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The Impact of E-commerce Competition on New Product Entry in the Manufacturing Sector: Evidence from the Republic of Korea's Manufacturing Establishments

Jung HUR

Department of Economics, Sogang University, Republic of Korea

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Abstract: *E-commerce has revolutionised the way firms and businesses operate and compete in the world economy. This paper examines the impact of e-commerce competition on new product entry in the manufacturing sector, using a unique dataset of the Republic of Korea's manufacturing establishments. Our empirical results suggest that in the era of e-commerce competition, only manufacturers with advanced technological capabilities can survive and create new products to overcome the competition. Moreover, the manufacturers that are able to create new products may be targeting the export markets. This study contributes to the broader literature on the relationship between competition and product innovation by examining how e-commerce participation promotes the creation of new products by manufacturers seeking to survive in a more competitive market.*

Keywords: e-commerce, competition, manufacturers, new product entry, export

JEL Classification: F0

1. Introduction

For decades, e-commerce[1] has emerged as a powerful sales tool in the world economy, fundamentally changing the way firms and businesses operate and compete (Einav, et al., 2014). The emergence of e-commerce has brought about new opportunities for many industries, the manufacturing sector included. One of the important challenges faced by manufacturing firms in the e-commerce world is how to effectively compete and innovate in a constantly evolving market environment.

The purpose of this paper is to examine the impact of e-commerce competition on new product entry in the manufacturing sector, with a focus on the Republic of Korea's manufacturing establishments. The development of new products in the manufacturing industries is an important feature of economic growth and innovation. So when e-commerce competition is promoted, new products may appear for firms to survive in the manufacturing industries, which leads to further market competition and positive effects on economic growth.

To achieve the objective of our research, we analyse product data from the Republic of Korea's manufacturing establishments matched with e-commerce business data. First, a unique dataset of e-commerce businesses is available from the Fair Trade Commission (FTC) of the Republic of Korea. Manufacturers[2] wishing to sell products through e-commerce must legally register with the FTC, regardless of whether they operate their own e-commerce platform or outsource it. Compared to manufacturers without e-commerce support, those with e-commerce capabilities[3] can potentially enter all local markets in the Republic of Korea through online channels, bypassing the need for physical stores or negotiations with traditional wholesalers or retailers. This cost advantage may enable even a small share of e-commerce manufacturers to intensify competition by entering almost all local markets through online platform firms.[4] To measure the impact of e-commerce competition on manufacturing industries, we match the e-commerce data with the Census on Establishments (CE) of the Republic of Korea, which provides basic information on establishments with at least one employee, such as establishment

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[1] E-commerce is broadly defined as transactions for purchasing or selling goods and services through the internet or electronic media, including telephone order, mobile app, email, fax order, online shopping mall, online market place, mobile shopping, social media commerce, and online auction.

[2] Whilst not limited to manufacturers, service providers and individuals must also register as e-commerce businesses with the FTC in order to sell products using e-commerce tools. However, this paper focuses solely on manufacturers with e-commerce support.

[3] The data do not provide which type of e-commerce platform an agent uses, so we cannot distinguish between different types of e-commerce businesses.

[4] In the Republic of Korea, the most popular online platform provider is *Coupang*. Similar types of online platform firms in other countries include *Alibaba* in China, *Rakuten* in Japan, and *Amazon* in the United States.

identification (ID) and industry code. Using this matched dataset, we measure the growth rate of e-commerce manufacturers in each 3-digit manufacturing industry from 2010 to 2018.

Second, manufacturers may introduce new products to stay competitive in the era of e-commerce. To analyse this strategy, we use the Mining and Manufacturing Survey (MMS) dataset provided by Statistics Korea, which contains product information of each manufacturing establishment over several years. We examine new product entries of each manufacturing establishments between 2010 and 2018. Although the dataset provides product classifications at 8-digit level, we focus on 5-digit level to better differentiate amongst competing manufacturers and provide more meaningful results. However, facing e-commerce competition, some individual manufacturers with a low level of technology may not be capable of creating new products to compete in the market. So, to control the level of productivity of each establishment, we measure an index of technology development level by measuring the gap from the most productive establishment.

This paper presents two noteworthy empirical results. First, industries with a higher number of e-commerce manufacturers tend to encourage manufacturing establishments with relatively high levels of productivity to create new products. Second, this relationship is more pronounced for exporting manufacturers. The first result suggests that in the era of e-commerce competition, only manufacturers with advanced technological capabilities can survive and create new products to overcome the competition. The second result suggests that manufacturers that are able to create new products may be targeting the export markets. In other words, the primary purpose of creating new products may be to sell them in foreign markets.

Previous literature on the effects of e-commerce on manufacturing industries has primarily focused on how it affects the production efficiency of manufacturers and may promote the growth for those who adopt online sales technology (Falk and Hasten, 2015; Liu, et al., 2013; Lorca, De Andres, and Garcia-Diez, 2019; Romero and Rodriguez, 2010; Soliman and Youssef, 2003; Wen, 2004). Our research is unique in that we examine the effect of e-commerce on new product entry amongst manufacturers as a means of overcoming the competitive environment in the manufacturing industry. Additionally, we demonstrate a potential linkage between new product entry and export market orientation.

Our perspective on e-commerce in manufacturing industries is that it is an advanced sales technology that allows manufacturers to reduce the costs associated with entering product markets. As more manufacturers adopt e-commerce platforms, competition within the industry may increase. As such, our study is situated within the broader literature on relationship between competition and product innovation. However, previous research in this area has rarely explored how e-commerce participation promotes the creation of new products by manufacturers seeking to survive in product markets that have become more competitive due to e-commerce. Our paper attempts to fill the gap.

The order of our study is as follows. In Section 2, we introduce the data and variable construction and empirical models used in the analysis. Section 3 presents the empirical results and their implications. Section 4 discusses robustness checks, and Section 5 concludes with some limitations of our approach.

2. Data and Empirical Models

2.1. Data

Our study uses several datasets to examine the growth of e-commerce in manufacturing industries and the new product entry of manufacturing establishments. We rely on the E-commerce Business Registration (EBR) from the Fair-Trade Commission of the Republic of Korea, the Census on Establishments (CE), and the Mining and Manufacturing Survey (MMS) from Statistics Korea, and the Republic of Korea Customs Service (KSC) data.

The EBR data include information on any individuals or legal entities in the Republic of Korea that sell products through e-commerce tools. We downloaded the EBR list from the site, which contains business IDs. However, the EBR data do not include the industry information for each business. Therefore, we matched the EBR and the CE datasets because the IDs from the EBR list are the same as the establishment IDs from the CE database. The CE is a quinquennial survey (ending years with 0 or 5) of all establishments in the Republic of Korea that hire at least one worker, and contains information on the number of employees, establishment IDs, and main industry codes for each establishment. Using the industry code in the CE, we were able to build up a list of manufacturing establishments with and without e-commerce methods.

The e-commerce tools covered by the EBR data refer to transactions for selling goods and services through the internet or electronic media, including telephone and fax orders, TV home shopping, mobile apps, email, online shopping malls, online marketplaces, mobile shopping, social media commerce, and online auctions. However, we have excluded a very small number of manufacturers who engage solely in telephone and fax orders or TV home shopping, which are old and traditional tools. Therefore, our EBR data primarily focuses on relatively new e-commerce, online sales businesses conducted through the internet.

We defined 'online sellers' entry growth rate' in each manufacturing industry at the 3-digit harmonised system (HS) level using the matched data. This variable reflects conceptually the competitive environment by the increased number of online sellers in each manufacturing industry from 2010 to 2018.

To examine new product entry, we used the MMS dataset from Statistics Korea. Unlike the CE data, this annual survey contains detailed information on production and costs, such as the number of employees, the value of physical capital, the value of sales, operation costs, total wages, 8-digit level of production information, establishment ID, industry code, and address. We aggregated the production information up to the 5-digit level[5] to examine how manufacturers in local markets avoid competition by differentiating themselves with new product entries. The MMS is also used to calculate the technology efficiency of each manufacturing establishment by measuring the productivity gap between frontier manufacturers and others in each 3-digit industry. We used the MMS information such as the value of sales, number of employees, and the value of physical capital to determine the productivity of each manufacturer. Additionally, we estimated a stochastic frontier model for technology efficiency as an alternative measure for the productivity gap. The MMS was used to control for other characteristics of establishments, such as establishment age, number of employees, the value of physical capital and industry code. These control variables potentially can affect the new product entry decision of manufacturers.

Lastly, we purchased the export status data for each manufacturer from the KCS. By matching the KCS data with the MMS, we were able to identify whether an establishment is an exporting one or not.

2.2. Empirical Model

Our idea regarding the impact of increased competition from e-commerce manufacturers on new product entries is illustrated in Figure 1. The figure assumes a specific industry with one manufacturer, online seller (On-1), who has entered the online sales platform is selling its products in five different local markets. In each local market, there is one manufacturer without e-commerce capabilities, referred to as offline sellers (Off-1 to Off-5), who have not used the online sales platform. These offline sellers are now facing competition from the online seller (On-1). Although there is only one online seller, its entry into the online sales platform could increase the number of sellers in each of the five local markets simultaneously. This example illustrates that even a small number of manufacturers who can sell online can increase competition within an industry through local market penetration.

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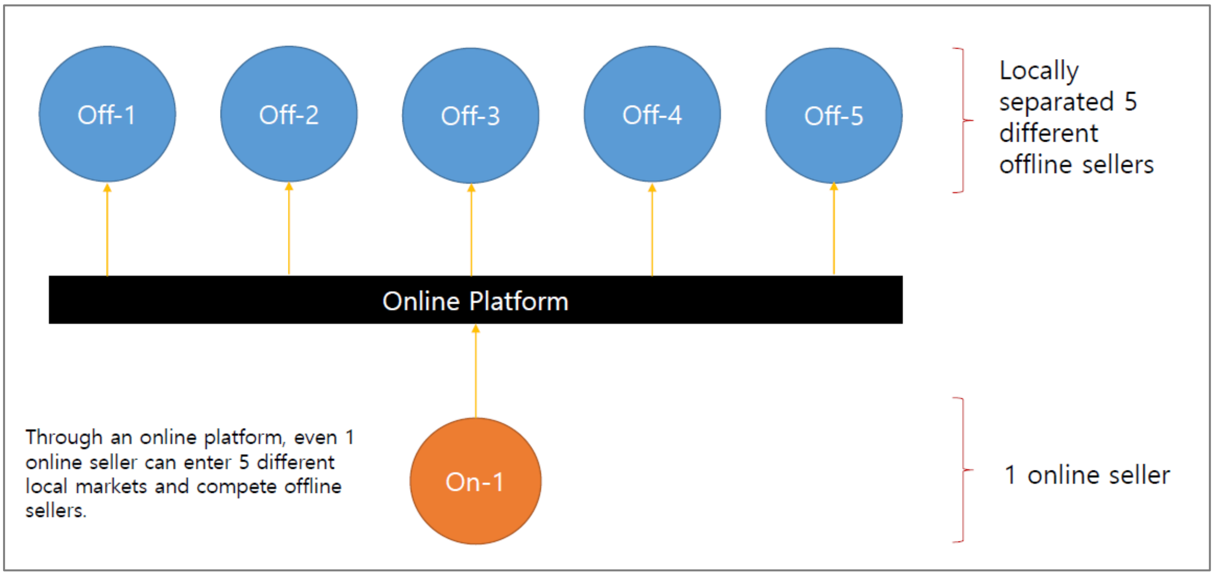
[5] For example, if a manufacturer produces two products with different 8-digit codes, we count them as one product.

Figure 1: Increased Competition Due to Online Sellers' Entry



Source: Author.

Given the increased competition within the industry, the manufacturers may attempt to overcome it by producing and selling new, differentiated products. These new products may not be as innovative as those of their competitors but can help the manufacturers to survive in the market or to secure a niche market. However, if the competition becomes too intense, the cost of producing new products may outweigh the revenues, discouraging the motivation to introduce differentiated products. A similar idea has been explored by Aghion et al. (2005), who found an inverse relationship between industrial competition and innovation on average. Our approach differs slightly as we examine individual manufacturers' response to the increased competitive environment, with a specific focus on online sellers.

To test this idea, we propose the following empirical model:

$$\begin{aligned}\Delta \mathrm{NP}_{ij(10-18)} &= \alpha + \beta_1 TD_{ij10} + \beta_2 TD_{ij10} \times \Delta ONEG_{j(10-18)} \\ &+ \beta_3 TD_{ij10} \times \left[\Delta ONEG_{j(10-18)}\right]^2 + \beta_4 \Delta ONEG_{j(10-18)} \\ &+ \beta_5 [\Delta ONEG_{j(10-18)}]^2 + \gamma X_{ij10} + \delta_J + \varepsilon_{ij(10-18)} \qquad (1)\end{aligned}$$

The dependent variable is $\Delta \mathrm{NP}_{ij(10-18)}$, which represents the change in the number of new product entries for establishment *i* in a 3-digit manufacturing industry *j* from 2010 to 2018. The products are classified at the 5-digit level. The independent variable, TD_{ij10}, measures technology development for establishment *i* in a 3-digit manufacturing industry *j* in 2010. Specifically, we define this variable as follows:

$$TD_{ij10} = \left(TFP_{ij10} - TFP_{Fj10}\right)/TFP_{Fj10} \qquad (2)$$

We estimate the total factor productivity (TFP) of a manufacturing establishment i in a 3-digit manufacturing industry j in 2010 using the Levinson–Petrin (2003) approach. Specifically, we select TFP_{Fj10} for the establishment (F) with the highest TFP within each industry j in 2010. We then calculate the difference between TFP_{ij10} and TFP_{Fj10}, divided by TFP_{Fj10}. This ratio represents the level of technology development for establishment i relative to the frontier manufacturer F. This variable is based on the idea of Aghion et al. (2005), where the technology gaps amongst firms are averaged out at the industry level. Our approach differs in that we measure the technology gap at the establishment level, which is similar to the concept of 'technology efficiency' of a manufacturing plant. We will later estimate the level of technology efficiency using a stochastic frontier model to verify the robustness of our main results.[6]

The key variables for the growing number of manufacturers with e-commerce tools in each 3-digit industry j are $\Delta ONEG_{j(10-18)}$ and $\Delta ONEG_{j(10-18)}{}^2$. $\Delta ONEG_{j(10-18)}$ is defined as follows:

$$\Delta ONEG_{j(10-18)} = \frac{Num(Online\ Sellers_{j18}) - Num(Online\ Sellers_{j10})}{[Num(Online\ Sellers_{j18}) + Num(Online\ Sellers_{j10})]/2} \tag{3}$$

The variable $\Delta ONEG_{j(10-18)}$ represents the difference in the number of manufacturers with e-commerce tools (i.e. online sellers) in a 3-digit industry j between 2010 and 2018, divided by the average number of online sellers in that industry for the years 2010 and 2018, using the mid-point method for calculating percentage change between two points in time. We exclude samples from industries with less than 10 online sellers both 2010 and 2018 to avoid overstating the online sellers' growth in smaller industries. So, we have total 62 different 3-digit level of manufacturing industries in our analysis. However, we will also test the robustness of our results by including all industries regardless of the relative size of online sellers.

We include both $\Delta ONEG_{j(10-18)}$ and $\Delta ONEG_{j(10-18)}{}^2$ in our regression, inspired by Aghion et al. (2005) who found an inverse U-shape relationship between competition and innovation at the industry level. However, our approach is different as we examine the impact of increased industrial competition from the emergence of online sellers on new product entry of individual plants. We anticipate a positive effect of $\Delta ONEG_{j(10-18)}$ on the change in the number product entries and a negative effect of $\Delta ONEG_{j(10-18)}{}^2$ on the change in the number

[6] We define efficiency of each plant in the robustness check section as follows:
$Eff_{ij10} = (Eff_{ij10} - Eff_{Fj10})/Eff_{Fj10}$

product entries.

To investigate the influence of technology development of manufacturers (TD_{ij10}) on the change in the number of new product entries ($\Delta \mathrm{NP}_{ij(10-18)}$), we aim to derive the partial effect equation form the regression model. This equation will allow us to measure the specific impact of TD_{ij10} on $\Delta \mathrm{NP}_{ij(10-18)}$ whilst controlling for other relevant factors in our analysis. The partial effect equation is as follows:

$$\frac{\partial(\Delta \mathrm{NP}_{ij(10-18)})}{\partial(TD_{ij10})} = \beta_1 + \beta_2 \Delta ONEG_{j(10-18)} + \beta_3 \left[\Delta ONEG_{j(10-18)}\right]^2 \tag{4}$$

The β_1 represents the direct effect of TD_{ij10} on $\Delta \mathrm{NP}_{ij(10-18)}$ without considering the competition effect. If a manufacturer's technology level directly determines its decision to enter the market with new products regardless of the competitive situation, a positive estimated value is expected. However, as argued in this paper, the introduction of new products by manufacturers could be influenced by competition from online sellers, in addition to their technology development level, and therefore, the estimated value of β_2 is expected to be positive. Lastly, since excessive competition may discourage manufacturers from creating new products, the estimated value of β_3 is expected to be negative. Thus, for estimating the partial effect of TD_{ij10} on $\Delta \mathrm{NP}_{ij(10-18)}$, we will estimate the values of β_1, β_2 and β_3, and use the mean values of $\Delta ONEG_{j(10-18)}$ and $\Delta ONEG_{j(10-18)}{}^2$.

Next, to examine the impact of competition from online sellers ($\Delta ONEG_{j(10-18)}$) on the change in the number of new product entries (TD_{ij10}), we will also derive the partial effect equation form the regression model as follows:

$$\frac{\partial(\Delta \mathrm{NP}_{ij(10-18)})}{\partial(\Delta ONEG_{j(10-18)})} = \beta_2 TD_{ij10} + 2\beta_3 TD_{ij10} \times \Delta ONEG_{j(10-18)} + \beta_4 + 2\beta_5 \Delta ONEG_{j(10-18)} \tag{5}$$

The direct effect of competition from online sellers on new product entry is represented by β_4, which is expected to be positive based on Aghion et al.'s (2005) idea. However, manufacturers with higher levels of technological development are better equipped to avoid competition by introducing new products. In such cases, the estimated value of β_2 may be positive. Additionally, we will estimate β_3 and β_5 to account for the inverse U relationship between industrial competition from online sellers and new product entry by manufacturers. Therefore, to determine the partial effect of $\Delta ONEG_{j(10-18)}$ on $\Delta \mathrm{NP}_{ij(10-18)}$, we will estimate β_2, β_3, β_4, and β_5, and use the mean value of $\Delta ONEG_{j(10-18)}$.

3. Summary Statistics and Empirical Results

3.1. Summary Statistics

Table 1 presents the means, standard deviations, and observations for each grouped sample. To group plants into exporters and non-exporters, we utilised the KCS database, which contains information on whether plants are exporters or not. Thus, Table 1 provides three grouped samples: whole samples, exporters, and non-exporters. Our analysis only considers plants that existed during 2010 and 2018. Therefore, the total number of samples is 19,341, with 8,122 exporters and 11,288 non-exporters.

Panel A of Table 1 shows statistics for the dependent variable, the number of new products for each group of samples during 2010 and 2018. In the whole sample, Column (2) shows that the average number of new products per plant is 0.263. However, when we decompose the whole sample into two subsamples of exporters and non-exporters, Columns (5) and (8) show the average number of new products is 0.325 and 0.156 respectively. This indicates that new products are generally adopted more by exporters.

Panel B provides statistics of main explanatory variables such as technology development and efficiency of each plant, and competition derived from online sellers' entry rate. The mean value of competition for each industry is 0.782 as shown in Column 2. On the other hand, Panel C shows statistics of control variables used in our analysis.

Table 1: Summary Statistics

Sample	Whole Obs	Whole Mean	Whole Std. dev.	Exporter Obs	Exporter Mean	Exporter Std. dev.	Non-Exporter Obs	Non-Exporter Mean	Non-Exporter Std. dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Dependent Variable									
Number of New Products	19,341	0.263	0.659	8,117	0.325	0.756	11,225	0.156	0.423
Panel B. Explanatory Variables									
Tech	19,341	–0.387	0.132	8,117	-0.368	0.132	11,225	–0.431	0.120
Eff	19,341	–0.192	0.123	8,117	–0.173	0.116	11,225	–0.233	0.128
ONEG	62	0.782	0.472	26	0.782	0.484	36	0.781	0.470
ONEGsq	62	0.829	0.755	26	0.836	0.804	36	0.825	0.730
Corr (ONEG, TD)	–0.104								
Corr (ONEG, Eff)	–0.028								
Panel C. Control Variables									
Age	19,341	13.314	9.689	8,117	15.248	10.451	11,225	11.923	8.844
Agesq	19,341	271.139	416.852	8,117	341.706	489.532	11,225	220.364	346.730
lnL	19,341	3.313	0.893	8,117	3.700	0.973	11,225	3.035	0.711
lnK	19,341	7.288	1.784	8,117	7.848	1.797	11,225	6.886	1.662

Obs = observation, Std. Dev. = Standard Deviation, Corr = Correlation, ONEG = equation (3) in section 2.2, TD = equation (2) in section 2.2, Eff = efficiency levels estimated by a stochastic frontier for each plant within each industry in 2010, InL = logarithmic value of number of employees, InK = logarithmic value of capital.

Sources: E-commerce Business Registration (EBR) from the Fair-Trade Commission of the Republic of Korea; the Census on Establishments (CE) and the Mining and Manufacturing Survey (MMS) from Statistics Korea; and Korea Customs Service (KSC) data.

3.2. Main Results with Whole Samples

In this section, we investigate how the growth rate of online sellers' entry in each 3-digit manufacturing industry level impacts each plant's new product entry during 2010 and 2018 as shown in Columns 2 and 3 of Table 2. We not only add TD_{ij10} variable in Columns 2 and 3 to examine how technological development affects each plant's ability to introduce new products differently but also introduce $\Delta ONEG_{j(10-18)}{}^{2}$ term in Column 3 based on the concept of an inverted U-shape (Aghion, et al., 2005).

Table 2: Main Result with Whole Samples

Dependent Variable	Number of New Products		
	(1)	(2)	(3)
TD	0.399	–0.542	–1.755**
	(0.443)	(0.602)	(0.730)
ONEG		0.480**	2.099**
		(0.204)	(0.990)
ONEG_sq			-1.065*
			(0.598)
ONEG x TD		1.135**	5.397**
		(0.528)	(2.373)
ONEGsq x TD			–2.752*
			(1.410)
Observations	19,342	19,342	19,342
R-squared	0.201	0.208	0.221

ONEG = equation (3) in section 2.2. TD = equation (2) in section 2.2.
Notes: ( ) indicates clustered standard errors at the firm level. All regressions include control variables such as age, age squared, log of regular workers and log of capital of each plant at the initial period 2010. All regressions are weighted by the number of regular workers of each plant at the initial period 2010. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.
Source: Author's regression.

According to Table 2, particularly in Column 2, when the growth rate of online sellers' entry increases during 2010 and 2018, on average, one establishment increases its introduction of new products. Furthermore, we found that when competition triggered by online sellers' entry arises and each plant is technologically efficient compared to others, each establishment is likely to adopt new products. These findings suggest that in order to stay competitive in the manufacturing sectors and maintain their market share in the local market, each plant needs to constantly introduce new products. Additionally, on average, new products are adopted by plants that are relatively efficient in each industry at the start of the period in 2010. However, as shown in Column 3, when such competition increases to an extreme level, each plant is less likely to adopt new products.

To capture the economic significance, we calculated marginal effects of TD_{ij10} and $\Delta ONEG_{j(10-18)}$ on $\Delta \mathrm{NP}_{ij(10-18)}$. Based on equation 4, the marginal effect of TD_{ij10} on $\Delta \mathrm{NP}_{ij(10-18)}$ is 0.380 and 0.409 in Columns 2 and 3, respectively. In other words, when one standard deviation of TD_{ij10} increases the number of new products for each plant increases by 0.380 and 0.409 in Column 2 and 3, respectively. This implies that establishment with a much higher level of technological efficiency are more likely to adopt new products.

On the other hand, based on equation 4, the marginal effects of $\Delta ONEG_{j(10-18)}$ on the introduction of new products in Columns 2 and 3 are 0.041 and 0.010, respectively. This means that when one standard deviation of competition derived from online sellers' entry increases, the number of new products of each plant increases by 0.041 and 0.068 in Columns 2 and 3, respectively. Overall, these results indicate that when competition increases, most new products are adopted by technologically efficient plants in each industry.

3.3. Main Results with Subsamples

To investigate the potential linkage between new product entry and export market orientation, we analyse equation 1 separately for exporting and non-exporting plants.[7] The results for exporters are shown in Columns 1 to 3 of Table 3, whilst Columns 4 to 6 show the regression results for non-exporters.

[7] By using a KCS dataset, we identify whether a plant is taking an exporting role or not at the initial period 2010.

Table 3: Main Result with Subsamples

Dependent Variable	Number of New Products					
	Exporter			Non-Exporter		
	(1)	(2)	(3)	(4)	(5)	(6)
TD	0.570	–0.740	–2.356**	–0.080	0.162	0.358
	(0.600)	(0.821)	(0.981)	(0.052)	(0.168)	(0.308)
ONEG		0.667**	2.811**		–0.149*	–0.376
		(0.266)	(1.182)		(0.089)	(0.330)
ONEG_sq			–1.407**			0.137
			(0.704)			(0.153)
ONEG x TD		1.638**	7.470**		–0.269	–0.850
		(0.721)	(2.989)		(0.164)	(0.634)
ONEGsq x TD			–3.766**			0.350
			(1.731)			(0.299)
Observations	8,117	8,117	8,117	11,225	11,225	11,225
R-squared	0.240	0.251	0.268	0.017	0.019	0.020

ONEG = equation (3) in section 2.2. TD = equation (2) in section 2.2.
Notes: ( ) indicates clustered standard errors at the firm level. All regressions include control variables such as age, age squared, log of regular workers and log of capital of each plant at the initial period 2010. All regressions are weighted by the number of regular workers of each plant at the initial period 2010. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.
Source: Author's regression.

We find that the positive impacts of competition and the interaction term between competition and technology efficiency on new product entry occur within the subsamples of exporting plants. On the other hand, there exists a negative impact of competition and the interaction term on new product entry for non-exporters. These results provide evidence that the positive impacts of competition and the interaction term between competition and technology efficiency on new product entry within the whole sample are dominated by exporters. The results suggest that the purpose of new products created by exporters may be oriented towards foreign markets.

To capture the economic significance, we also measure the marginal effect of competition and technology efficiency on new product entry for two groups of sub-samples respectively. First, the marginal effect of competition for exporters is 0.066 and 0.030 in Columns 2 and 3, respectively. On the other hand, the marginal effect of competition for non-exporters is –0.033 and –0.033 in Columns 5 and 6, respectively. Second, the marginal effect of technology efficiency for exporters is 0.556 and 0.600 in Columns 2 and 3, respectively. Conversely, the marginal effect of technology efficiency for non-exporters is –0.069 and –0.073 in Columns 5 and 6, respectively. These findings suggest that the positive impacts of competition and technology efficiency on new product entry are more significant for exporting plants, whilst non-exporters face negative impacts.

The results of marginal impacts of competition and technology efficiency on new product entry differ significantly between exporters and non-exporters. Specifically, when technology efficiency increases by on unit within exporters, each plant is likely to introduce 0.556 new product. Conversely, in the case of non-exporters, an increase in technology efficiency by one unit results in lower likelihood of adopting new products at a level of 0.070. These results suggest that most new products adopted by each plant are intended for foreign markets.

In the following robustness check section, we first report regression results that use each plant's efficiency level in each industry, which is estimated by stochastic frontier model, instead of technology efficiency level. Second, we exclude online sellers from our samples due to the possibility that most of new product adoption by each plant occurs through online-sellers, as they are likely to target more than one local market. Third, we include all samples that were excluded from our main results, as those samples are from industries where online sellers are less than 10 in both years 2010 and 2018.

4. Robustness Check

4.1. Efficiency Measurement

In this section, we utilise efficiency levels, Eff_{ij10} estimated by a stochastic frontier for each plant within each industry, instead of the TD_{ij10}[8] variable used in the main results. This approach is commonly used in the literature to study the impacts of efficiency on dependent variables. We present the estimation results for the whole samples and subsamples in Table 4 and Table 5, respectively, following the same format as in the main results section.

[8] The correlation between Eff_{ij10} and TD_{ij10} is 0.651. In other words, Eff_{ij10} can be used of proxy variable instead of TD_{ij10}.

Table 4: Robustness Check 1 with Whole Sample

Dependent Variable	Number of New Products		
	(1)	(2)	(3)
Eff	0.147	1.028*	1.908**
	(0.148)	(0.596)	(0.824)
ONEG		0.248**	0.855**
		(0.115)	(0.423)
ONEG_sq			–0.386
			(0.240)
ONEG x Eff		1.055*	3.849**
		(0.583)	(1.648)
ONEGsq x Eff			–1.758**
			(0.849)
Observations	19,341	19,341	19,341
R-squared	0.200	0.205	0.209

EFF = efficiency levels estimated by a stochastic frontier for each plant within each industry in 2010. ONEG = equation (3) in section 2.2.

Notes: ( ) indicates clustered standard errors at the firm level. All regressions include control variables such as age, age squared, log of regular workers and log of capital of each plant at the initial period 2010. All regressions are weighted by the number of regular workers of each plant at the initial period 2010. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Source: Author's regression.

Table 5: Robustness Check 1 with Subsamples

Dependent Variable	Number of New Products					
	Exporter			Non-Exporter		
	(1)	(2)	(3)	(4)	(5)	(6)
Eff	0.212	1.453*	2.692**	0.049	–0.120	–0.236
	(0.148)	(0.839)	(1.142)	(0.034)	(0.113)	(0.183)
ONEG		0.332**	1.119**		–0.074*	–0.141
		(0.143)	(0.480)		(0.042)	(0.150)
ONEG_sq			–0.499*			0.042
			(0.279)			(0.070)
ONEG x Eff		1.513*	5.454**		–0.193*	–0.562
		(0.817)	(2.254)		(0.112)	(0.380)
ONEGsq x Eff			–2.454**			0.235
			(1.128)			(0.189)
Observations	8,116	8,116	8,116	11,225	11,225	11,225
R-squared	0.238	0.245	0.252	0.016	0.019	0.019

EFF = efficiency levels estimated by a stochastic frontier for each plant within each industry in 2010. ONEG = equation (3) in section 2.2.

Notes: ( ) indicates clustered standard errors at the firm level. All regressions include control variables such as age, age squared, log of regular workers and log of capital of each plant at the initial period 2010. All regressions are weighted by the number of regular workers of each plant at the initial period 2010. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Source: Author's regression.

Although we employ Eff_{ij10} instead of TD_{ij10}, we find that our results remained unchanged compared to the main results in Table 2 and Table 3. Specifically, in the whole sample, an increase in competition derived from online sellers' entry leads to an increase in adoption of new products by each plant as a strategy to avoid competition. Furthermore, in cases where competition increases and a plant is more efficient than others within each industry, the establishment is more likely to adopt new products, which is consistent with the main results. In addition, the results for sub-samples of exporters and non-exporters in Table 5 are consistent with those in the main results in Table 3. These findings provide robust evidence for our main results.

4.2. Without Online Sellers in Our Samples

Given that online sellers have the ability to operate in multiple local markets whilst offline sellers are limited to one local market, it is possible that online sellers in the manufacturing sector are more likely to sell a greater number of products compared to offline sellers.[9] As a result, it is possible that most new product adoption is coming from online sellers. In this section, we exclude online sellers from our analysis samples who were identified as online sellers in either 2010 or 2018.[10]

[9] In 2018, the average number of products for online sellers is 1.211 whilst the average number of products for offline sellers is 1.142.

[10] Although we have excluded online sellers at whole period during 2010 and 2018, our results are still significant and consistent.

Table 6: Robustness Check 2 with Whole Samples

Dependent Variable	Number of New Products		
	(1)	(2)	(3)
TD	0.406	–0.539	–1.765**
	(0.447)	(0.607)	(0.735)
ONEG		0.481**	2.110**
		(0.206)	(0.993)
ONEG_sq			–1.072*
			(0.599)
ONEG x TD		1.140**	5.437**
		(0.532)	(2.383)
ONEGsq x TD			–2.774*
			(1.416)
Observations	19,164	19,164	19,164
R-squared	0.202	0.209	0.222

TD = equation (2) in section 2.2, ONEG = equation (3) in section 2.2.
Notes: ( ) indicates clustered standard errors at the firm level. All regressions include control variables such as age, age squared, log of regular workers and log of capital of each plant at the initial period 2010. All regressions are weighted by the number of regular workers of each plant at the initial period 2010. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.
Source: Author's regression.

Table 7: Robustness Check 2 with Subsamples

Dependent Variable	Number of New Products					
	Exporter			Non-Exporter		
	(1)	(2)	(3)	(4)	(5)	(6)
TD	0.581	–0.73	–2.367**	–0.081	0.170	0.373
	(0.604)	(0.828)	(0.991)	(0.052)	(0.171)	(0.310)
ONEG		0.665**	2.825**		–0.156*	–0.396
		(0.267)	(1.185)		(0.091)	(0.332)
ONEG_sq			–1.416**			0.145
			(0.705)			(0.155)
ONEG x TD		1.635**	7.520**		–0.280*	–0.878
		(0.724)	(3.004)		(0.167)	(0.639)
ONEGsq x TD			–3.795**			0.360
			(1.738)			(0.302)
Observations	8,037	8,037	8,037	11,127	11,127	11,127
R-squared	0.241	0.251	0.27	0.017	0.020	0.021

TD = equation (2) in section 2.2, ONEG = equation (3) in section 2.2
Notes: ( ) indicates clustered standard errors at the firm level. All regressions include control variables such as age, age squared, log of regular workers and log of capital of each plant at the initial period 2010. All regressions are weighted by the number of regular workers of each plant at the initial period 2010. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.
Source: Author's regression.

Tables 6 and 7 present the results of the analysis after excluding online sellers on 2010 or 2018. Despite the exclusion of these samples, the main results remain significant and consistent. This suggests that it is unlikely that the new product adoptions of online sellers dominate the main results.

4.3. Including Industries with Fewer Than 10 Online Sellers

To better measure the impact of competition derived from online sellers within industries, we excluded industries with less than 10 online sellers from our main results. However, the results in Tables 2 and 3 may be biased results due to sample selection. To address this issue, we include the previously excluded industries in this section, but still exclude online sellers at 2010 or 2018.

Table 8: Robustness Check 3 with Whole Samples

Dependent Variable	**Number of New Products**		
	(1)	**(2)**	**(3)**
TD	0.283	–0.344	–0.200
	(0.410)	(0.422)	(0.528)
ONEG		0.382***	0.501**
		(0.137)	(0.209)
ONEG_sq			–0.188
			(0.176)
ONEG x TD		0.899**	1.298**
		(0.353)	(0.595)
ONEGsq x TD			–0.519
			(0.449)
Observations	20,307	20,307	20,307
R-squared	0.179	0.192	0.194

TD = equation (2) in section 2.2, ONEG = equation (3) in section 2.2.
Notes: ( ) indicates clustered standard errors at the firm level. All regressions include control variables such as age, age squared, log of regular workers and log of capital of each plant at the initial period 2010. All regressions are weighted by the number of regular workers of each plant at the initial period 2010. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.
Source: Author’s regression.

Table 9: Robustness Check 3 with Subsamples

Dependent Variable	Number of New Products					
	Exporter			Non-Exporter		
	(1)	(2)	(3)	(4)	(5)	(6)
TD	0.406	–0.358	–0.233	–0.081	–0.036	–0.009
	(0.530)	(0.555)	(0.680)	(0.049)	(0.086)	(0.092)
ONEG		0.477***	0.606**		–0.053	0.003
		(0.160)	(0.236)		(0.043)	(0.062)
ONEG_sq			-0.188			–0.061**
			(0.195)			(0.030)
ONEG x TD		1.181***	1.732**		–0.051	0.047
		(0.453)	(0.791)		(0.072)	(0.080)
ONEGsq x TD			–0.624			–0.121**
			(0.545)			(0.054)
Observations	8,597	8,597	8,597	11,773	11,773	11,773
R-squared	0.228	0.243	0.246	0.016	0.018	0.019

TD = equation (2) in section 2.2, ONEG = equation (3) in section 2.2.
Notes: ( ) indicates clustered standard errors at the firm level. All regressions include control variables such as age, age squared, log of regular workers and log of capital of each plant at the initial period 2010. All regressions are weighted by the number of regular workers of each plant at the initial period 2010. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.
Source: Author's regression.

Based on the results presented in Tables 8 and 9, we observe a positive competition effect on the introduction of new products for each plant. This effect remains statistically significant in the whole sample and amongst exporters only. Furthermore, the effect of the interaction term on new product entry for each plant remains statistically significant. These findings suggest that our main results in Tables 2 and 3 are not biased due to sample selection.

5. Concluding Remarks

We investigated the impact of competition arising from online sellers and technology efficiency on new product entry at each establishment. Our findings suggest that in the era of e-commerce, manufacturing industries with a high number of online sellers and manufacturers with higher productivity levels encourage plants to adopt new products, particularly amongst exporting manufacturers. This indicates that establishments with higher productivity levels are better able to withstand competition and survive in the industry. Additionally, since the positive impact of competition and technology efficiency on new product entry is dominated by exporters, it is likely that the new products they adopt are targeted towards foreign markets.

Our research contributes to the literature in several ways. First, given the increasing number of people using smartphones and the internet to purchase goods, and changing purchasing habits from offline to online stores, studying the impact of competition triggered by manufacturing establishments' adoption of e-commerce tools on the new product entry is a significant research topic. Second, our study suggests that the new products adopted by exporters may be targeted towards foreign markets, highlighting the importance of considering international market orientation when exploring the impact of competition and technology on new product entry.

Despite these contributions to the literature, our study has some limitations. First, whilst we used novel data, such as the EBR from the Fair-Trade Commission of the Republic of Korea, to define the growth rate of online sellers' entry as a proxy variable for competition, this measure could reflect not only competition arising from e-commerce adoption but also competition from establishment entry. Second, our dependent variable, the number of new products at the plant level may, not truly present product innovation since innovation decisions are typically made at the firm level. We will explore them further in future research.

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