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Import Competition, Product Switching, and R&D activities[1]

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Abstract

Using Japanese plant product-level data, this study focuses on the impact of increasing import competition pressure on changes in product portfolios by examining product entry and exit. We also consider the role of R&D activities at the plant level. While previous research on the adjustment of product portfolios for multi-product firms has emphasized the narrowing of products to core products, we show that firms engaged in R&D activities actively replace existing products with new ones and expand into new business fields due to increased import competition. These results are consistent with those of several studies on the relationship between competition and innovation. We also find that these effects are more pronounced in regions with larger public R&D stocks and in high-tech sectors.

Keywords: Import competition, Product Portfolio, Research and Development
JEL classification: D22, F14, F15, F61, L25

[1]This study is conducted as a part of the Project "Globalization and regional economies" undertaken at the Research Institute of Economy, Trade and Industry (RIETI).
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This study utilizes the micro data of the questionnaire information based on "the Census of Manufacture" (Ministry of Economy, Trade and Industry), Economic Census for Business Activity (Ministry of Internal Affairs and Communications / Ministry of Economy, Trade and Industry) and "Survey of Research and Development" (Ministry of Internal Affairs and Communications). We also utilize plant id converter, which is provided by RIETI.

1. Introduction

The rapid increase in imports from emerging economies has garnered attention for its impact on employment and firm performance in high-income countries. One primary concern is the effect of import competition pressure from China on manufacturing plant closures and employment. While early research has primarily focused on the impact of imports from China on labor markets, recent studies across various countries have explored industry- and firm-level heterogeneity.

In contrast, little is known about how firms adjust their product lines in response to increased import competition pressure from China. For example, previous studies have revealed that import competition may lead to downsizing, reducing the number of products, or narrowing the focus to core products. However, the details of product portfolio restructuring—such as replacing existing products with new ones—remain relatively unexplored. This study focuses on the impact of increasing import competition pressure on product portfolios changes by examining product entry and exit.

Changes in a firm's product portfolio are key to structural transformations within industries. Bernard et al. (2010), using plant-product level data from the US manufacturing sector, found that the contribution of product entry and exit by plants to overall changes in US manufacturing output is nearly equal to the contribution of plant entry and exit. This suggests that, at the macro level, a significant portion of structural changes in the manufacturing sector are driven by product entry and exit among surviving plants. Additionally, Bernard et al. (2010) found that firms adding or dropping products exhibit higher corporate performance.

This study uses Japanese plant-product-level data to examine the relationships among import competition, product switching, and R&D activities. Previous research suggests that the impact of increasing competitive pressure on technological innovation activities depends on a firm’s proximity to the technological frontier. Firms with advanced technology increase their innovation activities to escape competitive pressure, while low-tech firms are discouraged and are more likely to withdraw. We examine whether such mechanics are at work in the product portfolio reorganization in response to increased imports from China.

The main findings of this study are as follows. First, rising imports from China are associated with a decrease in the number of products at the plant level. As the time lag is taken longer, from 3 to 5 years, the impact on product exit, turnover of products, and net change in the number of products becomes more pronounced. Second, firms with larger R&D stock tend to simultaneously drop existing products and introduce new ones as import competition intensifies, with this effect more pronounced in regions with greater public R&D stocks.

This study draws on three strands of literature. The first examines the impact of rising imports from emerging economies. For instance, a series of studies by Autor et al. revealed that the rise in imports from China to the US has had a significant negative impact on local labor markets using large-scale industry-regional-level datasets (Acemoglu et al., 2016; Autor et al., 2013). Subsequent studies have examined the impact of import competition in various countries, such as Dauth et al. (2014) for Germany, Malgouyers (2016) for France, Balsvik et al. (2015) for Norway, Dooso et al. (2014) for Spain, and Taniguchi (2018) for Japan.[2]

Beyond its impact on local labor markets, several studies have explored the effects of import competition on various aspects of firm- or plant-level activities. Bernard et al. (2006) examined industry-switching behavior using US plant-level data, while Mion and Zhu (2013) focused on skill upgrading in French firms. Matsuura (2022) found that Japanese manufacturing firms are shifting from product sales to services. Hombert and Matlay (2018) highlighted the role of R&D, using data on US publicly listed firms. They showed that R&D investment acts as a shield against import competition mitigating its negative impact on sales and profit margins.[3]

Other studies have used product-level data, such as Iacavone et al. (2013), using data from Mexico; Bellone et al. (2022), using data from Japan; and Chakraborty and Henry (2019), using data from India. These studies show that multi-product firms tend to drop marginal products in response to increased import competition pressure and concentrate resources on core products (with the largest share of total sales). While these studies present interesting results, they do not investigate the details of product restructuring, such as replacing existing products with new ones.

Second, this study contributes to the literature on identifying the determinants of "product portfolios" or "product scope," specifically regarding the addition of new products as an outcome variable. Using data from Indian manufacturing firms, Goldberg et al. (2010) demonstrated that the expansion of imported intermediate goods due to tariff

[2] Most studies from European countries have confirmed the negative impact of import competition from China. However, the effects in Germany and Japan differ. For example, Dauth et al. (2014) compared the impact of imports from Eastern Europe and China on German local labor markets, demonstrating that Eastern European imports exert a more prominent negative effect than Chinese imports. This is because increased capital goods exported to China mitigated the negative impact of Chinese imports. Taniguchi (2018) used data on Japan’s local labor market and found that imports of intermediate inputs from China have a positive effect.

[3] Some studies have focused on the impact on patent application at the firm level. Bloom et al. (2016), using European firm data, and Yamashita and Yamauchi (2019), using Japanese firm data, concluded that import competition from China promotes patent application at the firm level. in contrast, using US firm data, Autor et al. (2020) did not observe such an effect.

reductions promotes the introduction of new products, thereby increasing firms' product scope. Analyzing firm-plant-product level data from Turkey, Lo Turco and Maggioni (2016) examined the introduction of new products at the 10-digit product classification level as "product innovation" and the role of regional comparative advantage in its determinants. They noted that internal factors within firms, such as the competitiveness of other products, have a greater impact than regional factors. By contrast, Zhang (2015) used "new product sales" from a Chinese manufacturing firm survey as an indicator of product innovation and analyzed the impact of agglomeration economies. He showed that industry diversity within cities is key to promoting product innovation in China. Our study regards product entries and exits as innovation outcomes of firms and focuses on both external factors, such as import competition pressure, and internal factors, such as firm-level R&D stocks.

Our study is also related to the heterogeneous impact of competition on innovation activities. According to a series of studies by Aghion et al., whether competition fosters innovation depends on a firm's distance from the technological frontier. Firms far from the frontier tend to scale down or exit the market when faced with competition (the discouragement effect). In contrast, firms closer to the technological frontier, especially neck-and-neck competing incumbents, tend to intensify their innovation activities in response to increased competitive pressure to escape competition (the escape competition effect). Agihon et al. (2005) examined this hypothesis using a panel dataset of UK firms. Amiti and Khandelwal (2013) also tested this hypothesis using international trade data, focusing on product quality as a measure of innovation outcomes and changes in tariff rates as a measure of competition. This study examines whether import competition promotes new product development and considers its implications for structural changes within industries.

The remainder of this paper is organized as follows: Section 2 discusses the data used, and Section 3 explains our analytical framework. The estimation results are presented in Section 4, and Section 5 concludes the paper.

2. Data

Our primary data sources are the longitudinal plant-level datasets from the Census of Manufacture (COM),[4] compiled by the Ministry of Economy, Trade, and Industry (METI). The COM data cover all plants in Japan with four or more employees and include

[4] The 2011 survey was conducted as the Economic Census for Business Activity (Ministry of Internal Affairs and Communications / Ministry of Economy, Trade and Industry) in place of the COM. We supplement the 2011 data using the Economic Census.

information on plant characteristics such as location, number of employees, tangible assets, shipment value, and four-digit-level sector classification.[5] The COM also provides plant-product-level shipment data at the six-digit-level commodity classification. In this study, we use the plant-product-level dataset from 1998 to 2014.[6] Since product classifications are revised every four to five years, we use the METI's concordance table for product classifications to link product data over the sample period.

The import competition measure is the share of Chinese imports in total imports at the product level. To compute this share, we obtain product-level trade data at the HS six-digit-level from the BACI database.[7] We then match the HS six-digit-level product codes with the COM's six-digit product codes.[8]

For R&D data, we use the Survey of Research and Development (SRD), conducted by Japan's Ministry of Internal Affairs and Communications. This mandatory survey covers firms engaged in R&D and provides annual data on R&D expenditures for approximately 9,000 firms, with a response rate exceeding 90%. Larger firms with capital exceeding 100 million yen are surveyed annually, while smaller firms are selected through stratified sampling. Following Belderbos et al. (2013, 2022), for firms with capital of less than 100 million yen, we focus on those that report their R&D activities in the survey at least three times in our sample periods; from 1998 to 2014. In other words, the sample for this study excludes small firms without R&D expenditures.

Finally, because COM and SRD use different firm ID numbers, we match them at the firm level using the firm's name, phone number, and location information. First, we restrict the data to firms whose names do not overlap with those of other companies in each survey and match them based on name, phone number, and location. For firms that could not be matched through this process, we further restrict the data to those with no duplication in company name within the same capital or employee size class and attempt matching again using the same criteria. Since the matched database covers only firms with R&D expenditures, the sample size is smaller than the original data. For example,

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[5] Unfortunately, plant-level data on international trade activities is limited. While it provides the share of export revenue in total shipments from 2001 onward, there is no information available on imports.

[6] In this study, data from 2015 onward are not used for two reasons. First, the firm identification code for each plant in COM is only available up to 2014 and is not available for 2015 onward. Second, the impact of other external shocks such as the US-China trade dispute must be considered if we extend the estimation period to the second half of the 2010s.

[7] The BACI (*Base pour l'Analyse du Commerce International*) database is a comprehensive international trade database compiled by CEPII (*Centre d'Études Prospectives et d'Informations Internationales*). It provides detailed data on bilateral trade flows for over 200 countries and covers more than 5,000 products. The BACI reconciles discrepancies between reporting and partner countries in UN Comtrade data to provide more accurate trade data.

[8] We use the modified version of the concordance table, which is used in Baek et al. (2021).

while the COM covered 236,120 firms and 290,843 plants in 2002, our matched database includes only 3,016 firms and 7,908 plants.

3. Analytical Framework

3.1 Empirical specifications

We follow Chakraborty and Henry's (2019) specifications and estimate the following equation:

$$\Delta Y_{fijrt} = \alpha + \beta_1 \Delta IMP_{fijt} + \gamma X_{fijrt-s} + \lambda_{jt} + \mu_r + \epsilon_{fijrt} \qquad (1)$$

ΔY_{fijrt} is the change in the number of products for firm *f*, plant *i*, and two-digit industry *j* in region *r* from year *t-s* to *t*.[9] Because product restructuring may take time, we use three years as the short-term time lag and five years as the long-term time lag. For ΔY_{fijt}, changes in the number of products have often been used as the dependent variable in previous studies. By contrast, this study examines the impact of changes in product mix, product entry (*PEntry*), and exit (*PExit*). *PEntry* is defined as the sum of the number of newly introduced six-digit-level products within a plant's two-digit industry.[10] *PExit* is the number of products that have stopped production. We also use the sum of *PEntry* and *PExit*, namely, *Turnover*, and the net changes in the number of products (*NetChange*), which equals *PEntry-PExit*.[11] Since *PEntry*, *PExit,* and *Turnover* can take zero values, we use the inverse hyperbolic sine transformation instead of the log-plus-one transformation. This approach accommodates non-positive values and reduces the influence of outliers in right-skewed distributions. Our product reallocation indices capture the entry and exit of products at the six-digit level within a plant's two-digit industry to align with firm-level R&D stock at the two-digit industry level.

ΔIMP_{fijt} is defined as the average import penetration of Chinese imports, weighted by plant-level sales share at the six-digit product level in year *t-s*,

$$\Delta IMP_{fijt} = \sum_p w_{fijpt-s} \frac{\Delta M_{jpt}^{CHN}}{Z_{jpt-s} + M_{jpt-s}},$$

[9] One may ask why we do not examine the impact on the survival probability of products at the six-digit level, as in Iacovone et al. (2013) and Bellone et al. (2022). However, this approach makes it difficult to account for product entry. Instead, this study examines changes in the number of six-digit-level products within a two-digit industry category at the plant level. Using the average import penetration rate, calculated with sales share weights in *t-s*, we examine whether new products are introduced within the same two-digit industry when existing products are exposed to import competition.

[10] One concern that this index does not take into account how innovative new products are, and that it is dependent on the level of detail in the product classification. Nevertheless, it is still a meaningful index for evaluating changes in industrial structure.

[11] In studies on firm entry and exit (e.g., Johansson, 2005), the sum of entering and exiting firms is often referred to as *Turnover*.

where is $w_{fijpt-s}$ represents the product sales share in total sales for firm *f*, plant *i*, industry *j*, product *p,* and year *t-s*. Z_{jpt-s}, M_{jpt-s}, and ΔM_{jpt}^{CHN} denote domestic production, total import value, and the changes in import value from China for industry *j* and product *p* in year *t-s,* respectively. $X_{fijrt-s}$ in Equation (1) is a vector of control variables, including the log of the number of employees (*Plant Size*), average plant wage, log of the number of employees at the firm level (*Firm Size*), firm-industry-level R&D stock, and regional-industry-level public R&D stock in year *t-s*.[12] λ_{jt} and μ_r represents industry-year-fixed effects and region fixed effects.

As Agihon et al. (2005) and Amiti and Khandelwal (2013) predicted, the relationship between innovation and competition may depend on a firm's technological level. To examine this effect, we introduce an interaction term between import competition and a firm's industry-level R&D stock.

$$\Delta Y_{fijrt} = \alpha + \beta_1 \Delta IMP_{fijt} + \beta_2 RDStock_{fjt-s} + \beta_3 \Delta IMP_{fijt} \times RDStock_{fjt-s} + \gamma X_{fijrt-s} + \lambda_{jt} + \mu_r + \epsilon_{fijrt} \quad (2)$$

where $RDStock_{fjt}$ is the log of R&D stock for firm *f* in industry *j* in year *t-s*.

3.2 Variable Construction

For the import ratio, the value of domestic production by product, and the value of imports by product, origin, and destination countries, Z_{pt} and M_{pt}^{od}, are obtained from the COM and BACI databases, respectively. For firm-level R&D stock, we follow the methodology of Berdelbos et al. (2013, 2022) and Fukao et al. (2014). First, we obtain R&D expenditures by technology field *k* at the firm level. The SRD reports R&D expenditure (*RDInv*) for approximately 20 technology fields, *k*. We then construct R&D stock by firm and technology field *k* using the following equation:

$$RDStock_{fkt} = RDInv_{fkt} + (1 - \delta_k) RDStock_{fkt-1},$$

where δ_k is technology field-specific depreciation rate, sourced from NISTEP (2009). R&D expenditures are deflated using a private R&D deflator from the JIP database, calculated from the price indices of input factors for R&D expenditures in each industry. The initial R&D stock, $RDStock_{fk0}$, is estimated as follows:

$$RDStock_{fk0} = \frac{RDInv_{fk0}}{\overline{g_k}},$$

where $RDInv_{fk0}$ and $\overline{g_k}$ are the R&D expenditures for firm *f* in technology field *k* in the initial year, 0, and the industry-level average growth rate of R&D expenditure from 1993 to 1998 in sector, respectively (Hall and Oriani, 2006). R&D stock by firm and

[12] We assume that all plants belonging to the same firm have access to the firm's knowledge stock. Therefore, we include firm-level R&D stock in the plant-level regression equation.

industry is estimated as the weighted average of the firm-level, technology field-specific R&D stock.

$$RDStock_{fjt} = \sum_k RDStock_{fkt} \times T_{kj},$$

where T_{sj} is the technology and industry proximity matrix used by Belderbos et al. (2013, 2022).[13]

To assess the impact of the knowledge spillover effect from universities and public research institutes on the local market, we construct public R&D stock by region and sector following Belderbos et al. (2013, 2022). First, we estimate the R&D expenditures at universities and public research institutes by science field. As the R&D survey does not provide R&D expenditures for universities and public research institutes by science field, we estimate them by multiplying the total R&D expenditure by the share of the number of scientists in the relevant field. Using the public R&D expenditure deflator from the White Paper on Science and Technology Policy, the R&D expenditure for each scientific field is deflated, and the public R&D stock is constructed using the perpetual inventory method, in the same way as for private R&D stock.

Next, we calculate the public R&D stock for each technology field using the weights derived from the concordance matrix between the science and technology fields. This weighting is based on Van Looy et al. (2004), who compared the frequency of citations of patent documents in different technology fields with Web of Science publications in each science field. Finally, using the technology and industry proximity matrix, we obtain the public R&D stock by industry and region. For regional classification, we use the urban employment area (UEA), which is the Japanese version of the metropolitan statistical areas (MSAs) in the US. The UEA was proposed by Kanemoto and Tokuoka (2002), and the data are obtained from the UEA website maintained by the Center for Spatial Information Science at the University of Tokyo.

3.3 Endogeneity

Estimating Equations from (1) through (2) by OLS might suffer from endogeneity bias, as ΔY_{ijt}, ΔIMP_{fijt}, and $RDStock_{fjt-s}$ might be simultaneously determined. For $RDStock_{fjt-s}$, since R&D investment is affected by the investments of neighboring firms in the same industry, we use the total R&D investment of other firms in the same industry

[13] We use the technology and industry proximity matrix used in Belderbos et al. (2013, 2022) and Fukao et al. (2014). The matrix is derived from patent citation data and based on Leten et al. (2007). The relatedness between technologies is reflected in the extent to which technologies in a given patent field build on prior art from different patent fields. Patent citation data are available at the four-digit IPC level and are subsequently mapped onto industries using the industry-technology concordance table developed by Schmoch et al. (2003).

located in the same UEA as the instrumental variable. Industry-region-averaged R&D influences a firm's R&D decisions due to spillovers from neighboring firms in the same industry and region. However, firm-specific shocks do not affect it; thus, it does not correlate with changes in performance measures.[14] Since R&D investment is used to construct R&D stock and in the second-stage regression, we calculate the predicted value of R&D stock using the predicted value of R&D investment as follows:

$$RD\widehat{Stock}_{fkt} = RD\widehat{Inv}_{fkt} + (1-\delta_k)\, RD\widehat{Stock}_{fkt-1},$$

where δ_k is the depreciation ratio for technology field *k*. The predicted R&D stocks are then used in the second-stage estimation as the instrument variable.[15]

$\varDelta IMP_{fijt}$ might be affected by a potential demand shock in Japan. Therefore, we apply the identification strategy proposed by Autor et al. (2013), using the changes in the import ratio from China concerning seven high-income trading partners, excluding Japan, as an instrumental variable:[16]

$$\varDelta IMP_{fijt}^{OTH} = \sum_p w_{fijpt-s} \frac{\varDelta M_{jpt}^{OTH}}{Z_{jpt-s}+M_{jpt-s}}.$$

The identification strategy behind this specification is that import demand in other high-income countries is correlated with Chinese supply shocks, while import demand shocks are not correlated across high-income countries.

3.4 Data Overview

Figure 1 shows the penetration rate of imports from China into Japan. It stood at approximately 0.8% in 1994 and rose steadily throughout the 2000s, reaching 6.2% in 2015. This rise in imports may have significantly influenced the restructuring of Japanese firms.

=Figure 1=

Table 1 presents the basic statistics of the variables used in this study. As mentioned, we restrict the sample to firms with R&D expenditures for three or more periods during the sample period. Therefore, the data used in this study consist of relatively large plants. Reflecting this data structure, the average number of employees and number of products are relatively large. The average number of employees (*Plant size*) is 179 (=exp (5.189)), and the average number of employees at the firm level (*Firm size*) is 1100 (=exp(7.004)).

[14] This identification strategy was employed in previous studies, such as Lev and Sougiannis (1996) and Gupta et al. (2017).

[15] The estimation procedure and results for the predicted value of R&D investment are presented in Appendix A.

[16] For high-income countries, we use the same country set established in Dauth et al. (2014): Australia, Canda, Norway, New Zealand, Sweden, Singapore, and the United Kingdom.

While the number of firm-level employees in the first decile (P10) is 156 (=exp(5.050)), the 9th decile (P90) is 9948 (=exp(9.20527)). The average number of product entries and exits over the three years (*PEntry* and *PExit*) are 0.126 and 0.152, respectively. The average values of the net change in the number of products over three or five years (*Net Changes*) are negative, implying that, on average, the number of products at each plant is decreasing. Additionally, the 9th decile (P90) of the net change is 0, suggesting that less than 10% of the plants are increasing their number of products. The change in import penetration over three years (ΔIMP_{t-3}) is 0.6 percentage points in the 1st decile (P10) and 19 percentage points in the 9th decile (P90). This suggests a considerable variation in the change in import penetration rates across sectors.

= Table 1=

Figure 2 shows the number of plants based on the number of products. Among them, the largest group comprises single-product plants, accounting for approximately 3,500 of the 7,770 plants in 2000. By 2014, the number of single-product plants had decreased to around 3,300. The number of plants producing two or more products has also decreased significantly. Specifically, the number of plants producing 2–3 products decreased from around 2,700 to 2,300, and the number producing 4–5 products decreased from 1,000 to approximately 700. The number of plants producing six or more products has also decreased significantly. These trends suggest that many manufacturing firms are narrowing their product range.

= Figure 2=

Table 2 shows the average number of products per plant, the number of plants that added or dropped products over the past three years, and the percentage of plants that increased or decreased the number of products with no change. The average number of products decreases, albeit only slightly, throughout the sample period. However, examining the percentage of plants that added or dropped products over the past three years, not all plants necessarily reduced their number of products. The ratios of plants that added or dropped the products are both around 10%, with the ratio of plants that dropped products being slightly higher. Considering the changes in the number of products, the percentage of plants that did not change the number of products is about 84–86%, while the percentage of plants that decreased the number of products is around 9%, and the percentage of plants that increased the number of products is about 6–7%. This suggests that manufacturing firms are actively replacing existing products with new ones.

= Table 2=

4 Estimation results

Table 3 presents the estimation results for the impact of import competition on plant-level product adjustments. First, examining the coefficients for the change in import penetration rates over three years, the coefficient for the number of new products in Column (1) is positive but insignificant. However, the coefficients for product exits and *Net Changes* in the number of products in Columns (2) and (4) are statistically significant, indicating that the number of products decreases due to increased import competition pressure from China.

Examining the coefficients for R&D stock, those for entry, exit, and gross change (*Turnover*) of the products are all positive and significant. By contrast, *NetChange* in Column (7) is negative and significant. This finding suggests that the numbers of new products and product exits are higher for firms with larger R&D stocks. While the finding that firms with larger R&D stock tend to reduce their number of products may seem odd, this point will be discussed in more detail later.

Columns 5–8 present the results for the five-year changes. Overall, the results are not significantly different from those of the three-year changes. However, the coefficients for R&D stocks are larger in the five-year change results. This implies that it takes time to replace existing products with new ones in response to R&D investment. We also find that the coefficients of the import penetration ratio for product exit (*PExit*), *Turnover*, and *Net changes* become larger than those in the results for the three-year changes. Given that the effect of import competition is more pronounced in the five-year change results, the following estimations examine the results using the five-year difference in the import ratio.

For the other control variables, the coefficients for *Plant size* are positive and significant in the estimation results for product entry, product exit, and gross changes. For *Net changes* in Columns (4) and (8), the coefficients for *Wage, Firm size,* and *Plant size* become negative and significant, suggesting that larger plants tend to decrease the number of products. There is no statistically significant impact of Public R&D stock at region-industry-level.

==Table 3==

Table 4 presents the estimation results, including cross-terms for changes in firm-level R&D stock and import penetration rates, and explores the heterogeneity of the import penetration effects for firms with different levels of technology. For product entry, since the cross-term is positive and significant, firms with larger R&D stocks tend to introduce new products as competitive import pressure increases. This result is consistent with the findings Agihon et al. (2005) and Amiti and Khandelwal (2013). For product exits, the cross-term of changes in the import ratio and firm-level R&D stock is positive and significant. Given that firms with larger R&D stocks are relatively large and produce more items, this suggests that firms with multiple products are more likely to reduce their number of products. This result is consistent with the fact that multi-product plants tend to actively restructure non-core goods as the import penetration rate increases, as noted by Iacovone et al. (2013). Since *Turnover* has a similar pattern, these results indicate that larger firms that introduce new products simultaneously drop exiting ones. In other words, they tend to replace existing products with new ones. For *NetChanges*, the coefficients of the changes in the import penetration and the cross-term are insignificant. This may be because import competition affects both entry and exit, and these effects likely cancel each other out.

Hombert and Matray (2018) found that innovation activities play a role in mitigating the negative shock of increased imports. However, since they used firm-level sales and profitability as the outcome variables, it was not clear what kind of product restructuring occurs among firms with high R&D investment. Our results imply that R&D activities are important in product-restructuring strategies for plants exposed to fierce import competition.

==Table 4==

To verify the heterogeneous impact of import competition across different technology levels, we calculate the marginal effect of import competition by R&D stock percentiles based on Table 4. The results are presented in Table 5. For product entry, firms with small R&D stocks (at the 5th and 10th percentile) shows that increased competition pressure discourages innovation activities. In contrast, firms with large R&D stocks tend to introduce new products, likely due to the escape competition effect. The negative coefficient of import competition for product exit seems counterintuitive. However, the marginal effect of import competition on product exits is mostly positive.

==Table 5==

We conduct some additional estimations. First, we checked the robustness of the results by changing the fixed effects. In columns (1)-(3) of Table 6, we include region-year FE and industry FE, and in columns (4)-(6), we add industry-region-year FE. In the latter, the regional R&D stock was excluded due to multicollinearity. The results were generally the same as those in Table 4.

Second, although the public R&D stock is not statistically significant in most cases, firms' R&D productivity may increase in regions with large public R&D stocks. Therefore, we split our sample by region-industry depending on whether public R&D

stock is greater than its median.[17] Although regions with larger public R&D stock may have a variety of urban amenities, these factors are controlled for in the industry-region-year fixed effects in the following estimation. Table 7 shows the estimation results. The sign of the coefficient for the interaction term of firm-level R&D stock and the import penetration rate is consistent with that in Table 4. Although the results should be interpreted with caution due to the relatively poor performance of the first-stage test statistics, for regions with larger public R&D stocks, the coefficient of the cross-term for product entry in Column (1) becomes larger than in Table 4. In contrast, in Column (4), for regions with smaller public R&D stocks, the coefficient becomes insignificant.

Third, we restrict our sample to high-tech sectors, which is presented in Table 8. We regard the chemical, machinery, electric machinery, and transport equipment sectors as high-tech sectors, following Chakraborty and Henry (2019). We find that the coefficient of the cross-term is larger than that in Column (1) of Table 6, suggesting that the results are more pronounced for high-tech sectors.

==Table 6, 7, and 8 ==

5 Conclusion

Using Japanese plant-product-level data, this study examines the impact of increasing import competition pressure on changes in product portfolios by examining product entry and exit. We also consider the role of R&D activities at the plant level. While previous research on product portfolio adjustments for multi-product firms has emphasized the narrowing of products to core products in response to increased import competition, firms engaged in R&D are actively replacing existing products with new ones and expanding into new business fields. These results are consistent with those of several studies on the relationship between competition and innovation. We also find that these effects are more pronounced in regions with larger public R&D stocks and high-tech sectors.

We also draw important policy implications from these results. As Bernard et al. (2010) noted, since product replacement by surviving firms is an important element of industrial structural transformation, our results suggest that support for R&D activities and public R&D stock is crucial for driving industrial structural transformation.

Although this study presents various findings, it offers several avenues for future research. First, this study implicitly assumes that R&D investment is independent of

[17] An alternative approach is to interact the public R&D stock with the cross term of the firm's R&D stock and the import penetration rate. However, since multicollinearity occurs when including the cross terms of three variables and their coefficients become insignificant, we split the sample and examine our hypothesis.

import competition. However, R&D investments may increase in response to import competition. Future research should consider the impact of import competition on both R&D investment and product restructuring. Second, while this study investigates product restructuring at the six-digit product level within the two-digit industry, it would be insightful to compare the impact of R&D at a more granular level, say within a four-digit industry.

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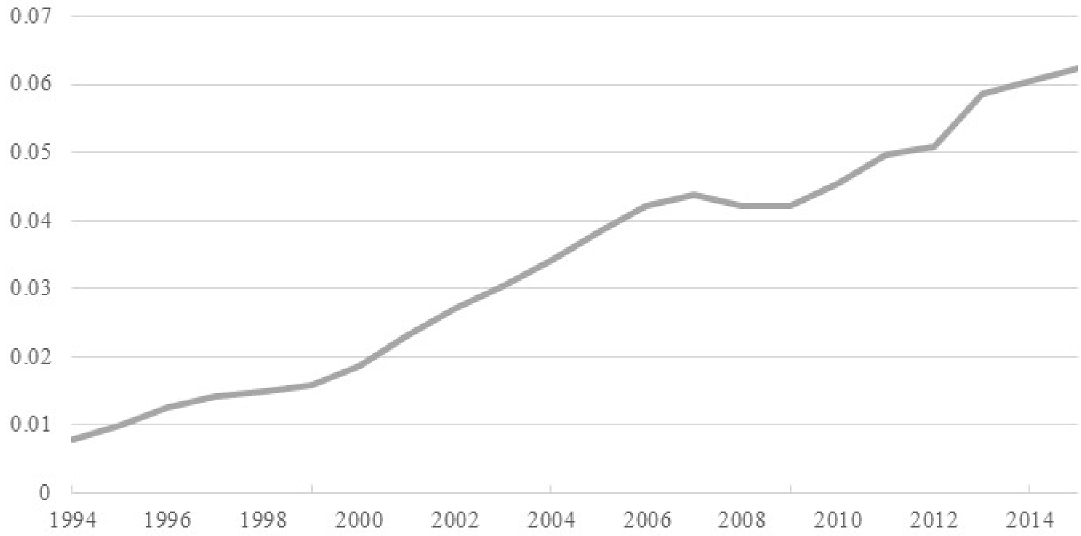
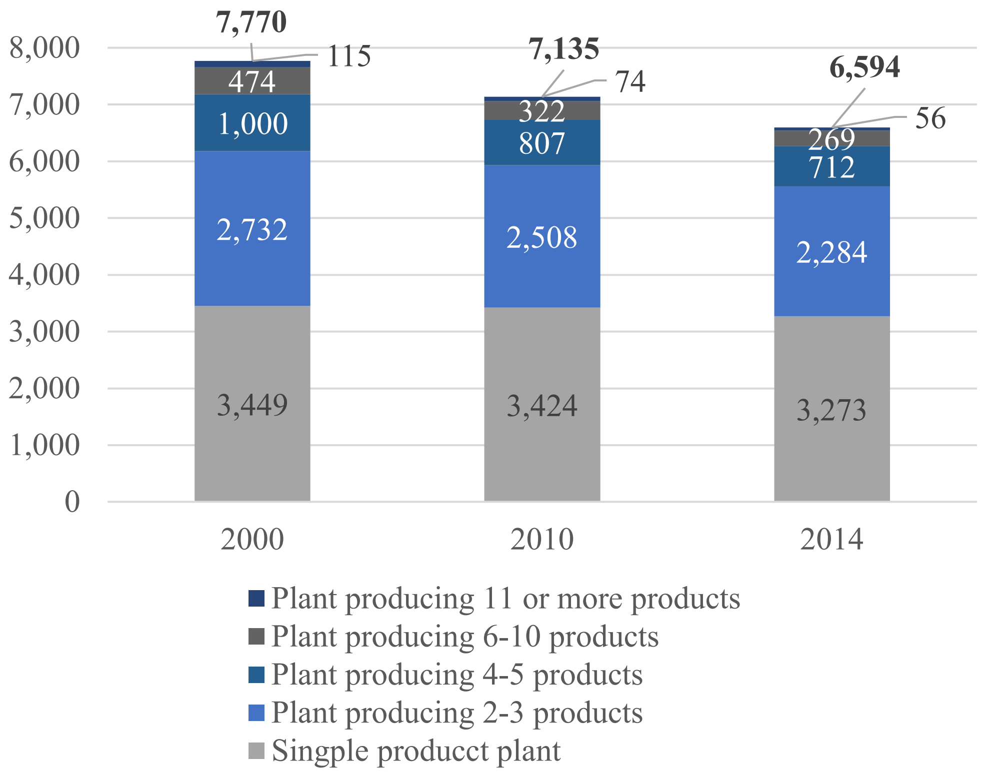
Figure 1 Import Penetration from China



Source: JIP Database

Figure 2 Number of plants by number of products



Source: Authors' calculation based on the matched database between COM and SRD.

Table 1 Descriptive Statistics

		# of obs	Mean	SD	P10	P90
PEntry (over 3 years)	# of product entry at plant-industry over 3 years	92688	0.126	0.356	0.000	1.000
Pexit (over 3years)	# of product exit at plant-industry over 3 years	92688	0.152	0.393	0.000	1.000
Turnover (over 3 years)	Sum of product entry and exit over 3 years	92688	0.359	0.941	0.000	1.000
Net Changes (over 3 years)	Changes in # of products at plant-industry over 3 years	92688	-0.036	0.623	0.000	0.000
PEntry (over 5 years)	# of product entry at plant-industry over 5 years	70308	0.198	0.443	0.000	1.000
Pexit (over 5years)	# of product exit at plant-industry over 5 years	70308	0.233	0.487	0.000	1.000
Turnover (over 5 years)	Sum of product entry and exit over 5 years	70308	0.576	1.280	0.000	2.000
Net Changes (over 5 years)	Changes in # of products at plant-industry over 5 years	70308	-0.064	0.758	-1.000	0.000
ΔIMP_{t-3}	Changes in import penetration ratio over 3 years	92688	0.011	0.021	0.006	0.019
ΔIMP_{t-5}	Changes in import penetration ratio over 5 years	70308	0.019	0.027	0.011	0.031
Plant Size	Logged number of employees at plant	92688	5.189	1.311	3.526	6.855
ln(wage)	Logged average wage at plant	92688	6.306	0.323	5.911	6.667
Firm Size	Logged number of employees at firm-level	92688	7.004	1.664	5.050	9.205
R&D stock	Logged R&D Stock at firm-sector	92688	11.802	3.508	8.486	15.310
Public R&D stock	Logged Public R&D Stock at UEA-sector	92688	13.782	6.638	0.000	19.856

Source: Authors' calculation based on the matched database between COM and SRD.

Table 2 The number of products and the ratio of plants that changes the number of products over the past three years

	Average Number of products	The ratio of plants that changes the number of products in past 3 years				
		Add	Drop	Net decrease	No change	Net increase
1998-2005	2.503	11.0%	11.5%	9.1%	84.3%	6.6%
2006-2009	2.464	8.0%	10.1%	8.6%	85.9%	5.5%
2010-2014	2.436	9.2%	12.0%	8.9%	83.6%	7.4%

Source: Authors' calculation based on the matched database between COM and SRD.

Table 3 Import competition and product restructuring

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	three-year changes (s=3)				five-year changes (s=5)			
	PEntry	*PExit*	*Turnover*	*Net Change*	*PEntry*	*PExit*	*Turnover*	*Net Change*
ΔIMP_{t-s}	0.0370	0.179***	0.277	-0.178***	0.0525	0.216**	0.244	-0.214***
	(0.0540)	(0.0617)	(0.166)	(0.0437)	(0.109)	(0.0816)	(0.150)	(0.0668)
Plant Size	0.00400	0.0108***	0.0261***	-0.0125***	0.00794	0.0213***	0.0258***	-0.0256***
	(0.00312)	(0.00310)	(0.00875)	(0.00385)	(0.00469)	(0.00479)	(0.00695)	(0.00640)
ln(Wage)	-0.00305	0.0282	0.0398	-0.0444***	-0.00114	0.0433	0.0360	-0.0624**
	(0.0123)	(0.0185)	(0.0409)	(0.0130)	(0.0200)	(0.0295)	(0.0381)	(0.0225)
Firm Size	-0.00410	0.000932	-0.00136	-0.00814**	-0.00644	-0.000165	-0.00556	-0.0114
	(0.00311)	(0.00390)	(0.0104)	(0.00389)	(0.00476)	(0.00622)	(0.00876)	(0.00710)
R&D stock	0.00624***	0.00771***	0.0209***	-0.00380**	0.00948***	0.0119**	0.0183***	-0.00767**
	(0.00180)	(0.00254)	(0.00631)	(0.00167)	(0.00264)	(0.00420)	(0.00573)	(0.00361)
Public R&D stock	0.000539	0.000164	0.000722	0.000417	0.00174	-0.000116	0.00128	0.00166
	(0.000771)	(0.000904)	(0.00193)	(0.00101)	(0.00106)	(0.00111)	(0.00142)	(0.00149)
First stage								
ΔIMP_{t-s}^{OTH}	0.538***	0.538***	0.538***	0.538***	0.506***	0.506***	0.506***	0.506***
	(0.0967)	(0.0967)	(0.0967)	(0.0967)	(0.0626)	(0.0626)	(0.0626)	(0.0626)
$R\&D\ stock^{OTH}$	0.382***	0.382***	0.382***	0.382***	0.393***	0.393***	0.393***	0.393***
	(0.0612)	(0.0612)	(0.0612)	(0.0612)	(0.0633)	(0.0633)	(0.0633)	(0.0633)
Observations	92,688	92,688	92,688	92,688	70,308	70,308	70,308	70,308
Kleibergen-Paap rk Wald F	15.49	15.49	15.49	15.49	32.64	32.64	32.64	32.64
F test (ΔIMP_{t-s}^{OTH})	15.50	15.50	15.50	15.50	33.68	33.68	33.68	33.68
F test ($R\&D\ stock^{OTH}$)	19.55	19.55	19.55	19.55	19.31	19.31	19.31	19.31

Note: Industry (two-digit)-Year FE and Region FE are included. Figures in parentheses are robust standard errors. *** indicates statistically significant at 1%.

Table 4 Import competition and firm-level R&D stock

	(1)	(2)	(3)	(4)
	PEntry	*PExit*	*Turnover*	*Net Change*
ΔIMP_{t-s}	-0.784**	-1.041***	-1.479***	0.551
	(0.338)	(0.289)	(0.403)	(0.454)
$\Delta IMP_{t-s} \times R\&D\ stock$	0.0670**	0.101***	0.138***	-0.0613
	(0.0274)	(0.0223)	(0.0292)	(0.0396)
Plant Size	0.00810*	0.0215***	0.0261***	-0.0257***
	(0.00465)	(0.00475)	(0.00689)	(0.00637)
ln(Wage)	-0.00162	0.0426	0.0350	-0.0620**
	(0.0196)	(0.0290)	(0.0374)	(0.0222)
Firm Size	-0.00650	-0.000257	-0.00569	-0.0113
	(0.00468)	(0.00607)	(0.00855)	(0.00706)
R&D stock	0.00802***	0.00972**	0.0153**	-0.00633*
	(0.00272)	(0.00402)	(0.00561)	(0.00355)
Public R&D stock	0.00169	-0.000194	0.00117	0.00171
	(0.00109)	(0.00109)	(0.00142)	(0.00149)
First stage				
ΔIMP_{t-s}^{OTH}	0.373***	0.373***	0.373***	0.373***
	(0.115)	(0.115)	(0.115)	(0.115)
$R\&D\ stock^{OTH}$	0.393***	0.393***	0.393***	0.393***
	(0.0665)	(0.0665)	(0.0665)	(0.0665)
$\Delta IMP_{t-s}^{OTH} \times R\&D\ stock^{OTH}$	0.475***	0.475***	0.475***	0.475***
	(0.0576)	(0.0576)	(0.0576)	(0.0576)
Observations	70,308	70,308	70,308	70,308
Kleibergen-Paap rk Wald F	16.61	16.61	16.61	16.61
F test (ΔIMP_{t-s}^{OTH})	47.37	47.37	47.37	47.37
F test ($R\&D\ stock^{OTH}$)	61.20	61.20	61.20	61.20
F test ($\Delta IMP_{t-s}^{OTH} \times R\&D\ stock^{OTH}$)	61.31	61.31	61.31	61.31

Note: Industry (two-digit)-Year FE and Region FE are included. Figures in parentheses are robust standard errors. ***, **, and * indicate statistically significant at 1%, 5%, and 10%, respectively.

Table 5 Marginal effect of ΔIMPt-5 at different percentile points of R&D stock

PEntry	Coefficient	Std. err.	t	P>t	[95% conf.	interval]
p5	-0.509	0.229	-2.22	0.038	-0.987	-0.031
p10	-0.240	0.128	-1.87	0.076	-0.507	0.028
p25	-0.089	0.083	-1.07	0.298	-0.262	0.085
p50	0.028	0.069	0.41	0.688	-0.116	0.172
p75	0.137	0.083	1.65	0.114	-0.036	0.311
p90	0.236	0.111	2.13	0.046	0.005	0.468
p95	0.297	0.131	2.26	0.035	0.023	0.571
PExit						
p5	-0.628	0.203	-3.09	0.006	-1.052	-0.204
p10	-0.223	0.127	-1.76	0.094	-0.488	0.042
p25	0.003	0.095	0.04	0.972	-0.196	0.202
p50	0.179	0.084	2.13	0.046	0.003	0.355
p75	0.343	0.089	3.84	0.001	0.157	0.530
p90	0.492	0.105	4.67	0.000	0.272	0.712
p95	0.583	0.119	4.92	0.000	0.336	0.831

Source: Authors' calculation based on the matched database between COM and SRD.

Table 6 Robustness checks: Using a different set of fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
	PEntry	*PExit*	*Net Change*	*PEntry*	*PExit*	*Net Change*
ΔIMP_{t-s}	-0.804**	-1.087***	0.551	-0.821**	-0.938**	0.346
	(0.306)	(0.284)	(0.454)	(0.383)	(0.355)	(0.543)
$\Delta IMP_{t-s} \times R\&D\ stock$	0.0670**	0.103***	-0.0613	0.0717**	0.0930***	-0.0489
	(0.0255)	(0.0223)	(0.0396)	(0.0309)	(0.0261)	(0.0470)
First stage						
ΔIMP_{t-s}^{OTH}	0.378***	0.378***	0.373***	0.334***	0.334***	0.334***
	(0.118)	(0.118)	(0.115)	(0.119)	(0.119)	(0.119)
$R\&D\ stock^{OTH}$	0.395***	0.395***	0.393***	0.433***	0.433***	0.433***
	(0.0669)	(0.0669)	(0.0665)	(0.0711)	(0.0711)	(0.0711)
$\Delta IMP_{t-s}^{OTH} \times R\&D\ stock^{OTH}$	0.473***	0.473***	0.475***	0.527***	0.527***	0.527***
	(0.0578)	(0.0578)	(0.0576)	(0.0555)	(0.0555)	(0.0555)
Firm-plant controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No	No	No
Region-Year FE	Yes	Yes	Yes	No	No	No
Industry-Region-yaer FE	No	No	No	Yes	Yes	Yes
Observations	70,186	70,186	70,308	65,414	65,414	65,414
Kleibergen-Paap rk Wald F	16.37	16.37	16.61	13.69	13.69	13.69
F test (ΔIMP_{t-s}^{OTH})	42.44	42.44	47.37	53.33	53.33	53.33
F test ($R\&D\ stock^{OTH}$)	64.04	64.04	61.20	62.01	62.01	62.01
F test ($\Delta IMP_{t-s}^{OTH} \times R\&D\ stock^{OTH}$)	65.42	65.42	61.31	70.81	70.81	70.81

Note: Figures in parentheses are robust standard errors. ***, **, and * indicate statistically significant at 1%, 5%, and 10%, respectively.

Table 7 Regional heterogeneity of the link between import competition and firm-level R&D stock

	(1)	(2)	(3)	(4)	(5)	(6)
	Public R&D stock >=median			*Public R&D stock* <median		
	PEntry	*PExit*	*Net Change*	*PEntry*	*PExit*	*Net Change*
ΔIMP_{t-s}	-1.051**	-1.505***	0.717	-0.793	-0.793	0.442
	(0.434)	(0.494)	(0.710)	(0.671)	(0.546)	(0.688)
$\Delta IMP_{t-s} \times R\&D\ stock$	0.0855**	0.121***	-0.0585	0.0727	0.0956*	-0.0776
	(0.0311)	(0.0357)	(0.0532)	(0.0591)	(0.0471)	(0.0648)
First stage						
ΔIMP_{t-s}^{OTH}	0.100	0.100	0.100	0.542***	0.542***	0.542***
	(0.0997)	(0.0997)	(0.0997)	(0.176)	(0.176)	(0.176)
$R\&D\ stock^{OTH}$	0.394***	0.394***	0.394***	0.462***	0.462***	0.462***
	(0.0719)	(0.0719)	(0.0719)	(0.0713)	(0.0713)	(0.0713)
$\Delta IMP_{t-s}^{OTH} \times R\&D\ stock^{OTH}$	0.721***	0.721***	0.721***	0.325***	0.325***	0.325***
	(0.0689)	(0.0689)	(0.0689)	(0.103)	(0.103)	(0.103)
Firm-plant controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,198	30,198	30,198	35,031	35,031	35,031
Kleibergen-Paap rk Wald F	9.924	9.924	9.924	6.331	6.331	6.331
F test (ΔIMP_{t-s}^{OTH})	64.40	64.40	64.40	16.43	16.43	16.43
F test ($R\&D\ stock^{OTH}$)	55.11	55.11	55.11	52.14	52.14	52.14
F test ($\Delta IMP_{t-s}^{OTH} \times R\&D\ stock^{OTH}$)	96.70	96.70	96.70	18.06	18.06	18.06

Note: Industry (two-digit)-Region-Year FE are included. Figures in parentheses are robust standard errors. ***, **, and * indicate statistically significant at 1%, 5%, and 10%, respectively.

Table 8 Regional heterogeneity of the link between import competition and firm-level R&D stock (High tech sector)

	(1)	(2)	(3)	(4)	(5)	(6)
	Public R&D stock >=median			*Public R&D stock* <median		
	PEntry	*PExit*	*Net Change*	*PEntry*	*PExit*	*Net Change*
ΔIMP_{t-s}	-1.397**	-1.374**	-0.216	2.099	-1.204	4.472
	(0.544)	(0.607)	(0.486)	(1.530)	(1.669)	(3.250)
$\Delta IMP_{t-s} \times R\&D\ stock$	0.112**	0.110**	0.00843	-0.195	0.0954	-0.372
	(0.0352)	(0.0431)	(0.0356)	(0.136)	(0.133)	(0.275)
First stage						
ΔIMP_{t-s}^{OTH}	0.196	0.196	0.196	0.0622	0.0622	0.0622
	(0.168)	(0.168)	(0.168)	(0.190)	(0.190)	(0.190)
$R\&D\ stock^{OTH}$	0.498***	0.498***	0.498***	0.300***	0.300***	0.300***
	(0.109)	(0.109)	(0.109)	(0.0710)	(0.0710)	(0.0710)
$\Delta IMP_{t-s}^{OTH} \times R\&D\ stock^{OTH}$	0.731***	0.731***	0.731***	0.419**	0.419**	0.419**
	(0.0700)	(0.0700)	(0.0700)	(0.183)	(0.183)	(0.183)
Firm-plant controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,807	16,807	16,807	13,391	13,391	13,391
Kleibergen-Paap rk Wald F	12.54	12.54	12.54	1.223	1.223	1.223
F test (ΔIMP_{t-s}^{OTH})	2761	2761	2761	37.55	37.55	37.55
F test ($R\&D\ stock^{OTH}$)	21.90	21.90	21.90	18.88	18.88	18.88
F test ($\Delta IMP_{t-s}^{OTH} \times R\&D\ stock^{OTH}$)	11602	11602	11602	22.46	22.46	22.46

Note: Industry (two-digit)-Region-Year FE are included. Figures in parentheses are robust standard errors. ***, **, and * indicate statistically significant at 1%, 5%, and 10%, respectively.

Appendix A The estimation procedure of the predicted value of R&D investment

This appendix explains the procedure to calculate the predicted value of R&D investment by the technology field at the firm level. As we explain in section 3, we use the log of the sum of other firms' R&D expenditure by technology field at the UEA -industry level as an instrument variable. Since the dependent variable, R&D expenditure includes zero values, we use the inverse hyperbolic sin transformation and estimated the model with OLS. The estimation result is presented in Table A1. We confirmed the coefficient is positive and statistically significant. Then, we calculate the predicted value of R&D investment based on the estimation results.

Table A1 Estimation results

$\ln(R\&D\ inv_{jrt}^{OTH})$	0.0104***
	(0.00397)
Observations	946,015
Firm-sector FE	Yes
Year FE	Yes
UAE FE	Yes
R2	0.843

Note: Figures in parentheses are robust standard errors. *** indicate statistically significant at 1%.