is obtained from the Global Trade Atlas (IHS Markit).

16 Our benchmark index and estimation of the index of China export controls mentions rely on all products. However, we also conduct a robustness check using an index of export controls computed for products for intermediate use only. In order to identify whether an HS10-digit level product belongs to the subset of intermediate products we use the correspondence between HS6-digit level products and Broad Economic Category (BEC) end-use categories. We use the following three BEC end-use categories: intermediate, capital, and consumption. We obtain the correspondence from Chen et al. (2023) and the dataset accompanying the paper, which is available at https://github.com/abumazan/Interprovincial-IO-database/tree/main.

17 Note that in this analysis we use the HS2017 classification. We therefore use the earliest possible year to calculate the index.

18 We assume that each HS 10-digit level product falls into one industry only. Although there are cases in which a product could be matched to several industries, we do not do so to eliminate complexity and potential measurement error bias that could result.

export control. We assume that $N_{i.t}^*$ grows at industry-specific constant rate g_i. Thus, we obtain

$$N_{i.t} = N_{i.0}^* \times \exp\left(g_i t - \alpha \sum_{\tau=-\infty}^{0} Index_{i,\tau} - \alpha \sum_{\tau=0}^{t} Index_{i,\tau}\right)$$

for $t \geq 0$.

Under these assumptions, the variety index can be expressed as follows:

$$\widehat{N}_i^M(t) = ln\,(N_{i.t}) - ln\,(N_{i.0}) = g_i t - \alpha \sum_{\tau=0}^{t} Index_{i,\tau}$$

where $Index_{i,\tau}$ is either $Export\ controls\ mentions\ index\ (Trade\ weighted)_{i,\tau}$ or $Export\ controls\ mentions\ index\ (Frequency)_{i,\tau}$. We regard an increase in $\widehat{N}_i^M$ as an increase in the strictness of U.S. export controls. Assuming that g_i is identical across industries, we use this variety index to compute changes in production costs at the industry level in China in 2017–2021 as described in the next section.

3. Theoretical framework and export controls index

As mentioned, we argue that one of the mechanisms that can lead to an increase in production costs is a decrease in the variety of intermediate inputs. To formalize this idea, we develop a simple theoretical framework.

We assume that the production function of the representative firm in industry i of country h is

$$x_{h,i} = \pi_{h,i}(k_{h,i})^{\alpha_{hi}}(l_{h,i})^{\beta_{hi}} \prod_{j=1}^{I}\left[D^H{}_{j,h,i}\right]^{\gamma^H{}_{j,hi}} \prod_{j=1}^{I}\left[D^M{}_{j,h,i}\right]^{\gamma^M{}_{j,hi}} \quad (1)$$

where $x_{h,i}$, $\pi_{h,i}$, $k_{h,i}$, and $l_{h,i}$ denote gross output, gross output-based TFP, capital input to industry i, and labor input to industry i. $D^H_{j,h,i}$ and $D^M_{j,h,i}$ denote the composite intermediate input to industry i from industry j's domestic output and from industry j's output produced abroad and imported, which are defined by

$$D^H{}_{j,h,i} = \left[N^H{}_j^{\{\nu_j(\sigma_j-1)-1\}/\sigma_j} \sum_{n=1}^{N^H{}_j}\left(d^H{}_{n,j,h,i}\right)^{(\sigma_j-1)/\sigma_j}\right]^{\sigma_j/(\sigma_j-1)} \quad (2)$$

$$D^M{}_{j,h,i} = \left[N^M{}_j^{\{\nu_j(\sigma_j-1)-1\}/\sigma_j} \sum_{n'=1}^{N^M{}_j}\left(d^M{}_{n',j,h,i}\right)^{(\sigma_j-1)/\sigma_j}\right]^{\sigma_j/(\sigma_j-1)} \quad (3)$$

$d^H_{n,j,h,i}$ denotes intermediate input of variety n, which is domestically produced in industry j, while $d^M_{n',j,h,i}$ denotes intermediate input of variety n', which is imported from industry j abroad. N^H_j and N^M_j denote the total number of varieties in industry j in country h and the total number of varieties in industry j of the rest of the world. ν_j denotes the elasticity parameter, characterizing degree of returns to specialization with regard to intermediate inputs for industry j products (Benassy 1998).[19] We assume $\sigma_j > 1$ and $\nu_j > 1/(\sigma_j - 1)$.

$\alpha_{hi}, \beta_{hi}, \gamma^H{}_{j,hi}, \gamma^M{}_{j,hi}$ are parameters, characterizing the production structure. We assume constant returns to scale:

$$\alpha_{hi} + \beta_{hi} + \sum_{j=1}^{I}\gamma^H{}_{j,hi} + \sum_{j=1}^{I}\gamma^M{}_{j,hi} = 1$$

Cost minimization of the representative firm yields the demand for intermediate input, labor,

[19] This approach to distinguish number of intermediate good varieties in production function was used in the literature on endogenous economic growth (Ethier 1982, Benassy 1998). Identical approach of modelling demand function, called love of or taste for variety, was used in international trade literature as well (Benassy 1996, Gouel and Jean 2023).

and capital:

$$d^H{}_{n,j,hi} = \gamma^H{}_{j,hi}\left(\frac{p^H{}_{nj}}{\varphi^H{}_{j,hi}}\right)^{-\sigma_j}\frac{1}{N^H{}_j}\frac{c_{hi}x_{hi}}{\varphi^H{}_{j,hi}} \tag{4}$$

$$d^M{}_{n\prime,j,hi} = \gamma^M{}_{j,hi}\left(\frac{p^M{}_{n\prime j}}{\varphi^M{}_{j,hi}}\right)^{-\sigma_j}\frac{1}{N^M{}_j}\frac{c_{hi}x_{hi}}{\varphi^M{}_{j,hi}} \tag{5}$$

$$l_{hi} = \beta_{hi}\frac{c_{hi}x_{hi}}{w_{hi}} \tag{6}$$

$$k_{hi} = \alpha_{hi}\frac{c_{hi}x_{hi}}{r_{hi}} \tag{7}$$

where $c_{h,i}$ denotes average production costs, $\varphi^H{}_{j,h,i}$ denotes the average price of intermediate inputs produced in domestic industry j, and $\varphi^M{}_{j,h,i}$ denotes the average price of intermediate inputs from industry j imported from abroad. Price indices $\varphi^H{}_{j,h,i}$ and $\varphi^M{}_{j,h,i}$ are given by:

$$\varphi^H{}_{j,hi} = \left\{\sum_{n=1}^{N^H{}_j}\frac{1}{N^H{}_j}\left(p_{nj}^{(1-\sigma_j)}\right)\right\}^{1/(1-\sigma_j)} \tag{8}$$

$$\varphi^M{}_{j,hi} = \left\{\sum_{n\prime=1}^{N^M{}_j}\frac{1}{N^M{}_j}\left(p_{n\prime j}^{(1-\sigma_j)}\right)\right\}^{1/(1-\sigma_j)} \tag{9}$$

The growth rate of the average production cost of the representative firm is approximated by

$$\hat{c}_{hi} = -\hat{\pi}_{hi} + \alpha_{hi}\hat{w}_{hi} + \beta_{hi}\hat{r}_{hi} + \sum_{j=1}^{I}\gamma^H{}_{j,hi}\left(\hat{\varphi}^H{}_{j,hi} - \nu_j\hat{N}_j^H\right) + \sum_{j=1}^{I}\gamma^M{}_{j,hi}\left(\hat{\varphi}^M{}_{j,hi} - \nu_j\hat{N}_j^M\right) \tag{10}$$

When the U.S. prohibits the export of some of industry j products, $N^M{}_j$ will decline. With elasticity parameter, characterizing degree of returns to specialization given by number of intermediate goods ($\nu_j > 1/(\sigma_j-1)$), this will raise the production cost of industries in country h that use imported products of industry j as intermediate inputs.

We approximate the growth rate using the log difference for each variable. The natural log of the average production costs of the representative firm in industry i of country h in year t can then be approximated by

$$\begin{aligned} lnc_{hi}(t) = {} & lnc_{hi}(0) - ln\pi_{hi}(t) + ln\pi_{hi}(0) + \alpha_{hi}\{lnw_{hi}(t) - lnw_{hi}(0)\} \\ & + \beta_{hi}\{lnr_{hi}(t) - lnr_{hi}(0)\} \\ & + \sum_{j=1}^{I}\gamma^H{}_{j,hi}\left[\left\{ln\varphi^H{}_{j,hi}(t) - ln\varphi^H{}_{j,hi}(0)\right\} - \nu_j\left\{lnN^H{}_j(t) - lnN^H{}_j(0)\right\}\right] \\ & + \sum_{j=1}^{I}\gamma^M{}_{j,hi}\left[\left\{ln\varphi^M{}_{j,hi}(t) - ln\varphi^M{}_{j,hi}(0)\right\} - \nu_j\left\{lnN^M{}_j(t) - lnN^M{}_j(0)\right\}\right] \end{aligned} \tag{11}$$

Equation (11) will guide us in the analysis of the effect of export controls on industry-level production costs in China using the change in $N^M{}_j$. We approximate $N^M{}_j$ using the variety index $\hat{N}_j^M$ mentioned earlier. Note, however, that the variety of imported intermediate inputs also has an indirect effect on production costs. If the variety of some product declines, then production costs in other sectors in China will also increase. We therefore use the China IO table and examine the direct and indirect effects of a decrease in the variety of imported intermediate inputs on sectoral production costs in China via input-output linkages. In fact, such direct and indirect repercussions exist worldwide as well, and we take them into account using world input-output tables (WIOTs). However, WIOTs at the disaggregated industry level have certain limitations. For instance, the University of Groningen WIOT covers only 56 industries, 18 of which are manufacturing industries. [20]

To address these issues, we take the following strategy in our analysis. First, we examine the effect of export controls using the relatively disaggregated industry-level China IO table to take direct and indirect effects into account. Second, we use the University of Groningen WIOT to take global repercussions, i.e., global input-output linkages, into account. Finally, we take the direct and indirect effects of factor prices and TFP growth on industries' production costs within China into account, as shown in equation (11).

We assume Dixit-Stiglitz-type monopolistic competition. The output price of the representative firm in industry i of country h then is

$$p_{hi} = \frac{\sigma_i}{\sigma_i - 1} c_{hi} \tag{12}$$

The increase in production cost will be transmitted to other sectors in country h though IO relationships. The idea of the IO framework for computing production cost changes is based on the following cost-push price model.[21] Let the price change of industry j intermediate output in China resulting from the increased export controls be expressed as follows:

$$ln\eta_{h,j}(t) - ln\eta_{h,j}(0) = \sum_i a_{ij}[ln\eta_{h,i}(t) - ln\eta_{h,i}(0)] - \sum_i m_{ij} v_i \widehat{N}_i^M \tag{13}$$

where, $\eta_{h,j}$ is the price of one unit of intermediate output of industry j in China, a_{ij} is the direct domestic input coefficient of industry i into industry j, $\eta_{h,i}$ is the price of domestic inputs from industry i in China, m_{ij} is the direct imported intermediate input coefficient of industry i into industry j, v_i is the elasticity parameter, characterizing degree of returns to specialization given by number of intermediate inputs from industry i, and $\widehat{N}_i^M$ is the variety index explained in the previous section (an increase in $\widehat{N}_i^M$ can be interpreted as a decrease in variety, which translates into a production cost increase). Thus, in equation (13), we incorporate the impact of export controls as input-output repercussions for all sectors in China.

We assume that when the U.S. tightens its export controls for industry i products, the total number of varieties of products exported from the U.S. and aligned countries to China declines by $\widehat{N}_i^M \times 100$ percent. We also assume that the ratio of the total number of varieties of products imported from the U.S. and aligned countries over the total number of product varieties imported from the rest of the world can be approximated by m_{ij}^W/m_{ij}, where m_{ij}^W denotes the direct imported intermediate input coefficient of industry i of the U.S. and aligned countries into industry j. Thus, we obtain

$$ln\eta_{h,j}(t) - ln\eta_{h,j}(0) = \sum_i a_{ij}[ln\eta_{h,i}(t) - ln\eta_{h,i}(0)] - \sum_i m_{ij} \frac{m_{ij}^W}{m_{ij}} v_i \widehat{N}_i^M(t) \tag{14}$$

In the case of products with a high elasticity parameter v_i, it is probably difficult to substitute imports from one country with imports from other countries. Therefore, we approximate the coefficient v_i by the inverse of the import-import substitution elasticity

20 The University of Groningen World Input-Output Database (WIOD) provides WIOT data for 43 countries plus the rest of the world covering 56 sectors for the period 2000–2014 (Timmer et al., 2015). Alternatives, such as the OECD Inter-Country Input-Output tables, also exist. However, we also want to consider the impact of factor prices and TFP growth as outlined in equation (11). These effects can propagate through global input-output linkages, and the relevant data can be sourced from the WIOD.

21 For details of cost-push model see, for example, Miller and Blair (2022, Section 2.6.6) and Aydoğuş et al. (2018).

obtained from the Global Trade Analysis Project (GTAP) database documentation.[22]

In matrix form, this can be expressed as follows:

$$\widehat{\boldsymbol{\eta}_{\mathbf{China}}} = \mathbf{A}'_{\mathbf{China}}\widehat{\boldsymbol{\eta}_{\mathbf{China}}} + \mathbf{M}'_{\mathbf{China}}\boldsymbol{Diag}(\boldsymbol{\sigma}_{\mathbf{m}_{\mathbf{China}}})\widehat{\mathbf{n}_{\mathbf{China}}} \tag{15}$$

where, $\boldsymbol{\eta}_{\mathbf{China}}$ is the domestic intermediate input price vector in China, $\mathbf{A}'_{\boldsymbol{China}}$ is the transposed direct domestic input coefficient matrix, $\mathbf{M}'_{\boldsymbol{China}}$ is the transposed direct imported intermediate input coefficient matrix, $\boldsymbol{Diag}(\boldsymbol{\sigma}_{\mathbf{m}_{\boldsymbol{China}}})$ is a diagonal matrix with elements of vector $1/\sigma_m$ of the inverse elasticity of substitution on the main diagonal, and $\widehat{\mathbf{n}_{\mathbf{China}}}$ is a vector of variety index $\widehat{N}_i^M$ computed based on the number of mentions in the Federal Register documents.

Solving this equation for vector $\boldsymbol{\eta}$ yields

$$\widehat{\boldsymbol{\eta}_{\mathbf{China}}} = (\mathbf{I} - \mathbf{A}'_{\boldsymbol{China}})^{-\mathbf{1}}\mathbf{M}'_{\boldsymbol{China}}\boldsymbol{Diag}(\boldsymbol{\sigma}_{\mathbf{m}_{\boldsymbol{China}}})\widehat{\mathbf{n}_{\mathbf{China}}} \tag{16}$$

We call $\widehat{\boldsymbol{\eta}_{\mathbf{China}}}$ the China IO export controls index, which measures the effect of export controls on production costs and depends on the change in the number of imported intermediate input varieties given by the variety index, $\widehat{\mathbf{n}_{\mathbf{China}}}$, the elasticity of substitution between imported intermediate inputs, $\boldsymbol{Diag}(\boldsymbol{\sigma}_{\mathbf{m}_{\boldsymbol{China}}})$, the direct domestic input coefficient matrix, $\mathbf{A}'_{\boldsymbol{China}}$, and the imported intermediate input coefficient matrix, $\mathbf{M}'_{\boldsymbol{China}}$. We use this index to examine the effect of export controls on the probability of exit of Japanese MNEs' affiliates from China. An increase in this index represents an increase in production costs due to a decrease in intermediate input varieties that might increase the likelihood of exit of Japanese MNEs' affiliates from China.

To calculate the China IO export controls index given by equation (16), we use the IO table or China for 2017, which is provided in competitive form. However, for our analysis, we need a non-competitive IO table for China. Therefore, in order to obtain $\mathbf{A}'_{\boldsymbol{China}}$ and $\mathbf{M}'_{\boldsymbol{China}}$, we use trade data and the BEC classification to separate competitive $\mathbf{Z}$ into $\mathbf{Z}^{\mathbf{d}}$ and $\mathbf{Z}^{\mathbf{m}}$:

$$z_{ij}^d = z_{ij}^o(1 - a_i^m)$$
$$z_{ij}^m = z_{ij}^o a_i^m$$

where z_{ij}^o is competitive IO intermediate input from industry i to industry j, z_{ij}^d is domestic intermediate input from industry i to industry j, and z_{ij}^m is imported intermediate input from industry i to industry j.

a_i^m is the share of intermediate input imports in total intermediate inputs and is given by

$$a_i^m = \frac{m_i^o}{g_i^o} \times \frac{mHS8_i}{m_i}$$

where m_i^o is imports of industry i reported in the competitive 2017 China IO table, g_i^o is the total intermediate inputs use of industry i reported in the competitive 2017 China IO table,

[22]The GTAP database is a detailed database of trade, production, and consumption for multiple regions and sectors (https://www.gtap.agecon.purdue.edu/databases/default.asp). It is used for global economic modelling and analysis. We obtain import-import substitution elasticities from GTAP documentation Chapter 20 – Behavioral parameters (Dimaranan and McDougall, 2002). We use elasticities shown as sourcing imports (sigma-M) in Table 20.2 GTAP Substitution Elasticities provided for 57 industries. For the purpose of our index computation, we create a correspondence between the China IO table industries and the GTAP industries, so that every China IO table industry is associated with an elasticity of substitution. As a robustness check, we also experimented with computing our China IO export controls index without the elasticity of substitution. The results are identical to the benchmark case taking the elasticity of substitution into account, and are shown in robustness check section.

$mHS8_i$ is China's imports from the U.S. and aligned countries at the HS 8-digit level of intermediate inputs according to the BEC classification in 2017, and m_i is total imports of industry i in 2017. [23]

We compute the China IO export controls index using equation (16). The results are obtained at the China IO industry classification level for the period 2017–2021. We create a concordance between the industries in Japan's Basic Survey on Overseas Affiliates and the sectors in the China IO table for 2017.[24] This allows us to obtain the China IO export controls index for Japanese MNEs' affiliates operating in China at the industry level using Japan's industry classification.[25]

As discussed above, our second strategy is to consider the global direct and indirect effects of export controls. To do this, we use the University of Groningen WIOT and compute the GVC export controls index using the following formula:

$$\widehat{\boldsymbol{\eta}_{\mathbf{GVC}}} = (\mathbf{I} - \mathbf{A}'_{\mathbf{GVC}})^{-\mathbf{1}} \boldsymbol{Diag}(\boldsymbol{\sigma}_{\mathbf{m}_{\mathbf{GVC}}}) \widehat{\mathbf{n}_{\mathbf{GVC}}} \tag{17}$$

where $\boldsymbol{\eta}_{GVC}$ is the intermediate input cost vector and $\mathbf{A}'_{\mathbf{GVC}}$ is the transposed global technical coefficient matrix constructed from the WIOT of dimension 2464x2464 (43 countries plus rest of the world x 56 sectors). $\boldsymbol{Diag}(\boldsymbol{\sigma}_{\mathbf{m}_{GVC}})$ is a diagonal matrix with elements of vector $1/\sigma_m$ of the inverse elasticity of substitution on the main diagonal. We assume the same elasticity of substitution for all countries in the world. $\hat{\mathbf{n}}_{GVC}$ is the vector of the variety index $\widehat{N}_i^M$ computed based on the number of mentions in the Federal Register documents. The $\widehat{\mathbf{n}_{\mathbf{GVC}}}$ vector elements for all countries except China are zero.[26] The resulting GVC export controls index represents the costs arising from the global transmission of U.S. export controls. Using the correspondence between the WIOD sectors and Japan's industry classification in the Basic Survey on Overseas Business Activities we map the computed production costs to our dataset at the affiliate level.

Finally, we consider the effect of factor prices and TFP growth on production costs in China as given by equation (11). As discussed above, this effect may be transmitted both directly and indirectly via input-output linkages. Therefore, we use the WIOT and compute the following production cost variable for each year t ($t \in [2017,2021]$) using:

$$IO\text{x}[w + r - tfp] = (\mathbf{I} - \mathbf{A}'_{\mathbf{GVC}})^{-\mathbf{1}} [\boldsymbol{w} + \boldsymbol{r} - \boldsymbol{tfp}] \tag{18}$$

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23 For our analysis, we classify "the U.S. and aligned countries" as countries falling into Country Groups A:5 and A:6 in Supplement No. 1 to Part 740 of the Export Administration Regulations. (https://www.ecfr.gov/current/title-15/subtitle-B/chapter-VII/subchapter-C/part-740/appendix-Supplement%20No.%201%20to%20Part%20740 accessed on March 10, 2024). The following countries are included as countries that have aligned themselves with U.S. export control policies: Albania, Argentina, Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, South Korea, Latvia, Lithuania, Luxembourg, Malta, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Singapore, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom. In our empirical analysis, we conduct a robustness check using only imports from the U.S. We use the mapping of HS8-digit level products to the China IO industries and the BEC classification from Chen et al. (2023). We thank Wenyin Cheng for providing us with import data for China at the HS8-digit level product classification.

24 The concordance is available upon request.

25 The total number of industries in Japan's classification is 84. We work with the 48 industries that belong to the manufacturing sector.

26 To obtain the GVC export controls index for the WIOD industries, we proceed as follows. We create the correspondence between the China IO table industries and the WIOD industries and then compute the GVC export controls index for the WIOD industries. The index for a particular WIOD industry is calculated as the average of the GVC export controls indexes of the corresponding China IO industries.

where $\mathbf{A}_{\boldsymbol{GVC}}$ is the global technical coefficient matrix, which is derived from the University of Groningen WIOT for 2014. $\boldsymbol{w}$ is a vector in which each element represents country-industry wage growth rates $(lnw_{hi}(t) - lnw_{hi}(0))$.[27] Wages are proxied by GDP per capita expressed in Japanese yen.[28] $\boldsymbol{r}$ is a vector where each element represents country-industry capital service cost growth rates $(lnr_{hi}(t) - lnr_{hi}(0))$. The data for capital service costs are taken from the Japan Industrial Productivity Database (JIP) 2023.[29] $\boldsymbol{tfp}$ is a vector where each element represents country-industry TFP growth rates $(ln\pi_{hi}(t) - ln\pi_{hi}(0))$. We obtain data for country-industry TFP growth rates from Cheng et al. (2024).[30]

Table 1 provides descriptive statistics of the China IO export controls index based on the China IO tables (domestic model) and the GVC export controls index based on the WIOT (GVC model) as well as the production cost variable for the period 2017–2021 for the 48 manufacturing industries in Japan's Basic Survey on Overseas Business Activities.

Table 1 Summary statistics of the export controls index and production cost

Export controls index	Obs.	Mean	Std. dev.	Min	Max
China domestic model ($\widehat{\boldsymbol{\eta}_{\mathbf{China}}}$)					
$\widehat{\boldsymbol{\eta}_{\mathbf{China}}}$ based on index $\widehat{N}_i^M$ via					
$IndexTrade_{i,\tau}$	240	0.016	0.034	-0.011	0.226
$IndexFrequency_{i,\tau}$	240	0.008	0.012	-0.002	0.075
GVC model (China part of $\widehat{\boldsymbol{\eta}_{\mathbf{GVC}}}$)					
$\widehat{\boldsymbol{\eta}_{\mathbf{GVC}}}$ based on index $\widehat{N}_i^M$ via					
$IndexTrade_{i,\tau}$	240	0.300	0.397	-0.051	2.408
$IndexFrequency_{i,\tau}$	240	0.187	0.225	-0.017	1.239
WIOD production cost (China part)					
$IO\text{x}[w + r - tfp]$	240	0.163	0.138	-0.050	0.653

Notes: The table shows statistics for the 48 manufacturing industries in Japan's Basic Survey on Overseas Business Activities classification, which are used in our regression analysis.

Figure 3 shows the China IO export controls index for 2021 computed using the trade weighted variety index $\widehat{N}_i^M$ and the China IO table. The figure shows that the manufacture of electronic computers and related equipment, the manufacture of communication, video and audio equipment, and the manufacture of electronic equipment have the highest China IO

27 See equation (11).

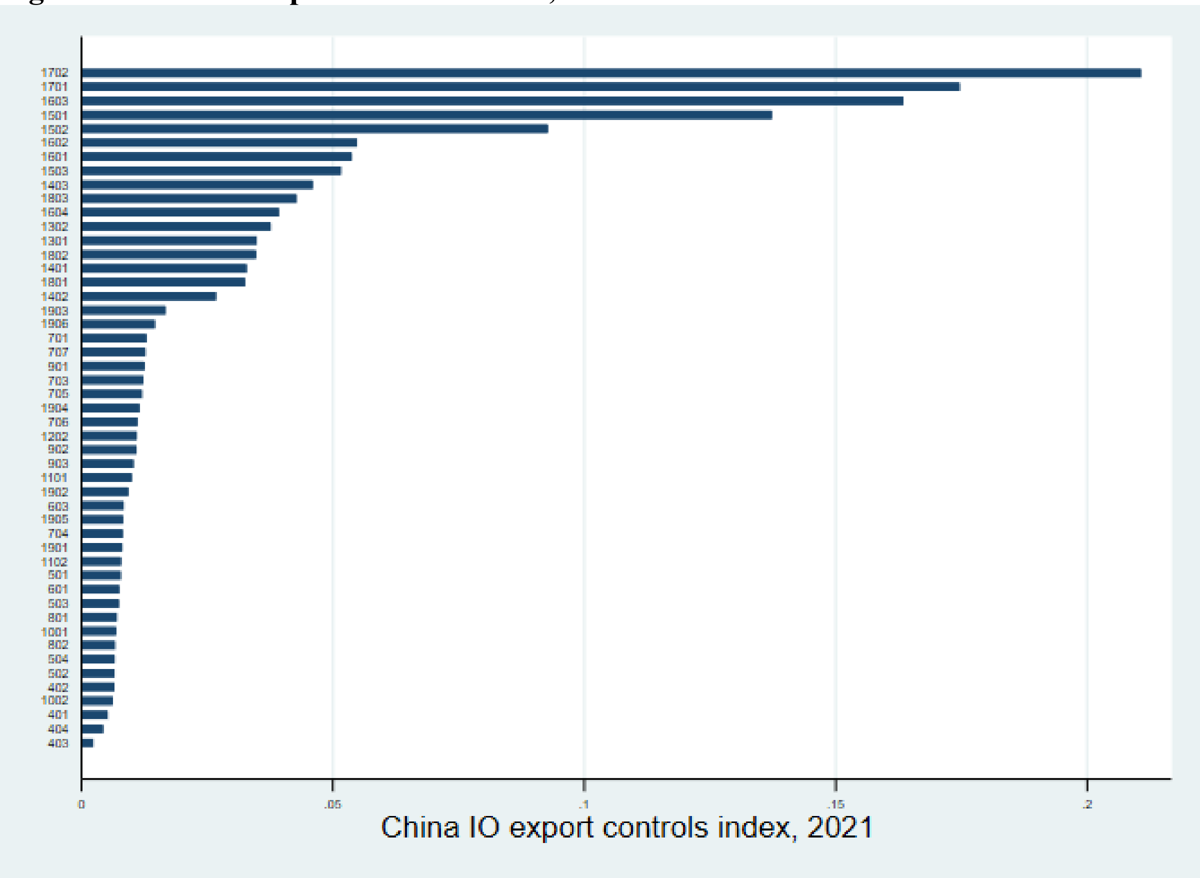
28 GDP per capita in U.S. dollars is taken from the World Bank World Development Indicators. The data are converted into Japanese yen using the nominal exchange rate between the U.S. dollar and the Japanese yen from the IMF International Financial Statistics.

29 We compute capital service prices as nominal capital costs divided by the real net capital stock. The data in the JIP Database are available for 99 sectors for the period 1994–2020. For the purposes of our analysis, we create the correspondence between the JIP Database industry classification and the Japan's Basic Survey on Overseas Business Activities industry classification. To fill in figures for 2021, we multiply each sectors' capital service prices by the change in the prices of the total fixed capital stock in the manufacturing sector in 2021. The deflator is computed from the nominal and real capital stock taken from: https://www.esri.cao.go.jp/jp/sna/data/data_list/kakuhou/files/2022/2022_kaku_top.html (accessed on March 19, 2024).

30 We thank Wenyin Cheng of IDE JETRO for providing us with the data on TFP growth for 2000–2014 computed from the WIOD data. We use the TFP growth rate computed using the intermediate inputs directly obtained from the Social Economic Account (SEA) in the WIOD and calculate the average for the 10 years from 2005 to 2014. Assuming constant growth, we then compute the TFP growth rates for 2017–2021, which we use as tfp in the equation for the production cost estimation. We use the correspondence between the WIOD industries to the industries of Japanese affiliates to obtain the variable for our empirical analysis.

export controls index values.[31] Semiconductor production technology has been one of the main concerns of the U.S. authorities in terms of technology leakage. For instance, the Wassenaar Arrangement 2018 Plenary Decisions Implementation targeted among other things equipment for the manufacture of semiconductor devices. Figure 5 shows the China IO export controls index computed using the frequency-based variety index $\widehat{N}_i^M$ for 2021. The pattern based on this index is similar to that in Figure 3.

Figure 3 China IO export controls index, 2021



Notes: The figure shows the China IO export controls index computed using the trade-weighted variety index.

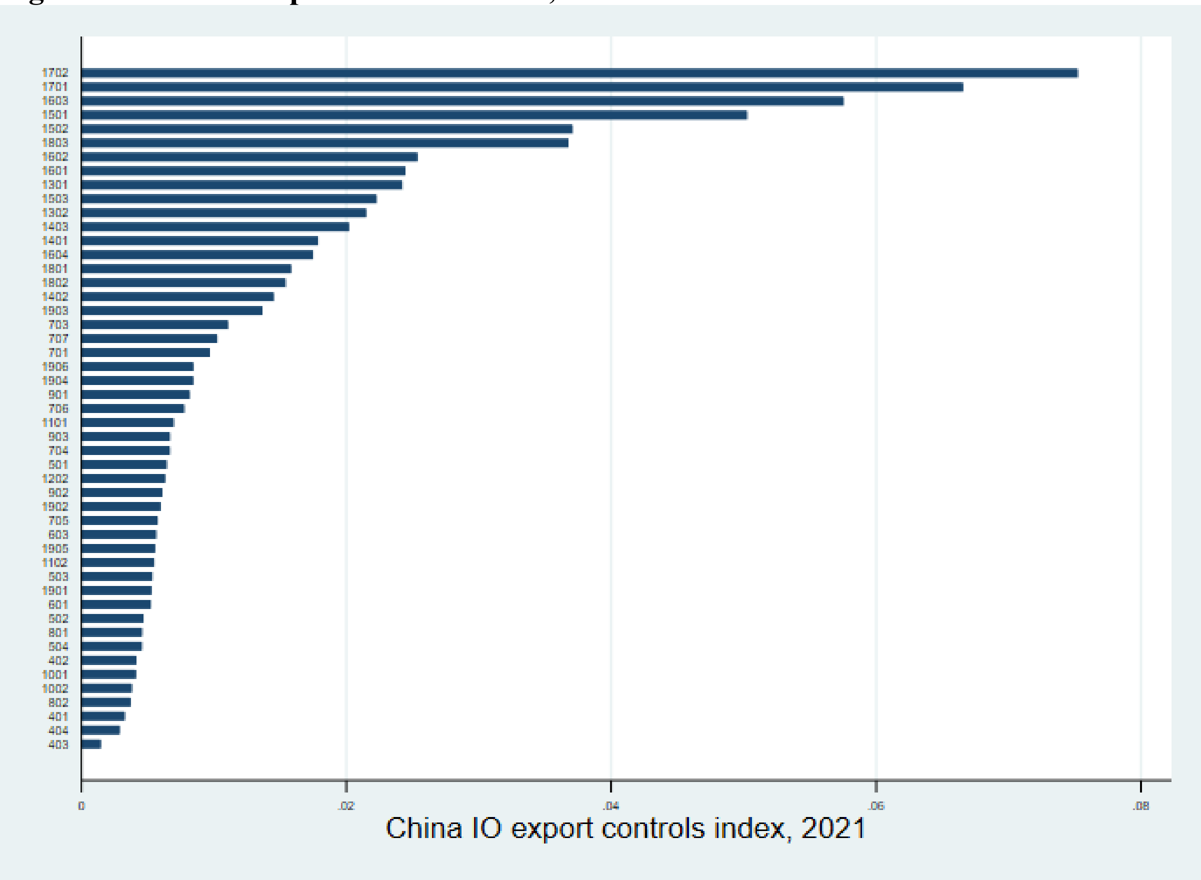
List of industries

1702 Manufacture of electronic computers and related equipment
1701 Manufacture of communication equipment and related equipment, video and audio equipment
1603 Manufacture of electronic equipment
1501 Manufacture of office, service and entertainment equipment
1502 Manufacture of optical instruments and lenses
1602 Consumer electrical appliances
1601 Industrial electrical machinery
1503 Misc. production and commercial machinery
1403 Metalworking machinery
1904 Manufacture of rubber products
706 Manufacture of cosmetics, toothpaste and other cosmetic preparations
1202 Construction, building and misc. metal products
902 Manufacture of cement and related products
903 Miscellaneous ceramic and clay products
1101 Non-ferrous metal smelting and refining
1902 Printing and related businesses
603 Paper products
1905 Tanned leather, leather products and furs
704 Oil and fat products, soaps, synthetic detergents, surfactants and paints

[31] To create the correspondence between the Japanese industry classification and the Chinese IO table industry classification, we merge three industries, namely, the (1) electronic parts, devices and electronic circuits, (2) semiconductor and flat panel display manufacturing equipment, and (3) manufacture of electronic equipment industries into one industry, the "manufacture of electronic equipment" industry.

1803 Miscellaneous transport equipment
1604 Miscellaneous electrical machinery
1302 Miscellaneous general-purpose machinery
1301 General industrial machinery and equipment manufacturing
1802 Motor vehicle parts and accessories
1401 Agricultural machinery, construction and mining machinery, and textile machinery
1801 Automobiles, automobile bodies and accompanying vehicles
1402 Life-related industrial machinery and basic materials industrial machinery manufacturing
1903 Manufacture of plastic products
1906 Miscellaneous manufacturing
701 Chemical fertilizer manufacturing
707 Miscellaneous chemical industry
901 Glass and related products
703 Chemical products
705 Pharmaceutical manufacturing
1901 Furniture and furnishings
1102 Miscellaneous non-ferrous metal products
501 Silk reeling, spinning, manufacturing of synthetic fibers and yarn
601 Wood and wood products
503 Dyeing, ropes, nets, laces and crude textile products
801 Petroleum refining
1001 Pig iron, crude steel and steel products
802 Miscellaneous petroleum and coal products
504 Clothing and other textile products
502 Textiles and knitted fabrics
402 Manufacture of beverages
1002 Castings and forgings and other iron and steel products
401 Manufacture of foodstuffs
404 Feed and organic fertilizer manufacturing
403 Tobacco manufacturing

Figure 4 China IO export controls index, 2021



Notes: The figure shows the China IO export controls index computed using the frequency-based variety index

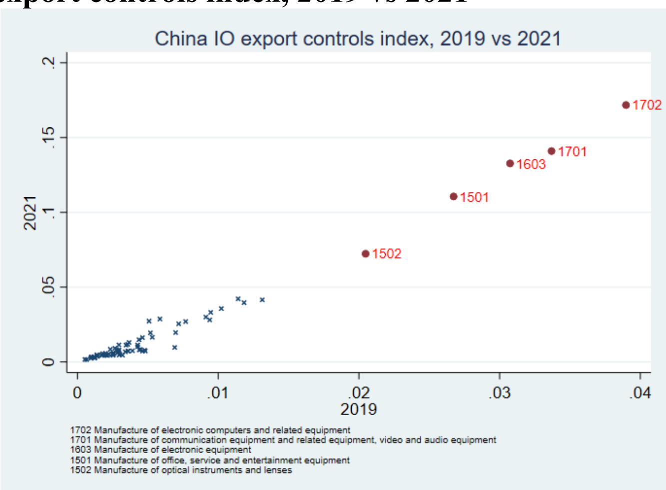
List of industries

1702 Manufacture of electronic computers and related equipment
1701 Manufacture of communication equipment and related equipment, video and audio equipment
1603 Manufacture of electronic equipment
1501 Manufacture of office, service and
1904 Manufacture of rubber products
706 Manufacture of cosmetics, toothpaste and other cosmetic preparations
1202 Construction, building and misc. metal products
902 Manufacture of cement and related

entertainment equipment
1502 Manufacture of optical instruments and lenses
1602 Consumer electrical appliances
1601 Industrial electrical machinery
1503 Misc. production and commercial machinery
1403 Metalworking machinery
1803 Miscellaneous transport equipment
1604 Miscellaneous electrical machinery
1302 Miscellaneous general-purpose machinery
1301 General industrial machinery and equipment manufacturing
1802 Motor vehicle parts and accessories
1401 Agricultural machinery, construction and mining machinery, and textile machinery
1801 Automobiles, automobile bodies and accompanying vehicles
1402 Life-related industrial machinery and basic materials industrial machinery manufacturing
1903 Manufacture of plastic products
1906 Miscellaneous manufacturing
701 Chemical fertilizer manufacturing
707 Miscellaneous chemical industry
901 Glass and related products
703 Chemical products
705 Pharmaceutical manufacturing
products
903 Miscellaneous ceramic and clay products
1101 Non-ferrous metal smelting and refining
1902 Printing and related businesses
603 Paper products
1905 Tanned leather, leather products and furs
704 Oil and fat products, soaps, synthetic detergents, surfactants and paints
1901 Furniture and furnishings
1102 Miscellaneous non-ferrous metal products
501 Silk reeling, spinning, manufacturing of synthetic fibers and yarn
601 Wood and wood products
503 Dyeing, ropes, nets, laces and crude textile products
801 Petroleum refining
1001 Pig iron, crude steel and steel products
802 Miscellaneous petroleum and coal products
504 Clothing and other textile products
502 Textiles and knitted fabrics
402 Manufacture of beverages
1002 Castings and forgings and other iron and steel products
401 Manufacture of foodstuffs
404 Feed and organic fertilizer manufacturing
403 Tobacco manufacturing

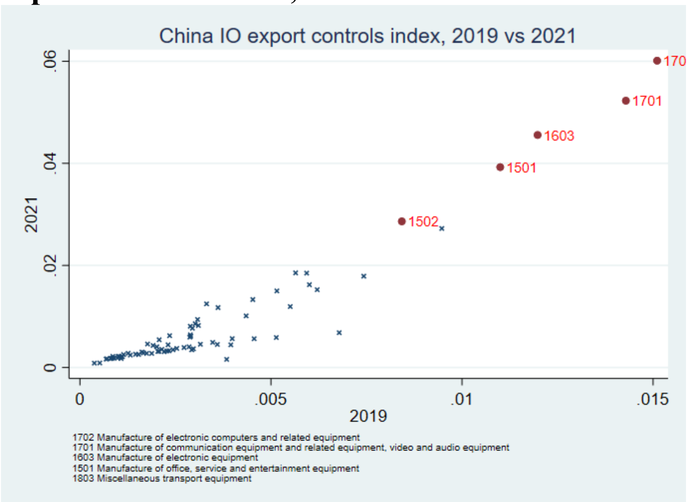
Figures 5 and 6 compare the China IO export controls index values for individual industries in 2019 and 2021, with the values for 2019 shown on the horizontal axis and those for 2021 shown on the vertical axis. We observe that the industries that saw the largest increase were the manufacture of electronic computers and related equipment, the manufacture of communication, video and audio equipment, and the manufacture of electronic equipment. Thus, we find that our index derived from Federal Register mentions of a tightening of export control captures the industries that are of primary concern to the U.S. authorities with regard to technology leakages to China. The construction of the index aims to capture a change in intermediate input imports. The figures suggest that it is an appropriate measure of the tightening of access to intermediate inputs containing advanced technology.

Figure 5 China IO export controls index, 2019 vs 2021



Notes: The figure shows the China IO export controls index values computed using the trade-weighted variety index.

Figure 6 China IO export controls index, 2019 vs 2021



Notes: The figure shows the China IO export controls index values computed using the frequency-based variety index.

Given the observed patterns, we conjecture that the increased pressure from U.S. authorities on exporting companies with respect to products under export control may have led to a decrease in exports at the extensive margin, particularly in the case of exports to China. As explained above, an increase in the China IO export controls index signifies a decrease in intermediate input imports variety, which translates into higher production costs. We therefore hypothesize that the China IO export controls index is positively associated with Japanese MNEs' propensity to exit from China. Our empirical analysis attempts to examine this hypothesis.

4. Firm-level data

To test empirically the effect of export controls on the probability of exit of Japanese MNEs' affiliates from China we use Japanese microdata from the Kaigai Jigyo Katsudo Kihon Chosa Hokokusho (Basic Survey on Overseas Business Activities) conducted by the Ministry of Economy, Trade and Industry (METI), which covers Japanese firms that own at least one affiliate in a foreign country. In the Basic Survey on Overseas Business Activities, in line with international norms, foreign affiliates are foreign-based companies in which a Japanese parent company holds an ownership stake of at least 10%. Furthermore, subsidiaries of such foreign affiliates are regarded as foreign affiliates themselves if the original affiliate holds a controlling interest of at least 50% of the voting shares in their capital. In our analysis, we use data for the period 2017–2021. In 2017, there were a total of 10,838 foreign affiliates in the manufacturing sector.

We create the following variables for our empirical analysis. $Exit_{acjt}$ is defined as the closure or suspension of activities of affiliate a in country c in industry j in year t. To define exit, we rely on the operational status of the company. The Basic Survey on Overseas Business Activities reports the following operational statuses of affiliates: 1 – in operation, 2 – before the first settlement, 3 – not established or has not started operations, 4 – business operations suspended, 5 – dissolution, 6 – withdrawal, 7 – decline in control share ("The total control share held by the Japanese corporation(s) has become a ratio between 0% and 10%"), 9 – unclear status. We define weak $Exit_{acjt} = 1$ if affiliate a's status changes for the first time to one of the statuses from 4 to 9 in year t or if the reporting of information about the affiliate is suspended by the parent company.[32]

32 Japanese MNEs are relatively conscientious in their reports to METI. We therefore assume that the

Table 2 shows the 2017–2021 pattern of exits from China using the weak definition for industries in which there were at least 90 affiliates in China in 2016. The industries are ordered based in terms of the average for 2017–2021. We note that the top 1 and top 3 industries are the manufacture of communication equipment and related equipment, video and audio equipment and consumer electrical appliances. The highest exit share is for the manufacture of communication equipment and related equipment, video and audio equipment is observed in 2021 (31%), while for consumer electrical appliances the highest share is observed in 2020 (15.3%). This provides indirect evidence of our conjecture that the decrease in intermediate input varieties due to increased U.S. export controls has led to an increase in the incentive for Japanese MNEs' affiliates to exit from China.

Table 2 Patterns of exit of Japanese MNEs' affiliates from China

Code	Japanese Industry Name	2017	2018	2019	2020	2021	Average 2017–2021
1701	Manufacture of communication equipment and related equipment, video and audio equipment	0.112	0.022	0.108	0.118	0.310	0.224
504	Clothing and other textile products	0.070	0.066	0.086	0.103	0.213	0.179
1602	Consumer electrical appliances	0.029	0.070	0.052	0.153	0.133	0.146
401	Manufacture of foodstuffs	0.090	0.079	0.070	0.086	0.110	0.145
1102	Miscellaneous non-ferrous metal products	0.041	0.054	0.074	0.089	0.155	0.138
1903	Manufacture of plastic products	0.097	0.056	0.072	0.064	0.118	0.136
1202	Miscellaneous metal products	0.054	0.052	0.084	0.089	0.118	0.133
1604	Miscellaneous electrical machinery	0.133	0.022	0.044	0.136	0.052	0.129
703	Manufacture of organic chemical products	0.039	0.039	0.153	0.037	0.097	0.122
1603	Manufacture of electronic equipment	0.073	0.041	0.075	0.102	0.073	0.122
1601	Industrial electrical machinery	0.076	0.033	0.071	0.036	0.143	0.119
1503	Miscellaneous commercial machinery	0.035	0.056	0.044	0.063	0.132	0.110
1302	Miscellaneous general-purpose machinery	0.018	0.070	0.045	0.055	0.089	0.092
1906	Miscellaneous manufacturing	0.050	0.075	0.061	0.034	0.053	0.091
1802	Motor vehicle parts and accessories	0.041	0.039	0.068	0.071	0.053	0.090

Note: Share of exits for industries that had at least 90 affiliates in China in 2016. The share is computed as the number of exits divided by the number of operating affiliates in China in the respective year.

We use several additional control variables at the affiliate level in our analysis. $Productivity_{acjt}$ represents the simple productivity of affiliate *a* in country *c* in industry *j* in year *t*. It is computed as an affiliate's value added divided by the number of employees, where value added is the difference between sales and intermediate inputs. To smooth out fluctuations in the data, we calculate the rolling average for three consecutive years and apply the inverse hyperbolic sine transformation, which is an alternative to the logarithmic transformation for values that are not strictly positive (Burbidge et al., 1988). In our regression analysis, we use the productivity observed in the year before the exit. We expect productivity to be negatively correlated with the probability of exit; that is, we expect that the higher Japanese MNEs'

suspension of reporting about the activities of an affiliate is identical to exit. We conduct robustness checks using a strict definition, in which we regard the first year in which the status changes to 4 to 9 as the year of exit.

affiliates' productivity, the lower is their probability of exit from foreign countries.

Employment$_{acjt}$ is the total number of employees of affiliate a in country c in industry j in year t. We again compute the three-year rolling average and logarithmically transform the employment variable. In the regression analysis, we use employment in the year prior to exit. We expect it to be negatively correlated with the probability of exit; i.e., larger affiliates are less likely to exit foreign markets. Summary statistics of these additional controls are provided in Table 3.

Table 3 Summary statistics for affiliate level explanatory variables

Variable	Observations	Mean	Std. dev.	Min.	Max.
Productivity	40,222	1.55	1.38	-8.45	8.69
Employment	49,512	4.81	1.67	-1.10	11.08

Notes: The summary statistics shown are for the affiliates used in our empirical analysis. They consist of affiliates in the manufacturing sector and cover the period 2017–2021.

Next, we turn to the empirical testing of our hypothesis that U.S. export controls have led to an increase in the exit probability of Japanese affiliates.

5. Empirical analysis

5.1. Econometric setting

We are interested in the effect of export controls on production costs in China due to the decreased variety of intermediate inputs as a result of U.S. export controls. In order to test our hypothesis, we estimate the following model:

$$Pr\left[Exit_{a,c,j,t} = 1\right] = \beta_1 Productivity_{a,c,j,t-1} + \beta_2 Employment_{a,c,j,t-1}$$
$$+\beta_3 IO\text{x}[w + r - tfp]_{c,j,t} + \beta_4 ExportControls_{China,j,t} + \{FE\} + \varepsilon_{a,c,j,t}, \qquad (19)$$

The probability of exit of affiliate a located in country c belonging to industry j in year t is a function of two affiliate-level explanatory variables in year $t-1$: $Productivity_{a,c,j,t-1}$ and $Employment_{a,c,j,t-1}$. We expect β_1 and β_2 to have a negative sign, implying that more productive and larger affiliates are less likely to exit foreign markets.

We add one more control variable, $IO\text{x}[w+r-tfp]_{cjt}$, which represents production costs in industry j in country c in year t. As explained above, the variables $IO\text{x}[w + r - tfp]_{c,j,t}$ and $ExportControls_{China,j,t}$ are derived from equation (11). $IO\text{x}[w + r - tfp]_{c,j,t}$ captures country-industry changes in production costs resulting from wage growth, capital service prices growth, and TFP growth transmitted via global input-output linkages. We expect the coefficient β_3 to be positive, since higher production factor costs are likely to discourage Japanese MNEs from continuing to do business in a particular country.

$ExportControls_{China,j,t}$ represents the export controls index computed as shown in equation (16) for China using Chinese IO tables or by equation (17) using the WIOD. This is our main variable of interest that measures an increase in production cost due to decrease in intermediate inputs varieties imported from abroad as a result of the U.S. export control policies. We expect β_4 to be positive, implying that a strengthening of export controls at the HS 10 digit-level increases production costs in China due to a decrease in the variety of imported intermediate inputs, which creates an incentive for Japanese MNEs' affiliates to exit from China. In what follows, we report the effect of the export controls index measured using $\widehat{N}_i^M$ variety index based on two types of export controls' mentions indexes: $IndexTrade_{i,\tau}$ and $IndexFrequency_{i,\tau}$.

Needless to say, many other factors at the country level, as well as broader time-related trends can affect MNEs' exit decision. We take these factors into account using country and time fixed effects. Further, to capture time invariant affiliate characteristics, we use affiliate fixed effects. In addition, a few econometric issues should be mentioned here. Traditional gravity variables, which are time-varying country level variables, such as GDP or distance, are usually insignificant in estimations with country fixed effects. We therefore do not use them as controls. In fact, our variable $IO\text{x}[w + r - tfp]_{c,j,t}$ attempts to capture the overall macroeconomic factors that may lead Japanese MNEs to withdraw from a particular market.[33] In sum, we use affiliate, country and year fixed effects to capture all possible factors that, in addition to increased production costs due to a decrease in imported intermediate inputs variety, could lead to the exit of affiliates.[34] Moreover, in our estimation, we cluster standard errors at the country-industry level to take potential correlation within groups into account. Finally, in addition to the benchmark model, we estimate a number of alternative models to check the robustness of our results.

5.2. Results and discussion

5.2.1. Benchmark estimation of the effect of export controls on Japanese MNEs' affiliates' probability of exit.

We start by presenting the results of our benchmark estimation of the effect of export controls on Japanese MNEs' affiliates' probability of exit using equation (19). The results are shown in Table 4. Columns (1) and (2) show the estimation without affiliate-level additional controls, while columns (3) and (4) report the results when we add affiliate level controls. The last three rows report the mean, the standard deviation, and the effect of a one standard deviation increase in the China IO export controls index on the likelihood of exit.

It should be noted that the increase in production costs is not statistically significant in any of the estimations. A possible explanation is that this effect was internalized by Japanese MNEs' affiliates long before the decision to exit the market. Alternatively, as we rely on input-output transmission mechanism, production cost shock could have been absorbed by other sectors prior to realizing in the sector where Japanese MNE's affiliate operate.

Our central finding is that the export controls effect due to the decrease in intermediate input variety resulting from export controls is positive and significant in all specifications. The results in column (1) show that export controls as measured by the China IO export controls index computed using the trade weighted variety index had a significant positive effect on the probability of exit. According to our estimation, a one standard deviation increase in the export controls China IO index for affiliates located in China is associated with an increase in the exit probability of 0.65 percentage points, holding other variables constant. For instance, the China IO export controls index for the manufacture of communication equipment and related equipment, video and audio equipment increased by about 4 standard deviations between 2019 and 2021 in China, which increased the probability of Japanese MNEs' affiliates' exit by about 2.63 percentage points.

Turning to the results for the China IO export controls index computed using the frequency-based variety index, we observe an identical pattern (column (2)). The coefficient

33 We run such regressions using GDP and distance as additional explanatory variables. The results were identical.

34 Trade literature indicates that trade policy can be endogenous, shaped by competitive forces rather than national security concerns (Grossman and Helpman, 1994). Similarly, export control policies may also exhibit endogeneity, which could influence our empirical findings. Due to the complexity of this issue, we defer its examination to future research.

estimate is positive and statistically significant. This result indicates that an increase in the China IO export controls index computed using the frequency-based variety index by one standard deviation increased the probability of exit by 0.79 percentage points.

Table 4 Export controls and probability of exit, Benchmark estimation

LPM	(1)	(2)	(3)	(4)
$IO\text{x}[w+r-tfp]_{c,j,t}$	-0.008	-0.007	0.002	0.003
	(0.013)	(0.013)	(0.014)	(0.014)
$ExportControls_{China,j,t}$	0.190***		0.097***	
	(0.022)		(0.026)	
$ExportControls_{China,j,t}$		0.606***		0.325***
		(0.076)		(0.082)
$Productivity_{a,c,j,t-1}$			-0.005***	-0.005***
			(0.002)	(0.002)
$Employment_{a,c,j,t-1}$			-0.055***	-0.055***
			(0.007)	(0.007)
Constant	0.022***	0.022***	0.289***	0.288***
	(0.001)	(0.002)	(0.036)	(0.036)
Observations	63,723	63,723	39,536	39,536
R-squared	0.325	0.325	0.341	0.341
Index used for $\widehat{N}_i^M$	$IndexTrade$	$IndexFrequenc$	$IndexTrade$	$IndexFrequenc$
Affiliate FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Period	2017–2021	2017–2021	2017–2021	2017–2021
Mean export controls effect	0.016	0.008	0.016	0.008
Std. dev. of export controls effect	0.035	0.012	0.035	0.012
Effect of 1 std. dev. increase, percentage points	0.66	0.75	0.34	0.40

Notes: Benchmark estimation of the effect of export controls as measured by the China IO export controls index on Japanese MNEs' affiliates' probability of exit from China. US and aligned countries' imports are used to split the competitive China IO table. The results were obtained using a linear probability model. The sample consists of all affiliates belonging to the manufacturing sector. The China IO export controls index is computed using the variety index based on all types of products. "FE" stands for fixed effects. The estimation period is 2017–2021. Standard errors in parentheses are clustered at the country-industry level. *** p<0.01, ** p<0.05, * p<0.1

Next, the results for the affiliate-level explanatory variables are statistically significant in both specifications and in line with expectations (columns (3) and (4)). That is, more productive and larger affiliates are less likely to withdraw from foreign markets. This is in line with the findings of Luo et al. (2022), who obtained similar results regarding the effect of size and productivity on Japanese MNEs' affiliates' probability of exit from China for the period 1995–2016. Meanwhile, the coefficients for export controls remain positive and significant, although their size decreases. For example, a one standard deviation increase in the China IO export controls index based on the trade weighted variety index is associated with an increase in the probability of exit of 0.33 percentage points.

These results support our hypothesis that an increase in production costs due to a decrease in intermediate input variety leads to an increase in the likelihood of Japanese MNEs' affiliates' exit from China. Moreover, the size of this effect is not negligible.

5.2.2. Global value chains, export controls, and the probability of exit of Japanese MNEs from China

In the regressions in Table 4, we used the China IO export controls index computed as described in equation (16) using the China Input-Output tables. One caveat regarding this approach is that global production structures are not taken into account. To address this issue, we use the University of Groningen WIOT and compute the GVC export controls index, which takes global input-output linkages as presented in equation (17) into account. We employ the econometric specification given by equation (19). The results are presented in Table 5. First of all, we now find that the coefficient on production costs is positive and significant, suggesting that an increase in production costs raises the probability of exit. Our measure of production costs, IOx[w+r-tfp], captures wage growth, capital service price growth and TFP growth that is transmitted via global input-output tables i.e. global repercussions. According to our theoretical framework, an increase in these production costs induces Japanese MNEs to exit the market.

Table 5 Export controls and probability of exit, GVC analysis

LPM	(1)	(2)	(3)	(4)
$IO\text{x}[w + r - tfp]_{c,j,t}$	0.045***	0.045***	0.040***	0.041***
	(0.011)	(0.011)	(0.011)	(0.011)
$ExportControls_{China,j,t}$	0.060***		0.049***	
	(0.006)		(0.006)	
$ExporControls_{China,j,t}$		0.112***		0.090***
		(0.010)		(0.010)
$Productivity_{a,c,j,t-1}$			-0.003	-0.003*
			(0.002)	(0.002)
$Employment_{a,c,j,t-1}$			-0.049***	-0.049***
			(0.007)	(0.007)
Constant	0.011***	0.010***	0.248***	0.247***
	(0.001)	(0.001)	(0.036)	(0.036)
Observations	63,723	63,723	39,536	39,536
R-squared	0.311	0.311	0.329	0.329
Index used for $\widehat{N}_i^M$	$IndexTrade$	$IndexFrequenc$	$IndexTrade$	$IndexFrequenc$
Affiliate FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Period	2017–2021	2017–2021	2017–2021	2017–2021
Mean export controls effect	0.300	0.187	0.300	0.187
Std. dev. of exp. cont. effect	0.397	0.225	0.397	0.225
Effect of 1 std. dev. increase, percentage points	2.38	2.52	1.95	2.02

Notes: Estimation of the effect of export controls as measured by the GVC export controls index on Japanese MNEs' affiliates' probability of exit from China. The results were obtained using a linear probability model. The sample consists of all affiliates belonging to the manufacturing sector. The GVC export control index is computed using the variety index based on all types of products. "FE" stands for fixed effects. The estimation period is 2017–2021. Standard errors in parentheses are clustered at the country-industry level. *** p<0.01, ** p<0.05, * p<0.1

Second, the coefficient on our main variable of interest, the GVC export controls index, which represents the increase in production costs due to the decrease in intermediate input variety is positive and significant in all specifications. The last row of the table reports the effect of a one standard deviation increase in the GVC export controls index on Japanese MNEs' affiliates' probability of exit of from China. The results indicate that when we consider global production structures using the WIOT, export controls raise the probability of exit between 1.95 percentage points (column (3)) to 2.52 percentage points (column (2)). Overall, we find that the effect is stronger when global interactions are considered.

Finally, the results in columns (3) and (4) show that the coefficients on productivity are negative and marginally significant in column (4), while those on employment are both negative and significant, indicating that larger affiliates were less likely to exit.

Table 6 Export controls and probability of exit ($\widehat{N}_i^M$ using intermediate inputs)

LPM	(1)	(2)	(3)	(4)
$IO\text{x}[w + r - tfp]_{c,j,t}$	-0.008	-0.007	0.002	0.003
	(0.013)	(0.013)	(0.014)	(0.014)
$ExportControls_{China,j,t}$	0.188***		0.096***	
	(0.022)		(0.025)	
$ExportControls_{China,j,t}$		0.545***		0.288***
		(0.070)		(0.074)
$Productivity_{a,c,j,t-1}$			-0.005***	-0.005***
			(0.002)	(0.002)
$Employment_{a,c,j,t-1}$			-0.055***	-0.055***
			(0.007)	(0.007)
Constant	0.022***	0.022***	0.289***	0.289***
	(0.001)	(0.002)	(0.036)	(0.036)
Observations	63,723	63,723	39,536	39,536
R-squared	0.325	0.325	0.341	0.341
Index used for $\widehat{N}_i^M$	$IndexTrade$	$IndexFrequenc$	$IndexTrade$	$IndexFrequenc$
Affiliate FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Period	2017–2021	2017–2021	2017–2021	2017–2021
Mean export controls effect	0.016	0.008	0.016	0.008
Std. dev. of export controls effect	0.035	0.013	0.035	0.013
Effect of 1 std. dev. Increase, percentage points	0.65	0.72	0.33	0.38

Notes: Estimation of the effect of export controls as measured by the China OI export controls index on Japanese MNEs' affiliates' probability of exit from China. US and aligned countries' imports are used to split the competitive China IO table. The results were obtained using a linear probability model. The sample consists of all affiliates belonging to the manufacturing sector. The China IO export controls index is computed using the variety index based on intermediate inputs as per BEC classification. "FE" stands for fixed effects. The estimation period is 2017–2021. Standard errors in parentheses are clustered at the country-industry level. *** p<0.01, ** p<0.05, * p<0.1

The analysis from a global perspective shows that export controls implemented by the U.S. create incentives for Japanese MNEs' affiliates to exit China. Thus, the decrease in the imported intermediate input variety due to the U.S. export controls mechanism described in our theoretical framework serves as a plausible explanation of Japanese MNEs' exit from

China.[35]

5.2.3. Robustness checks

In this section, we present various robustness checks using alternative ways of constructing our variables and alternative samples. For these robustness checks, we concentrate on the export control index based on the China IO tables.

Table 7 Export controls and probability of exit (China IO export controls index using U.S. imports)

LPM	(1)	(2)	(3)	(4)
$IO\text{x}[w+r-tfp]_{c,j,t}$	-0.008	-0.006	0.002	0.003
	(0.013)	(0.013)	(0.014)	(0.014)
$ExportControls_{China,j,t}$	2.104***		1.099***	
	(0.263)		(0.293)	
$ExportControls_{China,j,t}$		4.399***		2.190***
		(0.937)		(0.822)
$Productivity_{a,c,j,t-1}$			-0.005***	-0.005***
			(0.002)	(0.002)
$Employment_{a,c,j,t-1}$			-0.055***	-0.055***
			(0.007)	(0.007)
Constant	0.022***	0.021***	0.289***	0.289***
	(0.002)	(0.002)	(0.036)	(0.036)
Observations	63,723	63,723	39,536	39,536
R-squared	0.325	0.325	0.341	0.341
Index used for $\widehat{N}_i^M$	$IndexTrade$	$IndexFrequenc$	$IndexTrade$	$IndexFrequenc$
Affiliate FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Period	2017–2021	2017–2021	2017–2021	2017–2021
Mean export controls effect	0.002	0.001	0.002	0.001
Std. dev. of export controls effect	0.003	0.002	0.003	0.002
Effect of 1 std. dev. Increase, percentage points	0.70	0.83	0.37	0.41

Notes: Estimation of the effect of export controls as measured by the China IO export controls index on Japanese MNEs' affiliates' probability of exit from China. U.S. imports are used to split the competitive China IO table. The results were obtained using a linear probability model. The sample consists of all affiliates belonging to the manufacturing sector. The China IO export controls index is computed using the variety index based on all types of products. "FE" stands for fixed effects. The estimation period is 2017–2021. Standard errors in parentheses are clustered at the country-industry level. *** p<0.01, ** p<0.05, * p<0.1

Our variety index $\widehat{N}_i^M$ for the benchmark estimation was computed for all types of products to capture the overall effect of U.S. export controls. We found that the decrease in

35 In principle, other firm-level factors could also affect the probability of Japanese MNEs' exit of from China. For instance, Luo et al. (2022) show that affiliates' share of exports to Japan and parent firm characteristics play a role. In fact, Irarrazabal et al. (2013) show that trade between the parent and the affiliate are an important feature of MNEs' activities. In our analysis, we aim to highlight the decrease in imported intermediate input variety due to the U.S. export controls mechanism, so that we do not examine all other possible mechanisms.

intermediate input variety leads to a shortage of technologically advanced products, raising their costs and creating an incentive for Japanese MNEs to exit the Chinese market.

Nevertheless, given our theoretical discussion, one might argue that this effect potentially only concerns intermediate goods. Therefore, variety index $\widehat{N}_i^M$ should be computed only for intermediate use product. To address this concern, we estimate the model given by equation (19) using an alternative way to compute the China IO export controls index. Specifically, we recalculate the variety index $\widehat{N}_i^M$ for the subset of HS10-digit level products that belong to the intermediate use category according to the BEC end-use classification.[36] The results are presented in Table 6 and are identical to our benchmark estimation.

Table 8 Export controls and probability of exit (China IO export controls index without σ_m)

LPM	(1)	(2)	(3)	(4)
$IO\text{x}[w + r - tfp]_{c,j,t}$	-0.008	-0.007	0.002	0.003
	(0.013)	(0.013)	(0.014)	(0.014)
$ExportControls_{China,j,t}$	0.024***		0.012***	
	(0.003)		(0.003)	
$ExportControls_{China,j,t}$		0.069***		0.036***
		(0.009)		(0.009)
$Productivity_{a,c,j,t-1}$			-0.005***	-0.005***
			(0.002)	(0.002)
$Employment_{a,c,j,t-1}$			-0.055***	-0.055***
			(0.007)	(0.007)
Constant	0.022***	0.022***	0.290***	0.289***
	(0.001)	(0.001)	(0.036)	(0.036)
Observations	63,723	63,723	39,536	39,536
R-squared	0.325	0.325	0.341	0.341
Index used for $\widehat{N}_i^M$	$IndexTrade$	$IndexFrequenc$	$IndexTrade$	$IndexFrequenc$
Affiliate FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Period	2017–2021	2017–2021	2017–2021	2017–2021
Mean export controls effect	0.121	0.061	0.121	0.061
Std. dev. of export controls effect	0.270	0.104	0.270	0.104
Effect of 1 std. dev. Increase, percentage points	0.65	0.72	0.32	0.37

Notes: Estimation of the effect of export controls as measured by the China IO export controls index on Japanese MNEs' affiliates' probability of exit from China. U.S. and aligned countries' imports are used to split the competitive China IO table. The results were obtained using a linear probability model. The sample consists of all affiliates belonging to the manufacturing sector. The China IO export controls index is computed using the variety index based on all types of products without elasticity of substitution. "FE" stands for fixed effects. The estimation period is 2017–2021. Standard errors in parentheses are clustered at the country-industry level. *** p<0.01, ** p<0.05, * p<0.1

To construct $\mathbf{M}'$, the imported intermediate input coefficient matrix used in equation

36 To identify such products, we rely on the correspondence provided by Chen et al. (2023). Their HS-BEC correspondence for China is at the HS8 digit product level. We create a classification of U.S. HS10 digit level products via the HS6 digit level classification, which is the same for both countries.

(16) to compute the China IO export controls index, we employed intermediate input imports (as per BEC classification) from countries listed under country groups A:5 and A:6 in Supplement No. 1 to Part 740 of the Export Administration Regulations (see footnote 19 for a list of these countries). This approach is based on the assumption that these countries tend to comply with the export controls introduced by the U.S. authorities. As an alternative, we restrict intermediate input imports to imports from the U.S. only to construct $\mathbf{M}'$. This approach allows us to focus on the direct effects of U.S. export controls.

Table 9 Export controls and probability of exit (Treating China and Hong Kong as a single territory)

LPM	(1)	(2)	(3)	(4)
$IO\text{x}[w+r-tfp]_{c,j,t}$	-0.008	-0.007	0.002	0.003
	(0.013)	(0.013)	(0.014)	(0.014)
$ExportControls_{China,j,t}$	0.167***		0.079***	
	(0.026)		(0.029)	
$ExportControls_{China,j,t}$		0.484***		0.241***
		(0.075)		(0.080)
$Productivity_{a,c,j,t-1}$			-0.005***	-0.005***
			(0.002)	(0.002)
$Employment_{a,c,j,t-1}$			-0.055***	-0.055***
			(0.007)	(0.007)
Constant	0.022***	0.022***	0.290***	0.289***
	(0.001)	(0.002)	(0.036)	(0.036)
Observations	63,723	63,723	39,536	39,536
R-squared	0.325	0.325	0.341	0.341
Index used for $\widehat{N}_i^M$	$IndexTrade$	$IndexFrequenc$	$IndexTrade$	$IndexFrequenc$
Affiliate FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Period	2017–2021	2017–2021	2017–2021	2017–2021
Mean export controls effect	0.015	0.008	0.015	0.008
Std. dev. of export controls effect	0.034	0.013	0.034	0.013
Effect of 1 std. dev. Increase, percentage points	0.56	0.64	0.27	0.32

Notes: Estimation of the effect of export controls as measured by the China IO export controls index on Japanese MNEs' affiliates' probability of exit. China and Hong Kong are treated as a single territory. U.S. and aligned countries' imports are used to split the competitive China IO table. The results were obtained using a linear probability model. The sample consists of all affiliates belonging to the manufacturing sector. The China IO export controls index is computed using the variety index based on all types of products without elasticity of substitution. "FE" stands for fixed effects. The estimation period is 2017–2021. Standard errors in parentheses are clustered at the country-industry level. *** p<0.01, ** p<0.05, * p<0.1

Table 7 reports the estimation results when the China IO export controls index is computed using this alternative approach to construct the imported intermediate input coefficient matrix $\mathbf{M}'$. The table shows that in this case the size of the coefficients is larger than in the baseline results. For instance, a one standard deviation increase in the China IO export controls index based on the trade weighted variety index is associated with an increase in the probability of Japanese MNEs' affiliates' exit by 0.70 percentage points, which is slightly larger than in the benchmark case.

Next, we conduct a robustness check by omitting import elasticity of substitution. Equation (16) is based on our theoretical framework. This means that we approximate the elasticity parameter v_i by the inverse of the GTAP elasticity for the imported intermediate inputs. Although the assumptions underlying the use of the GTAP elasticity seem appropriate, using the GTAP elasticity potentially introduces bias in the estimation if it is much higher than the true elasticity of intermediate input imports. Therefore, to examine the sensitivity of our results to the use of the GTAP elasticity of substitution, we compute the China IO export controls index as given by equation (16) but exclude diagonal matrix $\boldsymbol{Diag}(\boldsymbol{\sigma_m})$. The results are presented in Table 8 and are quantitatively and qualitatively similar to the benchmark case. This suggests that using the GTAP elasticity does not introduce any bias in our results.

Table 10 Export controls and probability of exit (Strict definition of Japanese MNEs' affiliates' exit)

LPM	(1)	(2)	(3)	(4)
$IO\text{x}[w+r-tfp]_{c,j,t}$	-0.029*	-0.029*	-0.012	-0.011
	(0.017)	(0.017)	(0.016)	(0.016)
$ExportControls_{China,j,t}$	0.160***		0.068**	
	(0.030)		(0.032)	
$ExportControls_{China,j,t}$		0.476***		0.229**
		(0.090)		(0.093)
$Productivity_{a,c,j,t-1}$			-0.008***	-0.008***
			(0.002)	(0.002)
$Employment_{a,c,j,t-1}$			-0.081***	-0.081***
			(0.010)	(0.010)
Constant	0.028***	0.028***	0.421***	0.420***
	(0.002)	(0.002)	(0.047)	(0.047)
Observations	63,728	63,728	39,533	39,533
R-squared	0.316	0.316	0.341	0.341
Index used for $\widehat{N}_i^M$	$IndexTrade$	$IndexFrequenc$	$IndexTrade$	$IndexFrequenc$
Affiliate FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Period	2017–2021	2017–2021	2017–2021	2017–2021
Mean export controls effect	0.016	0.008	0.016	0.008
Std. dev. of export controls effect	0.035	0.013	0.035	0.013
Effect of 1 std. dev. increase, percentage points	0.55	0.63	0.23	0.30

Notes: Estimation of the effect of export controls as measured by the China IO export controls index on Japanese MNEs' affiliates' probability of exit. The strict definition of Japanese MNEs' affiliates exit is used. U.S. and aligned countries' imports are used to split the competitive China IO table. The results were obtained using a linear probability model. The sample consists of all affiliates belonging to the manufacturing sector. The China IO export controls index is computed using the variety index based on all types of products. "FE" stands for fixed effects. The estimation period is 2017–2021. Standard errors in parentheses are clustered at the country-industry level. *** p<0.01, ** p<0.05, * p<0.1

Next, we conduct another robustness check by extending the geography affected by the U.S. export control policies to the mainland China and Hong Kong. In our benchmark analysis, we treated China and Hong Kong as separate territories. However, since 2020, U.S. authorities have been concerned about the possible leakage of advanced technologies to mainland China via Hong Kong. Specifically, the BIS amended license exceptions for Hong Kong for export, re-export and in-country transfers on July 31, 2020. In addition, on December 23, 2020, the BIS enforced a final rule removing Hong Kong as a separate destination under the Export Administration Regulations. As a robustness check, we therefore re-run our estimations treating China and Hong Kong as a single territory. More specifically, we compute the variety index $\widehat{N}_i^M$ using imports to China and Hong Kong. We then use the obtained China IO export controls index to estimate the probability of Japanese MNEs' affiliates' exit from both China and Hong Kong. The results of this specification are presented in Table 9 and are similar to the results of the benchmark estimation, although the coefficients on our key explanatory are slightly smaller. The fact that we obtain similar results suggests that the decrease in intermediate input variety has led to an increase in Japanese MNEs' affiliates' probability of exit in Hong Kong as well as in mainland China.

Our final robustness check considers an alternative definition of our dependent variable, the probability of exit of Japanese MNEs' affiliates. As explained above, in our benchmark approach, when a Japanese MNE ceased reporting information about an affiliate, we treated this as an exit. We referred to this as the "weak definition" of exit. As a robustness check, we here use a strict definition of exit, where we set $Exit_{acjt}$ = 1 if the status of affiliate a changed to one of the statuses from 4 to 9 for the first time. Using this strict definition, we estimate the same specification as presented in Section 6.2.1. The results are presented in Table 10. The results are similar to the benchmark estimation, although the coefficients on our key explanatory variables are slightly smaller in magnitude.

6. Concluding remarks

MNEs activities have important implications on the formation and structure of GVCs. Recent tensions between the U.S. and aligned countries and China may have led to changes in the behavior of MNEs affecting GVCs. In this paper we attempt to look at this process from the perspective of Japanese MNEs' affiliates facing increased production cost due to decreased imported intermediate input varieties as a results of increased U.S. export controls.

Using information from Federal Register documents on changes in export controls at the most disaggregated HS 10-digit product level, we created an industry-level variety index. In addition, we present a theoretical framework featuring the demand for imported intermediate inputs. Using the variety index, the theoretical model, and input-output tables to consider the direct and indirect impact of export controls on industry-level production costs, we construct a China IO export controls index and a GVC export controls index. We then tested the effect of export controls on the probability of Japanese MNEs' affiliates' exit from China using the created indices. We find a positive and significant effect of increased U.S. export controls on the probability of exit of Japanese MNEs' affiliates.

Our findings are important from both a theoretical and a policy perspective. From a theoretical perspective, we confirm that the decrease in imported intermediate inputs due to the U.S. export controls is an important mechanism explaining MNEs' propensity to exit from foreign markets. From a policy perspective, we document that export controls' policies can achieve its goal of limiting the economic potential of affected countries. In particular, the strengthening of U.S. export controls with respect to technologically advanced products may lead MNEs from the U.S. and aligned countries to relocate production facilities back home or to friendly countries.

Although our framework is relatively simple, it can be applied in many other contexts.

For instance, it could be used in a global context using datasets that feature MNEs from all countries, such as the Orbis database. This would allow us to understand the restructuring of GVCs due to export controls from a global perspective. Another potential avenue for exploration is the impact of export controls on the services sector in addition to manufacturing. For instance, the sale of machinery products is often accompanied by maintenance services. As a result, export controls could influence not only the trade of physical goods but also the trade of related services. We leave such an analysis for future research.

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