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Offshoring Bias in Productivity Estimates: Evidence from Japanese customs data[*]

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Abstract

This study examines the extent to which imported intermediate inputs lead to biased estimates of firm-level total factor productivity (TFP) growth, a phenomenon referred to as "offshoring bias." To this end, we construct a novel firm-level dataset by linking the Japanese customs data with the financial information. We newly develop firm-specific import deflators at the granular Harmonized System 9-digit product level and use them to deflate import values. Comparing TFP estimates based on this approach with those based on commonly used industry-level deflators reveals that the conventional method tends to overestimate TFP growth. Moreover, our regression results indicate that the offshoring bias is more pronounced among firms with higher import shares. This suggests that conventional TFP estimation methods may systematically overestimate productivity growth for firms that rely to a greater extent on imported intermediate inputs.

Keywords: Productivity, global value chains, offshoring bias, customs data, Japanese firms
JEL classification: F114, F60, D24, D57

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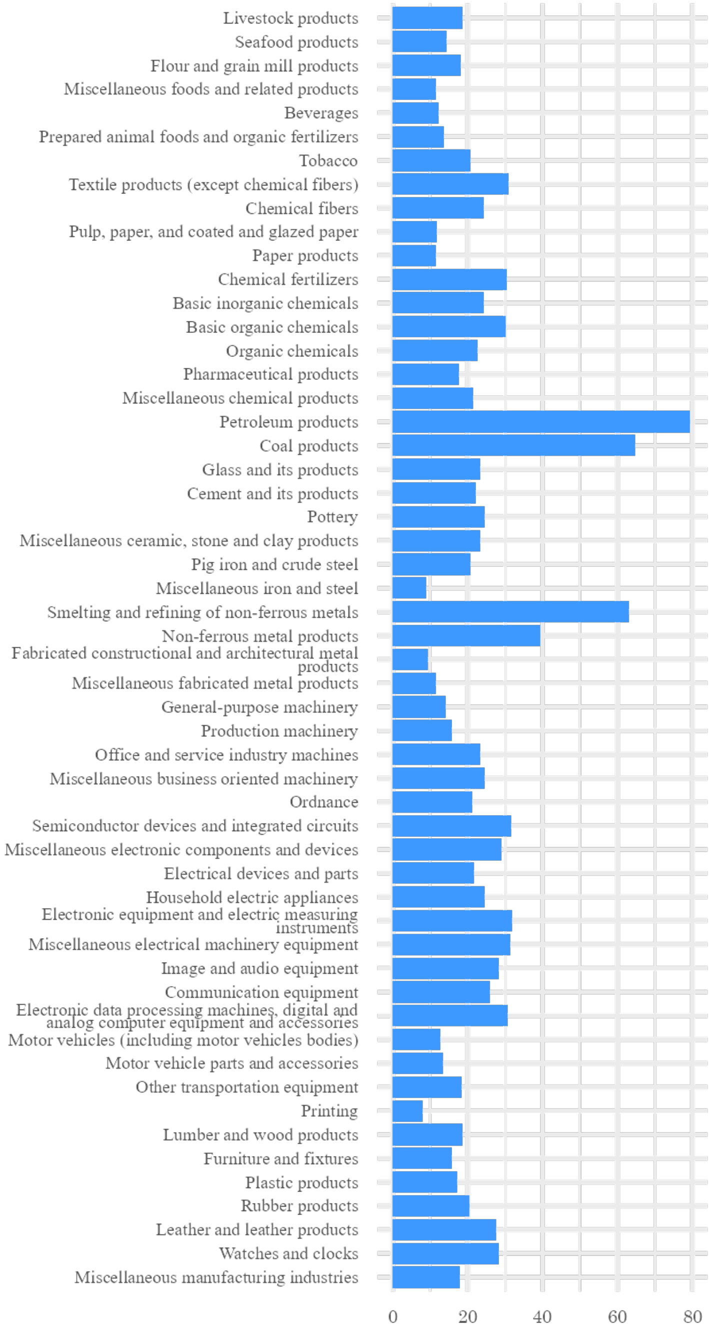
1 Introduction

From the 1990s through the 2010s, the global economy witnessed a pronounced increase in the fragmentation of international production, most notably within the machinery sector of advanced economies. This process, often referred to as the deepening of global value chains, was marked by the growing integration of emerging industrial economies—especially those in East and South Asia—into global production networks. A key driving force behind this trend was the offshoring of production by firms in advanced economies, which was often accompanied by technology transfers to local firms in host countries (Baldwin 2016).

Figure 1 presents the share of imported goods and services in the total intermediate inputs for each manufacturing industry in 2021. The figure indicates that, in many machinery-related industries, the import share is around 30%. While firms in advanced economies are naturally keen on maintaining product quality and preventing the leakage of technology, they generally seek to procure intermediate inputs at the lowest possible cost. Meanwhile, rapid technology transfer to emerging economies—particularly China—substantially increased the global supply of low-cost intermediate inputs.

Responses to the growing international production fragmentation vary significantly across industries and firms. Industries and firms that adapted swiftly to the new global division of labor experienced a substantial decline in the nominal value of intermediate inputs—even as the volume of real inputs has remained relatively stable—due to the adoption of lower-cost imported intermediates. This means that, when estimating productivity growth, failing to accurately take imports of low-cost intermediate inputs into account potentially leads to the overestimation of productivity growth, particularly in industries and firms that have adapted rapidly to the deepening of global production fragmentation compared to those that have not. This measurement issue is commonly referred to as the “offshoring bias.”

Figure 1. Imported goods and services as a percentage of total intermediate inputs for each manufacturing industry, by JIP Database industry classification, 2021



Note: The figure is based on the 2021 non-competitive imports input-output table estimated by Sonoe Arai for the Project on the Industrial Structure Projection Model at RIETI. The estimation draws on the 2021 input-output table from the JIP Database 2023 and the 2020 Input-Output Table published by the Ministry of Internal Affairs and Communications.

Offshoring bias was initially identified as a concern in industry-level productivity analyses (Diewert and Nakamura, 2011; Houseman et al., 2011; Fukao and Arai, 2015), but it can also pose a serious problem in firm-level productivity analyses. This paper quantifies the extent to which offshoring bias may have affected the measurement of total factor productivity (TFP) growth among manufacturing firms between 2015 and 2020 by combining Japanese customs data with firm-level data from the Basic Survey of Japanese Business Structure and Activities (BSJBSA) conducted by the Ministry of Economy, Trade and Industry (METI).

Differences in output prices across firms have been examined in prior studies using product-level unit price data from plant-level surveys in the United States and Japan (Foster et al., 2008; Kawakami et al., 2011). These studies have revealed, for example, that cement plants operating under regional monopolies may appear to exhibit higher productivity. However, little empirical analysis has been conducted on intermediate input prices, largely because plant-level surveys in countries such as the United States and Japan typically do not collect detailed information on the composition or unit prices of intermediate inputs.

This study addresses this gap by leveraging firm-level intermediate input data from Japanese customs data and the BSJBSA. To quantify the offshoring bias at the firm level, we compare TFP growth rates calculated using two distinct deflation methods. In the first method, we deflate nominal intermediate input expenditures using industry-level input deflators obtained from the growth accounting sheet of the JIP Database 2023.[1] In the second, we deflate firm-level import values—classified at the Harmonized System (HS) 9-digit product level and restricted to intermediate goods based on the Broad Economic Categories (BEC) classification—using newly constructed product-level import deflators[2] that reflect item-specific price variation. By comparing the TFP growth rates separately estimated by these two approaches, we evaluate the extent to which firm-level productivity growth estimates are mismeasured due to the offshoring bias.

The remainder of this paper is organized as follows. The next section provides a review of the existing literature on the offshoring bias. Section 3 describes the datasets used in this study, and outlines the

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[1] The data are constructed based on the input-output table containing 100 sectors and the corresponding sectoral output price data provided in the JIP Database 2023.

[2] The JIP Database Project has developed import deflators for approximately 270 product categories, and this paper uses those deflators. The product classification closely follows the commodity classification used in the Basic Transaction Table of the Input-Output Tables published by the Ministry of Internal Affairs and Communications.

methodologies for measuring TFP and offshoring bias. Section 4 presents the empirical results on the magnitude of the offshoring bias and explores the determinants of cross-firm variation in the severity of the bias. The final section concludes with a summary of the main findings.

2 Literature Review

This paper is closely related to a growing body of literature that examines how offshoring affects the measurement of productivity and value added. Diewert and Nakamura (2011) theoretically analyze the bias in price indices that arises when firms switch suppliers of intermediate inputs—a phenomenon referred to as the sourcing bias. They argue that when firms switch to new suppliers and secure lower prices, conventional price indices (such as producer price indices), which are typically based on continuing transactions, may not capture these price reductions. As a result, official price indices may fail to accurately reflect productivity and GDP growth. Using a simplified economic model, they derive a formal expression for the sourcing bias and show that its magnitude depends on the price differences across suppliers, the extent of supplier switching, and the index formula used.

Empirically, Houseman et al. (2011) demonstrate that cost savings from offshoring have led to an overestimation of productivity growth in the U.S. manufacturing sector. Their estimates suggest that, between 1997 and 2007, TFP growth was overestimated by 0.1 to 0.2 percentage points, while real value-added growth was overestimated by 0.2 to 0.5 percentage points, due to the increased use of imported intermediate inputs. They find that the computer and electronics sector accounted for most of the overall productivity growth, while growth in other manufacturing industries was limited. They argue that improving official statistics is necessary to more accurately reflect the effects of offshoring.

In Japan, Fukao and Arai (2015) have estimated the extent of offshoring bias in the manufacturing sector by comparing TFP growth rates derived from two alternative approaches. The first approach uses a non-competitive imports input-output table, which is constructed based on surveys identifying industries that have substantially increased their reliance on imported intermediate input. The second assumes that, for each intermediate good, the ratio of imported to domestically sourced inputs is uniform across all industries. By comparing the TFP estimates under these two approaches, they quantify the offshoring bias. Fukao and Arai's approach takes advantage of a unique strength of Japanese input-output statistics, namely, the availability of official non-competitive imports input-output tables. In contrast, given the lack of such non-competitive imports input-output tables for the United States, Houseman et al. (2011) estimate offshoring bias by analyzing differences in unit prices at the product level—such as those between imports from developing and advanced economies. However, as they acknowledge themselves, this approach does not adequately account for differences in product quality, which may significantly affect the interpretation of price differences.

To address concerns regarding product quality, Fukao and Arai (2015) estimate cross-border price differences using data from the "Survey on Price Differentials between Domestic and Foreign Industrial Goods and Services" conducted by METI, which aims to account for differences in product quality to the greatest extent possible. Their analysis demonstrates that failing to consider cross-industry variation in the ratio of imported to domestically sourced intermediate inputs can result in substantial positive or negative offshoring bias. Specifically, for the period from 1995 to 2008, they find that in six industries—including mobile phones, radio and television receivers, and other optical instruments—real intermediate input growth was overestimated by more than 3.3%, while TFP growth was underestimated by more than 1.9%.

Reinsdorf and Yuskavage (2018) focus on the period following China's accession to the WTO, during which sourcing patterns in the manufacturing sectors of advanced economies underwent substantial changes. They highlight that, although firms began obtaining imported goods at lower prices of supplier substitution, these price declines were largely not reflected in U.S. import price indices and GDP deflators. Their estimates suggest that, during the decade from 1997 to 2007—when sourcing patterns shifted rapidly—approximately one-tenth of the reported growth in TFP in the U.S. private sector may have been attributable to sourcing bias embedded in the import deflators.

Taken together, these studies show that offshoring introduces significant biases into productivity estimates and price indices. A consistent finding across the literature is that shifts in production toward low-cost countries and increased reliance on imported intermediate inputs are not adequately captured in official statistics, leading to a systematic overestimation of productivity. Addressing this issue requires improvements in statistics and the adoption of more refined measurement methodologies. This paper contributes to this line of research by utilizing Japanese customs data, which contain detailed information and allow us to construct more precise estimates of the offshoring bias. Methodologically, this approach offers a valuable contribution to the existing literature on productivity measurement.

Specifically, the contributions to literature are threefold. First, the study contributes to the measurement of offshoring bias by developing a novel set of import deflators for intermediate goods based on Japanese customs data. While previous studies (e.g., Houseman et al., 2011; Reinsdorf and Yuskavage, 2018) estimated offshoring bias at the industry level, this study is the first to construct deflators for imported intermediate inputs at the Harmonized System (HS) 9-digit level. By comparing these granular deflators with conventional industry-level input deflators, the study demonstrates that substantial offshoring bias exists at the firm level.

Second, the study examines firm-level heterogeneity in the magnitude of offshoring bias. Earlier research based on aggregate data was unable to take differences in import intensity or intra-firm trade across firms into account. By using micro-level customs data, this study shows for the first time that firms with higher import shares exhibit larger offshoring bias. This finding implies that the conventional methods of estimating TFP may overestimate productivity growth for firms that rely more heavily on imported intermediate inputs.

Third, the study contributes to the broader literature on the relationship between imports and firm productivity. Prior studies such as Amiti and Konings (2007), Kasahara and Lapham (2013), and Halpern et al. (2015) argue that importing firms are typically more productive and that access to imported intermediates enhances productivity. However, the data sets utilized in the preceding studies lack information regarding firm-specific product prices.[3] Consequently, the estimation results may be susceptible to measurement error issues. As this study illustrates, firms that procure intermediates from foreign suppliers or overseas affiliates at low prices may appear to experience greater productivity growth than they actually do. This finding calls into question the assumption of a monotonic positive relationship between import intensity and productivity.

3 Measuring Offshoring Bias

This study is based on Japanese customs data compiled by the Ministry of Finance and the Basic Survey of Japanese Business Structure and Activities (BSJBSA) conducted by the Ministry of Economy, Trade and Industry. Japan Customs data serve as the source for Japan’s published trade statistics, capturing all international trade transactions conducted within the country at the transaction level. These data include highly detailed information on individual transactions, such as which firm imported or exported which goods,

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[3] While Halpern et al. (2015) utilize customs and balance sheet data for Hungarian manufacturing firms, their estimation of TFP relies on two-digit industry-level input and output price indices.

the value, the amount of duties paid, and the corresponding HS classification of the items. To supplement the information about firms' financial and business performance, we additionally use the BSJBSA data. This study focuses on the six-year period from 2015 to 2020. Although customs data are available for the years 2014 through 2022, the analysis is restricted to the period for which complete linkage with the BSJBSA is possible. Further, while our study period includes fiscal year 2020, the start of the COVID-19 pandemic, the impact on our results should be limited, since we focus on TFP growth over five-year intervals.

The BSJBSA is one of the most comprehensive datasets available for firm-level analyses in Japan. Initially launched in 1991, the survey has been conducted on an annual basis since 1994. The survey primarily targets firms in the manufacturing, wholesale, retail, and service sectors, covering all firms with 50 or more employees and capital (or capital investment) of 30 million yen or more within these sectors. Data are collected through mandatory questionnaires. For example, in the 2020 survey (reflecting 2019 results), responses were obtained from 29,780 firms. The BSJBSA gathers a broad range of firm-level information, including financial data such as sales, assets, liabilities, and profits, in addition to employment statistics, investment activities, and details of firms' corporate structure.

3.1 Discrepancies in import values between Japanese customs data and the BSJBSA

Understanding the extent of discrepancies between import values reported in the BSJBSA and those recorded in the customs data is essential for ensuring comparability with prior studies. To this end, we matched the two datasets at the firm level and conducted a comparative analysis. Appendix A provides detailed matching procedure between the BSJBSA and Japanese customs data.

In the BSJBSA, firms report the value of imported goods included in their cost of goods sold, specifically identifying the portion attributable to imports. This provides a firm-level view of import activities based on self-reported accounting information. In contrast, Japanese customs data contain the administrative records of the value, quantity, product (HS 9-digit), and origin country for imports (destination country for exports) of each transaction for tariff calculation purposes, i.e., comprehensive information on the trade activities of Japanese firms. While the two sources are generally expected to yield similar figures, there are three factors that cause discrepancies between the two. First, the BSJBSA collects data in units of one million yen, which leads to rounding biases and thus mismatches in the lower digits of transaction values. Second, some import transactions may not be included in cost of goods sold—for example, imports of capital goods—making it difficult to determine ex post whether such transactions were considered relevant by the reporting firms. The same applies to intra-firm trade or other imports not recognized as purchases in a narrow accounting sense. Third, firms may differ in how they incorporate import activities into their financial reporting, potentially introducing systematic discrepancies between recorded imports and financial statements.

To quantify the discrepancy between the imports reported in the BSJBSA and the customs data, we employ the metric proposed by Davis et al. (1996). This measure is calculated based on the following formula:

$$DHS_i = \frac{F_i^{BS} - F_i^{Customs}}{\left(F_i^{BS} + F_i^{Customs}\right)/2},$$

where F_i^{BS} denotes the value of imports by firm i reported in the BSJBSA, while $F_i^{Customs}$ represents the value of imports by the same firm i recorded in the customs data. We refer to this metric as the DHS index, which, by construction, ranges from –2 to 2. When a DHS index has a value close to –2, it indicates that the value of imports recorded in the customs data is larger than that reported in the BSJBSA, whereas a value close to 2 indicates that the value of imports reported in the BSJBSA is greater. The DHS index takes a value of 0 if the import values in both data sources are identical. Moreover, when the value of imports is missing in one of the two data sources, the index becomes -2 or 2. Because the customs data cover all transactions, we exclude capital goods that are unlikely to be recorded as intermediate inputs in the BSJBSA. This exclusion is implemented based on the BEC classification.[4]

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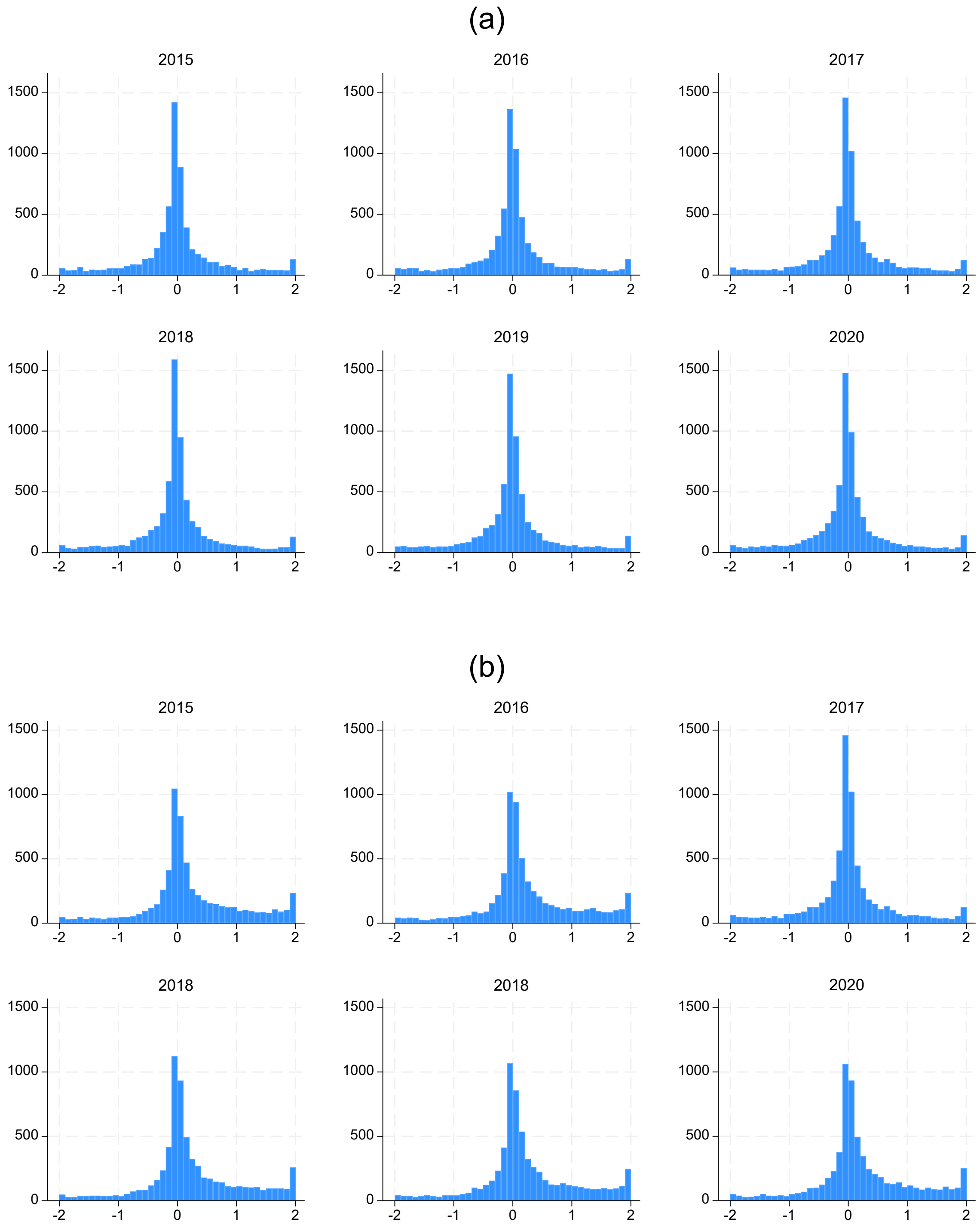
[4] The BEC classification aggregates traded goods into four categories—primary goods, intermediate goods, capital goods, and consumption goods—based on their role in the production process. Primary goods refer to resources such as oil, gas, and electricity that serve as sources of energy for production or consumption activities. Intermediate goods include raw materials and components that are further processed or assembled during manufacturing and become part of the final product. Capital goods are assets such as machinery, equipment, and buildings that are used in the production of other goods and services. Consumption goods are items intended for final consumption by households, including daily necessities, food, and household appliances. In this study, we classify traded goods based on their economic function using a concordance table between the BEC classification and the HS 6-digit codes. Since the Japanese customs data include product information at the HS 9-digit level, we can identify and exclude transactions in capital goods under the BEC framework. This allows us to focus on intermediate inputs relevant for the measurement of productivity.

Figure 2. Discrepancies in import values between Japanese customs data and the BSJBSA



Note: This figure shows histograms of the firm-level DHS index based on import values in the customs data and in the BSJBSA. Panel (a) includes capital goods as defined in the BEC classification in the import values taken from the customs data, whereas Panel (b) excludes capital goods.

Figure 2 presents histograms of the DHS index, calculated based on import values taken from the customs data and from the BSJBSA. Figure 2(a) shows the histograms when capital goods as defined in the BEC classification are included in the value of imports taken from the customs data. While the overall distribution appears roughly symmetric, there is a slightly heavier left tail, indicating a tendency for the customs-based import values to exceed those reported in the BSJBSA. This asymmetry suggests that firms do not always fully reflect their import activities in the BSJBSA—potentially due to differences in accounting definitions for procurements, rounding during survey reporting, and/or the exclusion of certain transactions. Moreover, the inclusion of capital goods in the customs data suggests that firms may be reporting imported capital goods as part of their purchases in the BSJBSA.

Figure 2(b) presents the histograms obtained after capital goods are removed from the import values in the customs data using the BEC classification. In this case, the distribution exhibits a consistently heavier right tail across all years, indicating that for many firms, the import values reported in the BSJBSA exceed those in the customs data. This finding implies that when using the BSJBSA to estimate productivity, capital goods may have been inadvertently included as intermediate inputs, potentially leading to inaccurate productivity estimates.

In the remainder of this paper, we use import values from the customs data to represent imported intermediate inputs. These values are adjusted by excluding capital goods based on the BEC classification to ensure a more accurate estimation of firm-level productivity.

3.2 Deflators for imported intermediate inputs at the HS 9-digit level

One of the key advantages of the customs data is the granularity of the data in that we can identify individual transactions at the HS 9-digit level. While previous studies have typically relied on industry-level intermediate input deflators, it is evident that firms face different price dynamics depending on the specific products they import. The inability to account for this heterogeneity across products has likely been a major source of mismeasurement in earlier analyses. To address this issue, this study is the first to construct deflators for imported intermediate inputs at the HS 9-digit product level.

The HS product classification undergoes frequent revisions, with minor adjustments occurring annually and major revisions at the 6-digit level taking place approximately every five years. They not only involve the creation or elimination of specific product codes but also include structural changes such as the splitting of a single code into multiple new categories or the merging of several codes into one. As a result, even if an HS code uniquely corresponds to a specific product at a given point in time, this does not guarantee that the correspondence remains valid over a longer period. To address this issue, we construct a concordance table that ensures one-to-one correspondence between HS 9-digit codes and physical goods over time.

The deflators for imported intermediate inputs were constructed based on the following procedure. First, we linked the import deflators from the JIP Database to HS 9-digit product codes using the 2015 Input-Output Table Concordance for Trade Statistics[5] (primary deflator, $p_{j,t}^1$), where $j \in \{1, \dots J\}$ corresponds to HS 9-digit products. However, in the Japanese customs data, there are cases where some items such as tariff-exempt items are only reported at the HS 6-digit level, which makes it difficult to assign the primary deflator to some transactions.

To address this issue, we constructed HS 6-digit level deflators (secondary deflators, $p_{j,t}^2$) by aggregating HS 9-digit import values using nominal import values as weights. For items that could not be matched even at the 6-digit level, we identified the relevant industry based on the concordance between the basic classification in the 2018 Input-Output Table and the JIP industry classification.[6] We then assigned a tertiary deflator ($p_{j,t}^3$) calculated as the ratio of nominal to real imports from the JIP input-output data for that industry.[7] All deflators are normalized to 1 in the base year, 2015. In assigning deflators to HS 9-digit products, we prioritized the primary, then the secondary, and finally the tertiary deflators in that order. If no appropriate match could be made, we assigned a value of 1. The resulting deflator for an HS 9-digit product j in year t is expressed as follows:

$$p_{j,t}^F = \begin{cases} p_{j,t}^1 & \text{if } p_{j,t}^1 \text{ exists} \\ p_{j,t}^2 & \text{if } p_{j,t}^1 \text{ does not exist} \\ p_{j,t}^3 & \text{if } p_{j,t}^1 \text{ and } p_{j,t}^2 \text{ do not exist} \\ 1 & \text{otherwise.} \end{cases}$$

To compare the conventional industry-level intermediate input deflators with the import-based intermediate input deflators constructed in this study, we define the following metric for each industry $c \in$

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[5] https://www.soumu.go.jp/toukei_toukatsu/data/io/sonota_index.html.

[6] https://www.rieti.go.jp/jp/database/JIP2018/index.html.

[7] We use nominal and real import values based on Tables 1-7 and 1-8 of the JIP Database 2023, which are publicly available on the RIETI website at https://www.rieti.go.jp/jp/database/JIP2023/index.html.

$\{1, \ldots, C\}$.

$$d_{c,t}^{F} = \sum_{i=1}^{N_c} \frac{\sum_{j=1}^{J} F_{i,c,j,t}}{\sum_{j=1}^{J}\left(F_{i,c,j,t}/p_{j,t}^{F}\right)} \frac{\sum_{j=1}^{J} F_{i,c,j,t}}{\sum_{i=1}^{N_c}\sum_{j=1}^{J} F_{i,c,j,t}},$$

where c denotes the industry to which firm i belongs, and N_c represents the total number of firms in industry c, with the total number of firms satisfying $N_1 + N_2 + \cdots + N_C = N$. The term $F_{i,c,j,t}$ indicates the import value of HS 9-digit product j for firm i in industry c during year t. Thus, to obtain our firm-level import deflator $d_{c,t}^{F}$, we first deflate each HS 9-digit item and then aggregate across products using nominal import values as weights. For comparison, the conventional index based on the industry-level intermediate input deflator[8] $p_{c,t}^{M}$ provided by the JIP Database is computed as follows:

$$d_{c,t}^{M} = \sum_{i=1}^{N_c} \frac{\sum_{j=1}^{J} F_{i,c,j,t}}{\sum_{c=1}^{C}\left(\sum_{j=1}^{J} F_{i,c,j,t} \frac{Sales_{i,c,t}}{\sum_{c=1}^{C} Sales_{i,c,t}} \frac{1}{p_{c,t}^{M}}\right)} \frac{\sum_{j=1}^{J} F_{i,c,j,t}}{\sum_{i=1}^{N_c}\sum_{j=1}^{J} F_{i,c,j,t}}.$$

In the deflation approach based on JIP industry-level intermediate input deflators, each firm's import value is allocated across industries according to the industry-level sales shares reported in the BSJBSA. The allocated values are then deflated using the corresponding JIP intermediate input deflators. The deflated values are subsequently re-aggregated to obtain the firm-level real import intermediate inputs. Finally, firm-level deflators are calculated as the weighted average using firms' nominal import values as weights.

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[8] It should be noted that the industry-level intermediate input deflators provided in the JIP database are not calculated separately for domestic and foreign sources of procurement.

Figure 3. Comparison between our deflator for imported intermediate inputs and the JIP intermediate input deflator

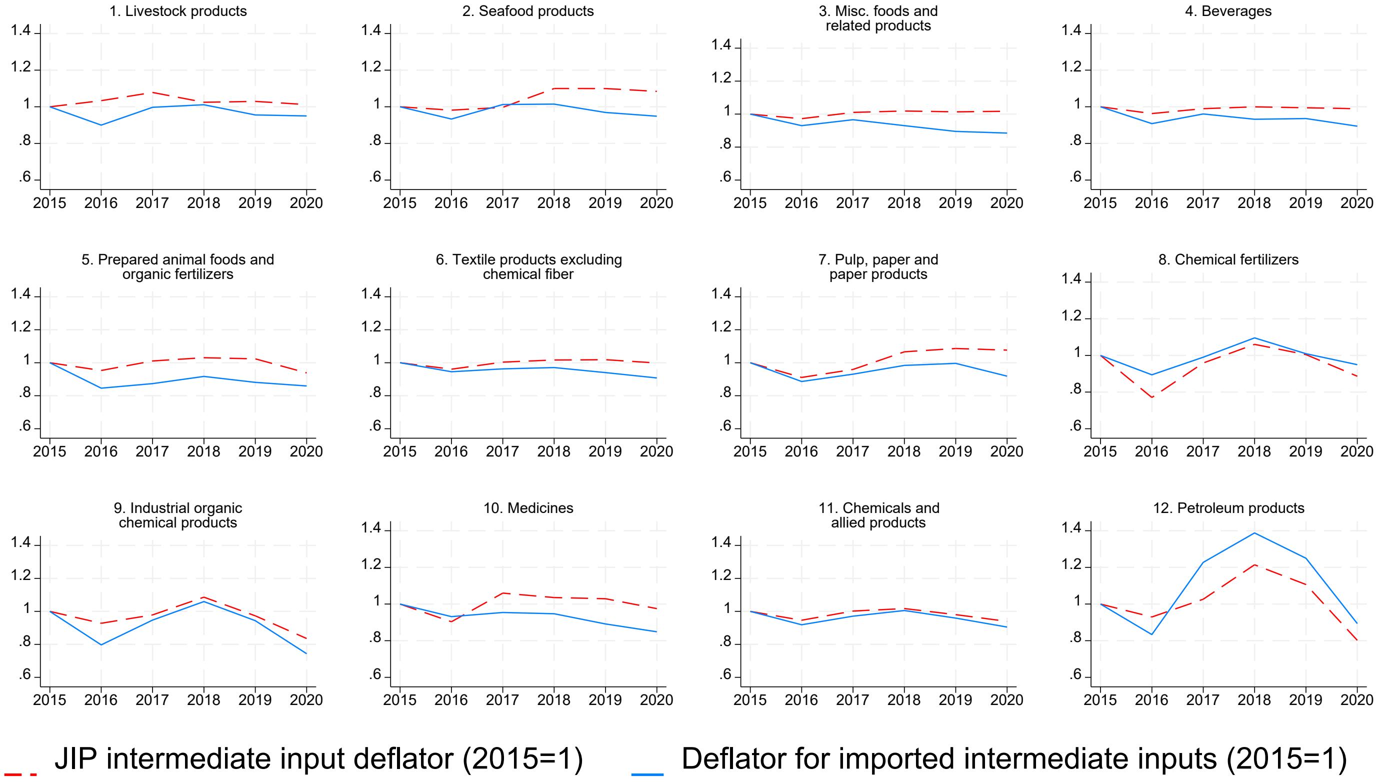


Figure 3. Continued

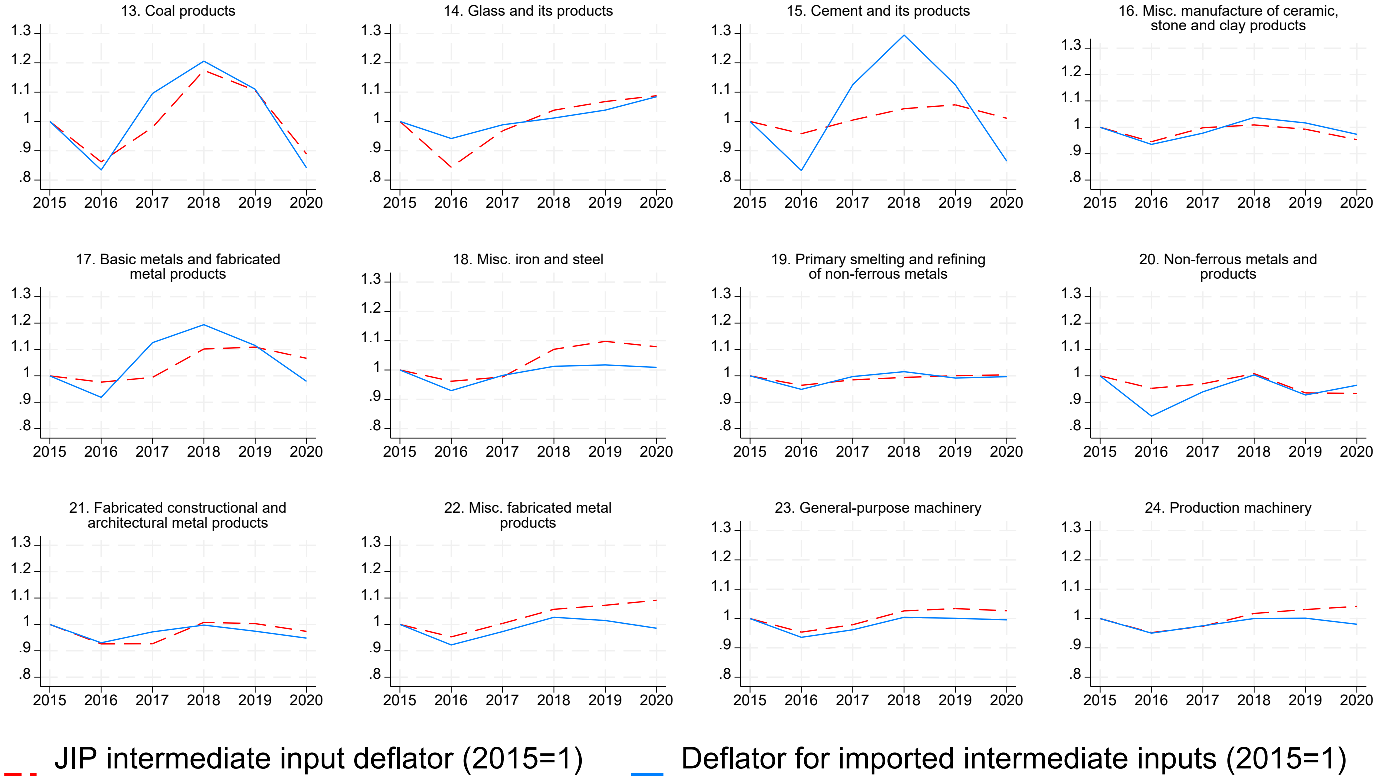


Figure 3. Continued

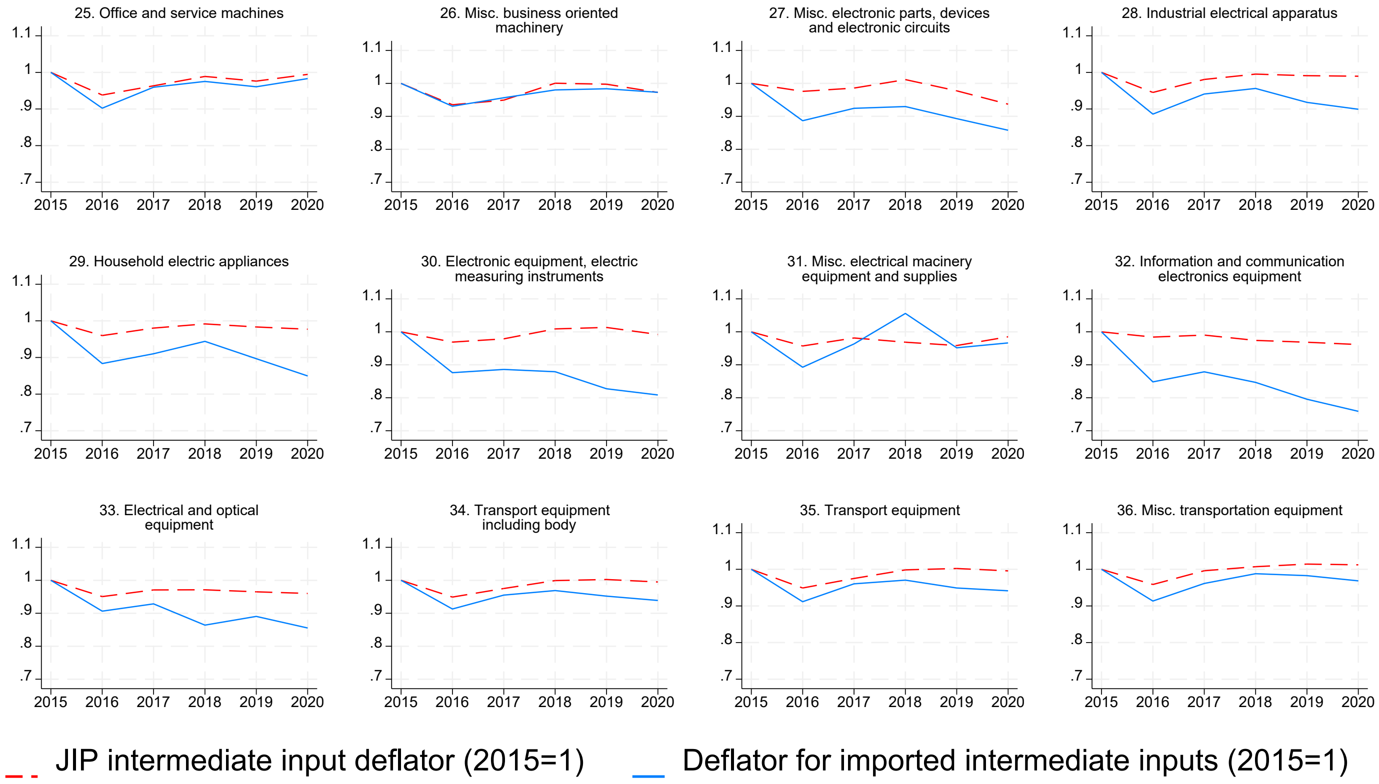
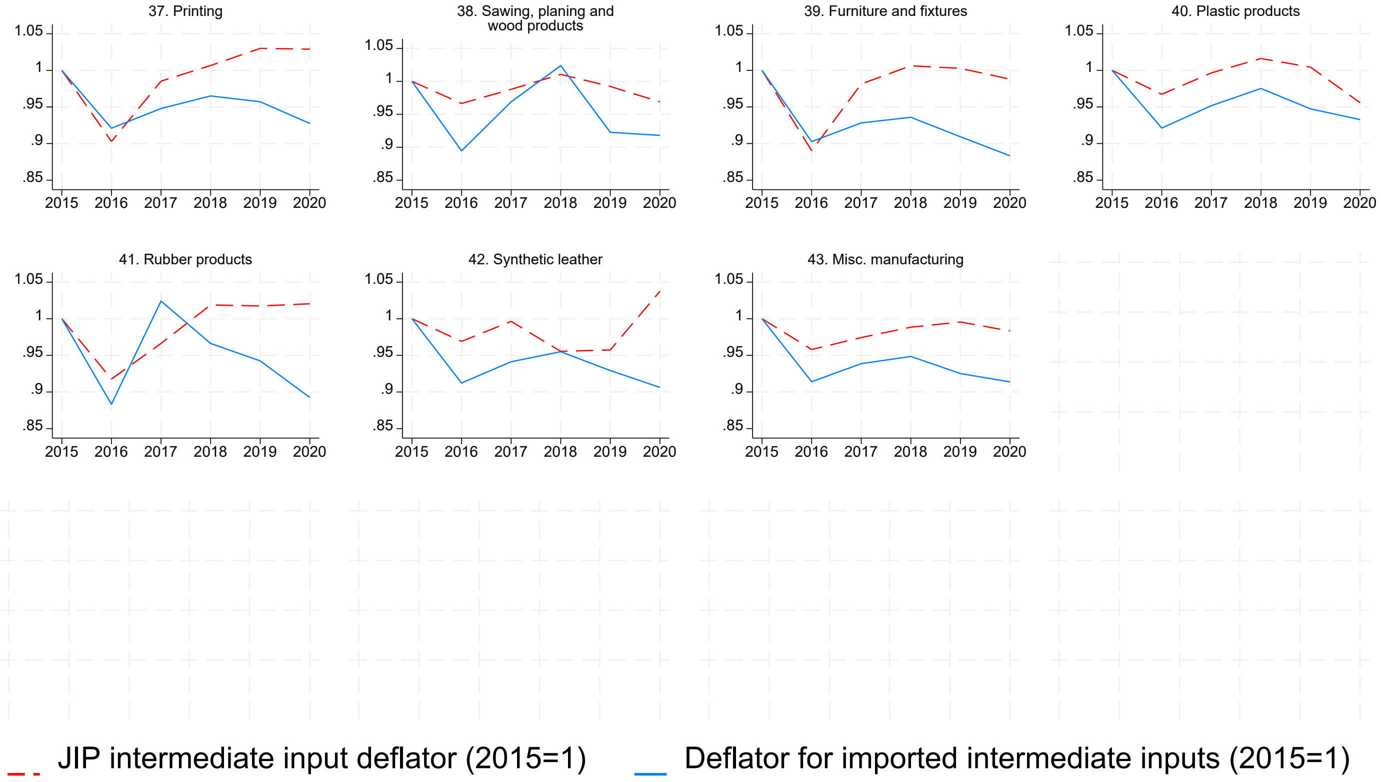


Figure 3. Continued



Note: Each panel corresponds to one of the 43 manufacturing industries defined in the JIP industry classification. In each panel, we compare the newly constructed import deflator for intermediate inputs ($d_{c,t}^{F}$, solid blue line) with the conventional industry-level intermediate input deflator provided in the JIP Database ($d_{c,t}^{M}$, dashed red line), using 2015 as the base year (normalized to 1). The observation period is from 2015 to 2020.

Each panel in Figure 3 represents one of the 43 manufacturing industries defined in the JIP industry classification and shows developments in our newly constructed import deflator for intermediate inputs ($d^F_{c,t}$) and the industry-level intermediate input deflator ($d^M_{c,t}$) in the JIP Database over the period from 2015 to 2020, with the values for 2015 normalized to 1. Overall, a growing divergence between the two deflators is observed in many industries over time. For industries such as electronic equipment, electric measuring instruments, and information and communication electronics equipment, the industry-level deflator remains relatively flat, whereas the newly constructed import deflator exhibits a clear downward trend. In many other sectors as well, the import deflator consistently lies below the industry-level deflator, suggesting that the exclusion of detailed product-level price information may undermine the accuracy of productivity measurement.

3.3 Construction of variables

In this section, we define the input variables used for our productivity measurement. Real values for output, capital input, and intermediate input are obtained by deflating nominal figures using the industry-level output deflator, investment deflator, and intermediate input deflator, respectively, from the JIP Database 2023. To apply these deflators, each firm's industry classification from the BSJBSA is matched to the corresponding industry category in the JIP classification.

The real output of firm i, denoted $Y_{i,c,t}$, is calculated by dividing its sales revenue from the BSJBSA ($Sales_{i,c,t}$) by the output deflator for the corresponding industry c in year t ($p^Q_{c,t}$):

$$Y_{i,c,t} = Sales_{i,c,t}/p^Q_{c,t}.$$

Capital input ($X^K_{i,c,t}$) is calculated by dividing the book value of tangible fixed assets excluding land ($X^{NK}_{i,c,t}$) by the capital deflator for the industry c to which the firm belongs ($p^K_{c,t}$):

$$X^K_{i,c,t} = X^{NK}_{i,c,t}/p^K_{c,t}.$$

Labor input ($X^L_{i,c,t}$) is calculated as the product of the total number of employees ($emp_{i,c,t}$) and the average annual hours worked per employee in industry c ($h_{c,t}$):

$$X^L_{i,c,t} = emp_{i,c,t} \times h_{c,t}.$$

Intermediate input ($X^M_{i,c,t}$) is calculated based on $M_{i,c,t}$, which is defined as the sum of the cost of goods sold and selling, general, and administrative expenses, minus total labor compensation and depreciation, for firm i in year t. As noted in Section 3.1, the import values reported in the BSJBSA do not necessarily match those recorded in the customs data. To address this discrepancy, we replace the import portion of intermediate inputs with values from the customs data and deflate these using our import-based intermediate input deflator and the JIP industry-level deflator to compare the results. When using the JIP industry-level intermediate input deflator ($p^M_{c,t}$), the real intermediate input is computed described as follows. Since the customs data allow us to capture all import transactions of each firm, we assume $\sum_{j=1}^{J} F_{i,c,j,t} = F_{i,c,t}$, and in some cases we observe that $M_{i,c,t} \leq F_{i,c,t}$, meaning the intermediate input is smaller than the import value. However, given that intermediate inputs do not become zero in such cases, we align the intermediate input value with the import value for consistency. The calculation is as follows:

$$X^M_{i,c,t} = \frac{\max\{M_{i,c,t} - F_{i,c,t}, 0\} + F_{i,c,t}}{p^M_{c,t}}.$$

When using the import deflators for intermediate inputs at the HS 9-digit level ($p^F_{j,t}$), real intermediate input is calculated as described below

$$X^F_{i,c,t} = \frac{\max\{M_{i,c,t} - F_{i,c,t}, 0\}}{p^M_{c,t}} + \sum_{j=1}^{J} \frac{F_{i,c,j,t}}{p^F_{j,t}}.$$

The cost of capital is calculated by multiplying the nominal industry-level capital cost from the JIP Database by the firm's real capital stock. Labor cost is measured using total compensation data from the BSJBSA. The cost of intermediate inputs is defined as $\max\{M_{i,c,t} - F_{i,c,t}, 0\} + F_{i,c,j,t}$, regardless of the input deflator used.

In the following productivity analysis, we use the variables defined above. In particular, we denote firm-level TFP based on intermediate inputs deflated using the import deflator ($X^F_{i,c,t}$) as $\ln TFP^{Customs}_{i,c,t}$. On the other hand, firm-level TFP based on intermediate inputs deflated using the conventional industry-level deflator ($X^M_{i,c,t}$), to which we compare our results, is denoted as $\ln TFP^{JIP}_{i,c,t}$.

Theoretically, an alternative would be to estimate firm-level TFP using intermediate inputs where the import component is not replaced with customs data, employing the expression $X_{i,c,t}^{BSJBSA} = M_{i,c,t}/p_{c,t}^{M}$, and use the resulting TFP – denoted as $\ln TFP_{i,c,t}^{BSJBSA}$ – for comparison. However, since the total value of a firm's imports recorded in the customs data often exceeds the firm's intermediate input reported in the BSJBSA, the nominal value of intermediate inputs may differ across $X_{i,c,t}^{BSJBSA}$, $X_{i,c,t}^{M}$, and $X_{i,c,t}^{F}$. In such cases, it becomes difficult to distinguish whether differences in estimated TFP stem from the deflator used or from differences in the underlying import values. Given that this study constructs new import-based intermediate input measures, we standardize the nominal intermediate input value and focus on comparing $\ln TFP_{i,c,t}^{JIP}$ and $\ln TFP_{i,c,t}^{Customs}$.

3.4 Estimation of productivity

Firm-level TFP using the index method is calculated following [Good et al. (1999), by measuring each firm's productivity relative to that of a hypothetical representative firm in its industry in the base year ($t_0 = 2015$). Specifically, the natural logarithm of the TFP of firm i in industry c at time t ($\ln TFP_{i,c,t}$) is defined in relation to the natural logarithm of the TFP of the representative firm in the same industry in the initial year $t = 2015$, for all $t \geq 2016$:

$$\ln TFP_{i,c,t} = \left(\ln Y_{i,c,t} - \overline{\ln Y_{c,t}}\right) - \frac{1}{2}\left(S_{i,c,t} + \overline{S_{c,t}}\right)'\left(X_{i,c,t} - \overline{X_{c,t}}\right) \quad \text{for } t = 2015,$$

$$\ln TFP_{i,c,t} = \left(\ln Y_{i,c,t} - \overline{\ln Y_{c,t}}\right) - \frac{1}{2}\left(S_{i,c,t} + \overline{S_{c,t}}\right)'\left(X_{i,c,t} - \overline{X_{c,t}}\right)$$

$$+ \sum_{s=1}^{t-t_0}\left(\overline{\ln Y_{c,t-s+1}} - \overline{\ln Y_{c,t-s}}\right) - \sum_{s=1}^{t-t_0}\frac{1}{2}\left(\overline{S_{c,t-s+1}} + \overline{S_{c,t-s}}\right)'\left(\overline{X_{c,t-s+1}} - \overline{X_{c,t-s}}\right) \quad \text{for } t \geq 2016,$$

where $S_{i,c,t} = \left(S_{i,c,t}^{K}, S_{i,c,t}^{L}, S_{i,c,t}^{M}\right)'$, $\overline{S_{c,t}} = \left(\overline{S_{c,t}^{K}}, \overline{S_{c,t}^{L}}, \overline{S_{c,t}^{M}}\right)'$, $X_{f,t} = \left(\ln X_{i,c,t}^{K}, \ln X_{i,c,t}^{L}, \ln X_{i,c,t}^{M}\right)'$, $\overline{X_t} = \left(\overline{\ln X_t^{K}}, \overline{\ln X_t^{L}}, \overline{\ln X_t^{M}}\right)'$. In this context, $S_{i,c,t}^{l}, l \in \{K, L, M\}$ denotes the cost share of input l for firm i, and $X_{i,c,t}^{l}$ represents the natural logarithm of input quantity l. Variables marked with a bar denote the arithmetic mean within industry c. K, L, and M refer to capital input, labor input, and intermediate input, respectively.

We estimate the production function using the method proposed by Wooldridge (2009). This approach provides a unified extension of the methods developed by Olley and Pakes (1996) and Levinsohn and Petrin (2003), while also addressing the identification problem highlighted by Ackerberg et al. (2006) through the use of a GMM framework. One advantage of this method, particularly in comparison with the index approach, is that it allows productivity to be estimated as the residual term. The production function is estimated based on the following model:

$$\ln Y_{i,c,t} - \ln X_{i,c,t}^{M} = \alpha + \beta \ln X_{i,c,t}^{L} + \gamma \ln X_{i,c,t}^{K} + \nu_{i,c,t} + e_{i,c,t},$$

where $\nu_{i,c,t}$ represents the productivity of firm i in industry c at time t, and $e_{i,c,t}$ denotes the error term. The coefficients α, β, and γ correspond to the output elasticities with respect to capital, labor, and intermediate inputs, respectively. Based on this specification, firm-level TFP is calculated as follows:

$$\ln TFP_{i,c,t} = \ln Y_{i,c,t} - \ln X_{i,c,t}^{M} - \hat{\alpha} - \hat{\beta} \ln X_{i,c,t}^{L} - \hat{\gamma} \ln X_{i,c,t}^{K}.$$

In the following analysis, we estimate TFP using both the index method and Wooldridge's approach and compare TFP growth when using $X_{i,c,t}^{M}$ (intermediate input deflated by industry-level deflators) versus $X_{i,c,t}^{F}$ (intermediate input deflated by product-level import deflators).

3.5 Estimation of offshoring bias

We measure offshoring bias as the difference between the TFP growth rate over the period $t - s$ calculated using intermediate inputs deflated by the JIP industry-level deflator, and the TFP growth rate over the same period calculated using intermediate inputs deflated by the deflator for imported intermediate inputs. That is, we define the difference in TFP growth rates as offshoring bias calculated as follows:

$$OB_{s,t} = \left(\ln TFP_{t}^{JIP} - \ln TFP_{s}^{JIP}\right) - \left(\ln TFP_{t}^{Customs} - \ln TFP_{s}^{Customs}\right).$$

As discussed in Sections 1 and 2, when productivity growth in intermediate goods production in countries such as China leads to sharper price declines (or slower price increases) for imported intermediate goods than their domestic counterparts, firms with a higher share of imported intermediates in their total intermediate input are expected to exhibit a larger and positive offshoring bias. Another factor to consider is that the relative price trends of domestic and imported intermediate goods are influenced by exchange rates. If the currencies of countries exporting intermediate goods depreciate (i.e., the yen appreciates), the relative cost of imported inputs declines. Under these circumstances, firms with a higher share of imported intermediates are more likely to exhibit a positive offshoring bias. In fact, as shown in Figure 4, the nominal effective exchange rate of the yen appreciated steadily from 2015 to 2020. It is important to note that this appreciation may have contributed to the positive offshoring bias among firms that relied heavily on imported intermediate inputs during that period.

Figure 3. Japan's nominal effective exchange rate

Source: Federal Reserve Economic Data.

4 Estimation Results of Offshoring Bias

4.1 Summary statistics

Table 1. Descriptive statistics.

Variables	Obs.	Mean	S. D.	P10	P50	P90
Panel A: Offshoring bias						
$OB_{2015,2020}$						
Index	8913	0.0039	0.0159	-0.0012	0.0002	0.0124
Wooldridge	8913	0.0053	0.0460	-0.0020	0.0001	0.0126
Panel B: TFP growth						
JIP intermediate input deflator: $\ln TFP_{2020}^{JIP} - \ln TFP_{2015}^{JIP}$						
Index	8913	0.0553	0.3452	-0.1330	0.0354	0.2454
Wooldridge	8913	0.0319	0.5803	-0.3140	0.0278	0.3941
Deflator for imported intermediate inputs: $\ln TFP_{2020}^{Customs} - \ln TFP_{2015}^{Customs}$						
Index	8913	0.0514	0.3447	-0.1374	0.0334	0.2380
Wooldridge	8913	0.0266	0.5837	-0.3194	0.0238	0.3891
Panel C: Firm characteristics						
Import share	8913	0.1057	0.2410	0.0000	0.0006	0.3678
Affiliate import share	8913	0.0393	0.1453	0.0000	0.0000	0.0693
Import share from China	8913	0.2117	0.3549	0.0000	0.0000	0.9585
Import share from the U.S.	8913	0.0651	0.1966	0.0000	0.0000	0.1725
Employment	8913	459.8410	1850.2993	68.0000	154.0000	769.5455
R&D share	8913	0.0114	0.0286	0.0000	0.0003	0.0344

Note: Panels A and B report descriptive statistics on TFP growth rates and differences in TFP growth rates between 2015 and 2020. Panel C presents descriptive statistics for the explanatory variables used in the regression analysis, all of which are based on values from the year 2015. P10, P50, and P90 indicate average values near the respective percentiles. In accordance with the joint research guidelines, these averages are calculated such that the number of firms included from the Japanese customs data is at least 10 for each group. As such, they do not represent exact percentiles. The import share and affiliate import share are the shares of total imports or imports from affiliated firms in total intermediate inputs. The import shares from China and the U.S. are the shares of imports from China and the United States, respectively, in total imports. The R&D share is the ratio of R&D expenditure to total sales, while employment represents the number of employees, which serves as a proxy for firm size. Observations with $OB_{2015,2020} = 0$ are excluded, so the sample includes only firms that engaged in continuous importing activities throughout the period from 2015 to 2020.

Table 1 presents descriptive statistics on the estimated offshoring bias and TFP growth rates between 2015 and 2020. The sample consists of 8,913 firms that continuously engaged in import activities over this period and for which the offshoring bias $OB_{2015,2020}$ is non-zero. There are two main cases where $OB_{2015,2020} = 0$. First, for firms that do not import at all, the deflator used in this study has no effect, resulting in no offshoring bias—such firms are excluded from the analysis. Second, in cases where the conventional deflator and the newly constructed deflator for imported intermediate inputs are identical for certain product types, the bias is undetectable, and these firms are also excluded.

The average offshoring bias is approximately 0.004, indicating an average bias of around 0.4% over the period. P10, P50, and P90 represent average values near the corresponding percentiles. At the median, the bias is about 0.02%, suggesting that TFP growth estimates for most firms are only minimally affected. In contrast, the value for P90 indicates that estimates for some firms are biased by about 1%, which is non-negligible. Comparing the results obtained under the index and Wooldridge methods, the variance in TFP growth is larger under the Wooldridge method, but the percentile distribution of the offshoring bias is quite similar between the two, suggesting a fat-tailed distribution.

Panel C provides descriptive statistics for firm characteristics and import-related variables used as explanatory variables in the regression analysis. Import share represents the share of imported inputs out of the total value of the intermediate inputs. Affiliate import share indicates the share of intermediate input imported from affiliated companies. This is based on the information of the BSJBSA that asks firms to report the value of imports from affiliates within their total overseas purchases. Although average import share is about 10%, the median is near zero, indicating that while many firms do import, imported goods make up only a minimal share of intermediate inputs. The standard deviation is approximately 24%, suggesting that some firms rely heavily on imports. A similar pattern can be observed for the affiliate import share.

Import share from China represents the proportion of a firm's total imports that originate from China and Import share from the U.S. is similarly the share of the imports from the United States. Looking at the country-specific import shares, the import share from China is as high as 95% at the 90th percentile, indicating a high dependency on China among these firms. In contrast, the import share from the United States at the 90th percentile is only 17%. To control for firm size, we include the number of employees in the regression analysis. The minimum value is 50, since the BSJBSA covers only firms with 50 or more employees; however, the standard deviation is around 1,850, reflecting the presence of large firms. The reason for controlling for firm size is that engaging in imports is likely to be easier for large than for small firms, thus potentially affecting the extent of imports and hence offshoring bias. The R&D share is defined as the ratio of total R&D expenditure (including in-house, outsourced, and commissioned research) to total sales. On average, firms allocate around 1% of sales to R&D, although there are large differences across firms, with the R&D share reaching about 3% at the 90th percentile.

Figure 5 presents binscatter plots for importing firms, where the vertical axis indicates the offshoring bias and the horizontal axis shows the share of imports in total intermediate inputs as of 2015.[9] Each bin represents a group of at least 10 firms to satisfy MOF guidelines for the use of customs data. The straight lines represent the univariate regression lines estimated from the full (unbinned) sample, with the offshoring bias as the dependent variable and the import share as the single explanatory variable. Blue lines with blue bins correspond to the offshoring bias based on the index method, whereas the red ones correspond to the offshoring bias based on Wooldridge's (2009) method. The industry classification follows the SNA framework.[10] Across all industries, offshoring bias increases with the import share. This implies that when TFP growth is measured using the JIP industry-level deflator, it tends to be overestimated relative to the TFP measured using the deflator for imported intermediate inputs. This upward bias is evident regardless of whether productivity is based on the index method or Wooldridge's (2009) method, although the latter estimates tend to exhibit greater dispersion, as shown in the descriptive statistics.

Figure 6 depicts the average offshoring bias by industry. Offshoring bias is observed across all industries in both estimation methods. Wooldridge's (2009) method tends to yield greater variance and relatively larger estimates of offshoring bias than the index method. This discrepancy is particularly pronounced in the general-purpose production and business-oriented machinery industry and the information and communication electronics equipment industries.

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[9] In accordance with the usage policy of the Japanese customs data, this study does not analyze or identify any individual firms. The figure presented is a binned scatterplot, which depicts representative values for groups of neighboring firms. Each point is plotted to ensure that it represents at least ten firms included in the customs data.

[10] Under the terms of the joint research agreement, only information representing at least ten importing firms in the Japanese customs data may be disclosed. Since a number of industries classified under the JIP industry classification do not meet this requirement, the results in this study are reported using a more aggregated industry classification.

Figure 4. Offshoring bias and import shares

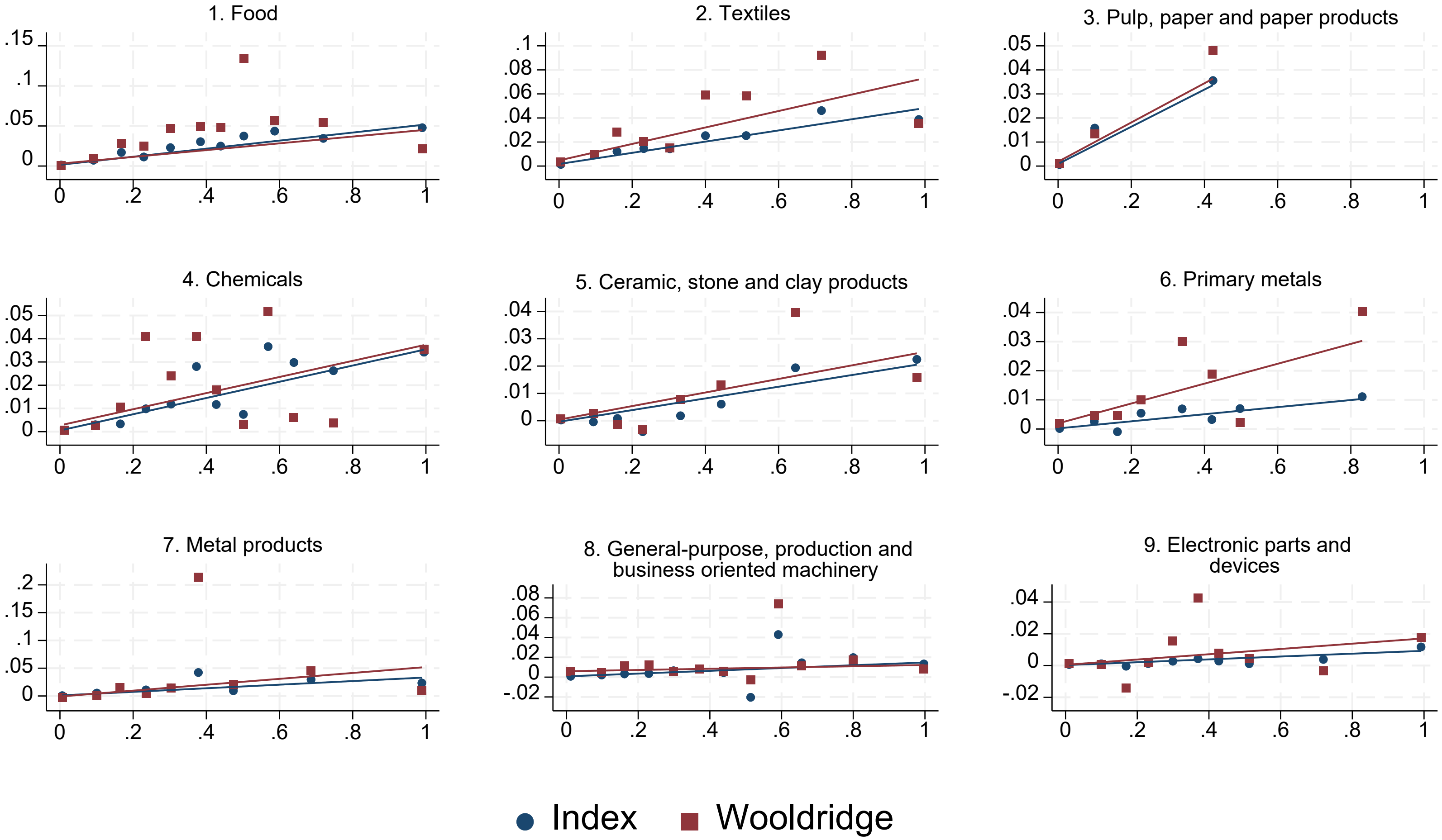


Figure 5. Offshoring bias and import shares, *Continued*

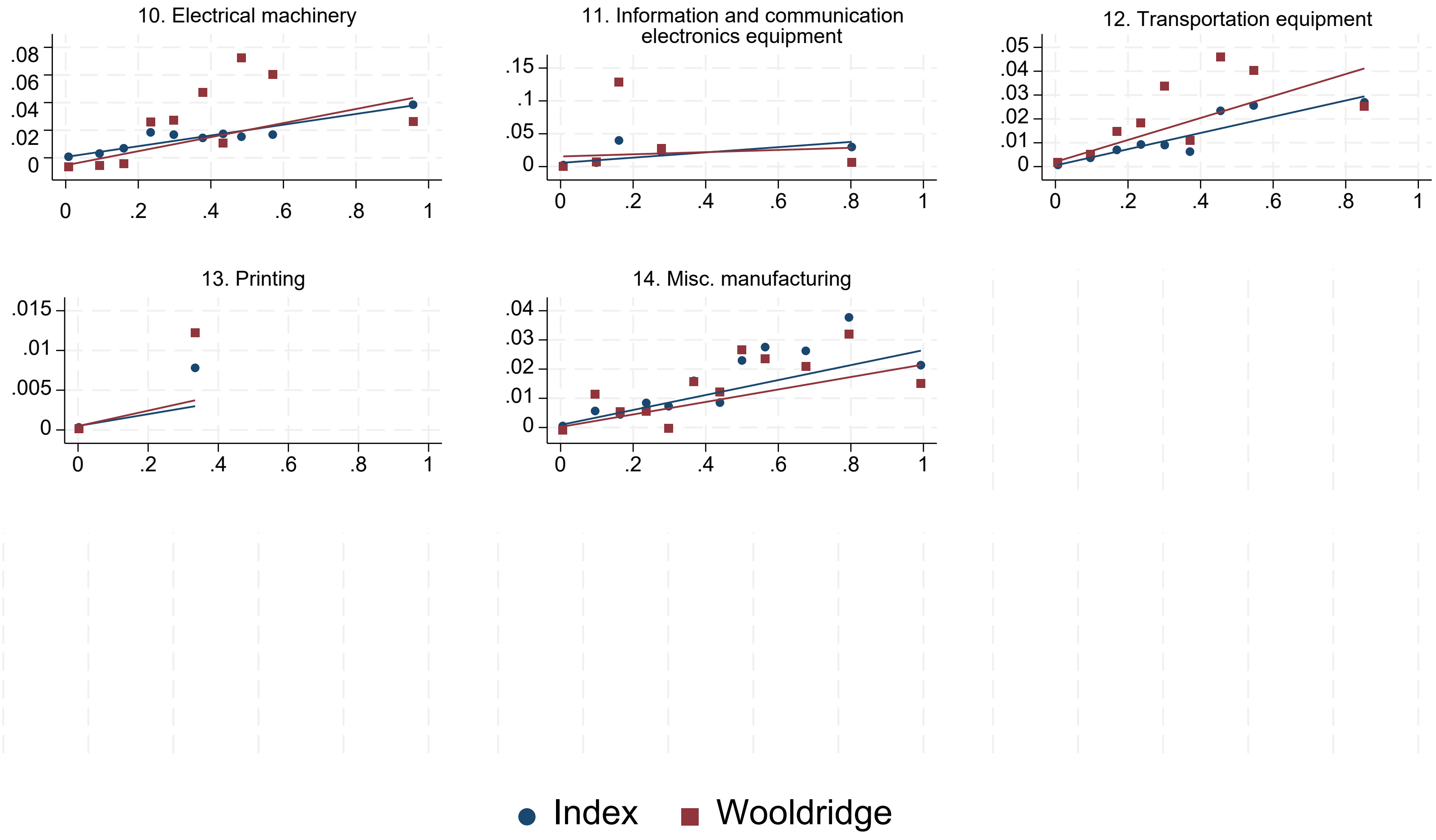
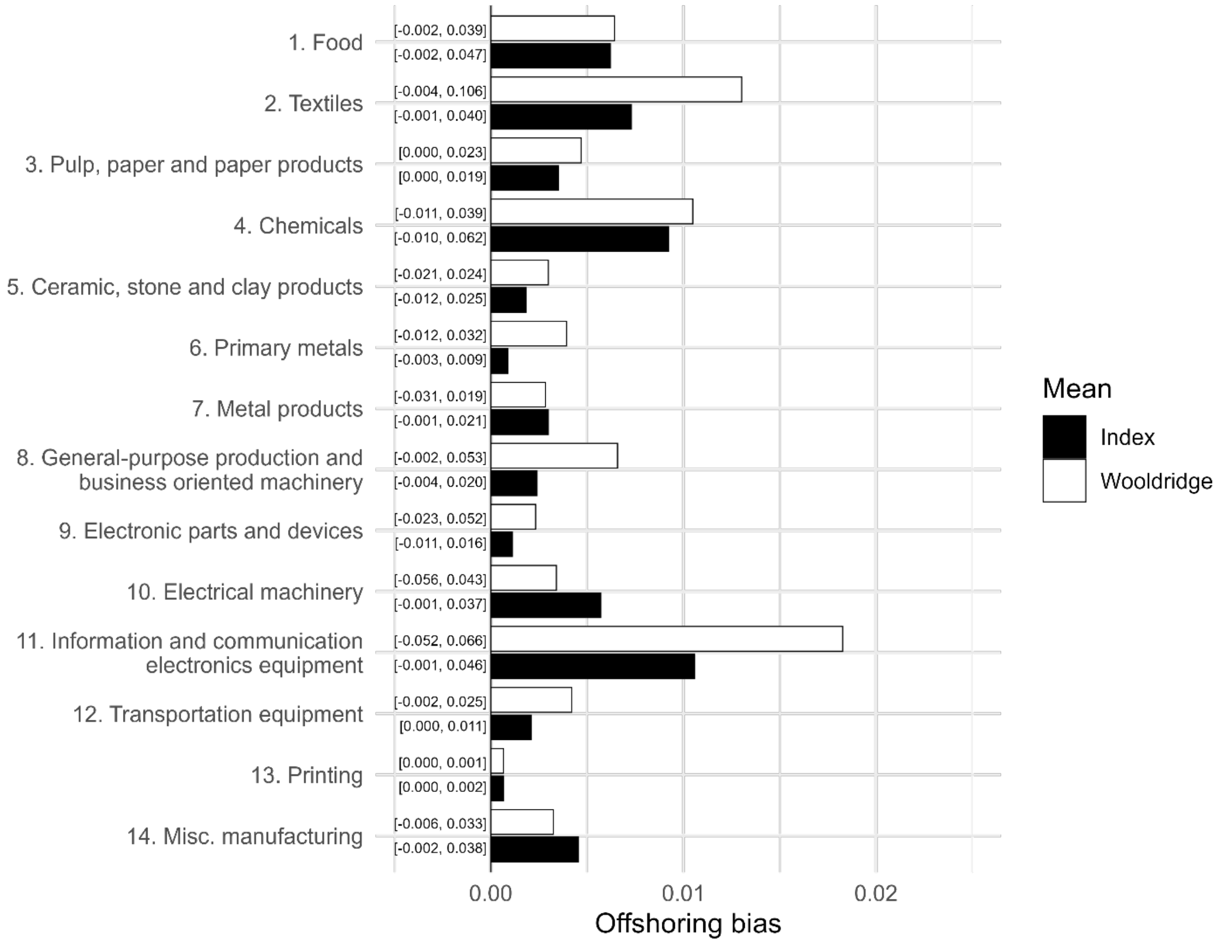


Figure 6. Average offshoring bias by industry and method



Note: This figure shows the average offshoring bias by industry. Values in brackets represent the corresponding 95% confidence intervals.

4.2 Firm-Level Heterogeneity in Offshoring Bias

Next, we examine firm-level heterogeneity in the offshoring bias. The regression sample is restricted to firms for which the offshoring bias is non-zero and that continuously engaged in imports from 2015 to 2020. This leaves us with a total of 8,913 firms, which constitute our sample for the analysis. The regression uses the firm-level offshoring bias as the dependent variable. As independent variables, we use a firm's import share, affiliate import share, and the natural logarithm of the number of employees. In addition, we include the interaction terms between import share, affiliate import share, and import shares from China and the U.S. to study the differential impacts. All variables, except for the offshoring bias, are based on values from the year 2015.

Table 2 presents the estimation results obtained when using the offshoring bias calculated using the index method as the dependent variable, while Table 3 shows the corresponding results when using Wooldridge's method. We find that, after controlling for the other variables and industry fixed effect, the coefficient on the import share is significant and stable at approximately 0.03 across the estimates. This implies that a 0.1 increase in the import share leads to an expansion of the offshoring bias by about 0.3%. The coefficient on the affiliate import share is also significant across all model specifications, suggesting that a larger share of intermediate imports from affiliates is also associated with greater offshoring bias. However, the interaction term between the import share and the affiliate import share is negative and significant, indicating that the offshoring bias is mitigated when a higher share of imports comes from affiliated firms, even if a firms' overall import intensity is high. While the coefficients on the import shares from China and the United States are not significant, the interaction term between the import share and the import share from China is positive and significant. This suggests that as the import share increases, the offshoring bias becomes more pronounced when a higher share of imports originates from China.

Similar patterns are observed in Table 3, where the offshoring bias is measured using Wooldridge's (2009) method. However, the interaction term between the import share and the import share from China is not statistically significant in this specification. The additional tables in Appendix B provide regression results for alternative periods (2015–2019 and 2016–2020), where we use the four-year

TFP growth rates. In all cases, the import share remains statistically significant, consistently confirming the presence of offshoring bias.

Table 2. Offshoring bias (2015-2020) based on the index method

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Import share	0.0298 ***	0.0312 ***	0.0327 ***	0.0323 ***	0.0308 ***	0.0306 ***	0.0297 ***	0.0292 ***	0.0288 ***
	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0009)	(0.0009)	(0.0010)	(0.0010)	(0.0010)
Affiliate import share		- 0.0054 ***	0.0053 ***	0.0044 **	0.0045 **	0.0045 **	0.0046 **	0.0037 *	0.0034 *
		(0.0012)	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Import share × Affiliate import share			- 0.0193 ***	- 0.0184 ***	- 0.0196 ***	- 0.0195 ***	- 0.0195 ***	- 0.0186 ***	- 0.0184 ***
			(0.0027)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)
Import share from China				0.0013 ***	0.0005	0.0006	0.0006	0.0003	0.0003
				(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Import share × Import share from China					0.0056 ***	0.0059 ***	0.0067 ***	0.0074 ***	0.0077 ***
					(0.0017)	(0.0017)	(0.0018)	(0.0018)	(0.0018)
Import share from the U.S.						0.0011	0.0005	0.0001	0.0001
						(0.0008)	(0.0009)	(0.0009)	(0.0009)
Import share × Import share from the U.S.							0.0047 *	0.0051 *	0.0045
							(0.0028)	(0.0028)	(0.0028)
Employment								0.0006 ***	0.0005 ***
								(0.0002)	(0.0002)
R&D cost share									0.0161 ***
									(0.0061)
Observations	8,913	8,913	8,913	8,913	8,913	8,913	8,913	8,913	8,913
R-squared	0.218	0.220	0.224	0.225	0.226	0.226	0.226	0.227	0.228

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. All explanatory variables are based on values for 2015. All estimations include a full set of industry dummies.

Table 3. Offshoring bias (2015-2020) based on Wooldridge's (2009) method

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Import share	0.0294 ***	0.0288 ***	0.0305 ***	0.0298 ***	0.0306 ***	0.0305 ***	0.0327 ***	0.0326 ***	0.0360 ***
	(0.0021)	(0.0023)	(0.0024)	(0.0024)	(0.0028)	(0.0028)	(0.0033)	(0.0033)	(0.0034)
Affiliate import share		0.0025	0.0146 **	0.0129 **	0.0128 **	0.0128 **	0.0126 **	0.0124 **	0.0143 **
		(0.0037)	(0.0061)	(0.0062)	(0.0062)	(0.0062)	(0.0062)	(0.0063)	(0.0063)
Import share × Affiliate import share			- 0.0219 **	- 0.0202 **	- 0.0196 **	- 0.0196 **	- 0.0197 **	- 0.0195 **	- 0.0207 **
			(0.0089)	(0.0089)	(0.0090)	(0.0090)	(0.0090)	(0.0090)	(0.0090)
Import share from China				0.0025 *	0.0029 *	0.0029 *	0.0030 *	0.0030 *	0.0030 *
				(0.0014)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Import share × Import share from China					- 0.0027	- 0.0026	- 0.0048	- 0.0046	- 0.0069
					(0.0054)	(0.0055)	(0.0057)	(0.0057)	(0.0057)
Import share from the U.S.						0.0004	0.0020	0.0019	0.0020
						(0.0025)	(0.0028)	(0.0028)	(0.0028)
Import share × Import share from the U.S.							- 0.0120	- 0.0119	- 0.0077
							(0.0089)	(0.0089)	(0.0089)
Employment								0.0001	0.0009 *
								(0.0005)	(0.0005)
R&D cost share									- 0.1164 ***
									(0.0196)
Observations	8,913	8,913	8,913	8,913	8,913	8,913	8,913	8,913	8,913
R-squared	0.027	0.027	0.028	0.028	0.028	0.028	0.028	0.028	0.032

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. All explanatory variables are based on values for 2015. All estimations include a full set of industry dummies.

5 Conclusion

This study provides the first empirical examination of offshoring bias—the overestimation of TFP growth due to the use of imported low-cost intermediate inputs—using a firm-level dataset constructed from Japanese customs data and the Basic Survey of Japanese Business Structure and Activities for the period 2015–2020. We find that when TFP growth is estimated using more refined, product-level import deflators that correct for offshoring bias, the resulting TFP growth rates are lower than those calculated using conventional industry-level deflators. This finding is broadly consistent with prior studies. Moreover, the offshoring bias is shown to be more pronounced among firms with higher import intensity. This implies that failing to account for offshoring bias may lead to an overestimation of TFP growth, particularly among large firms that heavily rely on imported intermediate goods.

While Fukao et al. (2016) argue that the slowdown in Japanese TFP growth during the so-called "lost two decades" was primarily driven by small and medium-sized enterprises, and that TFP growth among large firms remained stable, our results suggest that this conclusion may not hold if offshoring bias is properly addressed. This represents a novel contribution to the ongoing on the causes of Japan's sluggish productivity growth. Although it is widely believed that firms participating in global value chains—allowing them to source cheaper intermediate inputs from abroad—tend to exhibit higher TFP growth, our findings indicate that, once offshoring bias is taken into account, TFP improvements may be more modest. This suggests that policy makers should consider the offshoring bias when designing policies to promote productivity growth among Japanese firms.

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Appendix

A. Merging the Basic Survey of Japanese Business Structure and Activities with the Japanese Customs Data

In this study, we link importer/exporter codes from the Japanese customs data with corporate numbers from the BSJBSA. In addition, we incorporate statistical matching based on firm registry information to enhance the accuracy of the linkage. Importer/exporter codes consist of a 17-digit alphanumeric identifier assigned to each firm registered in the NACCS.[11] These codes fall into four categories: a corporate number with a 4-digit branch suffix, the Japan standard importer/exporter code, customs-issued importer/exporter codes, and unidentified entities.[12] The codes in the different categories are issued by different authorities and have been consolidated into a unified system. The corporate importer/exporter code represents the head office of a firm, while the consolidated importer/exporter code aggregates multiple codes identified by customs as belonging to the same entity.[13] Corporate numbers have been retroactively assigned even to data from before the official adoption of Japan's corporate number system.

For this study, we adopt a hierarchical rule that prioritizes the consolidated code, followed by the corporate code, and finally the basic importer/exporter code. The first 13 digits of the selected code are used as the corporate number within the Japanese customs data. Although corporate numbers are also recorded in the BSJBSA, they have only been available from the 2018 survey year (based on

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[11] Ito et al. (2023) provide a detailed overview of the importer/exporter codes included in the Japanese customs data.

[12] While Ito et al. (2023) exclude unidentified entities from their analysis, this study includes firms that could not be linked via corporate numbers in the matching process.

[13] For example, when an importer or exporter obtains a new corporate number, and customs authorities are able to confirm that the entity previously filed declarations using an importer/exporter code, the newly obtained corporate number is recorded as the consolidated importer/exporter code.

FY2017 results).[14] Therefore, for the years 2014 to 2016, corporate numbers were not included.

To address this, we retroactively assigned corporate numbers using company name, telephone number, postal code, and address information from the BSJBSA firm registry and the National Tax Agency's corporate number database. Further, to deal with cases where we were unable to link firms due to inconsistencies in the way the information was formatted, we converted address information to geographic coordinates and compared entries with data from other survey years and the National Tax Agency. Additionally, we manually corrected apparent typographical errors as necessary.

We employ a two-stage procedure to merge firm-level data from the BSJBSA with the customs data. In the first stage, we matched the corporate numbers listed in the BSJBSA with importer/exporter codes, corporate importer/exporter codes, and consolidated importer/exporter codes in the customs data. We match the data on a monthly basis to ensure that the customs data for a firm aligns with the financial year of the firm reported in the BSJBSA. For instance, for a firm whose financial year ends in March 2016, we use customs data from April 1, 2015 to March 31, 2016 to correspond to the data in the 2016 BSJBSA survey for fiscal 2015. For firms whose financial year ends in September, we match their BSJBSA data for that financial year with customs data for October 1, 2014, to September 30, 2015. Overall, our matching covers data from January 1, 2014, through March 31, 2022.

Next, in the second stage, we link firms that were not matched in the first stage using a statistical matching procedure. Specifically, we calculate similarity scores based on firms' name, telephone number, and postal code, and then confirm potential matches through manual inspection. We group firms geographically using postal codes, and exclude firms whose postal codes have changed over time from the similarity calculation.

Table A1 shows the number of firms in the BSJBSA that we were able to match with the customs data. The column labeled "Fiscal year" indicates the survey year, based on each firm's fiscal year. The next column presents the number of matched firms in Panel A and the associated import value in Panel

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[14] A corporate number is a 13-digit identification code assigned by Japan's National Tax Agency to corporations and certain types of organizations, based on the Act on the Use of Numbers to Identify a Specific Individual in Administrative Procedures. Its use began in October 2015.

B when only the base importer/exporter code is used. While a similar approach is taken by Ito et al. (2025), our study observes an increase of approximately 1,000 to 2,000 matched firms from 2018 to 2020 based on corporate number linkage, reflecting improved matching accuracy. In addition, the absence of missing corporate numbers in the 2021 and 2022 BSJBSA datasets, as well as the extension of the analysis period to 2022 in our study, contributed to the improvement in the number of firms to which retroactive corporate numbers could be assigned. The third column shows the number of matched firms and corresponding import value when the corporate number is reconstructed based on all available importer/exporter codes, including corporate and consolidated codes. As shown in the last column, this approach results in a substantial improvement in the matching rate—by up to 23% in 2015—and a 7% improvement in import value coverage over the full analysis period.

Table A1. Number of matched firms and import value from the linkage between the BSJBSA and the Japanese customs data.

Fiscal year	(1) Firms that are matched based on importer-exporter code	(2) Firms that are matched based on corporate numbers	Ratio (2)/ (1)
Panel A: Importer			
2015	9,844	12,141	123.33%
2016	10,134	12,400	122.36%
2017	10,938	12,777	116.81%
2018	12,401	13,200	106.44%
2019	12,759	13,233	103.72%
2020	13,158	13,520	102.75%
Total	69,234	77,271	111.61%
Panel B: Import Value (in Billion Yen)			
2015	41,291	45,046	109.09%
2016	37,495	40,586	108.24%
2017	44,457	48,860	109.90%
2018	49,507	52,800	106.65%
2019	46,370	49,079	105.84%
2020	39,092	41,149	105.26%
Total	258,213	277,520	107.48%

Note: The column labeled "Fiscal year" indicates each firm's fiscal year. The next column shows the sample of firms that are matched using only the importer-exporter code. The third column shows the sample of firms that are matched using not only the importer-exporter code but also geo-matching and statistical matching methods. The last column represents the ratio of the third column to the second column, indicating the improvement rate in the number of matched firms.

B. Regression Results Using Four-Period TFP Growth as the Dependent Variable

Table A2. Offshoring bias (2015-2019) based on Index method.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Import share	0.0262 ***	0.0271 ***	0.0281 ***	0.0279 ***	0.0265 ***	0.0263 ***	0.0256 ***	0.0253 ***	0.0251 ***
	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)
Affiliate import share		- 0.0033 ***	0.0037 **	0.0033 *	0.0034 **	0.0034 **	0.0035 **	0.0030 *	0.0028
		(0.0010)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
Import share × Affiliate import share			- 0.0125 ***	- 0.0121 ***	- 0.0130 ***	- 0.0130 ***	- 0.0129 ***	- 0.0125 ***	- 0.0123 ***
			(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Import share from China				0.0007 *	0.0000	0.0001	0.0000	- 0.0001	- 0.0001
				(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Import share × Import share from China					0.0048 ***	0.0051 ***	0.0058 ***	0.0061 ***	0.0063 ***
					(0.0015)	(0.0015)	(0.0016)	(0.0016)	(0.0016)
Import share from the U.S.						0.0014 **	0.0009	0.0007	0.0007
						(0.0007)	(0.0008)	(0.0008)	(0.0008)
Import share × Import share from the U.S.							0.0037	0.0039	0.0036
							(0.0024)	(0.0024)	(0.0024)
Employment								0.0003 **	0.0003 *
								(0.0001)	(0.0001)
R&D cost share									0.0091 *
									(0.0054)
Observations	9,754	9,754	9,754	9,754	9,754	9,754	9,754	9,754	9,754
R-squared	0.207	0.208	0.210	0.210	0.211	0.211	0.211	0.212	0.212

Note: Standard errors in parentheses. *** p < 0.01, ** p < 0.05, and * p < 0.1. All explanatory variables are based on values for 2015. All estimations include a full set of industry dummies.

Table A3. Offshoring bias (2016-2020) based on Index method.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Import share	0.0143 ***	0.0155 ***	0.0159 ***	0.0159 ***	0.0178 ***	0.0179 ***	0.0180 ***	0.0176 ***	0.0175 ***
	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)
Affiliate import share		- 0.0049 ***	- 0.0019	- 0.0020	- 0.0021	- 0.0021	- 0.0021	- 0.0029	- 0.0030 *
		(0.0010)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Import share × Affiliate import share			- 0.0051 **	- 0.0051 **	- 0.0041	- 0.0041 *	- 0.0041 *	- 0.0033	- 0.0033
			(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Import share from China				0.0000	0.0010 **	0.0010 **	0.0010 **	0.0008 *	0.0008 *
				(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Import share × Import share from China					- 0.0069 ***	- 0.0070 ***	- 0.0071 ***	- 0.0064 ***	- 0.0063 ***
					(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Import share from the U.S.						- 0.0007	- 0.0006	- 0.0010	- 0.0010
						(0.0007)	(0.0008)	(0.0008)	(0.0008)
Import share × Import share from the U.S.							- 0.0004	0.0000	- 0.0002
							(0.0025)	(0.0025)	(0.0025)
Employment								0.0006 ***	0.0005 ***
								(0.0001)	(0.0001)
R&D cost share									0.0047 **
									(0.0023)
Observations	9,840	9,840	9,840	9,840	9,840	9,840	9,840	9,840	9,840
R-squared	0.091	0.093	0.093	0.093	0.095	0.095	0.095	0.097	0.097

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. All explanatory variables are based on values for 2016. All estimations include a full set of industry dummies.

Table A4. Offshoring bias (2015-2019) based on Wooldridge (2009)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Import share	0.0180 ***	0.0176 ***	0.0192 ***	0.0184 ***	0.0173 ***	0.0162 ***	0.0139 ***	0.0142 ***	0.0158 ***
	(0.0026)	(0.0029)	(0.0030)	(0.0030)	(0.0036)	(0.0036)	(0.0042)	(0.0042)	(0.0043)
Affiliate import share		0.0017	0.0132 *	0.0112	0.0113	0.0114	0.0116	0.0122	0.0131 *
		(0.0047)	(0.0077)	(0.0078)	(0.0078)	(0.0078)	(0.0078)	(0.0079)	(0.0079)
Import share × Affiliate import share			- 0.0209 *	- 0.0189 *	- 0.0196 *	- 0.0193 *	- 0.0192 *	- 0.0197 *	- 0.0204 *
			(0.0112)	(0.0112)	(0.0113)	(0.0113)	(0.0113)	(0.0113)	(0.0114)
Import share from China				0.0031 *	0.0025	0.0029	0.0028	0.0029	0.0030
				(0.0018)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Import share × Import share from China					0.0038	0.0051	0.0074	0.0070	0.0059
					(0.0069)	(0.0069)	(0.0072)	(0.0072)	(0.0073)
Import share from the U.S.						0.0064 **	0.0049	0.0051	0.0052
						(0.0032)	(0.0035)	(0.0035)	(0.0035)
Import share × Import share from the U.S.							0.0121	0.0118	0.0133
							(0.0111)	(0.0112)	(0.0112)
Employment								- 0.0004	0.0000
								(0.0006)	(0.0007)
R&D cost share									- 0.0536 **
									(0.0249)
Observations	9,754	9,754	9,754	9,754	9,754	9,754	9,754	9,754	9,754
R-squared	0.011	0.011	0.012	0.012	0.012	0.012	0.012	0.012	0.013

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. All explanatory variables are based on values for 2015. All estimations include a full set of industry dummies.

Table A5. Offshoring bias (2016-2020) based on Wooldridge (2009)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Import share	0.0138 ***	0.0124 ***	0.0100 ***	0.0101 ***	0.0147 ***	0.0154 ***	0.0192 ***	0.0191 ***	0.0192 ***
	(0.0020)	(0.0022)	(0.0023)	(0.0023)	(0.0027)	(0.0028)	(0.0031)	(0.0032)	(0.0032)
Affiliate import share		0.0052	- 0.0136 **	- 0.0133 **	- 0.0136 **	- 0.0136 **	- 0.0139 **	- 0.0141 **	- 0.0140 **
		(0.0036)	(0.0063)	(0.0063)	(0.0063)	(0.0063)	(0.0063)	(0.0064)	(0.0064)
Import share × Affiliate import share			0.0324 ***	0.0321 ***	0.0346 ***	0.0342 ***	0.0336 ***	0.0338 ***	0.0338 ***
			(0.0088)	(0.0088)	(0.0089)	(0.0089)	(0.0089)	(0.0089)	(0.0089)
Import share from China				- 0.0004	0.0020	0.0018	0.0020	0.0019	0.0019
				(0.0014)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Import share × Import share from China					- 0.0166 ***	- 0.0174 ***	- 0.0210 ***	- 0.0209 ***	- 0.0210 ***
					(0.0053)	(0.0053)	(0.0055)	(0.0055)	(0.0055)
Import share from the U.S.						- 0.0050 *	- 0.0020	- 0.0021	- 0.0021
						(0.0026)	(0.0028)	(0.0029)	(0.0029)
Import share × Import share from the U.S.							- 0.0217 **	- 0.0217 **	- 0.0214 **
							(0.0088)	(0.0088)	(0.0088)
Employment								0.0001	0.0002
								(0.0005)	(0.0005)
R&D cost share									- 0.0066
									(0.0082)
Observations	9,840	9,840	9,840	9,840	9,840	9,840	9,840	9,840	9,840
R-squared	0.016	0.016	0.017	0.017	0.018	0.018	0.019	0.019	0.019

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. All explanatory variables are based on values for 2016. All estimations include a full set of industry dummies.