Specialize or Innovate? Product Scope Adjustment and Productivity Growth under Competition

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Abstract

How do multiproduct firms adjust their product scope under rising competition? This paper studies South Korean manufacturers exposed to heightened competition from new EU member states following EU enlargement. Consistent with standard models, firms respond by reducing product scope and reallocating resources to core products. However, contrary to prior predictions, we observe an overall decline in productivity. To understand this pattern, we analyze firm heterogeneity and identify two offsetting mechanisms. First, the well-known *product specialization channel*—focusing on core products—can raise productivity. Second, a *product addition channel* emerges: firms with strong innovation capabilities develop new high-productivity products. This highlights an often-overlooked form of heterogeneity—knowledge. We develop a theoretical model extending standard frameworks, which predicts that: (1) competition does not always raise productivity; (2) product specialization can increase productivity; (3) innovation-driven product addition can also improve productivity, especially for high-knowledge firms; and (4) responses of high-knowledge firms differ from those of high-productivity firms. While standard models explain (2), our framework accounts for all four patterns observed in the data.

Keywords: Export competition, Directed innovation, Knowledge, Productivity, Resource reallocation, Heterogeneity

JEL Codes: F12, F14, F15, L25, O31

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1 Introduction

When competition intensifies, multiproduct firms can adjust their product scope in two ways to escape it: by dropping less competitive products or by adding new, more competitive ones. While the former channel has been widely studied in both theoretical and empirical literature, the latter remains relatively understudied, despite its potential to enhance firm competitiveness. This paper highlights the product addition channel and shows, both theoretically and empirically, that it is particularly effective for firms with higher knowledge.

This mechanism may appear familiar, as the product addition channel has been implicitly addressed in the literature on innovation. Innovation is widely recognized as a strategic response to heightened competition, and the introduction of new competitive products is often an outcome of innovative activity. Accordingly, it is plausible that firms with greater knowledge capacity engage more intensively in innovation, and thus are more likely to add new competitive products in response to competition.

Nevertheless, the relationship between competition and innovation remains contested, both theoretically and empirically (Arrow, 1962; Schumpeter, 1942; Aghion et al., 2005). Furthermore, the link between innovation and new product addition is not straightforward. Innovation may manifest in improved production processes, enhanced managerial practices, or increased market power, rather than the introduction of new products. In empirical research, innovation is often treated as the final outcome of interest, while the specific mechanisms through which it enhances firm competitiveness—such as through adding new products—have received comparatively less attention.

In this regard, we contribute to the multiproduct firm literature by emphasizing the role of product addition in enhancing firm productivity. We also add to the competition and innovation literature by highlighting how knowledge facilitates product addition, offering a specific mechanism through which innovation enhances firm competitiveness.

We develop a simple model—described below—to derive the productivity consequences of product scope adjustment in response to competition, emphasizing the roles of innovation and knowledge in this process. Empirically, we examine how South Korean manufacturing establishments respond to rising competition driven by the enlargement of the European Union (EU), which offers several advantages for analysis.

First, following the EU's largest expansions in 2004 and 2007, the Central and Eastern European countries that joined the EU[1] rapidly integrated into the global economy.

[1]Czech Republic, Estonia, Cyprus, Latvia, Lithuania, Hungary, Malta, Poland, Slovakia, and Slovenia joined in 2004, followed by Bulgaria and Romania in 2007.

The share of these new EU member states (NEMs) in global exports increased from 2.8% in 2003 to 4.1% in 2016. Their share in 2016 is comparable to that of major exporting countries—United States (8.7%), Germany (8%), Japan (3.9%), and Korea (3%). Notably, NEMs' share exceeds that of Japan and Korea, suggesting that the expansion of NEMs' exports constitutes a quantitatively nontrivial development in global trade. For a small open economy like South Korea, this rise of NEMs has introduced significant competitive pressure. We exploit this exogenous increase in competition faced by South Korean manufacturing establishments as a source of variation for causal inference.

Second, due to the substantial geographical and historical distance, South Korea's imports from NEMs have remained limited.[2] This feature allows us to focus on competition in export markets, or *export competition*, without confounding factors—such as an increase in intermediate inputs from NEMs—that often complicate analyses of import competition in the domestic market. As a result, we can more cleanly investigate the relationship between competition, product scope adjustment, and productivity.

Third, examining the impact of EU enlargement on South Korean manufacturing establishments contributes to our understanding of its third-country effects, a dimension that remains understudied. While existing research has extensively analyzed the consequences of EU enlargement for NEMs and old member states (Baier et al., 2008; Martínez-Zarzoso et al., 2020; Kaplan et al., 2018; Caliendo et al., 2021; Antimiani and Costantini, 2013; Dauth et al., 2014), its broader impact on other countries via heightened competition is largely unexplored. To our knowledge, this paper is the first to address this gap by focusing on multiproduct firms.

Leveraging these advantages, we construct an establishment-level measure of export competition by extending the approach of Kang (2025) to examine the product scope adjustment and productivity consequences of competition. Similar to his measure, we compute a weighted sum of competitive pressure across all export destinations, using each destination's importance as a weight. However, our establishment-product-level shipment data enable a more granular assessment by capturing each establishment's exposure to competition at the product level, allowing for a more precise measurement of competitive intensity.

The empirical evidence can be summarized as follows. First, South Korean manufacturing establishments reduce the number of products they produce in response to export competition with NEMs. In particular, they drop products from their portfolios and reallocate resources toward core products—a strategic response to heightened competitive

[2]The share of NEMs in South Korea's manufacturing imports was only 0.3% in 2003 and 0.9% in 2016. See Appendix B.

pressure. These product scope adjustments align with theoretical predictions and are consistent with existing empirical findings on multiproduct firms (Bernard et al., 2010; Eckel and Neary, 2010; Bernard et al., 2011; Mayer et al., 2014, 2021).

However, while the literature generally predicts that reallocation toward core products enhances productivity, we observe an overall decline in productivity. To better understand this pattern, we conduct heterogeneity analyses to examine whether establishments with higher productivity or knowledge respond differently—drawing on insights from the literature (Qiu and Zhou, 2013; Qiu and Yu, 2020; Hombert and Matray, 2018).

In what follows, we use the term "knowledge capital" to refer to a firm's intangible assets—such as technical expertise or innovation capacity—that facilitate the introduction of new products. This is conceptually distinct from productivity, which measures the efficiency of existing production. While both are positively correlated, they shape firm responses to competition in distinct ways.

First, we find that high-productivity establishments reallocate more intensively toward their core products in response to export competition and experience smaller productivity losses relative to low-productivity establishments. This finding is consistent with the product specialization channel emphasized in standard multiproduct firm models, which link product switching to productivity improvements.

Second, in contrast, we find that high-knowledge establishments reduce their product scope to a lesser extent than low-knowledge establishments and are more likely to introduce new products in response to export competition. Interestingly, while standard models typically associate product addition with a decline in productivity, we observe the opposite: high-knowledge establishments experience smaller productivity losses than their low-knowledge counterparts. This pattern suggests an alternative channel through which product switching can enhance productivity—what we refer to as the product addition channel. These results are robust when imports from China or the EU are considered.

We develop a theoretical model of multiproduct firms that incorporates both the product specialization and product addition channels. The model yields several key implications: (i) competition does not always lead to productivity gains; (ii) competition-induced product specialization can enhance firm productivity; (iii) competition-induced product addition can also improve firm productivity, particularly for high-knowledge firms; and (iv) the responses of high-knowledge firms may differ from those of high-productivity firms. While these predictions align well with the empirical evidence, standard multiproduct firm models can account for only implication (ii), leaving the others unexplained.

Specifically, our model features firms producing a portfolio of differentiated products under CES demand, where each product has firm-product-specific productivity and faces

its own level of competitive pressure. When competition intensifies—due to trade liberalization, foreign entry, or policy changes—firms may drop unprofitable products. While this often involves low-productivity products, it can also include high-performing products if those markets become particularly competitive.

Dropping products releases internal resources, lowering the marginal cost of innovation. Firms can then invest in innovation to develop new products, drawing from a productivity distribution that improves with greater innovation effort. Crucially, firm-level knowledge capital accumulates through innovation experience and increases the expected productivity of new product draws. Thus, competition can trigger a dynamic adjustment: product exit facilitates innovation, enabling new product entry and reshaping the firm's product mix. This response can enhance firm productivity, particularly for high-knowledge firms.[3]

This framework departs from canonical multiproduct firm models in several important respects. First, product dropping is not modeled solely as a selection mechanism that removes low-performing products to raise average productivity. Instead, we emphasize the "trapped resources effect": product exit endogenously reduces the marginal cost of innovation, enabling new product entry. This dynamic mechanism builds on the innovation literature, highlighting internal resource reallocation under resource constraints (e.g., Bloom et al., 2013).

Second, we introduce firm-level knowledge as a distinct dimension of heterogeneity—alongside productivity—that shapes firm responses to competition. High-knowledge firms are more likely to invest in innovation and respond to competition by expanding into less contested markets—a form of "directed innovation"—through adding new products. This extends the "knowledge-based innovation effect" identified by Bloom et al. (2013) to the multiproduct firm setting.

Third, as knowledge accumulates through innovation experience—and since knowledge capital affects the productivity of new products—the productivity of newly added products is likely to exceed that of dropped products, as formalized in Proposition 3. This underscores the role of product addition in enhancing firm productivity.

Together, these features provide a richer and more realistic account of how multiproduct firms adjust to competitive shocks, offering new insights into firm dynamics in response to EU enlargement and intensified export competition.

[3]Our data suggest the existence of this trapped resources effect as reported in Section 7.3.

Related literature

Our research is related to four strands of literature: (i) the economic impact of EU enlargement; (ii) export competition in third markets; (iii) multiproduct firm and product scope adjustment; and (iv) competition and innovation.

First, empirically examining the impact of EU enlargement on South Korean manufacturing establishments, this study connects to the line of research on the impact of EU enlargement. However, while studies have investigated its impact on exports (Baier et al., 2008; Martínez-Zarzoso et al., 2020; Martinez-Zarzoso et al., 2015; Campos et al., 2022; Felbermayr et al., 2022; Kaplan et al., 2018), employment (Kaplan et al., 2018; Caliendo et al., 2021; Dauth et al., 2014), inward foreign direct investment, which resulted in technology spillovers (Antimiani and Costantini, 2013; Bailey et al., 2024), and productivity (Campos et al., 2022; Kaplan et al., 2018; Dauth et al., 2014) within the EU, the impact of EU enlargement on non-EU third countries remains underexplored, with only few exceptions such as Kang (2024).

Second, by focusing on the rise of competition with NEMs in export markets as a primary channel through which EU enlargement affects third countries, this paper adds new evidence to emerging studies on export competition. For instance, Medina (2024) and Kang (2025) study how export competition with China affects Peruvian firms' product quality and South Korean firms' innovation. More closely related to ours, Choi et al. (2023) examine how South Korean manufacturing establishments adjust their product scope in response to export competition with China. However, while they solely focus on product switching activity, we take a step further by drawing productivity implications of product switching and examine export competition with NEMs.[4] While Kang (2024) explores export competition with NEMs focusing on South Korean firms' innovation response, multiproduct firms' response has not been analyzed to our knowledge.

Third, by investigating the product scope and productivity consequences of export competition, this paper adds causal evidence to the literature on multiproduct firms' product churning effects under competition. More importantly, the heterogeneity analyses focusing on productivity and knowledge shed light on the novel product addition channel, in addition to the conventional product specialization channel, through which product switching improves firm's productivity. Our model developed in this paper incorporates both of these channels, extending conventional models (Eckel and Neary, 2010; Bernard et al., 2010, 2011; Mayer et al., 2014, 2021), providing new insights into modelling

[4]Competition with China has been studied using Mexican data by others, including Utar and Ruiz (2013), Iacovone et al. (2013), and Robertson et al. (2020). However, they all focus on a single export market, the United States.

multiproduct firm behavior.

Finally, exploring product addition driven by innovation in response to competition, this study relates to a large literature on competition and innovation (Arrow, 1962; Schumpeter, 1942; Aghion et al., 2005; Bloom et al., 2016; Autor et al., 2020), with more focus on the heterogeneity arising from knowledge. Similar to ours, Hombert and Matray (2018) find that the negative impact arising from import competition from China is weaker for firms with higher R&D intensity because innovation enables greater product differentiation. Expanding this intuition to multiproduct firms, we provide the explicit evidence that high-knowledge firms add more products and exhibit better productivity consequences in response to export competition. We also provide a theoretical framework to understand the observed patterns.

2 Background: EU Enlargement and Export Competition

Since the EU was founded in 1993, 15-EU members[5] achieved deep economic integration through adopting one single market, which enables free movements of goods, services, capital, and labor across member states. Moreover, they eliminate internal tariffs, quotas, and other administrative barriers to trade and investment. Furthermore, they implement common external tariff policies against non-EU countries, negotiate as a single bloc in international trade relations, and adopt one single currency, the Euro. Building on this integrated foundation, the EU expanded further in 2004 with the accession of 10 Central and Eastern European countries. Moreover, EU enlargement continued with the accession of Bulgaria and Romania in 2007, followed by Croatia in 2013.[6]

This enlargement intensified the competition faced by South Korean exporters through three channels. First, the removal of internal tariff deepened the EU's internal integration, and NEMs' exports to old member states increased rapidly. Second, local firms in NEMS not only gained greater access to the non-EU markets as a part of the EU but also enhanced their international competitiveness, resulting in a surge in their exports to the rest of the world (Baier et al., 2008; Martínez-Zarzoso et al., 2020; Martinez-Zarzoso et al., 2015; Campos et al., 2022; Felbermayr et al., 2022; Kaplan et al., 2018; Kang, 2024). Third, globally renowned European firms offshored production to NEMs to benefit from lower costs and the increased mobility of capital under the EU's single market policy.

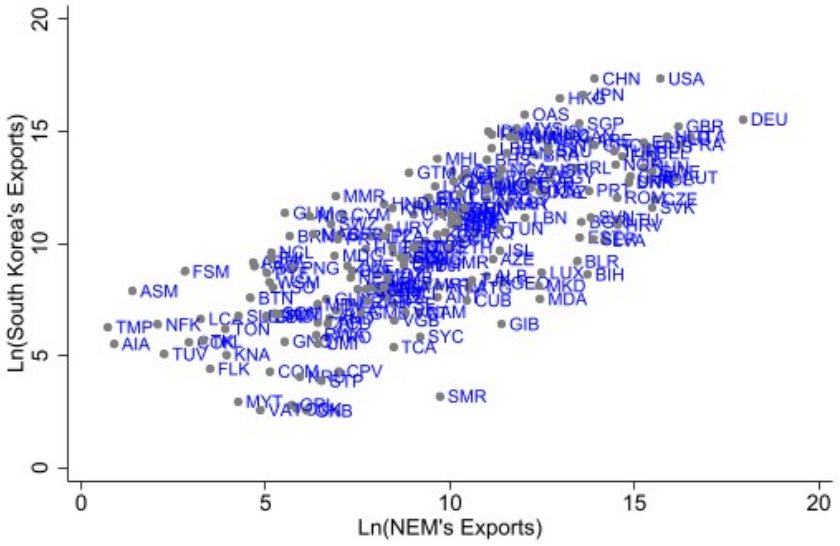
Figure 1 illustrates where South Korea and NEMs export to as of 2003. Both South Ko-

[5]The 15-EU members include Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, and the United Kingdom.

[6]We focus on the 2004 and 2007 enlargement. So NEMs do not include Croatia.

rea and NEMs export substantial amount to major economies such as the United States, China, Germany, the United Kingdom, and Japan. This pattern suggests that the two exporters compete against each other not only within the EU but also in global markets.

Figure 1: Exports of South Korea and NEMs by destination



Source: UN Comtrade database, 2003

For instance, South Korean steel company POSCO experienced increased rivalry from European firms like ArcelorMittal, which expanded into Romania, Slovakia, and the Czech Republic. These firms benefited from tariff reductions, enabling them to supply high-quality steel at lower costs and gain market share in the EU. Between 2003 and 2016, basic metal exports from NEMs to the EU grew faster than South Korea's, widening the export gap—a trend also observed in non-EU European markets.

In shipbuilding, South Korean firms like Hyundai and Daewoo faced intensified bidding competition from lower-cost, EU-supported shipyards in Poland and Romania, especially for small and medium-sized vessels. Similarly, in textiles, South Korean exporters lost ground as brands like H&M and Zara shifted production to Eastern Europe to leverage lower production costs in these regions. The resulting surge in NEMs textile exports has narrowed—and in some cases surpassed—South Korea's export share in global markets. Volkswagen shifted automobile production to Slovakia, which became the world's largest car producer per capita; and IKEA established plants in Poland, which became the world's largest furniture production site. The resulting expansion of offshored firms' exports further intensified the competitive pressure faced by South Korean exporters in global markets.

Importantly for our purpose, this competition was exogenous to South Korean manufacturing establishments' decisions, as well as its impact has been underexplored. Therefore, we leverage export competition with NEMs induced by EU enlargement as an example to examine how South Korean manufacturing establishments adjust their product scope to competition, and what the productivity consequences of such activities are.

3 Data

3.1 Data Sources

We use three primary datasets: the Mining and Manufacturing Survey (MMS) from Statistics South Korea; bilateral international trade flow data from UN Comtrade database (UCD); and lists of exporters from South Korea Customs Services. First, the MMS data provide detailed establishment-level information, such as employment, value-added, and tangible assets. Additionally, this dataset provides shipment for all products that each establishment produces at the 8-digit level, which allows us to explore product-switching behavior at the establishment level.

Second, the UCD offers standardized trade statistics for nearly all global merchandise trade, covering over 200 countries and more than 6,000 products at the 6-digit Harmonized System (HS) level. To link these data with the MMS, which uses the Korea Standard Industry Classification (KSIC) system, we employ 5-digit Industrial Statistics Analysis System (ISTANS) codes, developed by the South Korean Institute for Industrial Economics and Trade (KIET). There are 313 manufacturing products among 707 whole products at the 5-digit level, which are as detailed as rice wines (11021) versus refined rice wines (11022); men's suits (14111) versus women's suits (14112); passenger motor vehicles (39102) versus motor vehicles for the transport of goods (39103), allowing us to capture switching to different products. At the same time, it is broad enough to exclude subtle changes such as color or design. More detailed information about the data and the matching process can be found in Appendix A.

Third, we supplement the MMS dataset with the lists of exporters obtained from the Korea Customs Services (KCS). The KCS dataset provides establishment IDs that have a positive amount of exports. By matching the KCS dataset with the MMS dataset, we are able to identify whether an establishment is an exporter or not.

The MMS data cover all South Korean mining and manufacturing establishments with more than 10 employees. However, we restrict our sample to manufacturing establishments that remain operational between 2003 and 2016 and have non-negative value

added for several reasons. First, we focus on surviving establishments because we are interested in how export competition influences the productivity growth of manufacturing establishments, especially through product-switching activities. This information is available only for establishments that survive during the period.[7]

Second, we analyze the changes between 2003 and 2016, spanning from the year before the 2004 EU enlargement to the year of the Brexit referendum. This period is particularly suitable for two reasons. On the one hand, it captures the major expansion of the EU, which substantially increased the intensity of export competition faced by South Korean firms. On the other hand, ending the sample in 2016 allows us to avoid confounding effects from subsequent global shocks, such as the U.S.-China trade tensions, while still covering more than a decade of adjustment. The 2003-2016 window therefore provides a long enough horizon to study medium-run responses to competition, while also offering a clean comparison between the pre- and post-enlargement periods.[8]

3.2 Measuring Export Competition

To gauge export competition with NEMs, we build on the measure developed by Kang (2025) and modified by Kang (2024). Using a more disaggregated dataset at the establishment-product level, we construct an establishment-level measure of export competition with NEMs, considering the level of competition in export destination countries and the effective exposure to those markets. Specifically, export competition that establishment i experiences between 2003 and 2016 is defined as:

$$\Delta XC_i = \sum_k \frac{y_{ik,03}}{y_{i,03}} \sum_C \frac{X_{k,03}^{KRtoC}}{\sum_{C'} X_{k,03}^{KRtoC'}} \Delta_g \frac{X_{k,03-16}^{NEWtoC}}{M_{k,03-16}^{C\setminus KR}}, \tag{1}$$

where the first component, $y_{ik,03}/y_{i,03}$, is product k's share in establishment i's pre-period shipment. Turning to the second component, as C (or C') refers to a third country other than NEMs and South Korea, $X_{k,03}^{KRtoC}$ indicates South Korea's exports of product k to third country C in 2003. So, the second component, $X_{k,03}^{KRtoC} / \sum_{C'} X_{k,03}^{KRtoC'}$, captures the importance of market C in South Korea's exports of product k in 2003. The third component, $\Delta_g(X_{k,03-16}^{NEWtoC}/M_{k,03-16}^{C\setminus KR})$, is the Davis-Haltiwanger growth rate of NEMs' share in country C's imports of product k between 2003 and 2016, computed relative to imports from all sources except Korea. This exclusion ensures that variation in NEMs' import shares

[7] We drop 75 observations with negative value added since it is difficult to define and estimate their productivity using the production function approach as in Levinsohn and Petrin (2003).

[8] Since this period coincides with the surge in Chinese exports, we control for the China shock to ensure the robustness of our analysis in Section 7.1.

arises from changes in NEMs or in country C, rather than from South Korean exporters themselves.

Put differently, the time-varying intensity of competition is captured by changes in NEMs' share of imports in third-country C. Following the instrumental variable strategy of Autor et al. (2013), these aggregate changes in third countries are regarded as plausibly exogenous, with the validity of this research design further supported by Borusyak et al. (2022). Building on this approach, we additionally exclude South Korea from the import base of third countries to eliminate potential endogeneity arising from Korean establishment i's activities. Accordingly, our export competition measure captures exogenous variation in competition intensity.

3.3 Measuring Product-Switching Activities and Productivity

We observe the level of shipment for products that each establishment produces at the 5-digit level. Using this information, we count the change in the number of products that each establishment produces between 2003 and 2016 and decompose the change into the creation of new products and the destruction of existing products. More formally, the change in the number of products at the establishment level can be attributed to two different margins as:

$$\Delta N_i = add_i - drop_i, \tag{2}$$

where ΔN_i is the change in the number of products that establishment i manufactures between 2003 and 2016; add_i is the number of new products that establishment i added between 2003 and 2016; $drop_i$ is the number of existing products that establishment i discarded between 2003 and 2016.

Moreover, as manufacturers reallocate their resources at the intensive margin, in addition to adding or dropping products, we use the Entropy index to measure the level of product diversification at the establishment level following the literature (Baldwin and Gu, 2009; Bernard et al., 2011; Mayer et al., 2014, 2021). The change in the Entropy index of establishment i between 2003 and 2016 is defined as follows :

$$\Delta E_i = \sum_{k}^{N_{i,16}} s_{ik,16} \ln\left(\frac{1}{s_{ik,16}}\right) - \sum_{k}^{N_{i,03}} s_{ik,03} \ln\left(\frac{1}{s_{ik,03}}\right), \tag{3}$$

where $s_{ik,t}$ denotes product k's share in establishment i's shipments at time t, and $N_{i,t}$ refers to the total number of products produced by establishment i at time t. Since the Entropy index measures product diversification, a negative value of ΔE_i indicates stronger

product specialization or the concentration of resources toward core products.[9]

To explore the productivity implications, we use two measures of productivity: labor productivity and total factor productivity (TFP). Labor productivity is proxied by value-added per worker, where value-added is deflated by the GDP deflator for manufacturing industries. TFP is estimated following the method of Levinsohn and Petrin (2003) over the period of our interest (2003-2016). Specifically, we specify a value-added production function using the log of value added as output, the log of employment, and the log of tangible assets as inputs, while employing the log of intermediate inputs as a proxy variable for unobserved productivity shocks.[10] For empirical analysis, we use the log difference between 2003 and 2016 of each productivity measure. Specifically, we define labor productivity growth as $\Delta LP_i = \ln(LP_{i,2016}) - \ln(LP_{i,2003})$, and TFP growth as $\Delta TFP_i = \ln(TFP_{i,2016}) - \ln(TFP_{i,2003})$.

3.4 Summary Statistics

Table 1 presents summary statistics. Panel A describes variables related to product-switching activities and productivity growth. On average, between 2003 and 2016, South Korean manufacturing establishments reduce the number of products they produce by 0.099, which is decomposed into the addition of 0.407 new products and the drop of 0.506 products—whose difference is identical to the change in the number of products. Given the number of products they produce in 2003 is 1.278 on average as shown in Panel B, South Korean manufacturing establishments seem actively participating in product-switching activities. They not only drop over one-third of their existing products but also introduce over one-third of their existing products. In other words, their product switching intensity—defined as the total number of added and dropped products divided by the number of products in 2003—is 0.714, indicating a high frequency of switching behavior relative to their initial product portfolios. At the same time, 45.2% of continuing plants switch their products either by dropping existing products or adding new products. These figures are comparable to existing studies.[11]

[9] For instance, a firm with two equally weighted products in 2003 has an entropy index of about 0.69. If by 2016 it shifts to a 90/10 split, the index falls to 0.33 (a change of -0.36), indicating greater concentration. Alternatively, if it expands to four equally weighted products (25% each), the index rises to 1.39 (a change of +0.70), reflecting increased diversification through product addition and reallocation. We alternatively use the Herfindahl-Hirschman Index (HHI) to measure product specialization in Section 7.2.

[10] Strictly speaking, due to the lack of price information, we estimate revenue-based total factor productivity (TFPR). While variation in TFPR may reflect changes in both productivity and markups, we show in Section 7.4 that markup responses are muted, supporting a productivity-based interpretation.

[11] Bernard et al. (2010) show that the product switching intensity among U.S. continuing manufacturing plants is 0.96, and approximately 54% of these plants experience product churning at least once. In contrast,

Table 1: Summary Statistics

	OBS (1)	Mean (2)	SD (3)	Median (4)	Min (5)	Max (6)
Panel A. Dependent Variables						
Change in the number of products (ΔN_i)	13,707	-0.099	0.655	0	-10	7
Creation of new products (add_i)	13,707	0.407	0.612	0	0	7
Destruction of existing products ($drop_i$)	13,707	0.506	0.729	0	0	11
Change in the Entropy index (ΔE_i)	13,707	-0.038	0.279	0	-1.579	1.357
Labor productivity growth (ΔLP_i)	13,707	0.368	0.675	0.360	-6.147	6.021
Total Factor productivity growth (ΔTFP_i)	13,654	0.353	0.674	0.348	-6.120	5.719
Panel B. Export Competition and Control Variables						
ΔXC_i	13,707	0.691	0.512	0.822	-1.546	1.988
Age in 2003	13,707	11.891	9.752	9	0	120
Labor productivity in 2003	13,707	11.131	0.711	11.077	5.102	14.723
Capital intensity in 2003	13,707	10.536	1.184	10.669	4.510	15.203
Intangible assets to total assets ratio in 2006	13,049	0.476	0.324	0.549	0	1
Number of products in 2003	13,707	1.278	0.686	1	1	15

Notes: Table presents the number of observations (OBS), mean, standard deviation (SD), min, max, and median for manufacturing establishments in the sample.

Meanwhile, the standard deviation and range of these variables are substantial, indicating that product scope adjustment is highly heterogeneous between establishments. Our data show that the number of products remains unchanged for approximately 79% of surviving manufacturers. However, these firms still engage in product switching, with an average intensity of 0.596—reflecting a nontrivial level of product turnover. On the other hand, about 13% of surviving establishments reduce their number of products through product switching, with an average intensity of 0.793. Finally, nearly 7% of establishments increase their number of products through product switching, with an intensity of 1.751. Overall, these patterns highlight the considerable heterogeneity in product scope adjustment among manufacturers.

Turning to the Entropy index, it decreases by 0.038 between 2003 and 2016, implying that establishments in the sample reallocate resources toward core products. However, its large standard deviation and positive maximum value indicate that some firms diversify their products as well. Labor productivity and TFP increase on average by 0.368 and 0.353, respectively, with considerable heterogeneity observed, similar to other variables.

Panel B describes the export competition measure and control variables. On average, export competition intensifies by 0.691 during the sample period. However, export com-

Bernard and Okubo (2013) report that about 38% of Japanese continuing plants undergo product switching at least once.

petition does not tighten universally, as its large standard deviation (0.512) and its range between -1.546 and 1.988 indicate. We leverage this variation. The summary statistics for age, labor productivity, capital intensity (tangible assets per worker in the logarithm), intangible assets to total assets ratio, and the number of products in 2003 are also reported.

4 Empirical Motivation

To investigate the impact of export competition with NEMs, we estimate the following equation:

$$\Delta Y_i = \alpha + \beta \Delta XC_i + \gamma X_i + \delta \Delta Xsize_i + \psi_{IND(i)} + \varepsilon_i \tag{4}$$

where the dependent variables of interest are product-switching activities and productivity growth rates. To account for establishment-level heterogeneity that may affect product-switching activities, we add X_i, a vector of control variables such as pre-period age, productivity, and capital intensity. We also control for the pre-period number of products (in logarithms) and pre-period exporter dummy variable as establishments with more products, and exporters with diverse markets have more room to adjust their products.

Furthermore, to accurately capture the competition effect in export markets, it is crucial to account for demand shocks, particularly because the size of export markets has grown significantly during the sample period. To address this and isolate the pure competition effect, we include a measure of export market size, $\Delta Xsize_i$, as an additional control variable, adapting the approach from Aghion et al. (2024) as follows:

$$\Delta Xsize_i = \sum_k \frac{y_{ik,03}}{y_{i,03}} \sum_C \frac{X_{k,03}^{KRtoC}}{\sum_{C'} X_{k,03}^{KRtoC'}} \Delta_g M_{k,03-16}^{C\setminus(KR\cup NEW)}, \tag{5}$$

where the first two components are identical to those of the export competition measure. The last component denotes the Davis-Haltiwanger growth rate of product k imports in third country C that are not from South Korea and NEMs. This measure captures the external factors affecting the size of export markets (or demand) that are unrelated to the exports from South Korea and NEMs, by excluding them.

Industry fixed effects, $\psi_{IND(i)}$, are included at the 4-digit level, defined by establishment i's largest product category in terms of shipments in 2003. These fixed effects capture sector-specific trends—such as technological change, shifts in profitability, and variations in markups—that are common within the sector. We use heteroskedasticity-robust standard errors and weight observations by each establishment's initial shipment level. The coefficient of interest is β.

Table 2 reports the results. Columns (1)-(4) show the impact of export competition on product-switching activities, whereas columns (5) and (6) show the impact of export competition on productivity growth.

Table 2: Product Switching Activity and Export Competition

Dependent variable	Product switching activity				Productivity	
	ΔN_i	add_i	$drop_i$	ΔE_i	ΔLP_i	ΔTFP_i
	(1)	(2)	(3)	(4)	(5)	(6)
ΔXC_i	-0.999***	-0.278	0.721***	-0.179***	-0.133**	-0.182***
	(0.263)	(0.176)	(0.153)	(0.047)	(0.067)	(0.065)
Observations	13,703	13,703	13,703	13,703	13,687	13,650

Notes: All columns include 4-digit industry fixed effects, and control variables including the size of export markets, initial period age, productivity, capital intensity, the logarithm of the number of products, and an exporter dummy. All regressions are weighted by shipment of each establishment at the initial period. Sample includes continuing manufacturing establishments. Standard errors in parentheses are heteroskedasticity-robust standard errors. ***, **, and * denote one percent, five percent, ten percent significance level, respectively.

Focusing on product switching activities in columns (1)-(4), three things are noteworthy. First, column (1) shows that South Korean manufacturing establishments reduce the number of products they produce in response to export competition with NEMs. The coefficient in column (1) is -0.999 and statistically significant at the one percent level. Second, the coefficients in columns (2) and (3) indicate that this reduction is mainly driven by dropping old products. While the coefficient in column (2) is insignificant, the coefficient in column (3) is positive and significant at the one percent level. The coefficients in columns (1)-(3) imply that 72.2% of the decrease in the number of products is explained by the drop of existing products.[12] Third, the negative and significant coefficient in column (4) indicates that South Korean manufacturing establishments decrease product diversification, strengthen product specialization, and concentrate resources toward core products facing tougher export competition.

These results show that the enlargement of the EU affects the scope of products of South Korean manufacturing establishments through the export competition channel. This evidence is novel but consistent with the theoretical predictions and empirical findings in the literature (Bernard et al., 2010; Eckel and Neary, 2010; Mayer et al., 2014, 2021) in that tougher competition leads to a decrease in product scope and the reallocation of resources toward core products.

[12]The contribution of dropping products is computed as $(-0.721)/(-0.999) \times 100$.

Now, turning to the productivity consequences, what conventional models predict from this reallocation of resources toward core products is the increase in productivity, as firms drop periphery products they are not efficiently producing. However, the productivity consequences of competition observed in columns (5)-(6) are in stark contrast with this expectation. Both columns show that export competition with NEMs negatively affects the productivity of South Korean manufacturing establishments, with its effect statistically significant at least at the five percent level.

To understand this inconsistency, we shed light on the underexplored dimension of product switching—product addition—in addition to the conventional dimension—product drop—both theoretically and empirically. To begin with, we conduct a heterogeneous analysis to examine whether the observed patterns arise universally to explore the mechanisms. We then develop a simple model that rationalizes the findings.

5 Exploring Mechanisms

5.1 An Old Channel: Productivity and Specialization

Although export competition decreases product scope and productivity on average, the impact may vary across establishments. Focusing on this potential difference, we conduct heterogeneity analyses to investigate how different margins of product scope adjustment—product addition and drop—affect the productivity of multiproduct manufacturers.

To begin with, we leverage the pre-period productivity of establishments, taking insights from the large literature underscoring productivity as a key determinant of firm behavior, including their product scope adjustment (Melitz, 2003; Qiu and Zhou, 2013; Qiu and Yu, 2020). Specifically, we construct a binary indicator, $High_i$, for establishments with above-median pre-period labor productivity within its 4-digit industry.[13] Then, we estimate the following equation:

$$\Delta Y_i = \alpha + \beta_1 \Delta XC_i + \beta_2 \Delta XC_i \times High_i + \beta_3 High_i + \gamma X_i + \delta \Delta Xsize_i + \psi_{IND(i)} + \varepsilon_i. \quad (6)$$

Table 3 shows the results. Focusing on product switching activities, column (1) indicates that high-productivity establishments reduce their product scope significantly more than low-productivity establishments in response to export competition. This is driven both by fewer additions and more (insignificant) drops, as columns (2) and (3) suggest.

[13]The results are qualitatively similar when we use TFP to categorize high-productivity establishments as shown in Appendix D.

As a result, column (4) shows that the Entropy index falls significantly more for high-productivity establishments, meaning that product specialization becomes stronger for high-productivity establishments.

Table 3: Heterogeneous Response by Productivity

Dependent variable	Product switching activity				Productivity	
	ΔN_i	add_i	$drop_i$	ΔE_i	ΔLP_i	ΔTFP_i
	(1)	(2)	(3)	(4)	(5)	(6)
ΔXC_i	-0.240	0.292	0.531**	-0.099**	-0.309***	-0.321***
	(0.353)	(0.208)	(0.228)	(0.041)	(0.087)	(0.090)
$\Delta XC_i \times High_i$	-0.829**	-0.635***	0.193	-0.084*	0.196**	0.200**
	(0.349)	(0.208)	(0.208)	(0.047)	(0.077)	(0.082)
Observations	13,703	13,703	13,703	13,703	13,687	13,650

Notes: All columns include 4-digit industry fixed effects, and control variables including the size of export markets, initial period age, capital intensity, the logarithm of the number of products, $High_i$ dummy, and an exporter dummy. $High_i$ is a dummy variable equal to one if establishment i with an above-median labor productivity within its 4-digit industry. All regressions are weighted by shipment of each establishment at the initial period. Sample includes continuing manufacturing establishments. Standard errors in parentheses are heteroskedasticity-robust standard errors. ***, **, and * denote one percent, five percent, ten percent significance level, respectively.

These more pronounced responses for high-productivity establishments—reduced product scope, fewer additions, more drops, and stronger product specialization—are what the product scope adjustment literature generally expects from negative competition shocks. More importantly, columns (5) and (6) imply that this stronger resource reallocation by high-productivity establishments results in better productivity consequences for them, consistent with the conventional models' prediction. The old product specialization channel through which productivity improves works.

This empirical pattern is consistent with a wide range of established studies, including Bernard et al. (2010), Eckel and Neary (2010), Mayer et al. (2014, 2021), which similarly document that exposure to competitive pressures leads multiproduct firms to focus on their most productive products.

5.2 A New Channel: Intangible Asset and Product Addition

Now, to highlight another dimension of product scope adjustment—product addition—we hypothesize that South Korean establishments with high pre-period knowledge capital are more likely to introduce new products as a way to escape from competition, which

could increase their productivity. Indeed, this hypothesis is in line with Hombert and Matray (2018)—who show that firms that have invested more in R&D are more resilient to import competition from China. However, we focus more specifically on how product addition affects productivity.

To examine this, we identify high-knowledge establishments as those that belong to firms with an above-median intangible assets to total assets ratio as of 2006[14], as establishments within the same firm share knowledge stock. Then, we estimate the following equation:

$$\Delta Y_i = \alpha + \beta_1 \Delta XC_i + \beta_2 \Delta XC_i \times IA_i + \beta_3 IA_i + \gamma X_i + \delta \Delta Xsize_i + \psi_{IND(i)} + \varepsilon_i, \text{`} \quad (7)$$

where IA_i is an indicator for high-knowledge establishments.

Table 4 shows that the responses of high-knowledge establishments are in stark contrast to those of low-knowledge establishments both in terms of product switching and productivity. All coefficients in the second row are statistically different from zero. Specifically, columns (1)-(4) show that high-knowledge establishments reduce their product scope by less, driven both by more additions and fewer drops.[15] In net, considering dropping products, product diversification falls to a lesser extent for high-knowledge establishments as column (4) indicates. This weaker resource concentration response to export competition by high-knowledge establishments is in stark contrast with the stronger resource concentration response by high-productivity establishments shown in Table 3.

From the conventional models' perspective, which emphasizes resource reallocation toward core products as the key channel of productivity improvement, this weaker concentration should imply a more negative impact of export competition on the productivity of high-knowledge establishments. However, columns (5) and (6) show the opposite response. The coefficients in the second row are positive and significant in both columns, in contrast to the conventional models' predictions.

We focus on the stronger product addition responses by high-knowledge establishments as a potential channel through which a better impact on productivity arises. Indeed, historical examples show that producers have tried to introduce new products when competition intensifies, hoping them to be game changers. For instance, Apple introduced the iPod and iPhone, facing fierce price competition in personal computers. In

[14]Because the firm–id and plant–id matching is available only from 2006, we use the firm-level intangible assets to total assets ratio in 2006 instead of 2003. Admittedly, the 2006 data may not capture the pre-period ratio precisely. However, for the dummy variable indicating an above-median ratio, we are less concerned about this issue since the ratio is used only in a relative sense.

[15]Interestingly, the sum of two coefficients in column (2) indicates that export competition increases high-knowledge establishments' product addition, although statistically insignificant.

Table 4: Heterogeneous Response by Knowledge

Dependent variable	Product switching activity				Productivity	
	ΔN_i	add_i	$drop_i$	ΔE_i	ΔLP_i	ΔTFP_i
	(1)	(2)	(3)	(4)	(5)	(6)
ΔXC_i	-1.696***	-0.838***	0.859***	-0.269***	-0.239***	-0.317***
	(0.363)	(0.254)	(0.181)	(0.072)	(0.083)	(0.078)
$\Delta XC_i \times IA_i$	1.318***	0.891***	-0.427***	0.174***	0.212*	0.269**
	(0.379)	(0.300)	(0.128)	(0.062)	(0.112)	(0.110)
Observations	13,046	13,046	13,046	13,046	13,032	13,001

Notes: All columns include 4-digit industry fixed effects, and control variables including the size of export markets, initial period age, productivity, capital intensity, the logarithm of the number of products, IA_i dummy, and an exporter dummy. IA_i indicates establishments that belong to firms with an above-median intangible assets to total assets ratio within their 4-digit industry. All regressions are weighted by the initial shipment of each establishment. The sample includes continuing manufacturing establishments. Standard errors in parentheses are heteroskedasticity-robust standard errors. ***, **, and * denote one percent, five percent, and ten percent significance level, respectively.

our South Korean context, LG Chem shifted from basic petrochemicals to energy storage, developing Nickel-Cobalt-Manganese batteries, while SK Hynix, originally a computer manufacturer, transformed into the world's second-largest memory chip maker in response to intense price competition.

We formalize this observed response and intuition into a model in Section 6, where we propose the addition of new products as a potential channel through which a better impact on productivity arises for high-knowledge establishments. While the model does not rule out the old product specialization channel, firms with better knowledge are more likely to add new products that are relatively more productive in response to competition, which conventional models do not capture.

6 Conceptual Framework

Motivated by the empirical evidence above, we develop a model not to provide a fully structural account of firm dynamics, but to isolate the minimal mechanisms required to rationalize four empirical patterns: (i) competition does not always raise productivity; (ii) product specialization can improve productivity; (iii) product addition can also improve productivity; and (iv) the responses of high-knowledge firms may differ from those of high-productivity firms. Standard multiproduct firm models with productivity heterogeneity can account for (ii) but not for (i), (iii), or (iv). We therefore introduce a parsimonious extension that adds an additional state variable—firm-level knowledge—that

governs the return to innovation and the productivity distribution of newly introduced products. All other elements follow canonical CES demand and monopolistic competition frameworks.

6.1 Setup

Consider a monopolistically competitive economy. We assume that labor is the only input, with wage normalized to one. Each firm i produces a set of differentiated products indexed by $j \in \mathcal{J}_i$ under CES preferences. Firm-product-specific productivity of product j is given by:

$$\theta_{ij} = \theta_i + \lambda K_i + \varepsilon_{ij}, \tag{8}$$

where θ_i represents firm i's persistent production efficiency or cost conditions—such as location, infrastructure, and established supplier network. K_i is a firm i's knowledge stock, which reflects its accumulated innovative capabilities. While θ_i does not change, we assume that K_i evolves with innovation experience, which is formalized below. ε_{ij} implies the stochastic product-specific draw, and λ denotes how strongly knowledge affects productivity. Once product j's productivity is realized, it does not change.

Each product j faces competition intensity $\phi_j \in (0, 1]$, which affects its profitability, where a higher ϕ_j implies weaker competition. CES demand implies that firm i's profit coming from product j is:

$$\pi_{ij} = A \cdot \phi_j \cdot \theta_{ij}^{\sigma-1} - f \tag{9}$$

where A is a constant, $\sigma > 1$ is the elasticity of substitution, and f is the fixed cost of production.[16]

6.2 Innovation, Product Addition, and Knowledge Accumulation

Firms may add new products to their product lineup by investing in innovation. In this process, they direct innovation efforts toward products with the highest expected profitability, draw product-specific productivity from a distribution, and then decide whether

[16] Alternatively, product-specific fixed cost (f_j) can be used, which results in a similar conclusion.

to introduce the product after observing realized productivity. Firms accumulate knowledge through these innovation experiences.[17]

More formally, firm i solves the following two-tier maximization problem:

$$\max_{j'} \left\{ \max_{r_{ij'} \geq 0} \mathbb{E}\left[\pi_{ij'}^{\text{new}}\right] \right\}, \tag{10}$$

where $\mathbb{E}\left[\pi_{ij'}^{\text{new}}\right]$ denotes the expected profit from adding a new product j'.

First, firm i chooses the optimal level of innovation investment $r_{ij'} \geq 0$. A positive investment ($r_{ij'} > 0$) allows the firm to draw productivity from a known distribution F, which depends on $r_{ij'}$ and K_i.[18] Specifically, firm-product-specific productivity of a new product j' is:

$$\theta_{ij'}^{\text{new}} = \theta_i + \lambda K_i + \varepsilon_{ij'}, \quad \varepsilon_{ij'} \sim F(r_{ij'}, K_i), \tag{11}$$

where the characteristics of $F(r_{ij'}, K_i)$ are explained below. We assume that firms can invest in innovation and add only one product at once. Once the productivity of the new product is realized, firm i decides whether to add it to the product line or discard it based on its profitability. Then, its knowledge stock K_i increases as a result of innovation, and the firm can invest in innovation for the next product with a higher knowledge stock.[19] To reflect this knowledge accumulation and to clarify that the level of knowledge stock differs for each productivity draw, we rewrite K_i as follows. Assuming that the firm has drawn productivity $n_{j'}$ times before drawing productivity for a new product j', we denote K_i that has been accumulated through $n_{j'}$ times of prior innovation experiences throughout its entire history as $K_i^{(n_{j'})}$. With this notation, the following law of motion indicates how firm i's knowledge stock evolves following innovation investments:

$$K_i^{(n_{j'}+1)} = K_i^{(n_{j'})} + \kappa r_{ij'}. \tag{12}$$

The level of knowledge stock after investing in innovation for product j' reflects the accumulated knowledge stock by then, the level of innovation investment ($r_{i,j'}$), and the learning efficiency parameter, κ. Noting this, for the simplicity of notation, we abstract

[17] Knowledge accumulation is a key assumption that allows new products to be more productive than incumbent products—product addition channel—as shown below.

[18] If adding product j' is not profitable for any $r_{ij'}$, firm i sets $r_{ij'} = 0$ and does not draw productivity for that product.

[19] Although we model knowledge as firm-specific, it can be interpreted as firm-sector-specific, reflecting the fact that multiproduct firms typically produce multiple varieties within the same sector. As long as knowledge is not purely firm-product-specific—that is, innovation experience spills over across products within the firm—our conclusions are unchanged.

away from the superscript (n) unless necessary.[20]

Innovation entails costs. We assume that the cost of innovation depends on the number of products ($N_i = |\mathcal{J}_i|$) that a firm produces and the level of innovation investment ($r_{ij'}$) as follows:

$$c(r_{ij'}; N_i) = \frac{r_{ij'}^2}{2} g(N_i), \tag{13}$$

where $g(N_i)$ is increasing in N_i, for instance, due to the limited managerial attention, engineering capacity or organizational complexity, similar to the trapped resource model developed by Bloom et al. (2013).[21] Therefore, the expected profit from innovation and product addition is given by:

$$\mathbb{E}\left[\pi_{ij'}^{\text{new}}\right] = \mathbb{E}\left[A\phi_{j'}(\theta_i + \lambda K_i + \varepsilon_{ij'})^{\sigma-1} - f\right] - \frac{r_{ij'}^2}{2} g(N_i), \tag{14}$$

which reflects the expected revenues from a new product, the fixed production costs it incurs, and the cost of innovation. Firms choose their optimal level of innovation investment $r_{ij'}$ to maximize this expected profit. The first order condition yields

$$\frac{\partial \mathbb{E}\left[\pi_{ij'}^{\text{new}}\right]}{\partial r_{ij'}} = \mathbb{E}\left[A\phi_{j'}(\sigma-1)(\theta_i + \lambda K_i + \varepsilon_{ij'})^{\sigma-2} \cdot \frac{\partial \varepsilon_{ij'}}{\partial r_{ij'}}\right] - r_{ij'} g(N_i) = 0. \tag{15}$$

We assume that the mean of the productivity distribution, $F(r_{ij'}, K_i)$, is first order stochastically increasing in $r_{ij'}$ and K_i, with $\frac{\partial \mathbb{E}[\varepsilon_{ij'}]}{\partial r_{ij'}} > 0$ and $\frac{\partial^2 \mathbb{E}[\varepsilon_{ij'}]}{\partial r_{ij'} \partial K_i} > 0$, meaning that the marginal benefit of $r_{ij'}$ is larger for high K_i. Moreover, we assume that $\frac{\partial^2 \mathbb{E}[\varepsilon_{ij'}]}{\partial r_{ij'}^2} < 0$ and $\frac{\partial^3 \mathbb{E}[\varepsilon_{ij'}]}{\partial r_{ij'}^2 \partial K_i} > 0$. Therefore, the expected productivity drawn from $F(r_{ij'}, K_i)$ is increasing in $r_{ij'}$ with diminishing returns, where the speed of decline is slower when the knowledge stock is high. In other words, a high-knowledge firm's MB curve (MB from innovation investment) is flatter than that of low-knowledge firms.[22] Also, the level of MB is higher for high-knowledge firms for all $r_{ij'}$. Figure 2 illustrates this, where the MB curves for high-knowledge and low-knowledge firms are indicated by MB_{high} and MB_{low}, respectively. Note that the MC line is a straight line from the origin with the slope of $g(N_i)$.

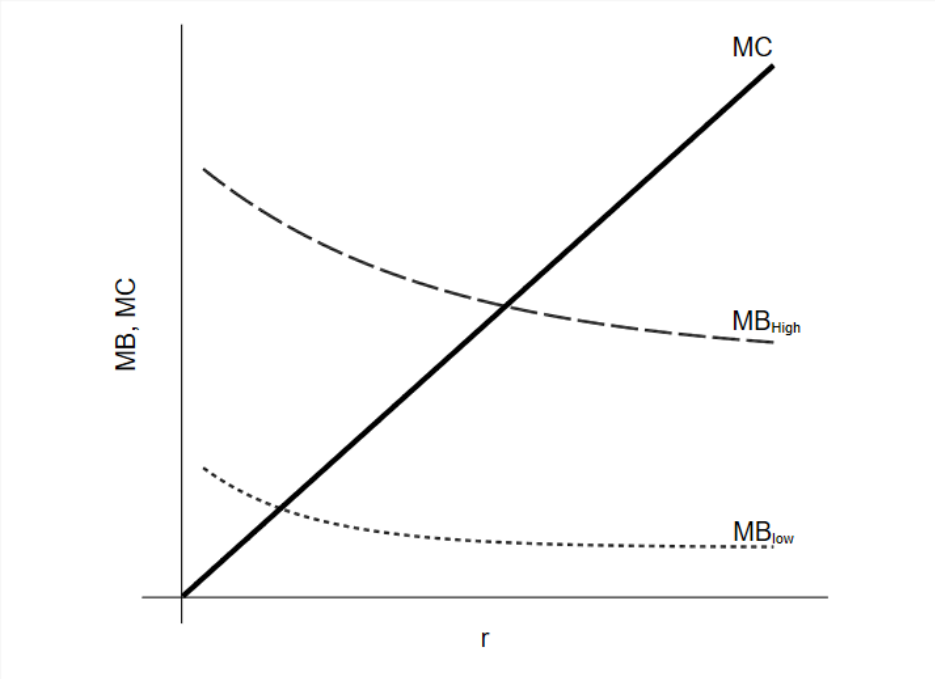
While the graph indicates that the optimal $r_{ij'}$ is always positive, the corresponding expected profit may be negative once the fixed cost f is considered. In that case, the firm

[20] This superscript is used below in Section 6.4.

[21] The quadratic specification is standard in the innovation literature, capturing the convexity of effort costs. Here, $r_{ij'}$ is interpreted as innovation effort, and the opportunity cost of such effort rises in a quadratic manner.

[22] Note that $\mathbb{E}\left[A\phi_{j'}(\sigma-1)(\theta_i + \lambda K_i + \varepsilon_{ij'})^{\sigma-2} \cdot \frac{\partial \varepsilon_{ij'}}{\partial r_{ij'}}\right]$ in equation (15) is the marginal benefit of $r_{ij'}$ and $r_{ij'} g(N_i)$ is the marginal cost of $r_{ij'}$.

Figure 2: Marginal benefits and costs of innovation for high- and low-knowledge firms



sets $r_{ij'} = 0$ and does not draw productivity for the product. Only when expected profit is positive does the firm choose $r_{ij'} > 0$ and draw productivity for a new product.

Comparing the expected profits across potential new products ($j' \notin \mathcal{J}i$), the firm directs its innovation investment to the product that solves the outer maximization problem in equation (10). Ultimately, the firm invests in the product with the highest $\phi j'$ (the weakest competition intensity) as a larger $\phi_{j'}$ raises expected profit both directly and indirectly through $r_{ij'}$. First, as shown in equation (14), the expected profit of a new product increases with $\phi_{j'}$ directly. Second, as implied by equation (15), the marginal benefit of innovation is greater for higher $\phi_{j'}$, leading to a larger optimal $r_{ij'}$. This, in turn, raises the expected productivity draw and thereby the expected profit from a new product. Taken together, these imply that firms add products beginning with those facing the weakest competition.

6.3 Equilibrium

In equilibrium, firms iterate this process until they do not add new products, as the expected profits of product addition through innovation are not positive. Note that the cost of innovation increases as firms add more products, discouraging innovation as firms produce more products. At the same time, firms' knowledge stock increases as they accumulate innovation experience through product addition, encouraging innovation as firms

produce more products. We assume that the former force eventually dominates the latter for the existence of the equilibrium. In other words, the increase in cost eventually prevents firms from adding new products as N_i increases. This is driven by two factors: (i) $g(N_i)$ is increasing in N_i; (ii) since firms start to add products under the weakest competition, firms have to add products under tougher competition as N_i increases. Eventually, these two forces dominate the knowledge accumulation, and the expected profit of adding a new product becomes negative as N_i increases.

Note that the number of products that each firm produces and the productivity of those products may differ based on firm characteristics and productivity draws in equilibrium. Additionally, the actual level of innovation investment $r_{ij'}$ is zero, and K_i does not change for all firms in equilibrium.

6.4 Consequences of Competition

Let's consider an economy in equilibrium. Suppose that competition intensifies for some products as NEMs expand their exports, represented by declines in ϕ_j for some j. The following propositions summarize the consequences of competition.

Proposition 1 (Product Drop): Firms may drop products when competition intensifies.

Proof. Equation (9) implies that there exists a cutoff productivity for each product to make a positive profit:

$$\theta_{\text{cut},j} = \left(\frac{f}{A\phi_j}\right)^{\frac{1}{\sigma-1}}. \tag{16}$$

Therefore, when competition intensifies for product j—a decline in ϕ_j—its cutoff productivity increases. Firms drop product j when the cutoff becomes higher than their product-specific productivity ($\theta_{ij} < \theta_{\text{cut},j}$). Put it differently, if the decline ϕ_j is so large that π_{ij} becomes negative, firm i drops this product j. ■

When competition intensifies broadly, firms are likely to drop products with relatively low productivity. This adjustment could raise firm-level productivity as resources are reallocated toward relatively higher-productivity products. This is the conventional product specialization channel through which product scope adjustment improves firm productivity.[23]

[23] In standard multiproduct firm models (Eckel and Neary, 2010; Mayer et al., 2014, 2021) with core-periphery products—where product productivity declines with distance from the core—stronger competition induces firms to drop peripheral products, thereby improving productivity.

However, in this model, competition is product-specific, and it may intensify for products in which a firm's productivity is relatively high. In that case, firms may drop high-productivity products and shift resources to lower-productivity ones. Thus, competition-induced product drops do not necessarily improve firm productivity. Although this pattern is not emphasized in the existing models, the empirical findings in Section 4 underscore its relevance.

Admittedly, allowing for product-specific competition in standard models can generate productivity-decreasing effects of competition. However, models with a core-periphery structure cannot explain why product addition can improve firm productivity—documented in Section 5.2—using product-specific competition alone, because newly introduced products are always less productive than incumbent ones. We therefore introduce two additional mechanisms, the trapped-resources effect and knowledge accumulation, to rationalize this empirical pattern (the product-addition channel).

Proposition 2 (Resource Slack and Innovation): When products are dropped, N_i falls, reducing the marginal cost of innovation. As a result, optimal $r_{ij'}$ increases for a new product, and this effect is stronger for firms with high K_i.

Proof. The first order condition in equation (15) can be rewritten as:

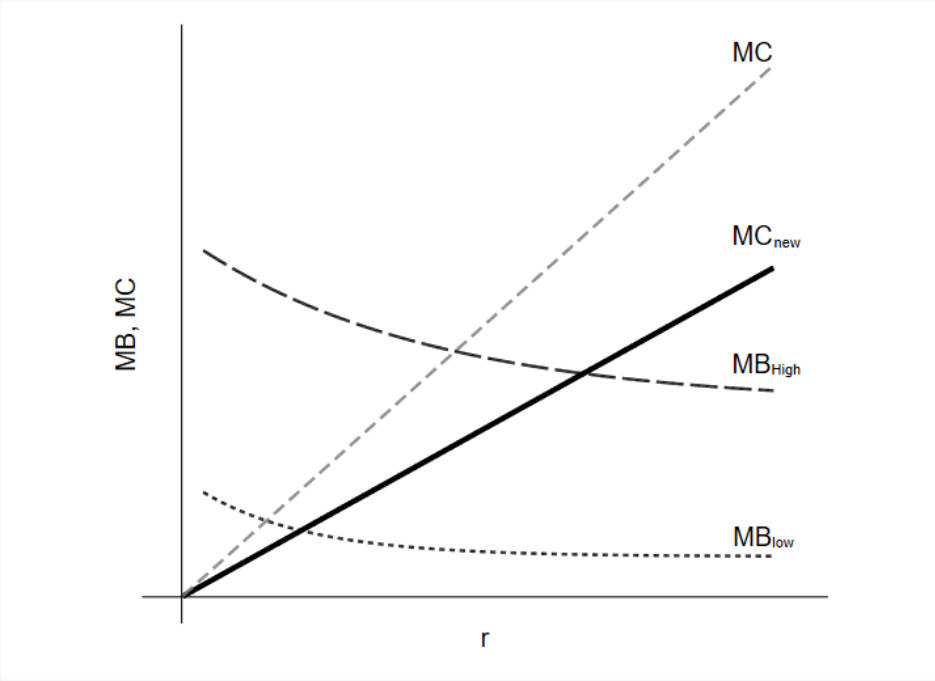
$$\mathbb{E}[\text{MB}(r_{ij'}, K_i, \phi_{j'})] = r_{ij'} g(N_i). \tag{17}$$

Suppose competition intensifies for some products $j \in \mathcal{J}_i$, inducing the firm to drop the set $D_i = \{j : \theta_{ij} < \theta_{\text{cut},j}\}$. This reduces the number of products that the firm produces from N_i to $N_i' = N_i - |D_i|$. Since $g(N)$ is increasing, we have $g(N_i') < g(N_i)$. Therefore, dropping products lowers the marginal cost of innovation, leading to an increase in $r_{ij'}$.

Figure 3 illustrates this result. Note that the marginal benefit curve is flatter for high-knowledge firms as they face slower diminishing returns, following the earlier discussion (Figure 2). The slope of the MC line declines, as indicated by the new MC line MC_{new}, reflecting lower marginal innovation cost. This change increases the optimal $r_{ij'}$ for both high-knowledge and low-knowledge firms, but this effect is stronger for high-knowledge firms as their MB curve is flatter than that of low-knowledge firms.

It is possible for the MB curves to shift downward—a stronger competition may shift the curves downward if $\phi_{j'}$ falls too—if competition intensifies for j' as well ($\phi_{j'}$ falls). In this case, if the decline in MC is strong enough, the optimal $r_{ij'}$ will increase. ■

Figure 3: Optimal innovation when dropping products



If this higher optimal $r_{ij'}$ leads to a positive expected profit accounting for the fixed cost of production, firm i actually engages in innovation. If the realized productivity drawn from a distribution is sufficiently high, the firm adds a new product. Similar to the previous discussion, this is more likely to happen for high-knowledge firms. Indeed, empirical evidence in Section 7.3 shows that plants dropping more products in response to export competition are more likely to add new ones, with this tendency stronger for high-knowledge plants, consistent with this proposition.

Note that some firms may replace products that become less profitable with new products—even when those products still yield positive profits.[24] However, such replacement is limited since innovation costs create friction: expected profit gains must be sufficiently large to justify the cost of innovation. Importantly, and realistically, innovation also acts as a barrier to active product switching in this model. Appendix C formalizes this idea.

What is the productivity implication of this product addition? Our model shows the possibility that firms can add new products whose productivity is higher than that of dropped products. This implies that product addition could also serve as a channel through which firm productivity improves through product scope adjustment.

[24]Products that generate negative profits are always dropped.

Proposition 3 (Productivity Implication of Product Addition): The productivity of newly added products can be higher than that of dropped products.

Proof: Let's denote firm i's knowledge stock when the dropped products were originally created as $K_i^{(n_d)}$ for $d \in D_i$ and its knowledge stock at the post-drop innovation attempt for a new product j' as $K_i^{(n_{j'})}$, where $n_d < n_{j'}$. Due to the knowledge accumulated from prior innovation experience, we have $K_i^{(n_{j'})} > K_i^{(n_d)}$ for all $d \in D_i$.

Considering this, two forces can make the productivity of new products higher than dropped products, noting that $\theta_{ij'}^{new} = \theta_i + \lambda K_i^{(n_{j'})} + \varepsilon_{ij'}$ and $\theta_{id} = \theta_i + \lambda K_i^{(n_d)} + \varepsilon_{id}$. First, without considering the stochastic components $\varepsilon_{ij'}$ and ε_{id}, the productivity of product j' should be larger than that of product d as $K_i^{(n_{j'})} > K_i^{(n_d)}$ for all $d \in D_i$ reflecting knowledge accumulation.

Second, recall that $\varepsilon_{ij'}$ is drawn from a distribution $F(r_{ij'}, K_i^{(n_{j'})})$. Noting that $K_i^{(n_{j'})} > K_i^{(n_d)}$, $\varepsilon_{ij'}$ drawn from $F(r_{ij'}, K_i^{(n_{j'})})$ is likely to be higher than ε_{id} drawn from $F(r_{id}, K_i^{(n_d)})$ unless $r_{ij'}$ is sufficiently smaller than r_{id}. While $r_{ij'}$ may not be larger than r_{id} for all $d \in D_i$ since $\phi_{j'}$ is likely to be smaller than the pre-shock level of ϕ_d,[25] $r_{ij'}$ could be higher than some r_{id} due to the accumulated knowledge. Therefore, $\varepsilon_{ij'}$ can be higher than that of dropped products.

Accounting for these non-stochastic and stochastic components of productivity, the new product's productivity can be higher than that of dropped products. ■

This underscores an underexplored channel through which product scope adjustment can increase firm productivity in response to competition: the product addition channel. Note that this channel is more likely to work for high-knowledge firms as their optimal $r_{ij'}$ increases more, and thereby their productivity draw is more likely to be higher.

Corollary (Importance of Knowledge): While this productivity increase is more likely to happen for firms with high knowledge, that is not always true for firms with high observed productivity. This is because observed productivity could be high due to large θ_i or favorable productivity draws, both of which are irrelevant for the slope of the MB curve for innovation. Therefore, it is important to distinguish high-productivity firms and high-knowledge firms, as the empirical findings in Tables 3 and 4 highlight in Section 5.

[25] As discussed in Section 6.2, firms add products beginning with the highest ϕ.

7 Additional Empirical Results

This section presents additional empirical results to (1) address potential concerns regarding the main findings and (2) strengthen the link between the empirical evidence and the theoretical model. First, we show that the main results are robust to including imports from China and to using an alternative measure of product diversification. We then provide suggestive evidence of the "trapped resources effect" and show that the observed productivity responses are not driven by changes in markups, consistent with the theoretical model.

7.1 Imports from China

One potential concern is the possibility that the observed product switching behavior and productivity dynamics are driven by a concurrent surge in import from China rather than export competition with NEMs.

To address this concern, we control for an establishment-level measure of exposure to Chinese import competition (and its interaction terms) when estimating equations (6) and (7). Specifically, we construct the measure as follows:

$$\Delta IC_i = \sum_k \frac{y_{i,k,03}}{y_{i,03}} \Delta_g \frac{M^{KR\ from\ CN}_{k,03-16}}{M^{KR}_{k,03-16}}. \tag{18}$$

Considering potential endogeneity issues,[26] we adopt instrument variable approach using other countries' imports from China following Autor et al. (2013).[27]

Table 5 presents the results. Our main results remain qualitatively similar after accounting for Chinese import competition over the period. Again, increased export competition with NEMs leads establishments to reduce product scope. High-productivity plants are more likely to drop their incumbent products and strengthen product specialization, achieving relatively greater productivity growth. In contrast, high-knowledge plants respond by adding new products, resulting in higher productivity gains. Overall, these findings suggest that the main results are robust and not driven by concurrent exposure to Chinese import competition.[28]

[26] Unobservable factors may simultaneously affect imports from China, product scope adjustment, and productivity. Also, changes in plant's product scope and productivity may affect imports from China.

[27] We employ the imports of Australia, New Zealand, Switzerland, Denmark, Spain, Japan, Germany, and Finland to construct an instrumental variable: $\Delta ICO_i = \sum_k \frac{y_{i,k,03}}{y_{i,03}} \Delta_g \frac{M^{OTH\ from\ CN}_{k,03-16}}{M^{OTH}_{k,03-16}}$.

[28] Appendix E shows that the results are robust when imports from the European Union are considered.

Table 5: Controlling for import competition from China

Dependent variable	Product switching activity				Productivity	
	ΔN_i	add_i	$drop_i$	ΔE_i	ΔLP_i	ΔTFP_i
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Overall impact						
ΔXC_i	-0.926***	-0.231	0.695***	-0.153***	-0.101	-0.138**
	(0.265)	(0.176)	(0.160)	(0.045)	(0.062)	(0.062)
Observations	13,554	13,554	13,554	13,554	13,538	13,501
Panel B. Heterogeneity by productivity						
ΔXC_i	-0.218	0.267	0.485**	-0.080**	-0.314***	-0.319***
	(0.346)	(0.215)	(0.197)	(0.038)	(0.089)	(0.092)
$\Delta XC_i \times High_i$	-0.770**	-0.529**	0.241	-0.078*	0.204**	0.205**
	(0.343)	(0.216)	(0.163)	(0.043)	(0.083)	(0.088)
Observations	13,554	13,554	13,554	13,554	13,538	13,501
Panel C. Heterogeneity by knowledge						
ΔXC_i	-1.612***	-0.824***	0.788***	-0.235***	-0.191***	-0.251***
	(0.358)	(0.255)	(0.182)	(0.070)	(0.071)	(0.070)
$\Delta XC_i \times IA_i$	1.318***	0.914***	-0.405***	0.163***	0.185*	0.234**
	(0.373)	(0.299)	(0.128)	(0.063)	(0.109)	(0.108)
Observations	12,907	12,907	12,907	12,907	12,893	12,862

Notes: All columns include 4-digit industry fixed effects, and control variables including the size of export markets, initial period age, productivity, capital intensity, the logarithm of the number of products, and an exporter dummy. All Panels controls for import competition from China (ΔIC_i) using other countries' imports as an instrument variable, and Panels B and C include interaction term $\Delta IC_i \times High_i$ and $\Delta IC_i \times IA_i$ as well. $High_i$ is a dummy variable equal to one if establishment i with an above-median labor productivity within its 4-digit industry, and IA_i indicates establishments that belong to firms with an above-median intangible assets to total assets ratio within their 4-digit industry. All regressions are weighted by shipment of each establishment at the initial period. Sample includes continuing manufacturing establishments. Standard errors in parentheses are heteroskedasticity-robust standard errors. ***, **, and * denote one percent, five percent, ten percent significance level, respectively.

7.2 Alternative Measure of Product Diversification

While the Entropy index is commonly used in the multiproduct firm literature as a measure of product diversification, it is not the sole measure that summarizes product diversification. As an alternative, we employ the following Herfindahl-Hirschman Index (HHI) as a product specialization (the opposite of product diversification):

$$\Delta HHI_i = \sum_{k}^{N_{i,16}} s_{ik,16}^2 - \sum_{k}^{N_{i,03}} s_{ik,03}^2 \tag{19}$$

where $s^2_{ik,t}$ indicates the square of product *k*'s share in establishment *i*'s shipments at time t. Positive ΔHHI_i implies stronger product specialization.

Table 6: Alternative Product Diversification Measure: Herfindahl-Hirschman Index

Dependent variable	ΔHHI_i (1)	ΔHHI_i (2)	ΔHHI_i (3)
ΔXC_i	0.091***	0.049**	0.134***
	(0.027)	(0.024)	(0.041)
$\Delta XC_i \times High_i$		0.044*	
		(0.026)	
$\Delta XC_i \times IA_i$			-0.084**
			(0.015)
Observations	13,703	13,703	13,046

Notes: All columns include 4-digit industry fixed effects, and control variables including the size of export markets, initial period age, capital intensity, and an exporter dummy. Both columns (2) and (3) includes $High$ dummy and IA_i dummy to control for baseline effect, respectively. While columns (1) and (3) contains productivity, column (2) employ $High_i$ dummy indicating high-productivity establishment instead of productivity. All regressions are weighted by shipment of each establishment at the initial period. Sample includes continuing manufacturing establishments. Standard errors in parentheses are heteroskedasticity-robust standard errors. ***, **, and * denote one percent, five percent, ten percent significance level, respectively.

Table 6 presents the results. Column (1) provides the overall effects of export competition on product specialization, whereas columns (2) and (3) show how high-productivity and high-knowledge establishments respond differently. Consistent with the main findings using the Entropy index, export competition increases product specialization (column 1), and this impact is more pronounced for high-productivity establishments (column 2). High-knowledge establishments rather diversify their product scope (column 3), as they are more likely to add new products as reported in Table 4. Our main findings based on the Entropy index are robust and not sensitive to its specific definition.

7.3 Trapped Resources Effect: Evidence

Proposition 2 suggests that dropping products releases trapped resources that can be reallocated toward the introduction of new products. We empirically examine whether plants

dropping more products are more likely to introduce new products as this proposition indicates. Specifically, we estimate the following equation:

$$add_i = \alpha + \beta_1 \Delta XC_i + \beta_2 \Delta XC_i \times PhaseOut_i + \beta_3 PhaseOut_i + \gamma X_i + \delta \Delta Xsize_i + \psi_{IND(i)} + \varepsilon_i, \tag{20}$$

where $PhaseOut_i$ indicates a dummy variable for establishment i of which the number of dropped products during the sample period is above median in each 4-digit industry. At the same time, we ask whether high-productivity or high-knowledge establishments respond differently by adding interactions with $High_i$ or IA_i.

Table 7 provides the results. In column (1), while export competition makes establishments less likely to add new products to their product portfolio, establishments that actively drop their products in response to competition are more likely to add new products, although the interaction coefficient is insignificant. While this tendency is observed for both high-productivity and high-knowledge establishments, columns (2) and (3) show that this tendency is stronger for high-knowledge establishments in line with the model's prediction,

Reflecting the trapped resources effect, the $\Delta XC_i \times PhaseOut_i$ coefficient in column (2) is positive and significant. However, high-productivity establishments are less likely to add new products as they specialize in their core products, as indicated by the negative and significant $\Delta XC_i \times PhaseOut_i \times High_i$ coefficient. In contrast, the $\Delta XC_i \times PhaseOut_i \times IA_i$ coefficient is positive and significant in column (3), implying that dropping products encourages product addition, particularly for high-knowledge establishments.

7.4 Markup Response

While our main empirical analyses highlight how South Korean manufacturing plants' product scope adjustment in response to export competition affects their productivity through two channels: product specialization and product addition. However, since we use the value added per worker and TFPR as productivity measures, one may wonder whether the observed increase in these proxies is driven by the changes in markup rather than productivity.

Due to data limitations, we cannot directly estimate the TFPQ. Alternatively, we estimate how export competition affects a crude measure of markup, defined as

$$\Delta MK_i = \frac{y_{i,2016} - Material_{i,2016} - Lcost_{i,2016}}{Material_{i,2016} + Lcost_{i,2016}} - \frac{y_{i,2003} - Material_{i,2003} - Lcost_{i,2003}}{Material_{i,2003} + Lcost_{i,2003}},$$

Table 7: Trapped Resources Effect

Dependent variable	add_i (1)	add_i (2)	add_i (3)
ΔXC_i	-0.902**	-0.931**	-1.016***
	(0.380)	(0.383)	(0.315)
$\Delta XC_i \times PhaseOut_i$	0.642	1.258***	0.155
	(0.412)	(0.428)	(0.406)
$\Delta XC_i \times PhaseOut_i \times High_i$		-0.640***	
		(0.221)	
$\Delta XC_i \times PhaseOut_i \times IA_i$			0.967***
			(0.312)
Observations	13,703	13,703	13,046

Notes: All columns include 4-digit industry fixed effects, and control variables including the size of export markets, initial period age, the logarithm of the number of products, capital intensity, exporter dummy, and $PhaseOut_i$ dummy. Additionally, column (2) includes $High_i$ dummy and interaction term with $PhaseOut_i$ dummy. Also, column (3) contains IA_i dummy and interaction term with $PhaseOut_i$. Columns (1) and (3) include productivity, while column (2) employ $High_i$ dummy indicating high-productive establishment instead of productivity. All regressions are weighted by shipment of each establishment at the initial period. Sample includes continuing manufacturing establishments. Standard errors in parentheses are heteroskedasticity-robust standard errors. ***, **, and * denote one percent, five percent, ten percent significance level, respectively.

where $y_{i,t}$, $Mateiral_{i,t}$, and $Lcost_{i,t}$ indicate plant i's shipment, material cost, and labor cost in year t. If the changes in productivity proxies in the main analyses are driven by the markup, we would expect the changes in ΔMK_i to be positive and significant.

Table 8 reports the results, accounting for heterogeneous responses by productivity and knowledge. Although some coefficients are positive, none are statistically significant. These results suggest that the observed changes in labor productivity and TFP in the main analysis are not primarily driven by changes in markups, alleviating this concern.

8 Conclusion

Our study examines the impact of heightened export competition with NEMs, resulting from EU enlargement, on product scope adjustment and productivity at the establishment level in South Korea. Empirically, we find that increased competition in export markets following EU enlargement leads, on average, to a reduction in product scope among South Korean establishments. In particular, establishments tend to drop peripheral prod-

Table 8: Markup Response

Dependent variable:	ΔMK_i (1)	ΔMK_i (2)	ΔMK_i (3)
ΔXC_i	0.041	-0.003	0.059
	(0.043)	(0.044)	(0.044)
$\Delta XC_i \times High_i$		0.042	
		(0.030)	
$\Delta XC_i \times IA_i$			-0.021
			(0.035)
Observations	13,679	13,679	13,025

Notes: All columns include 4-digit industry fixed effects, and control variables including the size of export markets, initial period age, the logarithm of the number of products, capital intensity, and exporter dummy. Both columns (2) and (3) includes $High$ dummy and IA_i dummy, respectively. Columns (1) and (3) include productivity, while column (2) employs $High_i$ dummy indicating high-productive establishment instead of productivity. All regressions are weighted by shipment of each establishment at the initial period. Sample includes continuing manufacturing establishments. Standard errors in parentheses are heteroskedasticity-robust standard errors. ***, **, and * denote one percent, five percent, ten percent significance level, respectively.

ucts and reallocate resources toward their core products. Despite the efforts of reallocating resources more efficiently, however, establishments' average productivity declines—a result that contrasts with much of the existing literature, which generally finds that intensified trade-induced competition reallocates resources and thereby enhances productivity.

Importantly, our analysis underscores that the effects of competition on product scope adjustment and productivity are shaped by establishments' initial heterogeneity. We investigate how an establishment's initial productivity and pre-existing knowledge capital influence both the direction and magnitude of product scope adjustment and subsequent productivity changes in response to increased competition. The results indicate that both highly productive establishments and those with substantial initial knowledge capital experienced smaller productivity declines in the face of intensified export competition with NEMs. However, the product scope adjustment strategies adopted by these two types of establishments are different. Specifically, establishments with greater initial knowledge are more inclined to introduce new products and drop fewer products, thereby pursuing a diversification strategy, rather than focusing on core products. Conversely, establishments with higher initial productivity are less likely to introduce new products, instead

concentrating resources on core products.

Our theoretical framework developed in Section 6 accounts for these heterogeneous adjustment patterns. In response to competition, firms drop their non-profitable products, and firms with higher initial knowledge capital are likely to invest in innovation targeting new products, both of which may improve firms' productivity.

Our theoretical model is distinct from existing multiproduct firm frameworks in several important ways. In standard models with core-periphery products (Eckel and Neary, 2010; Mayer et al., 2014, 2021)—where product productivity declines with distance from the core—stronger competition induces firms to drop peripheral products, thereby improving productivity. In these models, because firms add products starting with those closest to the core (i.e., the highest-productivity products), product addition does not raise firm-level productivity.

Our model departs from this conventional framework along three dimensions. First, by introducing product-specific competition, it captures the possibility that dropping products may not always improve productivity. Standard models can generate non-productivity-improving product drops once product-specific competition is incorporated, but they still do not predict product addition in response to tighter competition.

Second, by incorporating the trapped resources effect of Bloom et al. (2013), our model links product dropping to new product introduction. Dropping products frees resources, thereby lowering the marginal cost of innovation and triggering subsequent product addition. This dynamic mechanism distinguishes our model from static product-scope frameworks.

Third, unlike models where product productivity is deterministically tied to distance from the core, we allow for stochastic firm-product-specific productivity draws, with the expected draw increasing through knowledge accumulation. This feature implies that newly added products can be more productive than those dropped—a sharp contrast with the standard framework, where new products necessarily lie further from the core. While stochastic draws alone make this outcome possible, knowledge accumulation makes it more likely and endogenizes firms' differential responses to competition.

Finally, our model accommodates the realistic scenario in which, even when less competitive markets are available, firms may refrain from dropping products due to innovation frictions (Proposition A1). Not all firms engage in immediate or aggressive innovation; some strategically adopt a "wait-and-see" approach, introducing a conservatism absent from many previous models.

In sum, our study advances the literature by proposing a more dynamic and comprehensive representation of multiproduct firm behavior. By integrating product-specific

competition, trapped resources, stochastic productivity, and knowledge accumulation through innovation, the model moves beyond the standard view of product exit as the sole driver of productivity gains. These insights enrich both theoretical understanding and empirical interpretation of firms' micro-level responses to competitive shocks—such as those arising from EU enlargement.

Our research suggests promising directions for future research. The analytical framework and empirical findings need not be confined to EU enlargement as an exogenous source of competition. At the same time, with better datasets, future research could examine the impact of competition with NEMs on resource reallocation from multiple perspectives, including labor reallocation and cross-country product scope adjustment. For instance, subsequent studies could explore how intensified global competition induces multinational firms to reorganize production or reallocate resources across borders, which could provide important implications for domestic labor markets and policy formulation.

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Appendix

Appendix A Dataset Construction Process

We employ diverse datasets such as Mining and Manufacturing Survey (MMS) product information dataset and industrial information dataset, UN Comtrade database (UCD), and lists of exporters. To utilize essential information from these dataset, we need to combine these dataset. Here, we provide the matched data construction process.

Since 2007, KSIC 8th revision was reformed to 9th revision by Statistics Korea. This means that to measure our key independent variable, export competition, and dependent variables related to product dynamics during the period 2003 and 2016, we need to match both revisions of KSIC first. Moreover, to measure our key independent variable, export competition, we need to combine MMS product information dataset with UCD. However, these two datasets use different kinds of industry code such as KSIC and ISTANS, respectively. Thus, we need to match KSIC and ISTANS code.

During the reformation of the KSIC code, there were diversification and integration of KSIC codes, indicating that one class of 8th revision KSIC (KSIC8) is matched to several different classes of 9th revision KSIC (KSIC9) or several different classes of KSIC8 are matched to one class of KSIC9. This makes it difficult to distinguish accurately whether a product creation or a product destruction is occurred or not. In other words, direct matching between KSIC8 and KSIC9 cannot provide accurate information about establishment's product dynamics.

To resolve such limitations and to combine MMS product information database with UCD, we employ an ISTANS 5-digit product code as an intermediary for matching KSIC codes. Specifically, we match the KSIC9 with ISTANS by using concordance table provided by KIET. On the other hand, to match KSIC8 with ISTANS, we convert KSIC9 - ISTANS table to KSIC8 - ISTANS table by using KSIC8 and KSIC9 matching table sourced from Statistics Korea. While each KSIC9 is uniquely matched to an ISTANS, KSIC8 is matched to several ISTANS codes. To overcome such issue, we provide ISTANS that corresponds to KSIC9 with larger shipment value in 2007 to KSIC8.

Another issue is that KSIC9 - KSIC8 concordance is done completely at 5-digit level, whereas KSIC-ISTANS concordance includes 4-digit (or 3-digit) to 5-digit. This means all 5-digit KSIC codes, which are subcategories of the 4-digit code, should be matched to the 5-digit ISTANS code. However, those subcategory 5-digit KSIC codes are not clarified. To match these items, we develop the following algorighm:

1. Match KSIC8 - ISTANS at 5-digit level, and keep the matched observations.

2. Using the 4-digit codes of the unmatched KSIC codes, match with ISTANS, and keep the matched observations.

3. Using the 3-digit codes of the unmatched KSIC codes at step 2, match with ISTANS, and keep the matched observations.

4. Merge matched observations at step 1, step 2, and step 3.

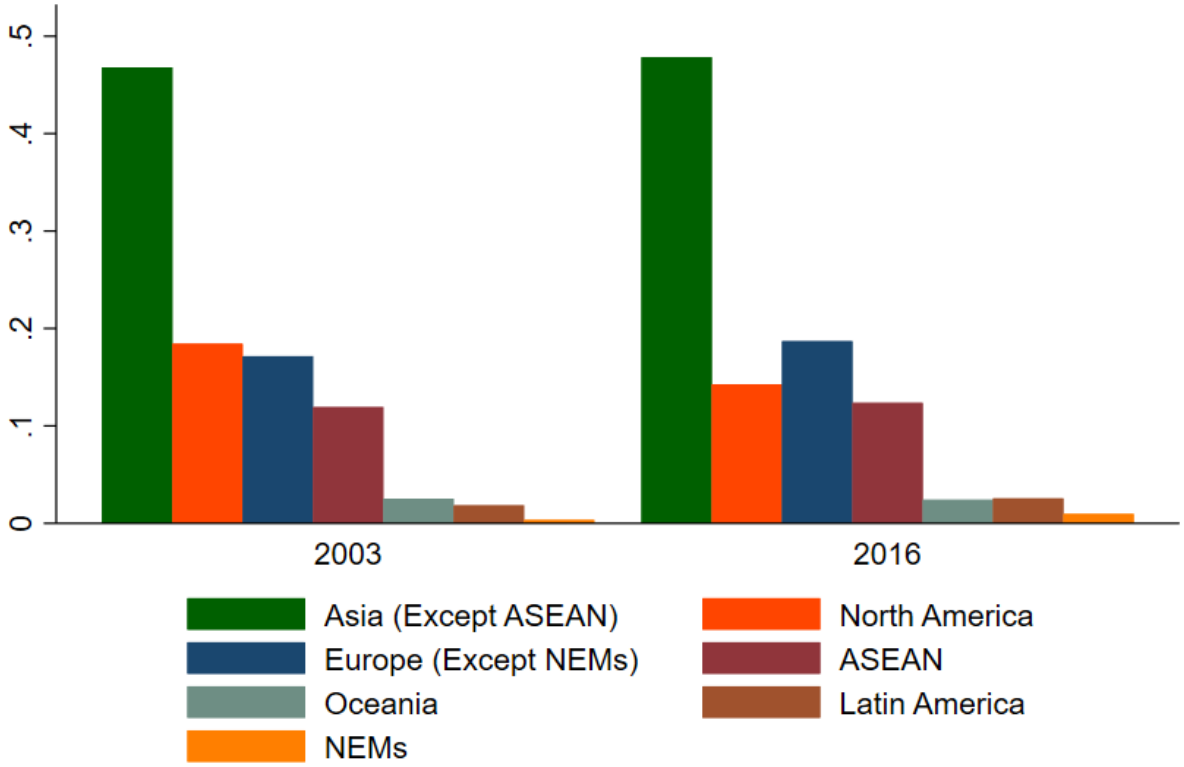
Note: 2-digit to 5-digit match exists in KSIC-ISTANS concordance table. However, in practice, all observations are matched by 3-digit level of aggregation.

With these two uniquely matched KSIC8 - ISTANS and KSIC9 - ISTANS tables, we mergeew MMS product information dataset with UCD by ISTANS codes. Also, we append MMS establishment-level information dataset with establishment IDs. Since all database such as MMS product information database, MMS establishment-level information and UCD employ same product industry classfication, ISTANS 5-digit, we combine these dataset first. With these combined dataset and upon equation (1), (2), (3), and Productivity definition, we define ΔXC_i, ΔN_i, add_i, $drop_i$, ΔE_i, ΔLP_i, and ΔTFP_i at the ISTANS 5-digit level for each establishment, and establishment-level control variables such as age, labor productivity, capital intensity, the size of export markets, and logarithm of the number of products. Lastly, to get information of export status, we merge KCS dataset with MMS – UCD matched dataset by using establishment IDs.

Appendix B South Korea's Limited Manufacturing Imports from NEMs

Figure A.1 illustrates South Korean manufacturing's reliance on different regions by showing the share of manufacturing imports by continent—Asia (excluding ASEAN), North America, Europe (excluding NEMs), ASEAN, Oceania, Latin America, and NEMs—in 2003 and 2016. In 2003, South Korea imported approximately 47% of its manufacturing goods from Asia, 18% from North America, 17% from Europe (excluding NEMs), 12% from ASEAN, 3% from Oceania, 2% from Latin America, and just 0.4% from NEMs. In both 2003 and 2016, import shares from NEMs remained negligible—0.4% and 1%, respectively. This pattern justifies our analysis focusing on export competition without considering confounding effects from import competition during this period.

Figure A.1: South Korea's Manufacturing Imports by Continents (Share)



Source: UN Comtrade database, 2003 and 2016

Appendix C Limited Product Replacement: Theory

Suppose competition intensifies for some products, so that existing products become less profitable than potential additions to the firm's lineup. Even in this case, the firm may not add new products, even if it can direct its innovation to products with a higher $\phi_{j'}$. This is because the expected profits from such products may still be insufficient to justify dropping the least profitable existing ones once innovation costs are considered. The following proposition formalizes this idea.

Proposition A1 (Limited Incentives to Drop and Replace Products): Let firm i consider replacing an existing product $j \in \mathcal{J}_i$ with known productivity θ_{ij} and market competition ϕ_j, by investing in innovation to discover a new product j'. Then, firms do not drop and replace existing product j when

$$\pi(\theta_{ij}, \phi_j) \geq \mathbb{E}\left[\pi\left(\theta_i + \lambda K_i + \varepsilon_{ij'}, \phi_{j'}\right)\right] - innovation\ cost. \tag{21}$$

Proof: We only need to consider a product that gives the highest expected profit among all products that firm i does not produce. Let's denote the product as j'. If the firm adds a new product j', the expected profit from the new product is:

$$\mathbb{E}\left[\pi(\theta_i + \lambda K_i + \varepsilon_{ij'}, \phi_{j'})\right] - innovation\ cost.$$

Since the firm loses profit $\pi(\theta_{ij}, \phi_j)$ by dropping product j, the firm will not replace product j if the expected gains from replacement are smaller than the current product's profit. Therefore, firms do not replace existing products when the following holds for any $j \in \mathcal{J}_i$:

$$\pi(\theta_{ij}, \phi_j) \geq \mathbb{E}_{\varepsilon_{ij'}}\left[\pi(\theta_i + \lambda K_i + \varepsilon_{ij'}, \phi_{j'})\right] - innovation\ cost.$$

■

Appendix D Alternative Classification of High-Productivity Establishments

The main analysis classifies Korean establishments in the sample as high- or low-productivity establishments based on the pre-period labor productivity. To examine whether the main results are sensitive to this classification, we alternatively use the pre-period TFP to categorize them.

Table A.1 shows the results. Focusing on product switching activity in columns from (1) to (4), column (1) provides statistically significant evidence that high-productivity establishments are more likely to reduce their product scope facing export competition than low-productivity establishments. Both columns (2) and (3) indicate that the stronger reduction of product scope by high-productivity establishments is driven by fewer product additions and more (insignificant) drops. In addition, column (4) implies that high-productivity establishments show stronger resource reallocation toward their core products. Lastly, high-productivity establishments experience smaller productivity loss facing export competition, as columns (5) and (6) indicate. All these results are qualitatively similar to the main results, showing that the main results are robust to the alternative definition of high-productivity establishments.

Table A.1: Heterogeneous Response by Total Factor Productivity

Dependent variable	Product switching activity				Productivity	
	ΔN_i	add_i	$drop_i$	ΔE_i	ΔLP_i	ΔTFP_i
	(1)	(2)	(3)	(4)	(5)	(6)
ΔXC_i	-0.523**	0.098	0.622***	-0.069	-0.313***	-0.303***
	(0.240)	(0.170)	(0.145)	(0.034)	(0.097)	(0.097)
$\Delta XC_i \times High_i$	-0.547***	-0.420***	0.126	-0.056*	0.192**	0.182**
	(0.197)	(0.147)	(0.104)	(0.034)	(0.090)	(0.092)
Observations	13,650	13,650	13,650	13,650	13,650	13,650

Notes: All columns include 4-digit industry fixed effects, and control variables including the size of export markets, initial period age, capital intensity, the logarithm of the number of products, high-productivity dummy, and an exporter dummy. In column (4), we include pre-period entropy index instead of log number of products to control for baseline effect. All regressions are weighted by shipment of each establishment at the initial period. Sample includes continuing manufacturing establishments. Standard errors in parentheses are heteroskedasticity-robust standard errors. ***, **, and * denote one percent, five percent, ten percent significance level, respectively.

Appendix E Imports from the European Union

While imports from NEMs is limited as shown in Appendix B, it is possible that the enlargement of the EU could have changed South Korea's imports from the EU, as old EU member states offshored their production to NEMs and sourced intermediate inputs from there. To mitigate this concern, we construct an establishment-level measure of exposure to EU import competition as follows:

$$\Delta IC_i^{EU} = \sum_k \frac{y_{i,k,03}}{y_{i,03}} \Delta_g \frac{M_{k,03-16}^{KR\ from\ EU}}{M_{k,03-16}^{KR}}. \tag{22}$$

Similar to our approach in Section 7.1, we adopt the instrumental variable approach using other countries' import from the EU.[29] Table A.2 reports that the results are qualitatively unchanged. High-productivity establishments specialize in their production, and high-knowledge establishments add new products, both experiencing better productivity growth.

[29] We use imports of Australia, New Zealand, Japan, Canada, and the United States.

Table A.2: Controlling for import competition from EU

Dependent variable	Product switching activity				Productivity	
	ΔN_i	add_i	$drop_i$	ΔE_i	ΔLP_i	ΔTFP_i
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Overall impact						
ΔXC_i	-0.967***	-0.222	0.746***	-0.155***	-0.104	-0.114*
	(0.293)	(0.194)	(0.170)	(0.050)	(0.068)	(0.067)
Observations	13,554	13,554	13,554	13,554	13,538	13,501
Panel B. Heterogeneity by productivity						
ΔXC_i	-0.160	0.376*	0.535**	-0.050	-0.355***	-0.365***
	(0.399)	(0.216)	(0.272)	(0.052)	(0.098)	(0.102)
$\Delta XC_i \times High_i$	-0.882**	-0.651***	0.231	-0.116**	0.248***	0.254***
	(0.382)	(0.200)	(0.248)	(0.056)	(0.093)	(0.098)
Observations	13,554	13,554	13,554	13,554	13,538	13,501
Panel C. Heterogeneity by knowledge						
ΔXC_i	-1.728***	-0.879***	0.849***	-0.249***	-0.215***	-0.269***
	(0.398)	(0.278)	(0.182)	(0.076)	(0.075)	(0.078)
$\Delta XC_i \times IA_i$	1.445***	1.014***	-0.431***	0.180***	0.203*	0.278**
	(0.438)	(0.334)	(0.147)	(0.069)	(0.120)	(0.122)
Observations	12,907	12,907	12,907	12,907	12,893	12,862

Notes: All columns include 4-digit industry fixed effects, and control variables including the size of export markets, initial period age, productivity, capital intensity, the logarithm of the number of products, and an exporter dummy. All Panels controls for import competition from the EU (ΔIC_i^{EU}) using other countries' imports as an instrument variable, and Panels B and C include interaction term $\Delta IC_i^{EU} \times High_i$ and $\Delta IC_i^{EU} \times IA_i$ as well. $High_i$ is a dummy variable equal to one if establishment i with an above-median labor productivity within its 4-digit industry, and IA_i indicates establishments that belong to firms with an above-median intangible assets to total assets ratio within their 4-digit industry. All regressions are weighted by shipment of each establishment at the initial period. Sample includes continuing manufacturing establishments. Standard errors in parentheses are heteroskedasticity-robust standard errors. ***, **, and * denote one percent, five percent, ten percent significance level, respectively.