ISSN 1229-828X

Journal of Korea Trade

Volume 25 Number 4 2021

The international scholarly journal of
The Korea Trade Research Association

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ISSN 1229-828X

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JKT Vol. 25, No. 4
Published 30 June 2021

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The International scholarly journal of
KTRA
The Korea Trade Research Association founded in 1974

ISSN 1229-828X

Journal of
Korea Trade

Volume 25 Number 4 2021

JKT
The Korea Trade
Research Association
www.newktra.org

Journal of Korea Trade Vol. 25, No. 4, June 2021, 1-16
https://doi.org/10.35611/jkt.2021.25.4.1
ISSN 1229-828X

An Analysis on the Competitiveness of Japanese Steel Products in Korea: Focus on the Structural Changes of Supply and Demand in Korea Steel Industry*

JKT 25(4)

Received 3 September 2020
Revised 15 November 2020
Accepted 15 December 2020

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Abstract

Purpose – This study reviews changes in the steel export-import structure between Korea and Japan to strengthen the competitive advantage of the Korea Steel industry using a trade-related index.

Design/methodology – This study focuses on analyzing comparative advantage based on the trade intensity index (TII), revealed comparative advantage index (RCA), and trade specialization index (TSI).

Findings – Korea's steel import from Japan increased due to the domestic supply shortage of HR (Hot Rolled Coil) and Plate, rather than the sharp decline of the domestic steel industry's competitiveness in 2010. However, after the completion of Hyundai Steel's blast furnace, the Korea Steel industry solved the supply shortage. Additionally, the import of Japanese steel products had decreased significantly from 2009 to 2019.

Originality/value – This study attempts to analyze Japanese steel products' competitiveness in trade and the domestic influence of high-quality Japanese steel products. These results are connected to domestic steel supply and demand structure and relations with the Japanese steel industry. After completing Hyundai Steel's blast furnace, the Korea Steel industry solved the supply shortage, and the import of Japanese steel products has decreased significantly from 2009 to 2019.

Keywords: Steel, Export, Japan, Competitiveness
JEL Classifications: D12, F23, M52

1. Introduction

The steel industry is the nation's key industry with a high impact on the inter-industries and has played a crucial role in Korea's economic growth by steadily providing materials to automobile, shipbuilding, and construction industries. The steel industry production marked 2.3% of the entire industry and 3.4% of the manufacturing industry in 2017. The steel industry has been trying to increase self-sufficiency in steel and improve trade balance by raising export. Therefore, exports have increased from USD 7.8 billion in 2000 to USD 31 billion in 2019, marking 5.7% in export of the entire industry in Korea. Similarly, imports have tripled from USD 7 billion in 2000 (KOSA) to USD 20 billion in 2019.

The development of the steel industry in Korea is very closely related to Japan. The Korean government had built Pohang Iron & Steel Co. in 1969 (POSCO). It produced one million tons of crude steel with financial support from the Japanese government and technical support from three companies; Yahata Steel, Fuji Iron & Steel Co., and NKK Steel Co., Ltd.

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In the period of rapid growth in 1973, HR Coil that lacked supply was procured from Japan to solve difficulties in the supply and demand of raw materials such as Bloom, Billet, and HR Coil from domestic demand industries and rolling companies. Additionally, POSCO and Nippon Steel have increased their interdependencies through a partnership stake.

Japan's METI (Ministry of Economy, Trade, and Industry) has changed relevant bulk licenses to an individual export license for the export of Fluorinated polyimide, Resist, and Hydrogen Fluoride, and their relevant technologies, which may include technology transferred with exports of manufacturing equipment to the Republic of Korea on July 1, 2019. Steel products used as major materials in Japan's controlled items, such as military items and dual-use items, could also be indirectly affected by trade disputes. There is also a possibility that the closed distribution structure of the Japanese steel industry, represented by Himotsuki, could negatively affect the steel trade between Korea and Japan.

Therefore, this study analyzes changes to Japanese steel products' competitiveness in trade and estimates the domestic influence of high-quality Japanese steel products. For this purpose, this study will use steel trade data from Steel Data of Korea Iron & Steel Association between 2009 and 2019 based on the trade intensity index (TII), reveal comparative advantage index (RCA), and trade specialization index (TSI). These results will be connected to domestic steel supply, and demand structure and relations with the Japanese steel industry to provide different views and implications.

2. Literature Review

2.1. Foreign Literature

According to Mattera(2018), China's degree of trade specialization in bars, flat alloy products, and other metallic coated sheets was much higher in 2014 than in 2004, while its RCA values remained well below one for various steel products such as plates, cold-rolled sheet strips, and galvanized sheets. Japan's RCA values remained significantly high for electrical sheets and increased substantially for hot-rolled sheets and plates in the period considered. However, Japan decreased its exports of galvanized sheets and pipes and tubes, with the latter RCA value falling below one.

Pervej and Anjum (2017) analyzed the comparative advantage of Indian Steel exports as revealed regarding that of the world. Secondly, though the export potential (capacity to export) of Indian steel has strengthened, it has been fluctuating downwards due to an overall improvement in the total global trade. Despite many existing shortcomings in the industry like fluctuating demand in the global market, shortage of raw materials, usage of outdated technology, labor-intensive market, etc., it possesses several inherent strengths that make it competitively strong on the global front, comparable to global giants like China, Japan, and the USA.

Fojtikova (2017) showed that China's exports of iron and steel articles recorded a higher value of the RCA index and were usually higher than the exports of iron and steel. However, a more detailed analysis showed the differences in China's trade competitiveness with respect to steel products and time. China's competitiveness in steel trade raises doubts on whether it is fair trade supported by the WTO.

2.2. Korean Literature

Kim and others (2005) selected Korea·China·Japan FTA sensitive product group, categorized products into export specialization, absolute import specialization, competitiveness vulnerable, and safeguard product groups, then appointed the last two product groups as the FTA sensitive groups. In this study, the critical value that is the basic standard for each product group is used asymmetrically.

Lee & Jae-sung (2014) reviewed changes in the steel export-import structure between Korea and Japan using a trade-related index based on time-series analysis statistics data using revealed comparative advantage index (RCA) and trade specialization index (TSI). The Korean steel industry has had a high comparative advantage against Japan for more than ten years from 2000.

Han & Liu (2010) classified international division of labor into; 1) export specialized vertical international specialization, 2) surplus-based horizontal international specialization, 3) balance, 4) deficit-based horizontal international specialization, and 5) import specialized vertical international specialization.

Noh, Hyun-Soo et al. (2014) figure out that even though the Japanese export ratio against the USA is getting bigger and Japan's export specialization is high, the Japanese steel industry has no strong comparative advantage against the USA and other industries throughout the whole research period even though its degree is different.

3. Competitiveness Analysis

3.1. Methodology

Major precedent studies on the competitiveness analysis of the steel industry[1] used steel trade data from 'UN COMTRADE' or 'ISSB world steel export.'[2] However, the data used in the studies are different from the domestic industry's classification, which may create small differences from a comprehensive view and large differences from individual items. Therefore, throughout this section, Korea Custom data and Japan Customs data, as the primary data source, will be used following the Korea Iron & Steel Association's steel classification standard. Furthermore, while previous studies include steel products and raw materials, this study focuses on 'steel' as a standard. The domestic steel industry and the Korea Iron & Steel Association commonly use to classify steel and analyze it from a different view.

If a certain product's trade specification index is above the steel industry's average, Kim and others (2005) classified them as export specialization groups. If less than the average and more than –0.5, they have classified them as a vulnerable group, if less than –0.5 and more than –0.9, classified as a safeguard product group, and if less than –0.9, then classified as absolute import specialization group. Thus, asymmetrical classification was set to find out competitiveness vulnerable and safeguard product groups. Han & Liu (2010) categorized to an absolute advantage when trade specification index to the world is above 0.34, to a competitive advantage when above 0.03 and below 0.34, to a competitive (balanced) when between –0.03 and 0.03, to a competitive inferior when above –0.34 and below –0.03, and to an absolute disadvantage when below –0.34. Classifying deficit-based horizontal international specialization as a competitive advantage was considered improper when the average trade specification index is between –0.34 and 0.03.

However, this paper will follow Im (2007)'s methodology, that even if the TSI value appears

[1] Analysis on trade competitiveness of Korea, China, and Japan by You, et al. (2004), Kim (2005), Im (2007), and Han(2010).

[2] Survey in 34 countries covering over 95% of total steel trade based on classification of ECSC established by the Treaty of Paris 1951. One of the representative researches providing long-term steel trade insights between the countries all over the world.

negative, the deficit range can be small and relatively competitive compared to given examples. Additionally, considering Japan as a steel export country, the export of steel materials exceeded its import, and the average global trade specification index was above 0. Therefore, this study will symmetrically use the steel industry average, and 0.8 or –0.8, as a critical value of trade specification index, for an objective competitiveness analysis and comparison. Applying research methods from Im (2007), items will be divided into 4 product groups by China's competitiveness against Korea; product group 1 – absolute advantage, product group 2 – competitive advantage, product group 3 – competitive inferior, product group 4 – absolute disadvantage. These classifications were carried out by 4-step processes, using the number of trade indexes. Each step was done as follows.

3.2. Competitive Analysis

1st step: Classifying Japan's trade specification index to the world

First, the trade specification index to the world (TSI^i_{jw}) is used. TSI^i_{jw} is the value of the differences between global import and export of a particular Chinese steel product divided by the trade volume of that specific product, which indirectly indicates global competitiveness of the product through the relative volume of export and import.

$$RCA^i_{jk} = \frac{X^i_{ck} / X^i_{cw}}{X_{ck} / X_{cw}}$$

where X^i_{jw} is Japan's i product export to the world,
and M^i_{jw} is Japan's i product import from the world.

If the value of TSI^i_{jw} is 0.8 or higher[3], it is classified as an absolute competitive item. If it is less than 0.8 and equal to or higher than the average of the Japanese steel industry's global trade specification index, it is classified as a competitive advantage item. If it is higher than –0.8 and less than the average of the Japanese steel industry's global trade specification index, it is classified as a competitive inferior item. Lastly, if it is –0.8 or less, it is classified as an absolute disadvantage item.

Table 1. 1st step: Classifying product groups by trade specification index to the world

Product group	Standard	Description
Product group 1	$0.8 \leq TSI^i_{jw}$	Absolute advantage
Product group 2	$mTSI_{jw} \leq TSI^i_{jw} < 0.8$	Competitive advantage
Product group 3	$-0.8 < TSI^i_{jw} < mTSI_{jw}$	Competitive inferior
Product group 4	$TSI^i_{jw} \leq -0.8$	Absolute disadvantage

2nd step: Adjustment by Japan's export rate of increase to the world

Second, among the product group 4 classified as an absolute disadvantage in the first step, if the corresponding item's current increase in the global export rate was more than twice that of the entire Japanese steel industry, the group was adjusted to one upper level, considering its possibility of growth in near future.

[3] If trade specification index shows 0.8, it would mean that the export to the world is about 9 times bigger than the import, which implies it has absolute advantage. Im(2007)

Table 2. 2^{nd} step: Adjustment by export rate of increase

Standard	1^{st} step	2^{nd} step
n.a	Product group 1	Product group 1
n.a	Product group 2	Product group 2
n.a	Product group 3	Product group 3
$rate^{i}_{jw} \geq 2 \times m{\cdot}rate_{jw}$	Product group 4	Product group 3

*$rate^{i}_{jw}$ is i product group global export increase from 2009 to 2019.

**$m{\cdot}rate_{jw}$ is Japanese steel industry's global export increase during 2009 – 2019.

3^{rd} step: Adjustment by Japan's trade specification index to Korea

While the items were classified according to their global competitiveness in the first and second steps, the competitiveness of each item was reclassified using Japan's trade specification index to Korea (TSI^{i}_{jk}) in the third step. When analyzing the competitiveness of partner countries, global competitiveness is considered because specific items' global competitiveness of Japan and Korea do not match. When analyzing the competitiveness of a partner country's particular item against Korea, global competitiveness can provide objectivity.

Using the trade specification index to Korea, 4 product groups were formed based on the critical value used in the first step. Comparing the items sorted in the second step and by TSI^{i}, if the item shows in product group 1 of the second step and product group 4 by TSI^{i}_{jk}, it is reclassified into product group 3. If the item shows in product group 2 of the second step and product group 3 or 4 by TSI^{i}_{jk}, it is reclassified into product group 3. Others are also reclassified, as Table 4 shows

Table 3. 3^{rd} step: Adjustment by trade specification index to Korea

Standard	2^{nd} step	3^{rd} step
if TSI^{i}_{jk} is categorized into product group 4	Product group 1	Product group 3
if TSI^{i}_{jk} is categorized into product group 3 or 4	Product group 2	Product group 3
if TSI^{i}_{jk} is categorized into product group 1 or 2	Product group 3	Product group 2
if TSI^{i}_{jk} is categorized into product group 1	Product group 4	Product group 2

Fourth, revealed comparative advantage (RCA^{i}_{jk}) is used. Revealed comparative advantage is an index used for calculating the relative advantage or disadvantage of goods or services evidenced by trade flows. A share of a country's particular item export from that of the world is divided by a country's total global exports. If the RCA of a particular item is greater than 1, it can be considered a global comparative advantage. Hence, to apply the RCA index to trade between Japan and Korea, the following variations were made[4].

$$RCA^{i}_{jk} = \frac{X^{i}_{ck} / X^{i}_{cw}}{X_{ck} / X_{cw}}$$

where X^{i}_{jk} is Japan's i product export to Korea, X^{i}_{jw} is Japan's i product export to the world, X_{jk} is Japan's export to Korea, and X_{jw} is Japan's export to the world.

[4] In the preceding studies, RCA of China to the world was calculated first, which requires the total world export value. However, as 2010 data is not available, the method in Han (2010)'s study will be modified in this paper.

This shows the weight of export to Korea from the total Japanese export and the weight of a particular industry's export to Korea, in percentages. Therefore, if this value is greater than 1, it means the export of that particular item to Korea is larger than other items. Thus, that particular item can be considered as having a comparative advantage over other items from Japan.

Table 4. 4th step: Adjustment by revealed comparative advantage to Korea

Standard	3rd step	4th step
$RCA^{i}_{jk} \geq 2 \times mRCA_{jk}$	Product group 1	Product group 1
$RCA^{i}_{jk} \geq 2 \times mRCA_{jk}$	Product group 2	Product group 1
$RCA^{i}_{jk} \geq 2 \times mRCA_{jk}$	Product group 3	Product group 2
$RCA^{i}_{jk} \geq 2 \times mRCA_{jk}$	Product group 4	Product group 3

* $mRCA_{jk}$ is the average of Japanese steel industry revealed comparative advantage to Korea.

4. Analysis Result

4.1. Change to the Competitiveness of the Japanese Steel Industry against Korea

Table 5 shows the Japanese steel competitiveness analysis against Korea, using the previous section's approach. Japan's steel exports to Korea recorded USD 5.24 billion in 2009, USD 4.2 billion in 2014, and USD 3.18 billion in 2019, showing a 39.3% decrease. However, Japan's steel imports from Korea recorded USD 1.67 billion in 2009, USD 2.94 billion in 2014, and USD 2.74 billion in 2019. Therefore, in 2003, Japan's steel export to Korea recorded USD 3.58 billion surpluses. However, in 2019, it recorded a USD 450 million surplus, trade surplus of Japanese steel products has decreased significantly.

The competitiveness of Japan's steel industry against Korea per product group is as follows. Regarding product group 1, having an absolute advantage, 48 items recorded USD 4.63 billion, taking 88.2% of the total export amount in 2009, decreased to 41 items with USD 2.56 billion taking 61.1% in 2014. Moreover, it further decreased to 39 items with USD 2.25 billion taking 70.8% in 2019. This makes a -6.96% annual growth rate of the amount of absolute advantage product group export. Meanwhile, import of product group 1 recorded USD 370 million in 2009 and increased slightly to USD 380 million in 2019, yet this was good compared to the decrease in export. Likewise, the number of absolute advantage items had decreased rapidly, resulting in a trade balance recorded at -18.73 annually, from USD 3.58 billion in 2009 to USD 450 million in 2019. This may confirm that Japan's exports of major items that have lost competitiveness since 2009 to Korea increased.

Regarding product group 2, which has a competitive advantage, 11 items recorded USD 150 million taking 2.8% of the total export amount in 2003, which increased to 11 items, with USD 1.05 billion taking 25.2% in 2014, showing the highest share. However, this was rapidly decreased to 10 items, with USD 610 million taking 19.2% in 2019. However, the import amount of product group 2 was different; USD 43 million taking 2.5% of the total import amount in 2009, which increased to USD 610 million taking 20.6% in 2014, which was reduced to USD 300 million, making it 19.2% in 2019. To sum up, the trade balance of product group 2 recorded USD 100 million in 2009, USD 460 million in 2014, reaching the highest, and then decreased to USD 310 million in 2019.

Table 5. Competitiveness of Japanese steel product to Korea (unit: million U$, %)

	product group	export	import	trade balance	number of products
2009	product group 1	4,632(88.2)	369(22.1)	4,263	48
	product group 2	147(2.8)	43(2.5)	104	11
	product group 3	471(9.0)	1,260(75.4)	△787	26
	product group 4	0(0.0)	0(0.0)	0	0
	total	5,252	1,672	△3,580	85
2014	product group 1	2,567(61.1)	238(8.1)	2,329	41
	product group 2	1,054(25.1)	614(20.9)	440	11
	product group 3	579(13.8)	1,931(65.8)	△1,352	31
	product group 4	0(0.0)	153(5.2)	△153	1
	total	4,200	2,936	1,264	84
2019	product group 1	2,254(70.8)	384(14.1)	1,870	39
	product group 2	610(29.2)	300(11.0)	310	10
	product group 3	318(10.0)	2,041(74.8)	△1,723	34
	product group 4	0(0.0)	4(0.1)	△4	1
	total	3,182	2,729	453	84

* summarized by the author based on China Customs Statistics 2010, percentages in parenthesis.

Regarding product group 3, which has a competitive inferior, USD 470 million taking 9.0% of the total export amount was recorded in 2009, USD 600 million taking 13.8% in 2014, and USD 320 million taking 10.0% in 2019. Between 2009 and 2014, a steady increase in exports to Korea was observed, but a sharp increase in China's total exports caused a reduction in the export amount and share. The portion of the export amount to Korea has been maintaining a similar level. In the meantime, Korea's imports recorded USD 1.26 billion in 2009, USD 1.93 billion in 2014, and USD 2.04 million in 2019, showing a continuous increase. Hence, the trade balance deficit increased from USD 800 million in 2009 to USD 1.72 billion in 2019. Regarding product group 4, significantly, only one item was recorded in 2014 and 2019.

Table. 6 shows, in 2009, product group 1 was the biggest, which accounted for 88.2% of the total export. Still, in 2019, many product group items transferred to product group 2, and their competence has been weakened. For product group 3, there has been no significant change in the proportion of exports, such as product group 1, but exports declined. This is due to the relatively low demand for Japanese steel products as Chinese steel exports to Korea have expanded because of the continued expansion of facilities and high technology. Particularly, the change in trade structure over the last decade clearly shows the rapid growth of its global competitiveness. It expanded exports to geographically close countries and Korea.

Table. 6 shows the rapid decrease in the competitiveness of Japanese flat products from 2009 to 2014. Among the flat products, the export of product group 1 was about USD 3.84 billion in 2009, which was decreased by 57.8% in 2014 to USD 1.48 billion, and product group 2 increased by USD 840 million. The level is similar to that of 2014 and 2019. Additionally, among the pipe & tubes, the export of items in product groups 1 and 2, having advantages in competitiveness, was USD 330 million in 2009 and increased to USD 510 million in 2014 and then again decreased to USD 240 million.

However, import shows a moderate growth rate. The largest share of the import amount is in flat products, which increased about 200% in 2014 compared to 2009, as Korea's steel industry has expanded its capacity for flat products.

Other items, such as long products and steel pipes and tubes, remain at a certain level, unlike flat products.

Table 6. Changes in Japan's export and import to Korea (unit: million U$)

		Export					Import				
		G1	G2	G3	G4	total	G1	G2	G3	G4	total
2009	Long Products	827	133	161	0	1,121	54	38	175	0	269
	Flat Products	3,483	5	151	0	3,639	295	1	716	0	1,012
	Pipe & Tubes	322	9	6	0	337	20	4	48	0	72
	Casting & Forgings	0	0	155	0	155	0	0	321	0	321
	Steel Wire	0	0	0	0	0	0	0	0	0	0
	Total	4,632	147	473	0	5,252	369	43	1,260	0	1,672
2014	Long Products	567	213	90	0	870	66	65	110	0	241
	Flat Products	1,484	841	315	0	2,640	148	549	1,364	153	2,214
	Pipe & Tubes	516	0	12	0	528	24	0	151	0	175
	Casting & Forgings	0	0	162	0	161	0	0	306	0	306
	Steel Wire	0	0	0	0	0	0	0	0	0	0
	Total	2,567	1054	579	0	4,200	238	614	1,931	153	2,936
2019	Long Products	580	50	42	0	672	160	26	121	0	307
	Flat Products	1,473	261	164	0	1,898	203	154	1,526	0	1,883
	Pipe & Tubes	200	41	8	0	249	21	13	118	4	156
	Casting & Forgings	0	259	104	0	363	0	108	275	0	383
	Steel Wire	0	0	0	0	0	0	0	0	0	0
	Total	2,253	611	318	0	3,182	384	300	2,040	4	2,729

* summarized by the author based on Japan Customs Statistics 2019 in KOSA Steel database.
** G1, G2, G3, and G4 refer to product groups 1, 2, 3, and 4, respectively.

4.2. Status and Characteristics of Competitive Advantage Items against Korea

In 2009, product group 1 was formed with 39 items, including Plate, H·R Coil, Section, and others[5]. Some of these exceeded USD 100 million of the export amount to Korea; Plate, H·R Coil, HR Coil for Special Use, Section, HR Strip, Other Section, Reinforcing Bar, Structural Seamless Pipes, etc. These items show very high trade specialization (TSI) indexes to the world, TSI to Korea, and RAC, meaning that export competitiveness is very strong against Korea and the world. However, only HR Coil, Plate, Section exceeded USD 100 million of the export amount to Korea. HR Coil for Special Use, Other Pipe, included in product group 1, was located in product group 2. Notably, product group 1 contains other seamless pipes for special pipelines. This resulted from the circumstances where only SeAH css has a special seamless pipe manufacturing facility, which cannot meet all the domestic demands.

Product group 2 was formed with nine items, including H-beam, STS Wire Rod(S), and others, in 2009. Like product group 1, most product group 2 items recorded a surplus in the trade balance, but the trade amount was insignificant. The items that exceed USD 10 million of the export amount to Korea were STS Wire Rod(S) only. In 2019 Forging, High Carbon & Alloy Steel H·R Coil for Special Use(S), STS Plate(S), Other Tube (Seamless), Bars for Other Special Use(S), Other Plate for Special Use(S), etc. are included in the product group 2. Forging, which was included in product group 3, were shifted to product group 2, and the export amount to Korea increased relatively.

[5] Hereafter steel for special use will be marked with S (Specialty).

Table 7. Japan's competitive advantage steel products against Korea 2009 (unit: million U$)

Group	Item	Export to Korea	Import from Korea	Trade Balance	To the world TSI	To Korea TSI	RCA
1	Plate(general)	1,197	9	1,192	0.99	0.99	3.41
1	H·R Coil	1,073	94	979	0.84	0.84	2.19
1	HR Coil for Special Use(S)	417	71	346	0.71	0.87	1.69
1	Section	346	34	313	0.82	0.86	2.34
1	H·R Strip	214	0	214	1.00	1.00	2.06
1	Other Section (Large)	207	0	207	1.00	1.00	3.32
1	Reinforcing Bar	180	0	180	1.00	0.99	4.40
1	Structural Seamless Pipes	131	0	131	1.00	0.81	1.21
1	Plate (High Strength)	124	48	76	0.44	0.25	2.59
1	Other Tube and Pipe (Seamless)	110	0	109	0.99	0.92	0.75
1	H·R Sheet	79	0	78	0.99	0.99	1.39
1	Clad Sheet	74	0	74	1.00	0.99	2.80
1	STS Plate(S)	68	12	56	0.70	0.74	1.73
1	Grain Oriented Electrical Sheet	60	0	60	0.99	1.00	0.17
1	STS Seamless Pipe(S)	58	3	55	0.90	0.97	0.20
1	Hot Dipped Zinc Coated Sheet(S)	45	0	45	1.00	1.00	0.42
1	Bars for Other Special Use(S)	30	6	25	0.68	0.88	0.82
1	Other Surface Treatment Plate	27	3	24	0.78	0.96	0.45
1	Other Plate of Special Use(S)	23	0	23	1.00	0.87	0.77
1	STS High Carbon & Alloy Steel H·R Strip(S)	20	13	7	0.21	0.93	0.23
1	Seamless Pipe for OCTG	19	15	5	0.13	1.00	0.22
1	Cold Drawn Bar(S)	18	1	17	0.91	0.87	0.39
1	Other High Carbon & Alloy Steel C·R Sheet for Special Use(S)	18	1	7	0.93	0.88	1.18
1	Steel Sheet Pile	13	6	10	0.36	0.91	0.43
1	Channel Section (Large)	12	1	6	0.81	0.91	1.80
1	Non-Oriented Electrical Sheet	10	4	4	0.40	0.92	0.15
1	Color Sheet	9	5	9	0.28	0.91	0.19
1	Other High Carbon & Alloy Steel C·R Coil for Special Use	9	0	6	0.99	1.00	0.17
1	Other Section (Medium)	7	0	6	0.95	0.74	2.06
1	STS High Carbon & Alloy Steel C·R Sheet(S)	9	0	9	1.00	0.80	0.44
1	Flat Bar	5	1	4	0.62	0.91	0.82
1	H-beam	92	23	69	0.61	0.65	2.36
2	STS Wire Rod(S)	33	15	17	0.37	0.76	0.82
2	STS Welded Pipes for OCTG(S)	9	4	5	0.42	0.48	0.76
2	High Speed Tool Steel Bars(S)	6	0	6	1.00	0.17	1.06
2	Other Surface Treatment Plate(S)	4	0	3	0.82	0.74	0.48
2	STS Section(S)	2	1	1	0.35	0.70	0.70
2	Cold Drawn Bar	1	0	1	0.58	0.68	0.19
2	Other Medium Plate	1	0	0	0.39	0.76	0.75
2	Other H·R Sheet for Special Use(S)	0	0	0	1.00	-0.11	0.29
2	Section for Other Special Use(S)	0	0	0	1.00	0.50	0.44

* summarized by the author based on Steel data 2019.

Table 8. Japan's competitive advantage steel products against Korea 2019 (unit: million U$)

Group	Item	Export to Korea	Import from Korea	Trade Balance	To the world TSI	To Korea TSI	RCA
1	H·R Coil	821	150	671	0.69	0.87	1.74
1	Plate(general)	385	5	380	0.98	0.98	3.85
1	Section	202	88	114	0.39	0.63	3.10
1	STS Seamless Pipe(S)	96	16	81	0.72	0.94	0.43
1	Reinforcing Bar	95	0	95	1.00	0.94	5.98
1	Other Section	77	0	77	1.00	1.00	3.58
1	Structural Seamless Pipe(S)	74	1	72	0.97	0.84	2.45
1	H-beam	73	51	22	0.18	039	3.52
1	Clad Sheet	50	0	50	1.00	0.97	2.43
1	STS Wire Rod(S)	49	13	36	0.58	0.82	1.46
1	Other Surface Treatment Plate	46	3	42	0.87	0.94	092
1	Channel Section (Large)	33	0	33	1.00	0.94	4.64
1	Hot Dipped Zinc Coated Sheet(S)	29	0	29	1.00	1.00	0.42
1	H·R Sheet	29	0	28	0.97	0.90	0.35
1	Seamless Pipe for OCTG	28	1	27	0.96	0.99	0.96
1	STS High Carbon & Alloy Steel H·R Strip(S)	21	10	12	0.37	0.94	0.42
1	H·R Strip	20	1	20	0.93	0.99	0.53
1	C·R Strip	18	18	0	0.00	0.84	0.22
1	Cold Drawn Bar(S)	17	5	12	0.56	0.84	0.44
1	Flat Bar	15	0	14	0.96	0.89	3.07
1	Grain Oriented Electrical Sheet	14	0	14	0.99	0.99	0.19
1	Other Surface Treatment Plate(S)	12	2	11	0.75	0.91	0.40
1	H·R Sheet for Alloy Tool Steel(S)	10	0	10	1.00	0.90	1.51
1	Angle Section (Medium)	7	1	6	0.85	0.87	4.69
1	Other High Carbon & Alloy Steel C·R Sheet for Special Use	5	1	4	0.65	0.91	0.37
1	Other Bars(s)	5	0	5	1.00	0.74	5.04
1	Tin Plate	4	0	4	1.00	1.00	0.07
1	H·R Sheet for High Speed Tool Steel	4	0	4	1.00	0.78	3.19
1	Other Section (Medium)	3	0	3	0.92	0.83	2.60
1	Other High Carbon & Alloy Steel C·R Coil for Special Use(S)	3	13	△10	-0.67	0.94	0.03
1	Electric Welded Square Pipe	2	3	△1	-0.22	0.80	0.35
1	Free Cutting Bar	2	0	2	1.00	0.98	0.32
1	Other H·R Sheet for Special Use(S)	2	0	1	0.73	0.88	0.61
1	Spring Steel Bar(S)	1	0	1	0.86	0.83	0.26
1	Rail	1	3	△2	-0.42	0.95	0.02
1	Other Seamless Pipe for Special Use(S)	1	0	1	0.40	0.98	0.02
1	Electrolytic Zinc Coated Sheet(S)	0	0	0	-0.42	0.99	0.01
1	High Speed Tool Steel Wire Rod(S)	0	0	0	1.00	1.00	1.99
1	Other Medium Plate	0	0	0	0.43	0.91	0.09

Table 8. (Continued)

Group	Item	Export to Korea	Import from Korea	Trade Balance	To the world TSI	To Korea TSI	RCA
2	Forging	258	107	160	0.41	-0.13	1.45
2	High Carbon & Alloy Steel H·R Coil for Special Use(S)	189	127	62	0.20	0.74	1.36
2	STS Plate(S)	50	21	28	0.40	0.70	1.84
2	Other Tube (Seamless)	41	13	28	0.52	0.79	0.89
2	Bars for Other Special Use(S)	33	25	8	0.14	0.62	0.84
2	Other Plate for Special Use(S)	22	5	16	0.62	0.02	1.01
2	High Speed Tool Steel Bars(S)	7	0	7	0.99	0.48	1.28
2	STS Section	7	0	7	0.87	0.74	2.24
2	Cold Drawn Bar	2	1	1	0.41	0.77	0.32
2	Other Steel Wire	1	0	1	0.76	0.13	0.83

4.3. Status and characteristics of competitive inferior items against Korea

Product group 3 (competitive inferior) comprises mainly flat products in 2009. Flat products, such as hot dipped zinc coated sheet (USD 80 million), C·R Strip (USD 36 million), STS C·R Strip (USD 26 million), and others, take a high share of import. Additionally, Wore Rod, Forging, and other technically developed Korean steel products are steadily imported, although the amount itself is rather small. In 2019, flat products such as Hot Dipped Zinc Coated Sheet, Plate (High Strength), and STS C·R Strip(S) were included in product group 3.

Japan ranks inferior in cold-rolled steel sheets, which are high value-added products because Korean steel companies have secured export competitiveness by pursuing advanced strategies consistent with the continued growth of domestic demand businesses such as automobiles and home appliances.

Product group 4 (absolute disadvantage) is neither in 2009 nor in 2019.

Table 9. Japan's competitive inferior steel products against Korea in 2009 (unit: million U$)

Group	Item	Export to Korea	Import from Korea	Trade Balance	To the world TSI	To Korea TSI	RCA
3	Wire Rod	145	99	45	0.19	0.53	1.05
3	Hot Dipped Zinc Coated Sheet	82	139	△57	-0.26	0.76	0.28
3	Forging	71	89	△18	-0.11	-0.09	0.36
3	Other Steel Wire for Special Use(S)	42	90	△48	-0.36	0.62	0.42
3	C·R Strip	36	322	△285	-0.80	0.33	0.19
3	STS C·R Strip(S)	26	95	△69	-0.57	0.73	0.17
3	Casting	17	52	△36	-0.51	0.03	0.30
3	Casting(S)	13	13	△1	-0.04	-0.21	0.52
3	Bar	10	8	2	0.12	0.61	0.70
3	STS Steel Wire(S)	8	29	△21	-0.58	0.18	0.29
3	Non-Planting Steel Wire	5	15	△10	-0.53	0.28	0.32
3	STS Bar(S)	4	16	△13	-0.62	0.22	0.36
3	Electric Welded Tube (Medium·Small)	4	40	△36	-0.83	0.63	0.05
3	ZN-AL Alloy Sheet	3	15	△11	-0.62	0.57	0.24

Table 9. (Continued)

Group	Item	Export to Korea	Import from Korea	Trade Balance	To the world TSI	To Korea TSI	RCA
3	Wire Rod	3	51	△49	-0.90	-0.54	0.32
3	Electric Welded Square Pipe	2	6	△4	-0.44	0.57	0.36
3	STS High Carbon & Alloy Steel C·R Coil(S)	2	14	△12	-0.78	0.32	0.23
3	STS High Carbon & Alloy Steel H·R Sheet(S)	1	4	△3	-0.68	-0.07	0.29
3	C·R Sheet	0	6	△6	-0.89	-0.04	0.11
3	Aluminum Coated Sheet	0	10	△9	-0.94	0.59	0.03
3	Other Steel Wire	0	0	0	-0.31	0.09	0.16
3	Other Welded Tube for Special Line(S)	0	0	0	0.07	0.34	0.04
3	Spiral Pipe (Large)	0	2	△2	-0.96	0.38	0.02
3	Galvanized Hard Drown Wire	0	32	△32	-1.00	-0.70	0.01
3	C-Section	0	1	△1	-0.95	0.55	0.02
3	H·R strip (High Strength)	0	113	△113	-1.00	-0.77	0.00

* summarized by the author based on KOSA Steel Data 2019.

Table 10. Japan's competitive inferior steel products against Korea in 2019 (unit: million U$)

Group	Item	Export to Korea	Import from Korea	Trade Balance	To the world TSI	To Korea TSI	RCA
3	Other Steel Wire for Special Use(S)	69	89	△20	-0.12	0.52	1.09
3	Hot Dipped Zinc Coated Sheet	56	494	△438	-0.80	-0.05	0.56
3	Plate (High Strength)	54	277	△224	-0.68	-0.44	3.10
3	STS C·R Strip(S)	39	177	△139	-0.64	0.44	0.41
3	Bar	18	22	△5	-0.11	0.49	0.74
3	STS Steel Wire(S)	18	41	△23	-0.40	0.53	0.86
3	Wire Rod	11	50	△39	-0.63	-0.18	0.70
3	STS Bar(S)	9	17	△8	-0.29	0.05	0.98
3	Casting	8	72	△64	-0.81	-0.13	0.22
3	Casting(S)	7	21	△14	-0.48	-0.31	0.34
3	Color Zinc Coated Sheet	5	27	△22	-0.67	0.63	0.23
3	Electric Welded Tube(Medium·Small)	5	94	△89	-0.90	0.36	0.11
3	Non-Oriented Electrical Sheet	4	16	△12	-0.59	0.69	0.12
	Steel Sheet Pile	3	27	△23	-0.77	0.68	0.30
3	STS Welded Pipe(S)	3	16	△13	-0.70	-0.07	0.39
3	STS High Carbon & Alloy Steel C·R Sheet(S)	2	19	△17	-0.78	0.66	0.27
3	Electrolytic Galvanized Iron	1	37	△36	-0.93	0.82	0.03
3	Non-Plating Steel Wire	1	28	△26	-0.91	0.11	0.13
3	STS High Carbon & Alloy Steel H·R Sheet(S)	1	7	△6	-0.77	-0.54	0.80
3	STS C·R Coil(S)	1	34	△33	-0.94	-0.20	0.25
3	Chrome Coated Sheet	0	20	△20	-0.96	0.79	0.01
3	Electric Welded Tube (Large)	0	5	△4	-0.84	0.73	0.09
3	C-Section	0	1	△1	-0.71	0.12	0.65

Table 10. (Continued)

Group	Item	Export to Korea	Import from Korea	Trade Balance	To the world TSI	To Korea TSI	RCA
3	Other Welded Tube for Special Line(S)	0	2	△2	-0.83	0.82	0.03
3	Galvanized Steel Wire	0	24	△24	-0.99	-0.60	0.06
3	C·R Sheet	0	24	△24	-0.99	-0.62	0.10
	Aluminum Coated Sheet	0	6	△6	-0.96	0.47	0.06
	C·R Coil	0	274	△274	-1.00	-0.50	0.00
	Structural Welded Pipes(S)	0	1	△1	-0.94	0.99	0.00
	Other Section for Special Use(S)	0	0	0	-0.96	-0.10	7.13
	H·R Strip(High Strength)	0	114	△114	-1.00	-1.00	0.00
	ZN-AL Alloy Sheet	0	0	0	1.00	-0.57	0.00
	Roll Bending Pipes (Large)	0	0	0	1.00	1.00	

* summarized by the author based on KOSA Steel Data 2019.

4.4. Analysis Result

As mentioned earlier, the competitiveness of Japan's export to Korea has decreased rapidly from 2009 to 2019; the export of products with competitive advantages decreased, both in terms of quantity and quality, from USD 4.78 billion in 2009 (share: 88.2%) to USD 2.86 billion in 2019 (share: 70.3%). This was possible with overall technology development and capacity expansion of the Chinese steel industry, resulting in increased exports of oversupplied products to Korea. However, a thorough analysis of the Korean steel industry is required before judging whether the export increase has occurred solely by strengthening Chinese steel product competitiveness.

Table 11. Korea's major steel production ability[6] (unit : one thousand ton, %)

Classification	1962	1970	1980	1990	2000	2005	2010
H·R Coil (A)	56	156	6,554	12,946	28,890	33,435	38,810
Down Stream (B)	6	10	4,779	12,202	30,507	36,842	50,641
CR Sheet & Strip	6	10	1,801	5,994	16,455	18,023	24,463
Surface Treatment Plate	-	-	724	3,059	7,715	11,250	16,175
Pipe & Tubes	-	-	2,254	3,149	6,337	7,569	10,003
Difference (B-A)	-50	-146	-1,775	-744	1,617	3,407	11,831

As shown in Table 11, based on the development of automotive and electronics, Korean C·R sheet & strip production capacity increased since 1980 from 1.8 million ton to 16 million ton in 2000, to 25 million ton in 2010, and surface treatment plate increased from 7.2 million ton in 1980 to 16.2 million in 2010. Additionally, the construction business-enhancement such as the government building 2 million households, and high pipe & tubes consumption of major oil-producing countries due to rising oil prices, has led to the production capacity of steel for ordinary piping for construction and oil country tubular goods (OCTG) increased from 3 million ton in 1990 to 10 million ton in 2010.

Meanwhile, the steel production capacity of downstream companies increased from 30.5

[6] Korea Iron & Steel Association, 『Steel Production Capacity 2009』, 2010.

million tons in 2000 to 50.64 million tons in 2010, H·R coil production capacity merely increased from 28.89 million tons to 38.81 million tons, causing a supply shortage of 11.83 million ton on facility capacity basis. As HR coil is produced through a blast furnace, the Korean steel industry suffered from this short supply until the 2000s due to the government policies, major facility investments to downstream steel mills, delay in blast furnace construction, and the bankruptcy of Hanbo Steel. Hence, the shortage has been fulfilled by imports from Japan.

Table 12. Changes in H·R coil supply and demand[7] (unit : one thousand ton, %)

Classification	2006	YOY	2010	YOY	2013	YOY	2019	YOY
Total demand	23,334	14.8	35,828	26.0	37,564	-2.8	37,272	-4.6
Nominal consumption	25,230	3.7	31,583	-2.1	32,545	-0.3	32,602	-2.7
Export	3,104	26.4	4,245	11.2	5,019	-16.9	6,670	19.4
Production	21,600	-1.2	28,605	26.7	33,083	-2.0	35,910	0.0
Import	6,734	23.5	7,223	23.4	4,481	-8.7	3,362	6.5

Moreover, since 2005, there have been significant changes to domestic H·R coil import structure, as low-cost Chinese H·R coil imports surged due to its rapid capacity expansion. However, the plate, produced through the hot rolled process from the semi-finished products such as slab, bloom, and billet, required separate facility investment as its manufacturing process is different from the H·R coil.

However, Korean steel companies could not actively respond to increasing demand. As one of the major steel industries, domestic shipbuilding companies had to import many plates from Japan and China to cope with its industry uptrend. Thus, even after the completion of Hyundai Steel's blast furnace, the Korean steel industry faces a constant shortage of plate and H·R coil. Simultaneously, China's increased import seems to be caused by replacing the majority of steel imports from Japan. Thus, the major products that show China's rapid rise in competitiveness against Korea, such as H·R coil and plate, are the domestic short-supplied items. Therefore, it can be considered that Japanese and Chinese steel imports to Korea increased due to the domestic supply shortage of some steel products, rather than the sharp decline of the domestic steel industry's competitiveness.

Table 13. Changes in the Import of Steel Products in Korea (unit: million U$)

Classification	2003	Weight	2010	Weight	2014	Weight	2019	Weight
World Total	6,411	100.0	21,112	100.0	20,525	100.0	14,707	100.0
China	649	10.1	6,839	32.4	9,673	47.1	6,523	44.4
Japan	3,710	57.9	9,054	42.9	6,350	30.9	4,554	31.0
Others	2,052	32.2	5,220	24.7	4,501	21.9	3,630	24.6

However, as Hyundai Steel's integrated blast furnace steel mill was completed in 2010, it is expected to solve the imbalance of supply and demand between upstream and downstream. It expects the synergy effect in the steel industry with the transition in the competitive system.[8] POSCO and Hyundai, being the two major integrated steel companies, competing mutually

[7] Korea Iron & Steel Association, 『Steel Supply and Demand Prospects 2011』, 2010, excluding stainless
[8] Ministry of Trade, Industry & Energy press release, Oct. 28, 2006.

in technological development and the international competitiveness improvements, automotive, shipbuilding, and other steel-intensive industries will achieve price stability and improvements in quality and service. The imports from Japan and China will possibly be reduced significantly.[9]

5. Conclusion

Even though the steel production capacity of downstream companies increased due to the strong demand from the steel-using industries, the Korean steel industry delayed investment upstream (processing semi-finished products such as pig iron). Therefore, it caused lasting structural imbalances of supply and demand in the Korean steel market, inevitably increasing imports of the high-quality slab, H·R coil, and other semi-finished steel products from Japan and China. Therefore, due to the domestic supply shortage of some steel products, Japanese steel imports to Korea increased, rather than the sharp decline of the domestic steel industry's competitiveness. However, Hyundai Steel's entry into the blast furnace business created opportunities to resolve imbalances in steel supply and demand by providing the basis for competition and increasing steel production capacity. Thereby, a significant part of increasing steel imports was solved, while finding new demand sources for increased steel production became the challenge.

Ever since the Pohang steel mill produced its first pig iron on June 9, 1973, the domestic steel industry became the foundation of Korean economic growth. Construction, shipbuilding, automotive, electronics, machinery, and other steel-intensive industries made remarkable growth based on the stable supply of high-quality steel by domestic blast furnace mills. Additionally, the steel demand rapidly grew with rising demand and exports in automotive production, increasing shipbuilding volume, and expanding the global market share of high-end electronics.

Hence, adapting to such changes, the Korean steel industry should continue managing the long-term and sustainable demand by maintaining the existing domestic demand sources. It is expected that the expansion of the domestic facility will ease the supply shortage, but the possibility of Japanese and Chinese steel inflow remains. An accurate understanding of key customers' needs in quality and service and efforts to develop products are required to overcome these risks. Then, a long-term trust relationship, sharing core information, can be formed. Steel industries can avoid the risk of demand fluctuation by sudden changes in the external environment, sharing information with steel industries on the environment and production planning, and production based on its supply and demand prospects.

Additionally, a distribution program should be conducted to plan and manage systematically and professionally, satisfying both manufacturers' and distributors' needs. Hence, steel companies require establishing distribution management departments, clarifying its necessity, planning sales targets, inventory levels, sales training, advertising, and promotion. Distributors need to understand that they can promote joint sales activities and not purchase steel products through tough negotiations with manufacturers. Additionally, steel manufacturers need to recognize distributors as partners with a common goal, not as mere buyers of the products. Furthermore, it should focus on exports; it needs to strengthen global distribution networks and customer-oriented marketing to expand exports. It needs to expand

[9] As Korean steel supply and demand structure changes due to Hyundai Steel's integrated steel mill operation, there needs fundamental changes to Japanese steel export paradigm to Korea, says the Masaki Moito, the head of department of steel industry in Japanese Ministry of Economy, Trade and Industry at 'the 12th Korea-Japan Steel Dialogue' May 23, 2011. Japanese Industry News, May 25, 2011.

steel processing centers in major exporting markets like China and India to build a stable export network and strengthen marketing strategies to the core and long-term customers by providing personalized services and value creation.

Therefore, it may lead to achieving the status of a global steel power by actively responding to the changes in the competitive structure of the domestic steel industry and the increase in the supply, by forming long-term trust relationship with the customers, by ensuring stable demand sources via efficient distribution management, and through aggressive development of foreign markets.

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Journal of Korea Trade Vol. 25, No. 4, June 2021, 17-36
https://doi.org/10.35611/jkt.2021.25.4.17
ISSN 1229-828X

A Baltic Dry Index Prediction using Deep Learning Models*

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JKT 25(4)

Received 1 April 2021
Revised 7 May 2021
Accepted 14 May 2021

Abstract

Purpose – This study provides useful information to stakeholders by forecasting the tramp shipping market, which is a completely competitive market and has a huge fluctuation in freight rates due to low barriers to entry. Moreover, this study provides the most effective parameters for Baltic Dry Index (BDI) prediction and an optimal model by analyzing and comparing deep learning models such as the artificial neural network (ANN), recurrent neural network (RNN), and long short-term memory (LSTM).

Design/methodology – This study uses various data models based on big data. The deep learning models considered are specialized for time series models. This study includes three perspectives to verify useful models in time series data by comparing prediction accuracy according to the selection of external variables and comparison between models.

Findings – The BDI research reflecting the latest trends since 2015, using weekly data from 1995 to 2019 (25 years), is employed in this study. Additionally, we tried finding the best combination of BDI forecasts through the input of external factors such as supply, demand, raw materials, and economic aspects. Moreover, the combination of various unpredictable external variables and the fundamentals of supply and demand have sought to increase BDI prediction accuracy.

Originality/value – Unlike previous studies, BDI forecasts reflect the latest stabilizing trends since 2015. Additionally, we look at the variation of the model's predictive accuracy according to the input of statistically validated variables. Moreover, we want to find the optimal model that minimizes the error value according to the parameter adjustment in the ANN model. Thus, this study helps future shipping stakeholders make decisions through BDI forecasts.

Keywords: Artificial Neural Network, Baltic Dry Index, Big Data, Long Short-Term memory, Recurrent Neural network
JEL Classifications: C45, F17, L91

1. Introduction

The tramp shipping market is a perfectly competitive market with a relatively low entry barrier. the market flourished in the mid-2000s until right before the financial crisis due to competitive new building development, China's massive absorption of freight volume for raw materials, and intensified demurrage from lack of port facilities. The shipping market then rapidly declined due to the global financial crisis in the United States in 2008. The decline was

* This research was supported by the 4th Educational Training Program for the Shipping, Port and Logistics from the Ministry of Oceans and Fisheries.
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caused by oversupply from the accumulated ship supply because the market has a low entry barrier. Meanwhile, the Baltic Dry Index (BDI), which had made slow progress, constantly decreased due to the effect of the oversupply, hitting an all-time low in 2016.

The tramp shipping market, which had recorded a low market in the 2010s, is hitting the highest level in 11 years after resolving the typical oversupply due to COVID-19. The BDI then has been rising to its maximum value since 2010.

Moreover, the tramp shipping market is one in which ships do not regularly sail fixed routes. They must respond to irregular freight requests of various shippers and match the right vessels by meeting the shipping demand. In addition, they are affected by other exogenous variables such as macroeconomic variables (i.e., LIBOR interest rate, exchange rate, and international oil price). In other words, the shipping market shows high volatility (Stopford, 2008), and the decision-making of shipping companies and other relevant firms participating in the shipping market is based on such movements of market conditions, making them highly sensitive to the prediction and forecasts of market conditions. Various factors instead of one specific factor have complex effects on tramp shipping market conditions; therefore, not only predicting market conditions but also making decisions in work-site operations are difficult. Even if demand exceeds supply, ship orders cannot increase, and rising raw material prices inevitably do not have a positive effect on the shipping market. All of these are mutually influenced, and the factor that can best represent these complex factors is BDI.

Therefore, forecasting market conditions with high accuracy is crucial for shipping companies. Moreover, market forecasting models perform a key role in corporate management and investment strategies (Yu and Bulut, 2019; Shin Sung-Ho, Lee Paul Tae-Woo and Lee Sung-Woo, 2019). In particular, industrial and academic circles showed significant interest because the volatility of market conditions directly affects the profitability of market participants, and various efforts have been made in studies predicting market conditions (Celik et al., 2009).

The BDI is a typical index used to predict ocean freight market conditions. An increase in the ocean freight index is accompanied by an increase in profits of shipping companies and ship demand and orders. It also exerts a considerable impact on the domestic real economy by improving the performance of the shipbuilding and steel industries. Therefore, both institutions doing business in the shipping finance and relevant institutions that must capture global real economy trends should enhance the competency to analyze and forecast the ocean freight market.

Econometric analysis, which is used as a predictive analysis method, has been widely used with price fluctuations and many variables. For example, in the trend of price fluctuations, models such as autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroskedasticity (GARCH) were used. Moreover, various variables such as international oil prices, exchange rates, world industrial output, and raw material prices were used to improve the accuracy of prediction.

The time series analysis using BDI, the typical index for tramp shipping market conditions, has been a major concern of several studies for a long time. The ARIMA model was mostly used in time series analysis, along with regression analysis for variable selection and vector autoregressive (VAR) and vector error correction model (VECM) models to increase the predictive power.

Several studies have considered univariate and multivariate models provided that the latter show better performance in terms of prediction accuracy (Tsioumas et al., 2017; Kagkarakis, Merikas and Merika, 2016). Multivariate models such as VAR and VECM that predict BDI with several variables were examined (Franses and Veenstra, 1997; Pelagidis and Tsahali, 2019; Yin, Luo and Fan, 2017; Xu, Yip and Marlow, 2011; Lin, Chang and Hsiao, 2019; Zhang and Zeng, 2015). Moreover, various studies on the relationship between freight and charter rates in tramps and between charter rate and FFA verified the effect of each variable on the freight rate using the VECM (Franses and Veenstra, 1997; Zhang and Zeng, 2015; Yin, Luo and Fan, 2017).

However, classifying various factors affecting shipping market conditions and collecting data are difficult; thus, the current study uses deep learning models such as artificial neural networks (ANN) (Jain, 2011) with high predictive power that can be analyzed and predicted. This study aims to predict a BDI using deep learning models based on the selected factors affecting BDI.

2. Literature review

2.1. Prediction Using Deep Learning Models in Other Industries

Studies on predicting shipping industries using deep learning models are still limited. Therefore, this study reviews and summarizes previous research in other fields such as stock price prediction, tourism demand forecast, and energy consumption prediction (Selvin et al., 2017; Cheng and Yang, 2021; Vidya and Prabheesh, 2020; Yucesan et al., 2021; Khadhir, Kumar and Vanajakshi, 2021).

Selvin et al. (2017) examined the stocks of companies listed on the New York Stock Exchange at 100-minute intervals to predict stock prices after 10 minutes. They used Infosys, TCS, and CIPLA data from July to November 2014, and selected ARIMA, RNN, LSTM, and CNN. The results showed the superiority of the CNN models. Meanwhile, Cheng and Yang (2021) used LSTM and GRU models that can handle both time series and nonlinear problems instead of the Arps decline curve, which is commonly used for oil well prediction. Results of their study revealed that LSTM shows better performance when the variables were many and data were large, whereas the GRU model shows excellent performance when the data were small.

Vidya and Prabheesh (2020) measured the trade interconnection between countries before and after COVID-19 and predicted future trade directions using ANN. Their study results showed that China continues to maintain its trade center despite COVID-19. Moreover, ANN predicted that both exports and imports would decline in all countries by December 2020. Meanwhile, Yucesan et al. (2021) studied an optimal deep learning model to predict the demand for natural gas to increase and minimize economic losses, such as storage costs and contracts in the future. Among the various models, the hybrid model of SARIMAX–ANN exhibits best performance, followed by the hybrid model of ARIMA–ANN. However, the worst result was the hybrid model of the genetic algorithm–ANN. In the future, the temperature, wind speed, and industrial production index were added as additional explanatory variables to provide implications for improving the model's performance.

Khadhir, Kumar and Vanajakshi (2021) conducted a study to determine the location of the vehicle using the GPS system installed on the bus. Results of the study of the spatio-temporal LSTM model verified that the prevalence of traffic delays is highest at six intersections, bus terminals (spatio), and morning/afternoon peaks (temporal). Therefore, traffic congestion and delay are expected to be eliminated by introducing excess buses to other routes, according to the visualization tool presented in the study.

Moreover, LSTM has shown the best performances among deep learning models with time-series data such as forecasting tourists in Jiuzhaigou, China, predicting the trend of nuclear power plant parameters, and predicting ship tracks (Zhang et al., 2020; Bae Jun-Yong, Ahn Jee-Yea and Lee Seung-Jun, 2019; Tang, Yin, and Shen, 2019).

2.2. Prediction Using Deep Learning Models in The Logistics-Shipping Industry

The following studies compared and verified the forecast accuracy of econometric models and deep learning models (Mostafa, 2004; Yun Hee-Sung, Lim Sang-Seop and Lee Ki-Hwan, 2018; Zhang, Xue, and Stanley, 2018).

Mostafa (2004) used monthly net tonnage data from June 1975 to June 1998 to predict the throughput of the Suez Canal. Comparing the result of using the traditional ARIMA and ANN models, he determined that the RMSE of the ANN models is lower than that of the ARIMA models, thereby proving superiority. Furthermore, the predictive power of the ANN models can vary by determining the number of input layers. Meanwhile, Yun Hee-Sung, Lim Sang-Seop and Lee Ki-Hwan (2018) investigated the valuation of options for time charter party extension. They used the Black–Scholes model (BSM) and ANN. Their result revealed that ANN shows higher correlation and lower root mean square error than the BSM, thereby confirming ANN's superiority.

In addition, Zhang, Xue, and Stanley (2018) compared and verified econometric and ANN models using the daily, weekly, and monthly BDI data from 1999 to 2018. The econometric models had greater predictive power than the ANN models in the daily (t+1) prediction, but the ANN models showed relatively better results in the daily (t+7) and weekly/monthly (t+1, t+7) prediction. Moreover, the Back Propagation Neural Network (BPNN) model showed superiority in both short and long-term predictions. Furthermore, Şahin et al. (2018) used three methods for BDI prediction. The first method was to verify the BDI by applying the past observation value of BDI(BDI_{t-1}), and the second was to apply the last two observation values of the BDI(BDI_{t-1} and BDI_{t-2}) and compare with BDI. The third method was to compare the index of the previous observation of the BDI and Brent oil price (BDI_{t-1} and $Brent\ oil\ price_{t-1}$). The results proved the superiority of the second model with the lowest MAPE. Meanwhile, Kamal et al. (2019) extracted weekly data from BCI, BPI, BSI, bunker price, and charter rate per route for BDI prediction. They used the Pearson correlation analysis to classify variables with a correlation of more than 0.7, and they examined DNN and LSTM using verified data. The results demonstrated the superiority of DNN with lower RMSE than the LSTM, implying the need to develop various models using ensemble methods and support vector machines (SVM).

Finally, the following studies used ANN models to predict other dependent variables besides BDI (Gurgen, Altin, and Ozkok, 2018; Tsai and Huang, 2017).

Gurgen, Altin, and Ozkok (2018) used ANN to compare the actual and predictive values of five output variables (LOA, LBP, Breadth, Draught, and Freeboard) of chemical tankers using deadweight tonnage and vessel speed, which are valued by ship-owners, as the input variables. The comparison result revealed that the actual and the predicted values are similar, suggesting the usability of two input variables (e.g., deadweight tonnage and vessel speed) for the preliminary design of vessels in the future. Meanwhile, Tsai and Huang (2017) selected 10 major ports of Asia for the prediction of container volume. The analysis used a multilayer perceptron (MLP), with variables such as GDP, exchange rate, economic growth rate, industrial production index, GDP per capita, import volume, and export volume. The results revealed the fewest errors in predictive values of import/export container volume in the Port of Hong Kong, proving the high potential of use.

2.3. Implications

The following are the limitations of previous studies. First, many studies have used BCI, BPI, BSI, and BHSI, which are sub-elements of BDI, as variables used to predict BDI. Second, a period exceeding at least one week must be forecasted in consideration of freight rate liquidity in the shipping market. However, in previous studies, many predictions were made one day later. Third, various variables were used for BDI prediction without a detailed explanation of the variable selection process. Fourth, all independent variables were collectively inputted to the BDI prediction; therefore, the effect of the variable combination cannot be presented. Lastly, the use of the model in the future is limited because overfitting of the selected model is not verified.

To overcome the limitations of previous studies, the present study is conducted in five aspects. First, this study excluded BCI, BPI, BSI, and BHSI that are announced simultaneously as subcomponents of BDI. Moreover, this study used external variables that affect market conditions. Second, considering that direct transactions are difficult in the shipping market, this study used the method for predicting a week after, thereby providing more useful and available models for stakeholders in the shipping market. Third, this study used items that have significance with BDI among independent variables used in previous studies and from which data can be collected. The variables were statistically analyzed using correlation analysis, multiple regression analysis, and Granger causality test. Fourth, by conducting additional research selecting the combinations of optimal variables, this study first selected the hyperparameter value with the lowest prediction error in each model, based on which, it established the final model through combinations of variables. Finally, to validate the overfitting of the selected model, this study compared the recent actual and predictive values of BDI to increase usability.

3. Methodology

Time series forecasting using machine learning methods such as ANN based on big data has begun to be implemented to compensate for the deficiencies of the traditional time series models (Zhang, Xue, and Stanley, 2018; Kamal et al., 2019; Tsai and Huang, 2017; Gurgen, Altin and Ozkok, 2018; Zhang et al., 2020).

Unlike the traditional time series models, forecasting time series data using deep learning models enables analysis and prediction, without considering the constraints on the distributions of error terms, assumptions of linearity among variables, and identification issues, thereby having a wide application of the model and high predictive power (Jain, 2011). The typical ANN model shows superior prediction performance compared to the VAR model in predicting BDI freight rate (Batchelor, Alizadeh and Visvikis, 2007). Additionally, BDI prediction using the RNN model shows better prediction performance to the classic econometric models, and time-series data by LSTM rather than other models (e.g., random decision trees and random walk model) show better prediction performance (Nelson, Pereira, and de Oliveira, 2017).

Based on these advantages, deep learning models can be a powerful modeling tool to examine the complicated nonlinearity issues of time series by learning the weights through the learning process of data provided and forecasting the future. Therefore, this study considers ANN, RNN, and LSTM model for the BDI forecast.

3.1. ANN Model

ANN refers to a structure that analyzes data using a computer in a similar way as the neural network inside human brains. In other words, ANN's role is to determine a certain pattern by analyzing what is hidden in the data. The greatest advantage of ANN is that it has a superior capability of learning hidden patterns in the data compared to traditional methods.

Neurons create output values using a function f that is referred to as the activation function. In the end, the activation function f becomes the function of the value obtained by multiplying input data (x) by weight (w) and adding deviation (b). In other words, the output value $f(K)$ is as follows.

$$f(K) = f(w_i x_i + b) \tag{1}$$

3.2. RNN Model

Recurrent neural network (RNN) is one of the various methods of ANN developed to handle time series data. Traditional ANN has the assumption that the input data are independent from one another, whereas RNN is a neural network that can learn the corresponding relationship between output and input data according to time while handling time series data. The hidden state value of time t in RNN is the function of the hidden state value of time t-1 and the input value of time 1.

ANN receives only one unit of data as input value, whereas RNN receives information from the present and the past, using both data to create output value. Therefore, RNN can be regarded as a neural network that analyzes the present data with past memories. However, RNN is in a structure that has one tanh or ReLU activation function, and thus has long-term dependency issues in which a longer chain leads to vanished results learned from the past.

RNN operates according to the time flow, comprising input, hidden, and output layers. In other words, it calculates time t using the calculated result of time t-1 and calculates time t+1 using the calculated result. In other words, the input value of the hidden layer in RNN can be obtained as follows.

$$h_t = g_n(W_{xh}X_t + W_{hh}h_{t-1} + b_n) \tag{2}$$

Here, h_t is the hidden layer of time t, g_n is the activation function, W_{xh} is the weight matrix in which the input value is sent to the hidden layer, W_{hh} is the weight matrix in which h_{t-1} is sent to h_t in the hidden layer, $X_t$is the input value of time t, h_{t-1} is the hidden layer of time t-1, and b_n is the deviation or limit.

The following is the final output value:

$$Z_t = g_n(W_{hz}h_t + b_z) \tag{3}$$

Here, $Z_t$is the output vector, W_{hz} is the weight matrix when sent from the hidden layer to the output layer, and b_z is the deviation or limit.

RNN learns through the process known as propagation through time (BPTT). However, BPTT has the vanishing or exploding gradient problem. In other words, the vanishing gradient problem exists when the individual gradient of the hidden layer for previous values is smaller than 1, and the exploding gradient problem exists when the individual gradient is greater than 1.

In other words, the hidden layer of RNN remembers data from the past, but cannot remember data selectively. Memories fade with time because only the inputs of all moments with the same weight are remembered. This problem is known as the vanishing gradient problem, whereas the opposite case is called the exploding gradient problem (Gulli and Pal, 2017).

3.3. LSTM model

The LSTM (Hochreiter and Schmidhuber, 1997) network is an algorithm that solves the vanishing or exploding gradient problem of RNN. LSTM can overcome the vanishing gradient problem that may occur in learning long-term patterns and thus can handle larger circulation networks and difficult sequence problems.

The LSTM network has three types of gates to control cell state information, such as input, forget, and output gates. The input gate determines which new data to store in the cell state, and the forgotten gate determines which data to discard at the previous time. Finally, the output gate determines the output data.

$$\begin{aligned} f_t &= k_z\left(W_f x_t + U_f h_{t-1} + b_f\right) \\ i_t &= k_z(W_i x_t + U_i h_{t-1} + b_i) \\ o_t &= k_z(W_o x_t + U_o h_{t-1} + b_o) \\ c_t &= f_t \times c_{t-1} + i_t \times k_c(W_c x_t + U_c h_{t-1} + b_c) \\ h_t &= o_t \times k_h(C_t) \end{aligned} \tag{4}$$

Here, x_t is the input value of time t. f_t, i_t, o_t each indicates forgotten, input, and output gate of time t. C_t indicates cell state. The LSTM network solved the vanishing gradient problem and thus is suitable for predicting long-range dependent time series.

4. Dataset and Empirical results

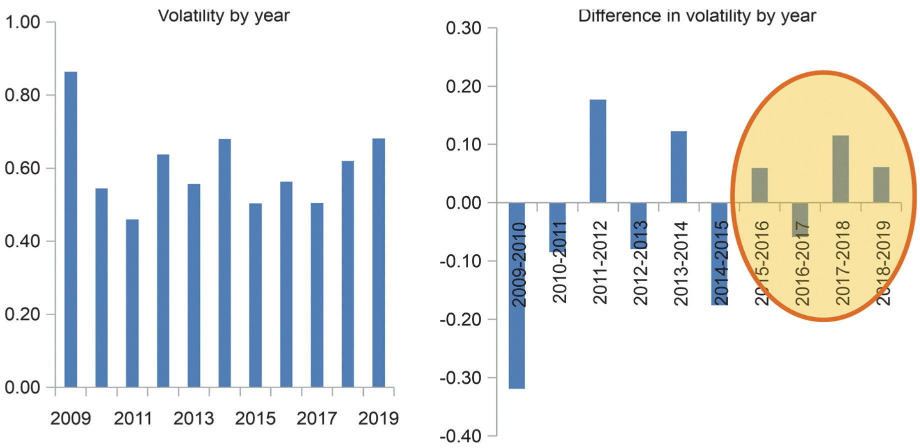
4.1. Dataset

The tramp shipping market conditions (BDI) have been stable at the BDI below 2,500, except for a rapid increase due to China's effect since the mid-2000s. In other words, the market showed a relatively stable balance from the 1980s until 2003. September 2019 shows a temporary increase due to the installation of scrubbers to comply with IMO 2020 taking effect starting 2020. Therefore, data from the period with high volatility (2009–2014) do not have to be used. This period is when the aftermath of the unprecedented situation (2003–2009) in the history of the shipping market conditions remained and when a bias existed. In contrast, to increase the predictive power in a situation where the market is stabilized, it may be more suitable to use the data from 2015 in which the bias has been eliminated as the market is becoming stable (see Fig. 1).

Moreover, in predicting shipping market conditions, the prediction for at least one week of time has significance in decision making. This is because, considering the fluidity of the freight market, direct transaction is highly unlikely to occur unlike stock trading, and thus, at least one week of precedence must be secured (Cooke et al., 2014).

Moreover, previous studies showed that the results of deep learning models showed the highest superiority in 8:2 data partitioning (Kamal et al., 2019; Zhang, Xue and Stanley, 2018). Therefore, from a total period of 25 years, the years 1995–2014 are classified as training data and 2015–2019 as validation data to predict a week after.

Fig. 1. BDI Volatility by Year Analysis



Source: Authors' calculation using Clarkson BDI data.

4.2. Variable Selection Process

The models used in studies predicting the shipping index can be classified into three types. First, a statistical approach constructs statistical function with supply and demand factors that affect the shipping index, while using the shipping index as a dependent variable. Second, the time series analysis uses autoregressive variables. Finally, the machine learning model exists, and most studies use ANN. Most studies support prediction performance superiority of the machine learning model (Eslami et al., 2017). Therefore, this study extracts and validates variables through a statistical approach and uses deep learning models for BDI forecast.

The variable selection process design for the empirical analysis of BDI is as follows. First, this study examines the level and direction of change among variables through correlation analysis using variables used in previous studies. Second, this study primarily selects variables when the significance level and VIF meet certain values through multiple regression analysis and multicollinearity test. Third, this study reviews stability for time series analysis with the selected variables and selects the final variables by checking whether they have causality with BDI through Granger causality analysis.

Among various factors proved to affect BDI, the current study used iron ore freight volume (Yin, Luo, and Fan, 2017), China's steel production (Tsioumas et al., 2017), new building development (Lee Sung-Yhun and Ahn Ki-Myung, 2018; Tsioumas et al., 2017), coal price (Bae Sung-Hoon, Ha Young-Mok and Park Keun-Sik, 2018), Brent oil price (Choi Ki-Hong and Kim Dong-Yoon, 2018), charter rate (Pelagidis and Tsahali, 2019), scrap price (Kagkarakis, Merikas, and Merika, 2016). Dow Jones Index and dollar/yen exchange (Kim Chang-Beom, 2011), LIBOR (Lee Sung-Yhun and Ahn Ki-Myung, 2018), China's GDP growth rate (Kim Do-Hee et al., 2019), China's industrial production index (Kim Chang-Beom, 2008), and the Clarkson Index (Han Min-Soo and Yu Song-Jin, 2019) as explanatory variables for multivariate analysis. Table 1 summarizes the data sources for the 16 independent variables and the dependent variable BDI.

Table 1. Data Sources

Variable	Definition	Unit	Source
BDI	Baltic Dry Index	Index	Baltic Exchange
ND	New Building Development	DWT/Mil	Clarkson
II	Iron Ore Export Volume (Korea, China, Japan Sum)	Ton/Mil	
CP	Coal Price	US$/Mil	Reuters
Bre	Brent Oil Price	US$/bl	Korea National Oil Corporation
Dow	Dow Jones Index	Index	Yahoo Finance
Dyen	Dollar/Yen Exchange	US$/¥	Reuters
Libor	Libor Index	%	
IPC	China Industry Production Index	%	Clarkson
CI	Clarkson Index	US$/daily	
CGDP	China GDP Growth Rate	%	
CSP	China Steel Production	Ton/Mil	
CT	Cape Time Charter	US$/daily	
PT	Panamax Time Charter	US$/daily	
ST	Supramax Time Charter	US$/daily	
CS	Cape Scrap Price	US$/Mil	
PS	Panamax Scrap Price	US$/Mil	

Notes: Dependent Variable= Baltic Dry Index.

For the relationship among factors affecting freight rate volatility of the tramp shipping market, this study first examined the correlation and direction among variables using correlation analysis and validated the effectiveness through multiple regression analysis. To solve the multicollinearity problem, VIF is validated to eliminate variables with VIF over 10. Finally, only the variables affecting BDI as antecedent variables in the Granger causality test are selected for analysis. The empirical analysis is conducted at the significance level of $p<0.01$ and $p<0.05$.

All selected variables had different units such as index, %, price, ton, DWT, and so on. As shown in Table 2, the natural log is used to for descriptive statistics. The analysis shows that LIBOR had the highest standard deviation and thus had a high dispersion, whereas dollar/yen exchange had the lowest standard deviation among the variables, thereby showing low volatility.

Table 2. Descriptive Statistics

Classification	Mean	Standard deviation	Skewness	Kurtosis	Jarque-Bera	Significance level
BDI	7.400	0.676	0.703	0.169	107.54	0.00***
II	3.782	0.694	-0.141	-1.514	127.33	0.00***
CSP	3.382	0.826	-0.365	-1.468	144.27	0.00***
ND	0.820	0.753	0.136	-0.466	15.793	0.0015***
CT	9.961	0.713	1.057	0.629	260.63	0.00***
PT	9.517	0.606	1.043	0.695	258.86	0.00***
ST	9.430	0.559	1.158	0.861	326.84	0.00***
CS	1.792	0.518	-0.417	-1.220	117.48	0.00***

Table 2. (Continued)

Classification	Mean	Standard deviation	Skewness	Kurtosis	Jarque-Bera	Significance level
PS	1.274	0.472	-0.391	-1.175	106.97	0.00***
CP	4.001	0.523	-0.011	-1.171	73.788	0.00***
Bre	3.910	0.622	-0.583	-0.528	88.126	0.00***
Dow	9.363	0.415	-0.014	0.075	0.306	0.86
Dyen	4.674	0.132	-0.792	0.204	136.78	0.00***
Libor	0.664	0.995	-0.380	-1.241	113.81	0.00***
CGDP	2.173	0.210	0.287	-0.501	31.315	0.00***
IPC	2.355	0.411	-0.419	-0.469	49.589	0.00***
CI	9.591	0.419	0.908	0.020	177.16	0.00***

Notes: 1. Dependent Variable: Baltic Dry Index.
2. *p<0.1, **p<0.05, ***p<0.001.

The results of the Jarque-Bera test of normality revealed that most variables except the Dow Jones index do not follow a normal distribution at the 5% significance level. This indicates that the variables have high volatility in the market. Moreover, BDI and China's GDP growth rate, Clarkson Index, Cape, Panamax, and Supramax charter rates have positive skewness, indicating that the samples are leaning toward the left from the mean. In other words, the right tail is longer. Additionally, the kurtosis of all variables is smaller than 3, and thus, a fat-tailed distribution exists rather than the normal distribution.

4.3. Variable Selection of Shipping Market

To test the models, correlation analysis was first conducted among independent variables. According to analysis results, most variables had low correlation with BDI below 0.3. However, BDI had a correlation of 0.85 with the Clarkson Index, 0.71 with China's GDP, 0.68 with China's industrial production index, and 0.9 with a charter rate by ship type, all showing high correlation.

Second, according to the results of multiple regression analysis, iron ore freight volume, Cape charter rate, Panamax charter rate, Cape scrap price, Panamax scrap price, dollar/yen exchange, China's GDP growth rate, China's industrial production index, and Clarkson Index showed significance at the p-value of 5% with BDI.

However, multicollinearity among variables must be reviewed before the final variable selection. In other words, even though a high correlation exists between the dependent variable and other variables, certain variables must be excluded if multicollinearity exists through the validation of VIF. Therefore, iron ore freight volume, dollar/yen exchange, Cape charter rate, Panamax charter rate, Cape scrap price, and Panamax scrap price must be excluded from the analysis because they have VIF higher than 10 (Myers, 1990; Chatterjee and Price, 1991). In conclusion, China's industrial production index, Clarkson Index, and China's GDP were selected as variables with VIF lower than 10 and p-value below 5%.

Third, for statistical estimation with multiple observed time-series data, the samples must be assumed to be stationary. Stationary means that the stochastic properties of the time series model do not change according to time, indicating that the mean and variance of data are consistent, and the difference in data must depend only on time lag regardless of the point of time.

This study verified the stationarity of time series variables using an augmented Dickey–

Fuller (ADF) unit root test. If the stationarity was not confirmed, the data were verified again through the first derivative.

According to the unit root test results, the variable test results are greater than the threshold in level variables, and are non-stationary time series data. Therefore, we conducted a unit root test again after the difference-stationary process securing stationarity through the first derivative of these variables; the test results of all variables were smaller than the threshold with 1% significance level, thereby satisfying stationarity.

Finally, the Granger causality analysis, which is used to study the lead–lag relationship among variables using the distributed lag model, can be used when the relationship between explanatory and dependent variables is difficult to analyze using traditional regression analysis due to uncertain cause and effect.

This study conducted the Granger causality test to analyze causality by examining the relationship between BDI and the selected independent variables.

$$X_t = C_1 + \sum_{i=1}^{p} \alpha_i X_{t-i} + \sum_{j=1}^{q} \beta_j Y_{t-j} + W_{1t} \tag{5}$$

$$Y_t = C_2 + \sum_{i=1}^{\gamma} \gamma_i Y_{t-i} + \sum_{j=1}^{q} \delta_j X_{t-j} + W_{2t} \tag{6}$$

To determine causality of X and Y, regression analysis is first conducted on X_t and Y_t with the past values and constant terms observed. Coefficients are identified using F statistics with the null hypothesis that no Granger causality exists among variables. Thus, rejecting the null hypothesis indicates no causality among variables and that they are mutually independent.

The Granger causality test results between explanatory variables and BDI are as described. The Clarkson Index impacted an antecedent variable on BDI after 1 week, and China's industrial production index and China's GDP impacted an antecedent variable on BDI after 2 weeks. Therefore, as antecedent variables that affect BDI, China's industrial production index, Clarkson Index, and China's GDP are used to conduct a multivariate analysis.

4.4. Univariate Analysis

For BDI analysis using deep learning models, out of a total 1,291 time-series data from January 1995 to December 2019, this study used 1,033 data samples from January 1995 to December 2014 as the training data. The data from January 2015 to December 2019 were then validated. To predict BDI, the ANN model used Deepnet library, and RNN and LSTM used Keras deep learning library and were developed through the R program (Arnold, 2017).

To fix the models when building RNN and LSTM, we must transform input data in three stages (Brownlee, 2017). The first stage is to align the price index of the past time stage (t-1) as input and the price index of this time stage (t) as output, thereby transforming time series input data into supervised learning data. The second stage is to transform input data to a measure of 0 to 1 using the Min-Max Scaler to improve the performance of predictive accuracy. The final stage is determining the variables of neural networks to find the optimal model using the transformed input data. Here, hyperparameter values of the models are estimated, which is an important process that determines the prediction performance. However, no theoretical method is provided, and it depends on the researcher's experience in repeated experiments and given data (Li and Parsons, 1997; Fan et al., 2013).

The deep learning models undergo the process in which the input signal of the hidden layer nodes delivered from the input layer node is transformed into the input variable of the output layer through the transfer function, and the function used is referred to as the activation function. This study used the sigmoid function, which is most widely used in ANN, as the activation function. In RNN and LSTM model design, research was conducted using the hyperbolic tangent (tanh) function verified as the activation function in previous studies (Gensler et al., 2016; LeCun, Bengio, and Hinton, 2015; Kim Do-Hee et al., 2019). The Adam algorithm was used as the optimization program.

Table 3 presents the design scope of hyperparameter values used in the analysis of the deep learning models. Moreover, the prediction model evaluation index is compared among values obtained for each case.

Table 3. Hyper–parameter Estimates

	ANN	RNN	LSTM
Normalization	MinMaxScaler	MinMaxScaler	MinMaxScaler
Learning Rate	0.01	0.01	0.01
Hidden layers	1-4	1-4	1-4
Epochs	1,000	1,000	1,000
Neurons	10-30	10-30	10-30
Batches	1-200	1-200	1-200
Activation Function	Sigmoid	Tanh	Tanh
Optimizer	Adam algorithm	Adam algorithm	Adam algorithm
Dropout Rate	0.2	0.2	0.2

Different results may occur due to different initial conditions in ANN; thus, this study compared how prediction errors (RMSE, MAE, MSE, and MAPE) are changed by changing the number of nodes (10, 20, and 30) and hidden layers (1, 2, 3 and 4) with the learning rate, number of epochs, and repeat count fixed. Moreover, the size of batches (16, 32, 64 and 128) and the ratio of dropouts (0.2) were applied to prevent overfitting of learned data and exclude interdependency within neurons. The hyperparameter values finally selected in each model are as described. In the ANN, prediction error was lowest when the batch size was 32, the number of nodes was 30, and the hidden layer was 2. In the RNN, prediction error was lowest when the batch size was 64, the number of nodes was 30, and the hidden layer was 3. In the LSTM, prediction error was lowest when the batch size was 32, the number of nodes was 20, and the hidden layer was 3.

This study compared the predictive power of the deep learning models applying selected hyperparameter values. Table 4 reports the results of univariate analysis on BDI. A comparison of MAPE (%) of RNN and LSTM reveals that LSTM has a structural benefit of approximately 16.21% improvement compared to RNN, and 17.52% improvement compared to ANN.

Table 4. Comparison of Univariate Prediction Errors

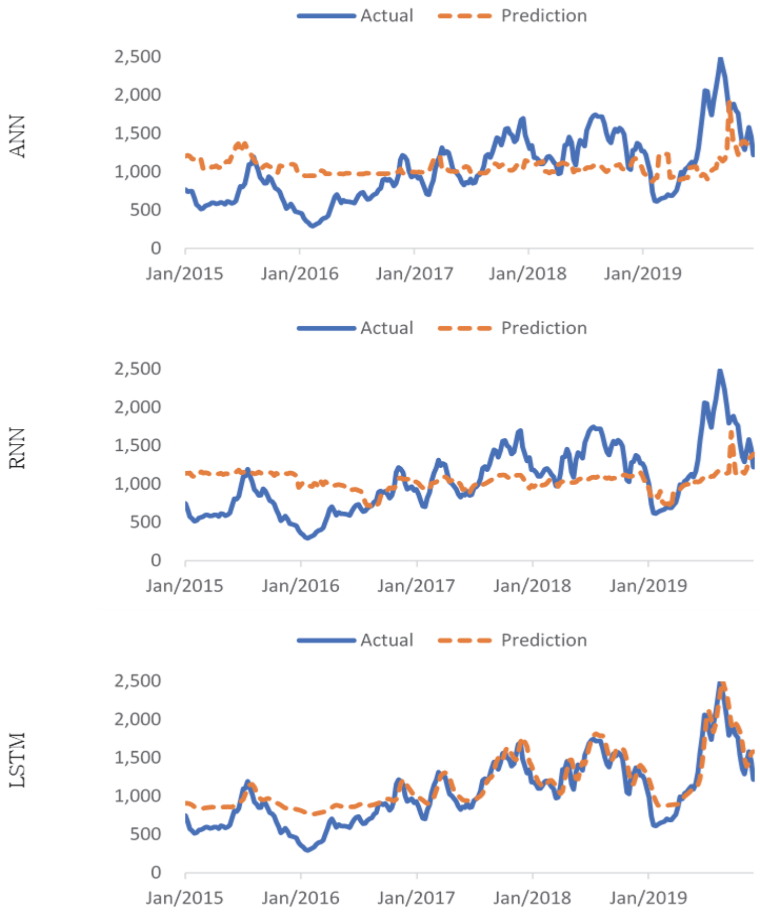
Classification	ANN	RNN	LSTM	ANN/LSTM(%)	RNN/LSTM(%)
RMSE	418.34	410.38	203.91	51.26	50.31
MAE	338.10	328.15	168.95	50.03	48.51
MSE	175,004.81	168,411.12	41.577.88	76.24	75.31
MAPE(%)	41.25	39.94	23.73	17.52	16.21

As a result, for univariate time series analysis using BDI, the predictive power of LSTM is greater than ANN and RNN.

In predicting freight rate of the tramp shipping market where most predictions are long-term forecasting, this study proved that LSTM is more suitable than the RNN model with long-term memory loss and the ANN model suitable for short-term forecasting. In other words, LSTM showed the highest predictive power in univariate BDI prediction among the three models.

Fig. 2 illustrates the predictive power of the univariate case for each model according to scenarios. Predictive values followed the pattern of actual values toward the RNN and LSTM specialized in time series forecasting, demonstrating the increasing predictive power.

Fig. 2. Comparison of Univariate LSTM Predictive Power (Unit: $/Daily)



4.5. Multivariate Analysis

In the multivariate ANN model, 1,033 samples of data were learned from January 1995 to December 2014, and the remaining 258 samples (January 2015 to December 2019) were used to test the predictive power. Normalization scope and use of hyperparameter values in the multivariate model design were applied in the same way as the univariate method. China's industrial production index, Clarkson Index, China's GDP growth rate, and BDI were combined to conduct an additional test for each model applying the finally selected hyperparameter values. The optimal model is determined through optimized hyper-parameter values for each model and combinations of variables.

The hyperparameter values of ANN, RNN, and LSTM for the finally adopted BDI prediction are as described. The following shows that the optimal hyperparameter values vary among models. In the ANN, prediction error was lowest when the batch size was 16, the number of nodes was 20, and the hidden layer was 3. In the RNN, prediction error was lowest when the batch size was 64, the number of nodes was 20, and the hidden layer was 2. In the LSTM, prediction error was lowest when the batch size was 32, the number of nodes was 30, and the hidden layer was 2.

The intention is to find the optimal combination of variables with selected hyperparameter values. The combinations of China's industrial production index, Clarkson Index, China's GDP growth rate, and BDI can be divided into seven types. Table 5 presents the predicted values of each combination. Finally, in the ANN model, optimal results were found in the combination of China's industrial production index, Clarkson Index, and BDI.

Table 5. Optimal Variable Selection Results for Each Model

Classification	Fixed value	Combination	RMSE	MAE	MSE	MAPE (%)
ANN	Number of nodes : 20 Batch : 16 Hidden lyaer : 3	IPC, CI, CGDP, BDI	243.63	183.74	59,353.79	26.61
		IPC, CI, BDI	213.06	184.60	45,395.75	25.62
		IPC, BDI	320.75	283.34	102,880.07	37.14
		IPC, CGDP, BDI	267.02	231.38	71,299.25	32.35
		CI, CGDP, BDI	372.75	306.47	138,943.13	44.44
		CI, BDI	263.95	206.20	69,670.95	31.40
		CGDP, BDI	283.64	216.70	80,449.05	33.46
RNN	Number of nodes : 20 Batch : 64 Hidden lyaer : 2	IPC, CI, CGDP, BDI	177.53	154.91	31,516.23	21.28
		IPC, CI, BDI	237.20	206.45	56,263.96	28.94
		IPC, BDI	313.01	277.74	97,978.14	38.64
		IPC, CGDP, BDI	257.07	221.12	66,086.78	31.01
		CI, CGDP, BDI	306.37	267.88	93,860.47	37.81
		CI, BDI	184.84	144.44	34,166.21	19.89
		CGDP, BDI	188.97	155.08	35,711.46	22.08
LSTM	Number of nodes : 30 Batch : 32 Hidden lyaer : 2	IPC, CI, CGDP, BDI	154.25	133.52	23,792.39	17.89
		IPC, CI, BDI	157.95	129.86	24,948.00	18.05
		IPC, BDI	225.11	181.08	50,676.26	26.88
		IPC, CGDP, BDI	188.71	159.27	35,609.91	21.29
		CI, CGDP, BDI	181.94	156.96	33,102.58	21.20
		CI, BDI	137.22	114.38	18,830.09	15.00
		CGDP, BDI	194.34	164.36	37,767.88	22.90

RNN and LSTM were also carried out in the same way as the ANN models above. The results in Table 5 reveal that RNN model shows the best results using the combination of Clarkson Index and BDI. LSTM model also showed the best results in the combination of Clarkson Index and BDI. As shown, 15.00% of LSTM's MAPE represents a predicted value of about ±15% of the actual BDI index from January 2015 to December 2019 during the test period.

A comprehensive summary based on the results of multivariate analysis is presented. Table 6 shows hyperparameter values of ANN, RNN, and LSTM for the finally selected BDI prediction and combinations of variables. The table shows that not only do the hyperparameter values vary among models, but the optimal combinations also vary among variables.

In other words, the smallest prediction error was found in the following combinations: China's industrial production index, Clarkson Index, and BDI for the ANN model; Clarkson Index and BDI for the RNN model; and Clarkson Index and BDI for LSTM.

Table 6. Finally Selected Hyperparameter Values and Combination of Variables

ANN			RNN			LSTM		
Neurons	Batch size	Hidden layer	Neurons	Batch size	Hidden layer	Neurons	Batch size	Hidden layer
20	16	3	20	64	2	30	32	2
IPC, CI, BDI			CI, BDI			CI, BDI		

Predictive power of each the deep learning models applying the selected hyperparameter values was compared. Table 7 presents the results of multivariate analysis on BDI.

Table 7. Comparison of Multivariate Prediction Errors

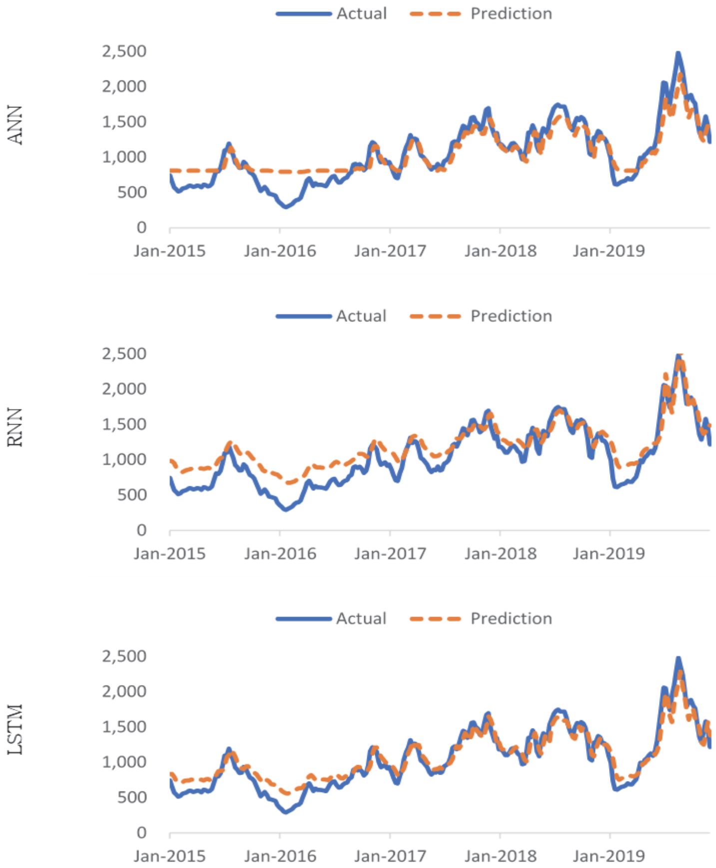
Classification	ANN	RNN	LSTM	ANN/LSTM(%)	RNN/LSTM(%)
RMSE	213.06	184.84	137.22	35.60	25.76
MAE	184.60	144.44	114.38	38.04	20.81
MSE	45,395.75	34,166.21	18,830.09	58.52	44.89
MAPE(%)	25.62	19.89	15.00	10.62	4.89

A comparison of MAPE (%) of RNN and LSTM provides that LSTM has a structural benefit of approximately 4.89% improvement, and 10.62% improvement between ANN and LSTM.

A comparison of predictive power among ANN models showed the superiority of LSTM that has an advantage in long-term forecasting in the multivariate analysis, as in the univariate analysis. Moreover, the prediction rate was highest in the combination of Clarkson Index and BDI through the comparison of the prediction error among variable combinations. In other words, predictive values vary among combinations and thus showed the importance among the combinations.

Fig. 3 illustrates the predictive power of multivariate analysis among the models. A difference in actual and predictive values exist in the ANN model, but it reduced toward the RNN and LSTM, with an increasing predictive power.

Fig. 3. Comparison of Multivariate LSTM Predictive Power (Unit: $/Daily)



4.6. Overfitting validation

To validate the finally selected model, the latest data are used to determine overfitting and compare prediction errors.

Overfitting validation is analyzed using the method of Kamal et al. (2019) in which the latest data are applied to the selected model. Therefore, the overfitting of the models is validated by comparing and analyzing the latest values of 2020 with high volatility.

Whether the selected model is overfitted is validated by predicting the latest values. As indicated in Table 8, for both the univariate and multivariate models, below the 6% difference in MAPE (%) exists when comparing the results from January 2015 to December 2019 and from January to June 2020. In other words, the slight difference of 6% implies the absence of overfitting.

January–June 2020 used in the overfitting validation section includes the period with poor market conditions due to COVID-19 and that in which they rapidly improved due to the expectation of economic recovery. This section showed a slight increase in MAPE compared to the result during the downward stabilization validation period (January 2015–December

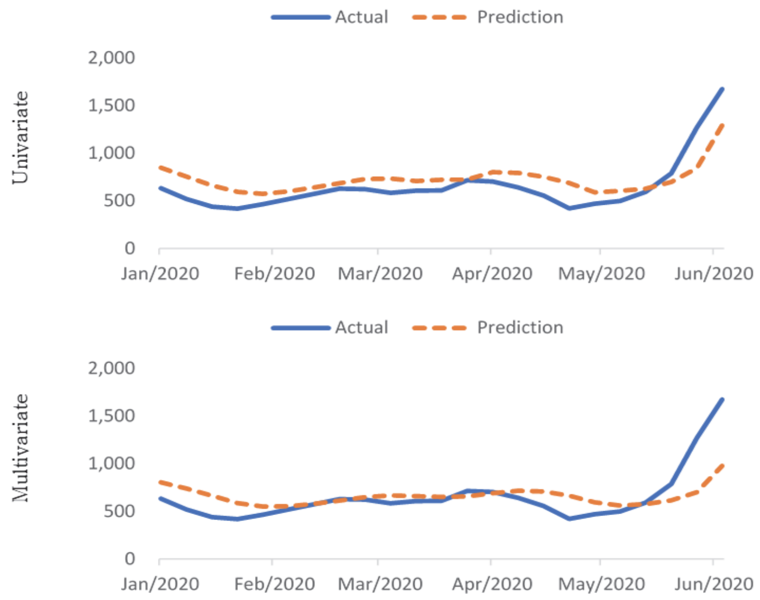
2019) with the univariate MAPE of 24.66 and multivariate MAPE of 20.92. However, although the slight decrease in the prediction rate, this model can be used as a forecasting model as it predicts the trend of rapid movement of the latest data.

Fig. 4 illustrates the results of overfitting validation.

Table 8. Comparison of Overfitting Validation Values

Model	Classification	Validation period	RMSE	MAE	MSE	MAPE (%)
LSTM	univariate	January 2015 - December 2019	203.91	168.95	41,577.88	23.73
		January 2020 -June 2020	182.97	152.64	33,479.44	24.66
	multivariate	January 2015 - December 2019	137.22	114.38	18,830.09	15.00
		January 2020 -June 2020	221.63	144.19	49,118.68	20.92

Fig. 4. Comparison of Overfitting Validation Values (Unit: $/Daily)



5. Conclusion and further research

The current study predicts BDI using deep learning models based on time series data from January 1995 to December 2019. For the analysis, 1,033 weekly data from January 1995 to December 2014 were used as learning data, and 258 weekly data from January 2015 to December 2019 were used as test data. In other words, the BDI time series data for 25 years were analyzed by dividing them into 8:2 of learning and test.

The results of this study can be summarized as follows. First, LSTM showed the highest predictive power among the three models, and the multivariate model showed better predictive power than the univariate model. Second, this study verified a difference in predictive power depending on the combinations of selected variables. Predictive power varied in the analysis through combinations of variables instead of overall variables in each model. Third, analyzing the latest values of January–June 2020 with the validated model using validation data yield a 6% difference in MAPE (%) when comparing the results from January 2015 to December 2019 and from January to June 2020, thereby passing the overfitting problem of the model.

However, from the results of this study, we would like to suggest the following limitations.

First, deep learning models require many trial and errors we need to consider an alternative way to find the hyperparameter value that determines the optimal model. Therefore, the predictive accuracy is limited in that it changes according to the selection of the hyperparameter value. Second, predictive accuracy also varied among combinations selected variables. Therefore, combinations with high effectiveness and accuracy of BDI prediction must be constantly determined through simulation validation among variables in the deep learning models. Third, in addition to ANN, RNN, and LSTM, research on hybrid models such as convolutional LSTM should be actively conducted to improve the predictive accuracy. This study is anticipated to provide a reference for decision making and future investments in the tramp shipping market and the shipping industry in general.

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Journal of Korea Trade Vol. 25, No. 4, June 2021, 37-59
https://doi.org/10.35611/jkt.2021.25.4.37
ISSN 1229-828X

Product versus Process Innovation and the Global Engagement of Firms

JKT 25(4)

Received 6 November 2020
Revised 15 June 2021
Accepted 18 June 2021

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Abstract

Purpose – Although models of innovation and exporting dominate recent studies of relations between innovation and access to foreign markets, relations between innovation and foreign direct investment (FDI) are less explored. This is especially true of relations between types of innovation and FDI. We fill that gap in the literature with empirical evidence that clarifies whether firms enter foreign markets through exports or FDI.

Design/methodology – In order to assess the role of innovation in firms' international engagement strategies, we develop research hypotheses and present new empirical evidence on firms' choice of entry – exports and FDI – based on firm-level data.

Findings – Our empirical results suggest that the impact of product innovation is more significant in transition from being a purely domestic firm to an exporter, while process innovation more significantly affect transition from being an exporter to a multinational enterprise. Our results also support 'self-selection into FDI' rather than 'learning-by-performing FDI' in the relationship between innovation and firms' overseas expansion.

Originality/value – Recent literature on the relationship between innovation and firms' participation in foreign markets is dominated by models of innovation and export behavior. However, foreign direct investment by multinational enterprises may also be associated with firms′ innovative activities. We first analyze how product and process innovations influence firms' choices to initiate exports or FDI.

Keywords: Export Competition Between Korea and China, Export Similarity Index, Korea's Bilateral Exports, Market Sophistication
JEL Classifications: D12, F14, O53

1. Introduction

Innovation is a core business competence, and extensive research analyzes its role in firms' strategy. Most studies classify innovation as process innovation and product innovation. The former entails improving extant and inaugurating new processes. The latter entails improving extant products plus developing and commercializing new products (Zakic, *et al*., 2008). Innovation enhances firms' viability and growth in foreign and domestic markets, where globalization intensifies competition and consumer preferences change rapidly. Castellani and Zanfei (2007), Ito and Lechevalier (2010), Lileeva and Trefler (2010) and Damijan *et al.* (2010) documents this innovation-trade relationship.

Although models of innovation and exporting dominate recent studies of relations between innovation and access to foreign markets, relations between innovation and foreign direct investment (FDI) are less explored. This is especially true of relations between types of

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innovation and FDI. We fill that gap in the literature with empirical evidence that clarifies whether firms enter foreign markets through exports or FDI. We link our empirical results to hypotheses emerging from studies of process and product innovations and international trade with heterogeneous firms (Melitz-type models). We first analyze how product and process innovations influence firms' choices to initiate exports or FDI.

We hypothesize that process innovation influences incumbent exporters to initiate FDI, whereas product innovation is a means of switching from purely domestic production to exporting. We base our hypotheses on firms exploiting increasing returns to scale to innovate processes, but marginal costs of innovation expand with firm size. As sales of incumbent exporters exceed those of domestic producers, incumbents more likely undertake process innovation to initiate FDI.

When domestic producers initially want to export, they must accommodate their product quality to foreign consumers' preferences via product innovation. Having already done so, incumbent exporters find it more important to lower production cost via process innovation to initiate FDI, the next advance in operating abroad. Also, incumbent exporters cannibalize extant products to introduce new products abroad, which discourages product innovation. New entrants do not have that concern.

We test these hypotheses by linking different innovative activities to firms' decisions regarding exports and FDI using data for Korean firms spanning 2006–2012. We employ a random probit model as our baseline and an average treatment effects model to check robustness. Our empirical results support our hypotheses that process innovation influences incumbent exporters' propensity to become multinationals (MNEs), whereas product innovation is more associated with purely domestic firms' decision to export.

The paper proceeds as follows. Section 2 reviews previous studies of firm properties and modes of innovation and proposes hypotheses for empirical testing. Section 3 describes empirical specifications and data. Section 4 reports results from the main regression and robustness check. Section 5 concludes.

2. Literature Review and Hypothesis Formulation

2.1. Firm Size and Mode of Innovation

Previous studies relate firm size to mode of innovation. They indicate larger firms have comparative advantage in process innovation and smaller firms have it in product innovation, although larger firms have absolute advantage in both. Accordingly, studies find a complementary relation between firm size and undertaking process innovation.[1]

Their findings primarily derive from increasing returns to scale in production. Since process innovation is said to reduce marginal production costs, it must be considered it in production cost (Bustos, 2009; Caldera, 2010). That is, the more sweeping process innovation is, the lower is production cost. Since firms with larger sales and/or markets earn greater payoffs by reducing production costs, declining marginal costs from process innovation will benefit them more (Cohen and Klepper, 1996; Plehn-Dujowich, 2009).

Similarly, because highly productive and efficient firms sell more and are large (Melitz, 2003), the same result obtains when considering benefits from process innovation and firm output (Cohen and Klepper, 1996), market share (Scherer, 1983), market size (Guerzoni,

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[1] See Link (1982), Mansfield(1981), Scherer (1991), Yin and Zuschovitch (1998), Baldwin and Sabourin (1999), Kaufmann and Tödtling (1999), and Tang (2006).

2010), number of goods produced (Petsas and Giannikos, 2005), labor productivity (Baldwin and Gu, 2004), and efficiency (Plehn-Dujowich, 2009).

In contrast, previous studies of innovation mode show that small firms are more likely to undertake product innovation, especially when entering new markets.[2] They find that production innovation induces increased marginal cost at accelerating rates (Gerschenkron, 1962; Maddison, 1987; Lee and Kang, 2007). Firms with lesser level of product innovation incur lower marginal costs from upgrading product quality because they more easily imitate firms operating at higher levels. However, firms undertaking substantial quality upgrades should create a new type of quality and thus incur higher marginal cost from product innovation. In general, large firms produce high-quality goods and small firms lower-quality products (Hallak and Sivadasan, 2009). Thus, large firms with high product quality encounter higher costs for upgrading product quality, inducing diminishing returns to scale from product innovation. The opposite is so for small firms with lesser-quality products.[3] Gerschenkron (1962) calls this "the advantage of backwardness" and Maddison (1987) a "catching-up bonus."[4]

2.2. Market Competition, Firm Evolution, and Mode of Innovation

Previous studies claim that firms respond to intense competition with innovation determined by a product lifecycle. Firms with products in early stages of the product lifecycle favor product innovation to counter competition. Firms with products in the mature stage of the product lifecycle address intense competition through process innovation.[5]

Birth of a new industry generates uncertainty about consumer preferences and product standards. Start-up companies hope to forestall competition by innovating a distinct product (product differentiation) (Weiss, 2003). Many firms offering variants of the product enter the market, investing in product development (Abernathy and Utterback, 1978) or seeking a market niche (Guerzoni, 2010).

Eventually customers refine their preferences. A dominant product emerges, and returns on product innovation fade (Abernathy and Utterback, 1978). At that point competitive companies refocus product development, investing more in manufacturing efficiencies (Utterback and Abernathy, 1975; Link, 1982). Investing in capital-intensive production methods taxes precedence over developing new products (Abernathy and Utterback, 1978).

This process in industry-level revolution applies at firm level. An incumbent can bring new products to foreign markets by cannibalizing extant products, whereas new entrants cannot. Incumbents are reluctant to innovate new products after entering a market successfully, whereas entrants offer new products in response to competition (Igami, 2017).[6]

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[2] See Scherer (1991), Cohen and Klepper (1996), Yin and Zuschovitch (1998), Baldwin and Sabourin (1999), Petsas and Giannikos (2005), Plehn-Dujowich (2009), and Igami (2017).

[3] In some cases, there may be IRS in undertaking product innovation because innovation development is a sunk cost. We defer that prospect for future studies. However, Igami (2017) show that large firms have less incentive for product innovation despite cost advantages, due to cannibalization.

[4] A narrow conception of product innovation suggests small firms create new products through knowledge spillovers, not innovation. A broader conception argues these new products are not the same as a dominant product. Although firms consult the dominant product to develop their own and cut innovation costs, they invest and have heterogeneous product properties. This is more prominent in monopolistically competitive markets.

[5] See Scherer (1983), Klepper (1996), Weiss (2003), Tang (2006), and Bos and Sanders (2013).

[6] Our theoretical framework in the Appendix supports our arguments in Sections 2.1 and 2.2. and connects firm properties to modes of innovation. Our framework extends Plehn-Dujowich (2009) to heterogeneous firms under monopolistic competition.

2.3. Exports and Mode of Innovation

Previous studies combine firm size and market competition as influences over mode of innovation to suggest why domestic firms invest in product innovation to become exporters.[7] One strand of literature argues that potential exporters have lower productivity (Melitz, 2003) and product quality (Hallak and Sivadasan, 2009). They look like startups to foreign markets, so they innovate products, securing diminishing returns to scale from product innovation and increasing returns to scale from process innovation. This is a supply-driven explanation for the affirmative relation between new exports and product innovation.

Another strand of literature insists firms must introduce a distinct product to make inroads in foreign markets and attract foreign consumers. This is specially so for firms in developing economies and/or small firms. Thus, innovation inclines toward creating variety. This is a demand-driven explanation for the affirmative relation between new exports and product innovation (Becker and Egger, 2013).[8] In contrast, cannibalization makes incumbent exporters reluctant to innovate products for foreign markets (Igami, 2017).

Empirical studies show that product innovation is relatively more important in raising propensity to export among small non-exporters.[9] By that logic, Southern producers export goods of higher quality than they sell at home to attract high-income Northern consumers. That logic is expressed in a model featuring heterogeneous plants and quality differentiation (Verhoogen, 2008; Alvarez and Robertson, 2004).

In sum, previous studies of mode of innovation label product innovation relatively more important in raising propensity to export (extensive margin of exports), but it does not increase subsequent export intensity, which is conditional on entering export markets (intensive margin of exports). This phenomenon seems closely tied to the relation between firm evolution and mode of innovation: to advance into foreign markets, new exporters (or incumbent exporters) should occupy early stages (or mature stages) of their evolution. Lileeva and Trefler (2010) find that Canadian firms undertake more product innovation to become exporters.[10] Damijan *et al.* (2010) show that incumbent exporters improve efficiency by stimulating process innovation.

2.4. Firm Characteristics and Global Engagement

Aside from mode of innovation, we draw upon studies of firm characteristics and global engagement for our research hypotheses. Melitz (2003) built the first theoretical model to consider firm heterogeneity in international trade. He shows that highly productive firms serve domestic and foreign markets (exporters), intermediately productive firms serve only domestic markets (purely domestic firms), and Firms with low productivity exit markets in open economies. If a country liberalizes economically, exporters have more chance to export and profit, whereas domestic firms more likely exit because of competition from foreign firms. In this respect, Melitz (2003) assures intra-sectoral redistribution of firms in response to trade liberalization.

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[7] See Lileeva and Trefler (2010), Damijan *et al.* (2010), and Becker and Egger (2013).

[8] For demand-side effects of product innovation in international trade, see Schott (2004), Hallak (2006), Crozet, Head and Mayer (2009), Hallak and Schott (2011), Baldwin and Ito (2011), Fajgelaum, Grossman and Helpman (2011), Feenstra and Romalis (2012), and Antoniades (2012).

[9] See Bratti and Felice (2009), Cassiman *et al.* (2010), and Caldera (2010).

[10] Refer also to Becker and Egger (2013), Belderbos et al. (2009), Cassiman et al. (2010), Caldera (2010), Ganotakis and Love (2011), Bocquent and Musso (2011), Higon and Driffield (2011), and Van Beveren and Vandenbussche (2013).

Helpman *et al.* (2004) present Melitz's (2003) argument in a model expanded to include FDI as an aspect of global engagement. They show that highly productive firms initiate FDI, whereas upper middle productive firms export. This ordering comes about because fixed costs of FDI are higher. In contrast, lower middle productive firms serve only domestic markets, and firms with low productivity exit.

Scholars must consider product quality and productivity as elements of firm heterogeneity when analyzing product and process innovations for overseas expansion. We can predict whether firms might become MNEs or exporters to profit by upgrading product quality and/or reducing marginal production cost. Hallak and Sivadasan (2009) expand Melitz's (2003) model to two heterogeneities. First, they define productivity as ability to produce a variety of goods at lower variable costs. Second, product quality represents such characteristics as design, shape, and color. Hallak and Sivadasan (2009) believe that innate levels of productivity and product quality exogenously determine a firm's original position concerning whether to exit markets, serve only a domestic market, to serve both by exporting. Consequently, they recapitulate Melitz (2003) and show that highly productive firms and/or firms with high-quality products become exporters and serve both domestic and foreign markets, whereas intermediately productive firms and/or firms with mediocre-quality products serve only a domestic market. Firms with low productivity and/or product quality exit.

2.5. Contribution and Hypotheses

In this paper, we address the question of how product innovation and process innovation have different impacts on varying strategies for global engagement. In order to more thoroughly assess the importance of innovation on firms' globalization strategies, we present new theoretical and empirical evidences on firms' choices of entry mode – exports and FDI – from strategies for both types of innovation. To our knowledge, this is the first attempt to analyze the different roles of product and process innovations on firms' choices between exports and FDI.

Combining the arguments of Hallak and Sivadasan (2009) with those of Helpman *et al.* (2004), we add another type of global engagement to a firm's original position in an international trade model featuring two firm heterogeneities—that is, serving both markets by initiating FDI. Fig. 1 depicts relations between heterogeneities of productivity (θ) and product quality (λ)[11]. There, $\bar{\theta}_D$ and $\bar{\lambda}_D$ are thresholds of productivity and product quality, respectively, for serving a domestic market. $\bar{\theta}_X$ and $\bar{\lambda}_X$ are thresholds of productivity and product quality, respectively, for exporting. $\bar{\theta}_I$ and $\bar{\lambda}_I$ are thresholds of productivity and product quality, respectively, for initiating FDI. Firms displaying productivity $\theta < \bar{\theta}_D$ or product quality $\lambda < \bar{\lambda}_D$ will decide not to produce and exit the market, whereas firms with $\theta \geq \bar{\theta}_D$ or $\lambda \geq \bar{\lambda}_D$ will operate. Among survivors, firms with $\bar{\theta}_D \leq \theta < \bar{\theta}_X$ or $\bar{\lambda}_D \leq \lambda < \bar{\lambda}_X$ will serve only a domestic market, and firms with $\theta \geq \bar{\theta}_X$ or $\lambda \geq \bar{\lambda}_X$ will expand abroad. Firms displaying $\bar{\theta}_X \leq \theta < \bar{\theta}_I$ or $\bar{\lambda}_X \leq \lambda < \bar{\lambda}_I$ will export. Firms with $\theta \geq \bar{\theta}_I$ or $\lambda \geq \bar{\lambda}_I$ initiate FDI for inroads overseas.

Fig. 1 ordinates three cut-off levels for firm heterogeneity to confirm relations between productivity or product quality and self-selection into markets. Firms with low productivity and/or product quality exit. Firms with low-middle productivity and/or product quality operate only domestically. Firms with high-middle productivity and/or intermediate-quality products export. Firms with high productivity or product quality initiate FDI.[12]

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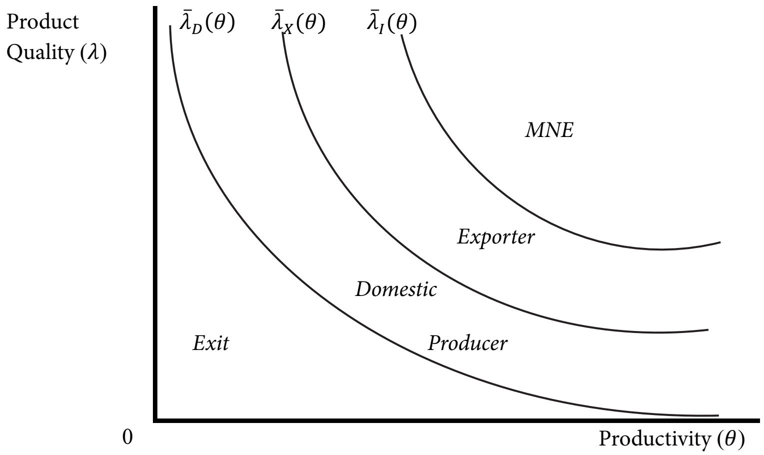
[11] Fig. 1 adds FDI to the original features in Hallak and Sivadasan (2009).

[12] Our firm-level dataset also illustrates this theoretical feature, as represented in detail in Fig. 2.

Fig. 1. Profit and Three Cut-off Levels of Firm Heterogeneity



Source: We add FDI to the original feature in Hallak and Sivadasan (2009).

Helpman *et al.* (2004) show that the highest profits at each level of productivity differ with mode of foreign entry. The most productive firms earn the greatest profit by turning MNE, whereas firms with intermediate productivity by starting exports. Higher profit is feasible if innovation can improve productivity or product quality and the firm can switch status. This rationale incentivizes purely domestic firms to export and exporters to become MNEs. Studies show that causality apparently stems from successfully entering foreign markets after innovating in anticipation of expanding overseas.[13] Processes of internationalizing based on a growing market commitment accord with the Uppsala model described by Johanson and Vahlne (2009).

Given a firm's place among the cut-offs for heterogeneity and the complement between size and process innovation in Section 2.1, we identify two properties of innovation mode and the decision to export or initiate FDI. First, as sales of incumbent exporters surpass those of domestic producers (Melitz, 2003; Helpman *et al.*, 2004), the former, enjoying increasing returns to scale more likely undertakes process innovation to turn MNE. Firms seeking to upgrade quality should create a new type of quality and endure the higher marginal cost of innovation. Since incumbent exporters produce higher-quality products than domestic producers (Hallak and Sivadasan, 2009), they are less inclined toward product innovation to become MNEs. Per Section 2.3, domestic producers are more (or less) likely to become exporters by innovating products (or processes) given decreasing (or increasing) returns to scale.

Second, the stage of evolution (Section 2.2) and standing in productivity and product quality (Fig. 1) encourage domestic firms to accommodate foreign preferences for quality through product innovation as new exporters. Having entered successfully and accommodated foreign preferences, firms do not prioritize changes in product quality. Instead, they cut

[13] For firms that self-select internationalization, see Melitz (2003), Schott (2004), Hallak (2006), Crozet, Head, and Mayer (2009), Hallak and Schott (2011), Baldwin and Ito (2011), Fajgelaum, Grossman and Helpman (2011), and Feenstra and Romalis (2012) for exports. See Helpman et al. (2004) for FDI. Some authors criticized arguments for self-selection by introducing causality from exports to growth—i.e., learning-by-exporting (Cassiman and Golovko, 2011; Gomes *et al.*, 2018).

production costs as an incumbent's strategy in a foreign market. That is, competition shifts to innovations in process efficiency. Incumbent exporters must significantly reduce variable production costs to overcome high fixed costs of overseas production facilities (Helpman *et al.*, 2004; Fasil, 2009). Accordingly, process innovation should tie closely to propensity to initiate FDI.

We propose two hypotheses about mode of innovation and decisions to export and initiate FDI:

Hypothesis 1. *Product innovation is important for purely domestic firms to become exporters (extensive margin of exports).*

Hypothesis 2. *Process innovation is important for exporters to turn MNE (the extensive margin of FDI).*

Our second hypothesis accords with empirical results in Damijan *et al.* (2010), ensuring that firms raise efficiency by stimulating process innovation once they begin exporting.[14] Although Damijan *et al.* (2010) did not consider FDI directly as a global engagement option, we predict exporters will self-select FDI after improving efficiency via process innovation.

3. Empirical Specification

3.1. Main Empirical Model

Following is our empirical strategy to test Hypothesis 1 and 2. Firms will export if profits exceed those from another mode of entry. This similarly applies to initiating FDI (Helpman *et al.* 2004). These conditions can be formalized in a binary choice model of internationalization strategies. We separately model binary decisions to export and initiate FDI. Given incidental parameters and inconsistent estimates of fixed effects[15], we adopt a random effects probit model. Index models to analyze export and FDI decisions can be specified respectively as:

$$EXP_{ikt} = \begin{cases} 1 \; if \; \alpha_1 Product\_Innov_{ikt-1} + \alpha_2 Process\_Innov_{ikt-1} + \alpha_3 Z_{ikt-1} + \gamma_k + \delta_t + \epsilon_{it} > 0 \\ 0 \; otherwise \end{cases} \quad (1)$$

$$FDI_{ikt} = \begin{cases} 1 \; if \; \beta_1 Product\_Innov_{ikt-1} + \beta_2 Process\_Innov_{ikt-1} + \beta_3 Z_{ikt-1} + \gamma_k + \delta_t + \epsilon_{it} > 0 \\ 0 \; otherwise \end{cases} \quad (2)$$

where *i, k,* and *t* respectively represent index firms, industry, and time.

EXP is a dummy that takes 1 if a non-exporting domestic firm in year *t-1* starts exporting in year *t* and 0 otherwise. *FDI* takes 1 if an exporter in year *t-1* initiates FDI in year *t* and 0 otherwise. *Product_Innov* denotes intensity of patent citations. It is a dummy that takes 1 if the firm invested in product innovation and 0 otherwise. *Process_Innov* is a dummy that takes 1 if the firm invested in process innovation and 0 otherwise. *Z* denotes other firm charac-

[14] These studies find that product innovation does not increase subsequent export intensity (intensive margin of exports): Becker and Egger (2013), Belderbos *et al.* (2009), Cassiman *et al.* (2010), Caldera (2010), Ganotakis and Love (2011), Bocquent and Musso (2011), Higon and Driffield (2011), Van Beveren and Vandenbussche (2013).

[15] As there cannot be found sufficient statistics allowing the fixed effects to be conditional out of the likelihood, fixed effects cannot be used for probit model for panel data. Also, estimates of unconditional fixed effects model can be biased.

teristics that can influence export or FDI decisions. We consider firm size, total factor productivity (TFP), and foreign ownership. γ_k and δ_t respectively represent industry and year dummies. ϵ_{it} is an error term.

To estimate how innovation influences initial decisions to export or initiate FDI and to control for potential simultaneity, we eliminated firms that had exported or initiated FDI or culled data only for domestic firms and exporters at time *t-1*:[16]

$$\text{Prob}(EXP_t = 1|Domestic_{t-1} = 1) = \text{f}(Innov_{t-1}) \tag{3}$$

$$\text{Prob}(FDI_t = 1|EXP_{t-1} = 1) = \text{f}(Innov_{t-1}) \tag{4}$$

Equations (3) and (4) define our two-equation probit model. The first equation in the baseline model specifies the probability that domestic firm *i* turns exporter:

$$\begin{aligned} EXP_{ikt} = \beta_0 + \beta_1 \ln Size_{ikt-1} + \beta_2 \ln TFP_{ikt-1} + \beta_3 Foreign_{ownership}{}_{ikt-1} + \\ \beta_4 Product\_Innovation_{ikt-1} + \beta_5 Process\_Innovation_{ikt-1} + \gamma_k + \delta_t + \varepsilon_{ikt} \end{aligned} \tag{5}$$

The second equation specifies effects of the same group of explanatory variables on the probability a former exporter initiates FDI:

$$\begin{aligned} FDI_{ikt} = \beta_0 + \beta_1 \ln Size_{ikt-1} + \beta_2 \ln TFP_{ikt-1} + \beta_3 Foreign_{ownership}{}_{ikt-1} \\ + \beta_4 Product_{Innovation}{}_{ikt-1} \\ + \beta_5 Process\_Innovation_{ikt-1} + \gamma_k + \delta_t + \varepsilon_{ikt} \end{aligned} \tag{6}$$

3.2. Robustness Check

We employ average treatment effects as a robustness check. Although we sample only domestic firms and exporters, endogeneity may persist given difficulty finding appropriate instrumental variables among firm-level data. Most studies support "self-selection into exporting" rather than "learning-by-exporting (LBE)," (Bernard *et al.*, 2011; Bravo-Ortega*, et al.* 2014). Others find that reverse causality between innovation and global activities supports LBE (Van Biesebroeck, 2005; Li, *et. al.*, 2016; Salomon and Shaver, 2005).

To resolve potential endogeneity and confirm empirical results for the impact of innovation on exporting and FDI using probit estimation, we combined propensity score matching (PSM) with average treatment effects. Doing so addressed potential endogeneity absent appropriate instrumental variables (Damijan *et al.*, 2010). We first identified the probability firms will innovate products or processes, which yields a propensity score. Second, we matched innovators and non-innovators and estimated average treatment effects of lagged innovation on exporting. We replicated that procedure to test average treatment effects of previous innovation on FDI.

[16] This restriction is consistent with our hypotheses, which considers only extensive margins of export and FDI. We exclude cases wherein domestic firms initiate FDI without exporting experience, based on logic underlying our hypotheses. MNEs generally begin by exporting to new markets rather than by switching directly from domestic operations to FDI. Nicholas et al. (1994) support this claim, suggesting 69% of sampled firms exported to Australia before FDI. Only 0.8% of our sampled firms initiated FDI as domestic firms and 2.6% of firms conducted FDI before choosing to export.

3.3. Data

We used annual firm-level data spanning 2006–2012 from The Survey on Business Activity by the National Statistical Office (NSO) of Korea. NSO annually surveys Korean enterprises with financial capital exceeding US$300,000 and at least 30 employees. The dataset captures 90% of total sales and 70% of value added in Korea's manufacturing sector. The survey encompasses financial statements, organizational structure, global engagement such as exports and FDI, and innovation-related activities. Initially, it included over 10,000 firms per year. Purging data with unlikely values[17] and measurement errors yielded an unbalanced panel dataset of 8,653 manufacturers and 40,040 observations spanning 2006–2012.

The binary indicator for export or FDI is our dependent variable (Table 1). It measures extensive margins of entry mode on innovative activities.

Table 1. Definition of Key Variables

Variables	Definition
Process Innovation	
ERP(Enterprise Resource	A dummy variable that takes a value of 1 if the firm reports the
Product Innovation	
Patent citation intensity	Number of citation of patents by its own development per labor
Patent citation dummy	A dummy variable that takes the value of 1 when the firm
Other Control Variables	
Size	Natural log of the number of employees
Productivity	Natural log of total factor productivity

Note: While there is possibility that patent citation may not necessarily mean new innovation, an increase (or switch from zero to one in dummy variable) in the number of citation controlled by firm size can largely reflect firms' growing effort adopt innovation.

Measurement of Innovation

The NSO survey asks firms to report innovation. Two indicators measure product innovation: a binary indicator of patents cited and citations per employee. To relate invention to product innovation, we followed Pavitt (1984) in only patents that firms had developed.

To measure process innovation, we used information indicating firms introduced Enterprise Resource Planning (ERP) to their e-business. The NSO survey defines e-business as network-based transfer and exchange of goods, services, information, and knowledge. It excludes simple accounting and human resource software. ERP integrates operational facets, including development, manufacturing, sales, and marketing. It includes modules for product planning, purchasing material, inventory control, distribution, accounting, marketing, finance and human resources. Since facilitating efficient processes is ERP's purpose and advantage, its introduction ties to process innovation. A firm-wide database generated and updated by ERP, for example, gives every employee real-time data, rendering data-mining obsolete and letting them be more innovative and flexible (Davenport 1998, Engelstatter, 2012). Thus, ERP[18] might add knowledge capabilities to process innovation (Srivardhana and Pawlowski, 2007).

[17] For example, 0 for number of employee is unlikely value for any firm.

[18] Firms using ERP enjoy greater labor productivity than firms that do not (Engelstatter et al., 2008). Firms adopting ERP exhibit significantly higher differential performance than a control group in their second year after adoption (Nicolaou et al., 2003). Matolcsy et al. (2005) show sustained operational efficiencies, improved liquidity, and increased profitability two years after adopting ERP.

Other Variables

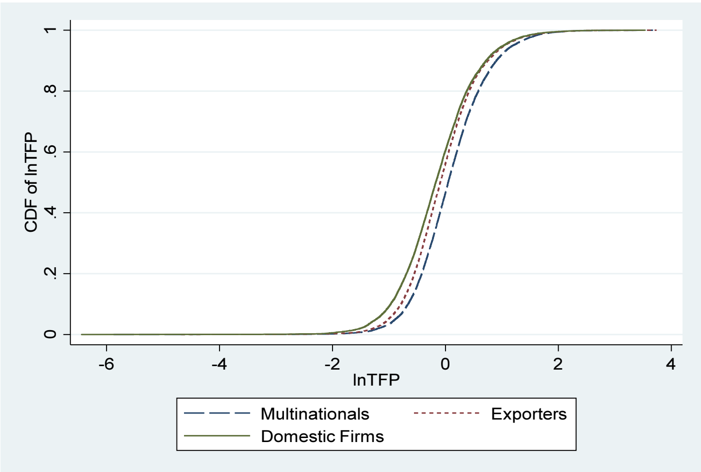
We used firm characteristics from financial statements in the NSO dataset. We constructed controls for number of employees, fixed capital assets, sales, and foreign ownership. Number of employees proxies firm size. It can affect global engagement because larger firms have more resources (e.g., liquid funds, collateral) with which to bear additional fixed costs of entering foreign markets (Wakelin, 1998; Oberhofer and Pfaffermayr, 2012).

TFP is a residual from regressing real output on labor input, real intermediate input, and real capital. We constructed it from the natural log of real total sales (proxy for real output), the log for number of employees (labor inputs), and real tangible assets (fixed capital assets). Intermediate inputs are the sum of sales costs, operating costs, net wages, depreciation, and purchased materials. Fixed capital assets include values of buildings, machinery, and vehicles. We deflated total sales and nominal intermediate inputs by output and intermediate input following two-digit industry-level Korea Standard Industrial Classification in the 2013 Korea Industrial Productivity (KIP) Database. We deflated fixed assets using capital asset formation in NSO data and KIP 2013. One can raise the problem of potential negative correlation between capital stock and probability of exit given TFP measured as residual from OLS estimates, as a firm with a larger capital stock vis-à-vis smaller capital stock is more likely to stay in the market despite the low productivity. To address this issue, value added per labor is employed to alternate TFP as robustness check.

3.4. Features of Firm Heterogeneity

Section 2.3 documents productivity differences across internationalization strategies in recent literature concerning heterogeneous trade models (Melitz, 2003; Helpman *et al*., 2004). Helpman *et al*. (2004) suggest that only the most productive firms can bear higher fixed costs of investing abroad and initiate FDI, whereas less-productive firms export, and least-productive firms operate only domestically. This feature of productivity endorses the logic underlying our hypotheses, and data in Fig. 2 confirm this argument. Graphed cumulative

Fig. 2. Productivity and Firms' Mode of Entry: Cumulative Distribution of Total Factor Productivity



Notes: Kolmogorov-Smirnov test shows that difference in cumulative distribution between domestic firms and exporters is 0.112 and between exporters and multinationals is 0.098 respectively.

distribution functions of productivity as a natural log of TFP situate exporters' TFP to the right of domestic firms and the distribution of MNEs to the right of exporters. This exhibit supports the productivity-centered order of entry suggested in our theory.

Table 2 Panel A compares basic characteristics of product innovators and non-product innovators. Panel B compares those of process innovators and non-process innovators grouped by mode of entry. Both show that MNEs that adopted innovation are largest, and exporters that adopted innovation are larger than domestic firms irrespective of type of innovation. In regard to TFP, process-innovating multinationals are most productive, exporters are less productive, and domestic firms are least productive. Our theoretical model and Helpman et al. (2004) predict that ordering. Within each grouping by entry mode, firms that invested in process innovation are on average more productive than non-innovators. This finding aligns with discussions in Section 2.1 that suggest complementary relation between productivity and process innovation.

However, rankings of product innovation reverse among MNEs. Non-innovators are more productive than innovators. No difference in productivity appears between innovators and non-innovators among exporters and domestic firms. This finding suggests the relation between productivity and product innovation is opaque. Table 3 reports summary statistics for variables in the regression.

Table 2. Firm Characteristics of Each Group of Firms

	Domestic Firms		**Exporters**		**Multinationals**	
Panel A.	**Product Innovator**	**Non-product innovator**	**Product Innovator**	**Non-product innovator**	**Product Innovator**	**Non-product innovator**
Size(Number of Employees)	127.21	108.00	149.81	127.12	258.34	208.82
Size(Sales, million won)	42403.41	37205.42	55469.00	54002.58	118778.60	132730.00
Productivity	-0.15	-0.15	-0.06	-0.06	-0.01	0.15
Number of Observations	2293	5353	689	869	640	396
	Domestic Firms		**Exporters**		**Multinationals**	
Panel B.	**Process Innovator**	**Non-process innovator**	**Process Innovator**	**Non-process innovator**	**Process Innovator**	**Non-process innovator**
Size(Number of Employees)	127.87	102.50	152.17	120.03	274.29	175.55
Size(Sales, million won)	51304.17	28754.77	67554.79	39939.43	148860.30	78805.82
Productivity	-0.03	-0.24	0.02	-0.15	0.10	-0.04
Number of Observations	3394	4252	830	728	670	366

Notes: Mean values are reported for each group. Each group is classified based on firms' global engagement in year t. Product innovators are those firms that cited patent, and process innovators are those firms that introduced ERP systems in previous years. Productivity is measured as natural log of total factor productivity.

Sources: NSO and authors' calculations.

Table 3. Summary Statistics

Variable	Observation	Mean	Std. Dev.	Min	Max
Employee (number)	40,040	276.97	1734.631	31	101973
Sales (million KRW)	40,040	184680.9	1829796	28	1.41E+08
Productivity (Natural log of total factor productivity)	40,022	-0.03	0.67	-6.44	3.67
Patent citation intensity	40,040	0.05	0.17	0	7.37
Patent citation dummy	40,040	0.52	0.50	0	1
ERP dummy	40,040	0.59	0.49	0	1

Notes: Patent citation intensity is the number of citation of patents developed by the firm itself per labor. ERP=enterprise resource planning.

4. Empirical Results

4.1. Baseline Model

Table 4 reports the effects of switching to exporting or FDI from baseline specification models in Equations (5) and (6). Columns (1) through (4) present two different variables for product innovation: Columns (1) and (2) patent invention intensity and Columns (3) and (4) patent citations.

Columns (1) and (3) present estimation results for the extensive margin of exports from the baseline model in Equation (5). Controlling for number of employees as a measure of firm size and TFP as a measure of firm productivity, purely domestic firms with higher intensity of patent citations or a patent dummy in t-1 more likely will have exported during the preceding year than firms with less intense product innovation. However, the coefficient of the ERP dummy is statistically insignificant for the extensive margin of exports. These results imply that only product innovation significantly affects it.

Columns (2) and (4) show that among exporters firms exhibiting greater patent intensity or patents cited the previous year had greater tendency to serve foreign markets via FDI the following year. This finding implies that product innovation significantly raises the probability of firms serving foreign markets via FDI.

Similarly, exporters undertaking process innovation via ERP are significantly more likely to become MNEs in year *t* than firms that did not undertake process innovation in year *t-1*. Hence, both types of innovation enhance the extensive margin of FDI. Note that coefficients of the ERP dummy become statistically significant in Columns (2) and (4) and remain statistically insignificant in Columns (1) and (3). In addition, coefficients for the ERP dummy exceed those for patent invention intensity in Column (2) (0.174*** > 0.029***).

These results suggest product innovation enhances exporting and FDI. Process innovation also exhibits a consistent positive impact on FDI, but its effect is not statistically significant for exporting. Thus, we confirm that process innovation becomes important in exporters' decision to switch mode of entry from exporting to FDI, supporting Hypothesis 2.

However, the relative effects of production innovation seem ambiguous for exporting and FDI in Table 4. The ambiguity likely stems from endogeneity attributable to reverse causality between innovation and firms' global strategies. A robustness check resolves this issue in the next section.

Among control variables, effects of firm size on exporting and FDI are positive and statistically significant at 1%. Productivity relates positively to both modes of entering foreign markets. This result accords with our theoretical model and previous literature (Melitz, 2003; Helpman *et al.*, 2004).

Table 4. Baseline Model

VARIABLES	(1) Export	(2) FDI	(3) Export	(4) FDI
Size	0.279***	0.274***	0.273***	0.262***
	(0.0413)	(0.0645)	(0.041)	(0.064)
Productivity	0.152***	0.136**	0.146***	0.116*
	(0.034)	(0.062)	(0.034)	(0.061)
Product Innovation				
Patent invention intensity	0.021***	0.028***		
	(0.003)	(0.006)		
Patent citation dummy			0.279***	0.371***
			(0.047)	(0.091)
Process Innovation				
ERP dummy	0.062	0.174**	0.063	0.181**
	(0.045)	(0.087)	(0.045)	(0.087)
Year Fixed Effect	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
Rho	0.371	0.484	0.372	0.484
Log Likelihood	-3938.55	-1375.34	-3940.61	-1376.97
Observations	9,528	7,538	9,528	7,528
Number of Firms	3,528	2,986	3,528	2,983

Notes: Random effect probit models are estimated. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 The dependent variable Export indicates whether a domestic firm in time t-1 switches its status to export at time t or not. The FDI dummy variable indicates whether an exporter at time t-1 starts FDI at time t or not.

4.2. Robustness Check

To address potential negative effect of capital stock and probability of exit when TFP is used, we use value added per labor as an alternative measure of productivity. The results are reported in Table A1. The results are largely consistent with those of baseline model in Table 4, though the level of statistical significance of the coefficient for process innovation in FDI decision is 10%.

To control for endogeneity in the baseline model we employed average treatment effects as additional robustness checks. Table 5 reports estimates and standard errors for average treatment of lagged innovation on current exporting or FDI based on PSM. We compared estimates of three types of matching: one-to-one, nearest neighbor, and local linear regression. We estimated standard errors by bootstrapping with 100 repetitions. Table A2 reports probit estimations from PSM, showing that large firms more likely pursue both product and process innovation. For exporting as an outcome of PSM, productivity measured as TFP is either not significant or negative, whereas it is significant and positive for MNEs. Balancing tests in Table A3 validate all specifications for covariates: bias < 5% and t-test not significant for all covariates.

Table 5 shows that matching confirms the link between lagged innovation and probability of exporting in the current year, which vary with the nature of innovation. Lagged product innovation variables exhibit significantly positive impacts on current propensity to export. Process innovation, which correlates positively with exporting, is statistically insignificant in nearest neighbor and local linear regression matching, and significant only at 10% in one-to-one matching. Even in one-to-one matching, the coefficient of product innovation exceeds that of process innovation (0.053***>0.014*), supporting Hypothesis 1.

Process innovators and product innovators are more likely to initiate FDI. Lagged process innovation becomes statistically significant and exhibits a positive impact on the probability firms enter foreign markets through FDI, but it is statistically insignificant for exporting, supporting Hypothesis 2.

Thus, robustness checks confirm our baseline model tests. They support our hypotheses that the positive effect of process innovation presides more for FDI, whereas product innovation presides relatively more for exporting.

Table 5. Robustness Checks: Average Treatment Effect

	Product Innovation					
	Probability of Exporting			Probability of FDI		
	ATT	SE	Obs.	ATT	SE	Obs.
One-to-One Matching	0.053***	0.011	3,100 (6,429)	0.023**	0.009	4,348 (3,190)
Nearest Neighbor Matching	0.053***	0.0103	3,100 (6,429)	0.021**	0.01	4,348 (3,190)
Local Linear Regression Matching	0.059***	0.008	3,100 (6,429)	0.02**	0.008	4,348 (3,190)
	Process Innovation					
	Probability of Exporting			**Probability of FDI**		
	ATT	**SE**	**Obs.**	**ATT**	**SE**	**Obs.**
One-to-One Matching	0.014*	0.008	4,401 (5,128)	0.022***	0.008	4,910 (2,628)
Nearest Neighbor Matching	0.012	0.009	4,401 (5,128)	0.018**	0.008	4,910 (2,628)
Local Linear Regression Matching	0.011	0.007	4,401 (5,128)	0.016**	0.008	4,910 (2,628)

Notes: Bootstrapped standard errors with 100 repetitions are reported. Number of treated observations and number of untreated observations in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

5. Conclusion

Using Korean panel data spanning 2006–2012, we have investigated how product and process innovation influence firms' decision to internationalize by exporting and by FDI. After reviewing the literature, including a Melitz-type model of firm heterogeneity, we hypothesized that process innovation inclines incumbent exporters toward FDI, and product innovation influences purely domestic firms’ preference for exporting. Empirical tests support our prediction. Process innovation positively influences incumbent exporters’ decision to invest abroad. Purely domestic firms emphasize product innovation to become exporters. No significant and positive association between process innovation and exporting is clear in the data.

Domestic firms should accommodate foreign consumer's preferences for product quality when first entering foreign markets as exporters. Thus, product innovation is more important in raising a firm’s propensity to export in its globalization strategies. Once a firm enters a foreign market, successfully accommodates consumer preferences, and become an incumbent exporter, cutting production costs becomes a more important market strategy.

This research provides empirical evidence that governmental R&D policy should focus on different types of innovations, depending on different types of firms' global engagement. That is, our results support self-selection into FDI rather than learning-by-initiating FDI in the relation between innovation and overseas expansion. Korea's global strategy[19] of emphasizing rapid growth in previous decades may bear implications for emerging markets pursuing development through openness.

Our paper has some limitations in the way that some important determinants of FDI in destination countries are excluded. For example, labor cost, import tariff, and demand level in host countries as well as innovations might jointly affect FDI. However, unfortunately our dataset does not contain information on destination countries. Also, it is possible that two types of innovation can be related each other and jointly affect FDI (Tang 2006; Weiss 2003). We do not consider it in the paper because this will complicate the model, deflecting from the main purpose of the paper which identifies the relationship between each innovation and firm strategy in a foreign market, not between two types of innovation. We leave these issues for future studies.

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Appendix A.

A1. Theoretical Framework for relating Firm Heterogeneity and Mode of Innovation

We develop the following supplementary theoretical framework to support qualitative arguments in Section 2.1 and 2.2. It expands Plehn-Dujowich's (2009) model to heterogeneous firms under monopolistic competition. We assume a country has homogeneous consumers and heterogeneous firms. Two firm heterogeneities are exogenously given. First, firm productivity is defined as ability to produce a variety of goods with lower variable costs. Second, product quality represents diverse product characteristics such as design, shape, and color. Product quality is represented as proximity to consumer preferences. Assumptions governing product quality and consumer preferences assure no *ex ante* correlation between firm productivity and its product quality.

The representative consumer has income M and CES preferences across a set of differentiated goods indexed by x,

$$U = \left[\int_{x\in X} q(x)^{\rho}(\lambda + d\ln e)^{1-\rho}dx\right]^{\frac{1}{\rho}}, \tag{1}$$

where q is demand, λ is corresponding quality, e is product innovation, X is a set of all potentially available goods, $d > 1$ is a constant, and ρ is elasticity of substitution between any two goods with $0 < \rho < 1$. This specific form of utility function satisfies all conditions with respect to product quality and product innovation:

$$\frac{\partial q}{\partial \lambda} > 0,\ \frac{\partial q}{\partial e} > 0, \frac{\partial^2 q}{\partial e^2} < 0 \text{ and } \frac{\partial^2 q}{\partial \lambda \partial e} = \frac{\partial^2 q}{\partial e \partial \lambda} = 0.$$

Its conditions assure that demand rises with product quality or product innovation but at a decreasing rate. Conditions also assure that firms with higher innate quality have no *ex ante* comparative advantage in product innovation, controlling for an *ex ante* bias between innate product quality and innovation strategy. From the consumer maximization problem, demand for x is derived as

$$q = p^{-\sigma}P^{\sigma-1}M(\lambda + d\ln e), \tag{2}$$

where $\sigma = \frac{1}{1-\rho} > 1$ and the aggregate price index, $P = \left[\int_{x\in X} (p(\lambda + d\ln e))^{1-\sigma}dx\right]^{\frac{1}{1-\sigma}}$.

Production occurs in a monopolistically competitive market with X firms. Marginal cost (MC) functions for process and product innovations are

$$MC = \frac{1}{\theta} - d\ln z + e^2, \tag{3}$$

where $\theta \geq 1$ is the firm's heterogeneous productivity and z denotes process innovation. This specific form of marginal function satisfies all conditions with respect to innate productivity and process innovation:

$$\frac{\partial MC}{\partial \theta} < 0, \frac{\partial^2 MC}{\partial \theta^2} > 0, \frac{\partial MC}{\partial z} < 0, \frac{\partial^2 MC}{\partial z^2} > 0 \text{ and } \frac{\partial^2 MC}{\partial \theta \partial z} = 0.$$

Its conditions ensure that production cost declines as firm productivity and process innovation rise, but at a decreasing rate. They also assure that highly productive firms have no *ex ante* comparative advantage in process innovation.

Also, the marginal function satisfies all conditions with respect to innate productivity and product innovation:

$$\frac{\partial MC}{\partial e} > 0, \frac{\partial^2 MC}{\partial e^2} > 0 \text{ and } \frac{\partial^2 MC}{\partial e \partial \theta} = \frac{\partial^2 MC}{\partial \theta \partial e} = 0.$$

Its conditions assure that MCs increase alongside product innovation at an increasing rate and that highly productive firms have no *ex ante* comparative advantage in product innovation.

Finally, we assume the fixed cost function for process innovation is identical for all firms, considering z and e as respective fixed costs of process and product innovation for simplicity. Hence the corresponding total cost (TC) function is $TC = MCq + f + z + e$. Also, the marginal cost function is satisfied with $\frac{\partial^2 MC}{\partial z \partial e} = \frac{\partial^2 MC}{\partial e \partial z} = 0$, representing that both innovations are not related each other for simplicity.

Given the demand function in (2), the first-order condition (FOC) with respect to price in the profit maximization problem yields:

$$p = \left(\frac{\sigma}{\sigma-1}\right)\left(\frac{1}{\theta} - d \ln z + e^2\right), \tag{4}$$

where equilibrium price (p) depends on a firm's markup $(\frac{\sigma}{\sigma-1})$ and MC $(\frac{1}{\theta} - d \ln z + e^2)$. FOC with respect to process innovation (z) yields:

$$\frac{d p^{-\sigma} P^{\sigma-1} M(\lambda + d \ln e)}{z} = 1 \tag{5}$$

Substituting (4) into (5) obtains

$$\frac{d\left(\left(\frac{\sigma}{\sigma-1}\right)\left(\frac{1}{\theta} - d \ln z + e^2\right)\right)^{-\sigma} P^{\sigma-1} M(\lambda + d \ln e)}{z} = 1 \tag{6}$$

The left of Equation (6) represents the marginal benefits of process innovation (MB_z).

Based on these equations, we propose:

Proposition 1. *Highly productive firms and/or firms with higher product quality are more likely to undertake process innovation.*

Proof. The proof of Proposition 1 is that firms with higher productivity and/or high-quality products enjoy greater marginal benefits through process innovation:

$$\frac{\partial MB_z}{\partial \theta} = \frac{\frac{d\sigma^2 P^{\sigma-1} M(\lambda + d \ln e)}{\theta^2(\sigma-1)}\left(\left(\frac{\sigma}{\sigma-1}\right)\left(\frac{1}{\theta} - d \ln z + e^2\right)\right)^{-\sigma-1}}{z} = \frac{d}{z}\frac{\partial q}{\partial \theta} > 0$$

$$\text{and } \frac{\partial MB_z}{\partial \lambda} = \frac{d\left(\left(\frac{\sigma}{\sigma-1}\right)\left(\frac{1}{\theta} - d \ln z + e^2\right)\right)^{-\sigma} P^{\sigma-1} M}{z} = \frac{d}{z}\frac{\partial q}{\partial \lambda} > 0.$$

Proposition 1 originates with process innovation; since firms with higher productivity and/or product quality have larger markets (i.e. $\frac{\partial q}{\partial \theta} > 0$ and $\frac{\partial q}{\partial \lambda} > 0$), they also enjoy payoff from cost reductions.

Proposition 1 addresses increasing returns to scale of process innovation and considers firm productivity and product quality as determinants of firm size. In our firm-level dataset, Table 2 empirically supports this feature of relation between a heterogeneous firm characteristics and process innovation.

Meanwhile, FOC with respect to product innovation (e) is

$$p^{-\sigma}P^{\sigma-1}M\frac{d}{e}\left(p-\frac{\tau}{\theta}+d\ln z-e^2\right)=2ep^{-\sigma}P^{\sigma-1}M(\lambda+d\ln e)+1. \quad (7)$$

Substituting (4) into (7) obtains

$$P^{\sigma-1}M\frac{d}{e}\frac{1}{\sigma}\left(\left(\frac{1}{\sigma-1}\right)\left(\frac{\tau}{\theta}-d\ln z+e^2\right)\right)^{1-\sigma}=2e\left(\left(\frac{\sigma}{\sigma-1}\right)\left(\frac{\tau}{\theta}-d\ln z+e^2\right)\right)^{-\sigma}P^{\sigma-1}M(\lambda+d\ln e)+1 \quad (8)$$

The left of Equation (8) represents the marginal benefits of product innovation (MB_e), and the right represents its MCs (MC_e). Using these equations we raise Proposition 2:

Proposition 2. *Firms with low productivity and/or lesser product quality are more likely to undertake product innovation.*

Proof. The relation between product quality (λ) and product innovation (e) is derived from two facts. First, considering MB_e, we obtain $\frac{\partial MB_e}{\partial \lambda}=0$ as the equilibrium price. It consists of mark-up and MC and is unrelated to λ, implying innate product quality does not affect production cost in our original framework. Considering MC_e, we obtain $\frac{\partial MC_e}{\partial \lambda}=2e\left(\left(\frac{\sigma}{\sigma-1}\right)\left(\frac{1}{\theta}-d\ln z+e^2\right)\right)^{-\sigma}P^{\sigma-1}M=\frac{\partial MC}{\partial e}\frac{\partial q}{\partial \lambda}>0$ as $\frac{\partial q}{\partial \lambda}>0$ and $\frac{\partial MC}{\partial e}>0$, respectively.

In other words, if a firm with innately high product quality undertakes product innovation, its MC is relatively high because original demand or production for that product was greater. Hence product innovation entails diminishing returns to scale. As a result, firms with innately high product quality are less likely to undertake product innovation.

With regard to the relation between productivity (θ) and product innovation (e), we first obtain

$$\frac{\partial MB_e}{\partial \theta}=\frac{d}{e}\left(\left(\frac{1}{\sigma-1}\right)\left(\frac{1}{\theta}-d\ln z+e^2\right)\right)^{-\sigma}\frac{1}{\theta^2}P^{\sigma-1}M>0 \text{ as } \sigma>1$$

and $MC=\frac{1}{\theta}-d\ln z+e^2>0$.

The unpinning of this result is that $\frac{\partial MC}{\partial \theta}<0$ and thus $\frac{\partial p}{\partial \theta}<0$.

In other words, even though firms undertake identical product innovation, the firm with innately high productivity enjoys higher marginal benefits because it can charge less for a good of identical quality. Firms with innately high productivity reap greater benefit from product innovation.

We obtain $\frac{\partial MC_e}{\partial \theta} = 2e\left(\left(\frac{\sigma}{\sigma-1}\right)\left(\frac{1}{\theta} - d\ln z + e^2\right)\right)^{-\sigma-1}\left(\frac{\sigma^2}{\sigma-1}\right)\frac{1}{\theta^2}P^{\sigma-1}M(\lambda + d\ln e) = \frac{\partial MC}{\partial e}\frac{\partial q}{\partial \theta} > 0$ as $\frac{\partial MC}{\partial e} > 0$, $\frac{\partial p}{\partial \theta} < 0$ and thus $\frac{\partial q}{\partial \theta} > 0$, respectively. That is, firms with innately high productivity incur higher MC through product innovation because their output is greater. Like the effect of innate product quality on MC of product innovation (i.e., $\frac{\partial MC_e}{\partial \lambda}$), innately high productivity entails diminishing returns to scale.

Finally,

$$\frac{\partial MB_e}{\partial \theta} - \frac{\partial MC_e}{\partial \theta} = \frac{1}{\theta^2}P^{\sigma-1}M\frac{d}{e}\frac{\sigma}{\sigma-1}\left(\left(\frac{\sigma}{\sigma-1}\right)\left(\frac{1}{\theta} - d\ln z + e^2\right)\right)^{-\sigma-1}\left[\left(\frac{1}{\theta} - d\ln z + e^2\right) - \frac{2e^2\sigma}{d}(\lambda + d\ln e)\right].$$

Therefore, if $MC_l\left(= \frac{1}{\theta} - d\ln z + e^2\right)$ exceeds $\frac{2e^2\sigma}{d}(\lambda + d\ln e)$, then $\frac{\partial MB_e}{\partial \theta} > \frac{\partial MC_e}{\partial \theta}$. As innate firm productivity (θ) is greater, MC is lower and is more likely to exhibit $\frac{\partial MB_e}{\partial \theta} < \frac{\partial MC_e}{\partial \theta}$. Hence, high-productivity firms are less likely to undertake product innovation because its MC is more likely to exceed its marginal benefit.

Our theoretical result addresses that innately high product quality and/or productivity discourage product innovation.

A2. Additional Tables

Table A1. Results using value added per labor as productivity

	Export (1)	FDI (2)	Export (3)	FDI (4)
Size	0.238***	0.228***	0.233***	0.220***
	(0.042)	(0.062)	(0.042)	(0.062)
Value added per labor	0.171***	0.259***	0.167***	0.245***
	(0.035)	(0.066)	(0.035)	(0.065)
Product Innovation				
Patent invention intensity	0.020***	0.028***		
	(0.003)	(0.006)		
Patent citation dummy			0.273***	0.366***
			(0.047)	(0.090)
Process Innovation				
ERP dummy	0.063	0.160*	0.065	0.166*
	(0.045)	(0.085)	(0.045)	(0.085)
Year Fixed Effect	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
Rho	0.373	0.469	0.374	0.471
Log Likelihood	-3938.6	-1368.8	-3940.5	-1370.7
Observations	9,526	7,522	9,526	7,522
Number of Firms	3,526	2,982	3,526	2,982

Notes: Random effect probit models are estimated. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 The dependent variable Export indicates whether a domestic firm in time t-1 switches its status to export at time t or not. The FDI dummy variable indicates whether an exporter at time t-1 starts FDI at time t or not.

Table A2. Probit Estimation Results of Propensity Score Matching Estimation in Table 5

VARIABLES	(1) Product Innovation	(2) Process Innovation	(3) Product Innovation	(4) Process Innovation
Size	0.245***	0.217***	0.417***	0.283***
	(.026)	(0.022)	(0.026)	(0.023)
Productivity	0.008	-0.180***	0.306***	0.184***
	(.020)	(0.023)	(0.02)	(0.024)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Log Likelihood	-5575.592	-4717.929	-6119.164	-4638.507
Pseudo R-squared	0.0724	0.0813	0.0696	0.0483
Observations	9,529	7,538	9,529	7,538

Notes: Column (1) and (2) report results on probit estimation when outcome of propensity score matching is exporting. Column (3) and (4) report results on probit estimation when outcome of propensity score matching is FDI. *** p<0.01, ** p<0.05, * p<0.1.

Table A3. Balancing Test from Propensity Score Matching Estimation in Table 5

Product Innovation-Exporting						
Variable	Treated Mean	Control Mean	%bias	t	p>t	V(T)/V(C)
Size	4.653	4.647	1.1	0.42	0.671	1.09*
Productivity	-0.146	-0.119	-4.1	-1.60	0.109	0.85*
Product Innovation-FDI						
Variable	Treated Mean	Control Mean	%bias	t	p>t	V(T)/V(C)
Size	4.916	4.903	1.8	0.80	0.424	1.14*
Productivity	-0.046	-0.052	0.9	0.43	0.665	0.81*
Process Innovation-Exporting						
Variable	Treated Mean	Control Mean	%bias	t	p>t	V(T)/V(C)
Size	4.674	4.669	1	0.44	0.663	0.92*
Productivity	-0.042	-0.039	-0.4	-0.19	0.846	0.94*
Process Innovation-FDI						
Variable	Treated Mean	Control Mean	%bias	t	p>t	V(T)/V(C)
Size	4.93	4.918	1.7	0.78	0.438	0.96
Productivity	0.036	0.064	-4.4	-2.1	0.036	0.87*

Journal of Korea Trade Vol. 25, No. 4, June 2021, 60-87
https://doi.org/10.35611/jkt.2021.25.4.60
ISSN 1229-828X

JKT 25(4)

Received 10 March 2021
Revised 17 May 2021
Accepted 18 June 2021

Effect of Country Distance on E-commerce Export: Focusing on the Moderating Effect of Entrepreneurship

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Abstract

Purpose – This study examines the role of e-commerce resulting from technological innovation as a new approach toward internationalization. We study the relationship between e-commerce export and country distance, measured in CAGE distance, which has hindered traditional internationalization. As a control variable, entrepreneurship was introduced to check the moderating effect on the relationship between country distance and e-commerce export.

Design/methodology – Based on empirical analysis, e-commerce exports from the Republic of Korea to 96 countries were used as dependent variables. First, hierarchical regression analysis was conducted to test the hypothesis about each country's distance, measured by CAGE distance, and each dimension of CAGE, on e-commerce exports. Next, the hypothesis was tested through the interaction term to examine the moderating effect of entrepreneurship.

Findings – The analysis showed that the hypothesis, which postulated e-commerce exports as affected negatively by the country's distance, was supported but not that all CAGE dimensions affected it. Specifically, geographical distance and economic distance have negative effects, but cultural distance and administrative distance did not affect e-commerce exports. Thus, in contrast to the expectation that distance restrictions in e-commerce would not exist, this study confirmed that distance still matters to internationalization and that entrepreneurship can mitigate the adverse effects.

Originality/value – Through these results, when export firms try to enter new markets and start internationalization through e-commerce, the entrepreneurship of the importing country should be considered.

Keywords: Country Distance, E-Commerce Export, CAGE Distance, Entrepreneurship, Internationalization
JEL Classifications: F14, F18, M16

1. Introduction

Once upon a time, a black swan suddenly flew to a village lake. The villagers, who had only ever seen white swans, began to panic. They were shocked and worried by the abnormal phenomenon, which went beyond their understanding. Taleb (2007) introduced the “theory

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of black swan event" and described it as a metaphor for a rare historical or social event that causes chaos and has a massive impact on people. Therefore, strategic leaders need to consider how black swan events might affect planning (Rothaermel, 2019). From this perspective, the COVID-19 pandemic could be considered a black swan event that has shocked and appalled global "villagers."

COVID-19 has caused significant changes in our political, economic, and cultural systems. At this moment, the consequences and impact on human life are uncertain. However, some people feel that the pandemic may be a turning point in our civilization. Before the COVID-19 pandemic, "the globalization of markets" by isomorphism (Levitt, 1983) was debated globally, and people listened carefully to the argument that the world is flattening (Friedman, 2006). Because of the emergence of the black swan, many government authorities urged social distancing and suggested that firms re-shore because of a possible collapse of the global supply chain network. A taper integrate strategy (Rothaermel et al., 2006), emphasizing balancing vertical corporate integration and strategic outsourcing, is also gaining attention. In this context, we strongly argue the appropriateness of revisiting country distance, a topic that has lost relevance because of internationalization or globalization. Therefore, the authors revisit country distance measured in Cultural, Administrative, Geographic, and Economic (CAGE) distance (Ghemawat, 2001).

Various business environmental factors, such as economic, social, political, cultural, and psychological factors, differ globally. These differences create an engaging business environment for firms (Kotler et al., 2019). From a local country's perspective, a foreign firm, although unfamiliar with the target country's ways and mores, creates diverse and attractive business opportunities, and when it does this, local firms are in a better situation (Hymer, 1976). In addition, there are liability differences for foreign companies. For example, a foreign firm looking for new opportunities in a local country will not be familiar with the discriminative local environment, such as language, markets, information, and laws, and therefore, it incurs and pays more costs than a local firm does. In addition to competition from local firms, a foreign firm must consider the accelerating match against multinational rivals because of market globalization. This is the reason for which it should pay attention and spend time making strategic decisions on which overseas markets to enter (Craig and Douglas, 2011). The most critical decisions for firms considering entering an overseas market are regarding evaluation and selection (Aliouche and Schlentrich, 2011). Of several determinants, a country's distance is a vital variable for decisions regarding overseas markets.

A country's distance does not necessarily mean physical distance. According to the eclectic theory from Dunning (1980), from a multidimensional perspective, the distance between two countries includes geographical location and multidimensional concepts, such as culture, institution, politics, language, religion, and industrial difference. Because a country's distance is often regarded as foreign market uncertainty, some aspects might be understood as negative factors, for instance, a gradual internationalization (Johanson and Vahlne, 1977), a decrease in foreign direct investment (FDI) (Blomkvist and Drogendijk, 2013), and a fall in exports (Dow, 2000). However, studies on entrepreneurship recognized a country's distance as an opportunity (Oviatt and McDougall, 2005; Zahra, 2005; Zahra et al., 2005). Another important decision is choosing an entry mode, which involves great diversity, from simple export and licensing to FDI. Madhok (1996) argued that corporate capability affected the decision of entry mode based on evolutionary approaches (Nelson, 1985). The Uppsala model (Johanson and Vahlne, 1977) also suggested that the internationalization of a firm expands from a country with a closer psychological distance. Erramilli (1991) emphasized the importance of overseas market experience.

There are many current studies on the effect of country choice and entry mode on internationalization. A technological innovation, among other things, significantly affects the business environment and internationalization from the perspectives of time and speed. Because of the explosive growth of recent e-commerce, Coviello et al. (2017) urged additional studies on digitalization related to internationalization. A significant departure from traditional trade is that e-commerce includes online purchasers and e-commerce suppliers. In addition, suppliers can diminish psychological distance by using customers' purchasing history and personal information to create relevant websites written in customers' local languages (Kim et al., 2017). Hence, the advances of e-commerce stimulated by technological advances provide some contrast to traditional country distance. From this context, we may agree that the world is flat (Friedman, 2006). From a theoretical perspective, a firm can diminish the negative impact from the country's distance by employing e-commerce, which may help a firm decide on an entry mode. Although it looks impressive and attractive, the theory inevitably has a gap with reality; the country's distance still matters and cannot be ignored. If we identify the export of e-commerce with a new type of entry mode, we need to seek other avenues of overseas expansion.

Because of pervasive e-commerce propelled by technological innovation, a country's distance and entry mode, considered essential to overseas market entry, show outcomes that differ from those of a traditional theory of overseas market entry. There have already been several quantitative pieces of e-commerce research, for instance, studies related to e-commerce on the environmental part of the target country, strategies on the rivalry among existing competitors (Wymer and Regan, 2005), cost reduction (Raymond et al., 2005), and the speed of internationalization (Shaheer and Li, 2020). However, to consider that previous studies overlooked the concepts of e-commerce and overseas entry mode simultaneously and merely covered factors that affected the adoption of e-commerce, the speed of internationalization, and firm performance is a hard pill to digest.

Thus, this study simultaneously considers the relationship between e-commerce backed by a technological advancement and a country's distance. The study presently seeks to answer the questions of whether a country's distance, which is one of the hindrances to traditional internationalization, plays a significant role in international e-commerce and whether entrepreneurship can be one ingredient to overcome the distance.

2. Literature Review and Hypothesis

2.1. E-commerce and Internationalization

When describing e-commerce internationality, terms like “transboundary,” “cross-border,” and “international” are often used. Hereinafter, we define e-commerce as “the trading of goods or services over computer networks, such as the internet, by methods specifically designed to receive or place orders” (OECD, 2011).

Meanwhile, traditional internationalization has been conceptualized as a firm's process toward gradually entering foreign countries by establishing overseas subsidiaries or export networks (Johanson and Vahlne, 1977). Johanson and Vahlne (2009) explained the network factors of the modified internationalization process. Vahlne and Johanson (2017) also compared a new concept of internationalization with previous theories and emphasized modern corporations' core aspects. In detail, they are characterized by adaptation toward industry change because of business exchange, active entrepreneurial activities, and a dispersed structure, rather than production, passive adaptation, and hierarchical structure. In terms of structure, Coviello et al. (2017) stated that digitization must be premised regarding a firm's internationalization, along with established and recent structures.

In the early 21st century, people worried and referred to digitization as a dotcom bubble; however, it was established as a critical factor in internationalization. The Internet, especially, connects almost the entire global digital infrastructure. Hyperconnectivity (Quan-Haase and Wellman, 2004) is a widely accepted thought in the corridors of the 4th Industrial Revolution (Schwab, 2017). Enhancing speeds and reducing times for e-commerce allow firms to reach potential customers in geographically remote areas quickly; it is a novel tool for marketing and internationalization (Reuber and Fischer, 2011). A firm can enter a diverse overseas market via its website or another's online platform, thereby helping it overcome the time and space gaps between countries.

Internationalization through e-commerce may be default or active (Yamin and Sinkovics, 2006). In default internationalization, a firm's intention is not revealed through a simple website and store created in cyberspace. In active internationalization, a firm eagerly conducts activities related to creating its website and operations for business activities in foreign markets; even so, the website is created in cyberspace, which could be considered online internationalization. Lituchy and Rail (2000) suggest that when a firm creates a website, it starts internationalization regardless of whether it planned to do so. Through the website, a firm can provide various goods and services to customers in diverse markets, regardless of time and space (Gunasekaran et al., 2002), and it can communicate and interact efficiently with its customers (Ramanathan et al., 2012). Particularly for knowledge-based firms, becoming international through the Internet allows simple, convenient access to the world; there is no need to contact buyers physically (Arenius et al., 2005). Some specific attributes of e-commerce present contradictory elements of barriers on a traditional trade flow, and this phenomenon is usually referred to as the “death of distance” (Cairncross, 2002).

In their case studies of the internationalization of Hong Kong (China) firms, Child et al. (2002) indicated an average time gap of 4.5 years between entries into different markets. However, the consequence of near-simultaneous entry into several markets may reduce the extent to which knowledge acquisition regarding market entry is deliberately sought out (Yamin and Sinkovics, 2006). In this context, it is reasonable to compress the sequence of traditional internationalization through e-commerce, which allows simultaneous entry into multiple countries. In contrast, some adverse aspects of e-commerce in conjunction with internationalization exist. Such time-compression of internationalization may neglect key factors, such as institutions and cultures of the target country, and it can create so-called “time-compression diseconomies” (Jiang et al., 2014). In sum, there are favorable effects of e-commerce caused by the significant interaction between sellers and buyers. However, time-compression diseconomies, which are adverse effects of e-commerce, might possibly lower customer interaction with markets.

2.2. Country Distance

The liability of foreignness is mainly due to differences between countries; it costs more for a foreign firm to gain information about a destination country, including its economy, language, law, and politics (Hymer, 1976). In previous studies on internationalization, the distance between countries was used as a metaphor for differences (Shenkar, 2012). The expression of distance represents the collective differences between countries beyond geographic and physical differences (Zaheer et al., 2012). The concept of distance has been a focal area of study for scholars interested in explaining the variables in international management and marketing strategies (Prime et al., 2009).

Among other distance factors, cultural distance and psychological distance have been widely used and commonly employed interchangeably. However, they differ in scope, scalability, and analysis level (national vs. individual) (Dow 2000; Prime et al., 2009; Sousa and Bradley 2006). To date, the factors have expanded to cover geographical concepts and multidimensional concepts, such as differences in culture, economy, institution, politics, language, religion, and industry. The CAGE distance has been widely used to study a country's distance (Beugelsdijk et al., 2020; Ghemawat, 2001, 2007; Miloloža, 2015; Shaheer and Li, 2020; Toaks and Deb, 2020), and each distance has different effects on cross-border transactions. The smaller the distance between countries the more potential there is in the market. The greater the distance between countries the more adverse the effects on cross-border trade (Ghemawat, 2001).

It is more challenging to interpret information on foreign markets as a foreign country can be far from the home country (Sousa and Bradley, 2006). In a quantitative study on cultural distance, Kogut and Singh (1988) suggested and utilized the Hofstede index (Hofstede, 1984) to measure the cultural distance between countries. Other studies have also used the index to gauge distance (Blomkvist and Drogendijk, 2013). Kim and Jensen (2014) argued that the higher the cultural distance between two countries the more foreign the firms from one country appear to audiences in the other country. This results in less firm trade between them. A qualitative study on the effect of cultural distance diminishes the foreign market's adverse perception and uncertainty of its size when a large Internet firm chooses a foreign market to enter (Rothaermel et al., 2006). On the study of FDI in China, Blomkvist and Drogendijk (2013) argued that the greater the cultural distance the more adverse the effects on China's FDI. They emphasized the importance of the cultural gap of the target country for the FDI to enter. Goods and services sold through e-commerce exports are facing cultural differences, and these differences can be barriers across borders. For example, Lawrence and Tar (2010) referred to social culture in developing countries as one factor behind e-commerce. Most cultures in developing countries do not support e-commerce and lack confidence in technology and the online culture, indicating non-mature conditions under which to foster e-commerce. One of the most significant cultural barriers is the level of trust in institutions. In his study, Yoon (2009) applied a consumer acceptance model of e-commerce developed in advanced countries to demonstrate that national culture could influence customer behavior. The cultural factor is also crucial in e-commerce; a supplier can take immediate action on a buyer's response on the basis of interaction between the two parties even though some mistakes can be made during e-commerce transactions.

Administrative distance refers to the institutional difference between two countries, including, but not limited to, bureaucracy and political structures. Ghemawat (2001) asserted that attributes creating distance are the absence of colonial ties, political hostility, government policies, institutional weakness, and lack of shared monetary or political association. Institutional differences create administrative obstacles toward other countries, with lopsided measures (i.e., tariffs, quarter, restricted investment, subsidy, and so on). Because firms usually avoid transactions with corrupted or politically conflicted countries, a country's institutional system is vital in international trade (Miloloža, 2015). There are more difficulties in transferring management systems from a home country to a host country when there is a more significant institutional gap between the two countries. Therefore, multinational enterprises (MNEs) secure legitimacy in the host country (Kostova and Zaheer, 1999). Government can play an essential role in creating an institutional environment that promotes private investment (Oxley and Yeong, 2001). Public relations and investment, particularly in small businesses, are the primary drivers of e-commerce (Thatcher et al., 2006). Government policies, such as trade and communication liberalization, are also likely to significantly impact e-commerce by making IT cheaper for companies and by ratcheting up pressure to adopt e-commerce (Gibbs, 2003).

Geographic distance has a meaning of physical distance, which reduces both cooperation and conflict between countries. However, cooperation decreases more than conflict does, so that net conflict (conflict minus cooperation) rises as the geographic distance between two countries increases (Chang et al., 2004). In addition, the transportation cost and the depreciation cost of goods adversely influence international transactions when delivered to a geographically remote market (Clark et al., 2004). Many studies have proven that geographic distance negatively affects international trade (Frankel and Rose, 2002; Leamer, 1974). Davidson (1980), for example, observed that American MNEs entered culturally homogeneous and geographically closed markets, and Dow (2000) suggested that geographic distance had a negative relationship with the first market choice for an Australian exporting firm. In a gravitational model study, Kim et al. (2017) studied 721 regions in five European Union countries, showing that distance was not “dead” in e-commerce.

Ghemawat (2001) defined economic distance as the host country's economic development relative to that of the home country. The economic distance between countries mainly reflects discrepancies in wealth and economic size, often represented in factor costs, technological capability, infrastructure advancement, etc. Economic distance has been considered one of the critical factors significantly affecting FDI performance (Du et al., 2008; Tao et al., 2013). Economic distance is related to income, wealth distribution, and relative purchasing power. Consumer income has a substantial impact on trade, swings the possibility of achieving business cooperation (Miloloža, 2015), and constitutes a significant economic characteristic that can create differences between countries. Sizable economic distance also occurs if the host countries' economic status is lower than the home countries'. In this situation, the MNEs always develop further advantages through access to low-cost factors, including nature and labor (Tao et al., 2013).

Consider cross-national distance and digital innovation simultaneously; internationalization via digital innovation is still subject to CAGE distance. Digital innovations, developed in the context of home countries, may appear more foreign, less relevant, and even offensive to users as CAGE distances increase (Shaheer and Li, 2020). Because of the difficulties in delivering value to overseas users, derived from cultural distance and economic distance, the speed of internationalization might be delayed. Internationalization could be postponed because of administrative distance, such as limits of illegal copy associating technical patents.

As we have seen, distances are a matter of traditional international trade and international e-commerce trade. Although international trade can be digital, Ghemawat (2001) argues that the world will not be connected entirely without a complete solution for distance problems. We cannot object to his argument that the distances create issues between countries and make it challenging to internationalize a firm. In the international trade literature, geographic distance has been an indicator of trade resistance, mainly because of the associated transportation and communication costs (Beckerman, 1956; Leamer, 1974). However, over the past decade, transportation and communication costs have fallen dramatically (Hutzschenreuter et al., 2014). Absolute geographic distance increases communication costs because of uncertainty between firms, derived from physical attributes and transportation costs. A cross-border business incurs transportation and communication costs directly related to geographic distance (Hutzschenreuter et al., 2014). Leamer (2007) also insisted that the world is not flat physically, culturally, and economically; it never has been and never will be, especially concerning international trade. E-commerce might mislead people and ensnare them in a “virtuality trap” because of higher interaction levels between buyers and sellers, one of the typical attributes embedded in e-commerce (Yamin and Sinkovics, 2006).

In sum, while country distance, represented by CAGE, might be less crucial to international e-commerce trade than traditional international trade is, it can still be detrimental to e-commerce exports. Moreover, it might also decelerate the global penetration of digital innovation by impeding users from adopting foreign innovations. Therefore, we hypothesize:

H1. Country distance is negatively associated with e-commerce export.
H1-1: Cultural distance is negatively associated with e-commerce export.
H1-2: Administrative distance is negatively associated with e-commerce export.
H1-3: Geographic distance is negatively associated with e-commerce export.
H1-4: Economic distance is negatively associated with e-commerce export.

2.3. Entrepreneurship

A firm needs to capture new opportunities beyond its capability to survive in a rapidly changing environment (Mintzberg, 1994). A firm that creates a new market quickly seizes opportunities and secures competitive advantages. One typical attribute is entrepreneurship, which is a crucial factor in corporate success in global competition. Entrepreneurship has been defined in many ways and involving many criteria, including the creation of a new venture (Low and Macmillan, 1988), interpretation of the reason and pattern of entrepreneurial behaviors (Stevenson and Jarillo, 1990), entry into new markets (Lumpkin and Dess, 1996), and the identification, evaluation, and exploitation of opportunities (Shane and Venkataraman, 2000). While there has been no agreed-upon definition of entrepreneurship, the concept of opportunity is a critical factor common to its characterization (Chandra et al., 2009; Eckhardt and Shane, 2003). In entrepreneurship, an opportunity is another way for an individual or firm to innovate, seek profits, and improve their state of affairs. Eckhardt and Shane (2003) stated that while non-entrepreneurial decisions maximize scarce resources across previously developed means and ends, entrepreneurial decisions involve creating or identifying new ends and means (Gaglio and Katz, 2001) previously undetected or unutilized by market participants. For instance, we do not regard entrepreneurial opportunities as firms receiving less cost from headquarters or overseas markets (Lumpkin and Dess, 1996). Even so, identifying entrepreneurial opportunities leads to the development of new products and brands or entry into the global market (Gartner, 1990).

Chandra et al. (2009) described opportunity recognition as a process consisting of discovery and deliberate, systematic search. They introduced two schools of thought. One believes that opportunities are identified through purposeful, rational, and systematic search processes (Drucker, 1998; Herron and Sapienza, 1992), similar to formal strategic planning. The other school believes that a search for opportunities may respond to a particular problem, such as when a firm faces declining sales, lost market share, decreased profit, or tough competition. They emphasize that opportunities are unknown until discovered and that one cannot deliberately search for something that one does not know exists (Kaish and Gilad, 1991). Opportunity discovery is not pure luck in that various conditions influence who can and cannot discover different opportunities or the kinds of opportunities that are potentially discoverable (Chandra et al., 2009).

In studying the correlations of entrepreneurial behavior in a sample of 52 prominent Canadian firms, the term entrepreneurial orientation (EO), defined by Miller (1983), includes manager attributes, such as innovation, proactiveness, and risk-taking. EO is referred to as "the processes, practices, and decision-making activities that lead to a new entry" (Lumpkin and Dess, 1996). Lumpkin and Dess (1996, 2001) and Knight (1997) identified five dimensions of EOs. Among those, Chandra et al. (2009) proposed that three dimensions, innovativeness, autonomy, and proactiveness, drove opportunity recognition in international markets, which they referred to as follows:

Innovativeness is a firm's tendency to engage in and support new ideas, novelty, experimentation, and creative processes that may result in new products, services, or technological processes . . . Autonomy is the independence and freedom in bringing forth an idea or vision and carrying it through to completion . . . Proactiveness is a forward-looking perspective that accompanies innovative or new venturing activity and enables a firm to think and see new means-ends frameworks ahead of others . . . The other two dimensions of EO affect the willingness and ability of people and firms to exploit (rather than recognize) new opportunities. Risk-taking is the proclivity to engage in risky business activity and the preference for bold vs. cautious acts to achieve a firm's objectives. It is a prerequisite for entry into unfamiliar foreign markets with untried and untested new approaches, where resources are at risk and expected returns are uncertain. Competitive aggressiveness is the firm's propensity to directly and intensely challenge its competitors to achieve entry, to improve its market position, or to outperform rivals in the marketplace. It drives the firm to enter new foreign markets. (Chandra et al., 2009)

EO is interested in technology, creating new products, procedures, and services, and e-commerce is a generally acknowledged competitive tool (Mehta and Shah, 2001). Li et al. (2008) argue that small firms should enhance innovativeness and proactiveness, avoid taking excessive risks, and maintain proper market positioning based on the moderating effect of EO on the relationship between market orientation and firm performance. A manager with EO also tends to seek opportunities and technology to maintain market competitiveness; therefore, such managers have higher probabilities of leveraging the benefits of e-commerce technology.

A future-oriented perspective explains opportunity recognition as eagerly seeking new products, services, and opportunities (Kropp et al., 2005); proactively exploring the attractive niche market; and promoting new entry modes into the market (Lumpkin and Dess, 2001). Such a definition might include the capability of a firm to enter an exporting market. Innovativeness raises creativity, which leads to the independent production of products and services through research and development (Lumpkin and Dess, 2001). Because they tend to think outside the box and have nontraditional creative views, entrepreneurs can recognize opportunities and adapt to uncertain environments (Timmons et al., 2004). A risk-taking propensity is associated with the will of an entrepreneur to commit large-scale resources and bear the risk associated with finding opportunities (Miller and Friesen, 1978). An entrepreneur with a higher risk-taking propensity tends to adapt better to local environments by reestablishing opportunity and organizational capability, which influence the performance of the exporting firm (Zahra et al., 1999). In a study on the relationship between entrepreneurship and internationalization, with a sample of 500 small and medium English corporations, Balabanis and Katsikea (2003) argued that entrepreneurship positively connected with overseas entry performance. In another study, with a sample of family-owned firms, based on the link among innovativeness, creativity, and entrepreneurship, Carvalho and Williams (2014) identified entrepreneurship as a virtue of the firms entering the global market.

In sum, entrepreneurship has a positive impact on internationalization, and it overcomes and leverages adverse environments. Therefore, we hypothesize the following:

H2. Entrepreneurship is positively associated with e-commerce export.

H3: Entrepreneurship will moderate the relationship between the country's distance and e-commerce export.

H3-1: Entrepreneurship will moderate the cultural distance and e-commerce export.

H3-2: Entrepreneurship will moderate the relationship between the administrative distance and e-commerce export.

H3-3: Entrepreneurship will moderate the relationship between geographic distance and e-commerce export.

H3-4: Entrepreneurship will moderate the relationship between the economic distance and e-commerce export.

3. Methodology

3.1. Data and Model

Our primary statistical test employed 9 years of country-level data from the e-Commerce Export and Import Database developed by the Korea Trade Statistics Promotion Institute. The dataset consisted of countries that the Republic of Korea (Korea) has exported to via e-commerce. However, some countries were excluded from the final dataset of 96 countries; the excluded countries were not listed on the Global Entrepreneurship Index (GEI) from the Global Entrepreneurship and Development Institute (2018) or the Logistics Performance Index (LPI) of the World Bank (2020).

We observed the dataset to study the distance between Korea and the 96 selected importing countries. In terms of geographical region, the observed countries included 12 from East Asia and Pacific, three from Eurasia, 33 from Europe and North America, 16 from Latin America and the Caribbean, 15 from the Middle East and North Africa, four from South Asia, and 13 countries from Sub-Saharan Africa.

Based on Blomkvist and Drogendijk (2013), we integrated the concept of country distance and established a research model to identify the effect of distance on e-commerce exports. We used hierarchical regression analysis to test the moderating effect of entrepreneurship on the causal relationship between country distance (independent variable) and e-commerce performance (dependent variable). In particular, we created and analyzed interaction terms to check the moderating effects of distance between countries on e-commerce exports. Furthermore, to avoid multicollinearity problems, a mean-centered treatment was performed for the moderating variables entrepreneurship and country distance.

3.2. Operationalization of Variables

3.2.1. Dependent Variable

For our dependent variable, we used the volume of Korean e-commerce exports to 96 countries from 2010 to 2018. The e-commerce export data were obtained from the Korea Export Statistics Promotion Institute (2020) database. The selection criterion for the sample countries was the export amounts declared to the Korea Customs Service. We set up the data period from 2010 to 2018 to eliminate the effects of the global financial crisis in 2008 and account for the rapid diffusion of smartphones and large-scale e-commerce platforms from 2010. The Covid-19 pandemic, which broke out in December 2019, has had a significant impact on e-commerce exports. However, we wanted to focus this study on seeing the effectiveness of distance when external shocks are controlled because the external impact effects may be biased between countries. In addition, the considerable temporary rise in e-commerce exports following the impact is likely to distort the effectiveness of distance. Therefore, changes in performance should be seen at a certain point in time after the impact period. The e-commerce export amount was averaged country by country from 2010 to 2018; the amount is denoted in US dollars; and we took a natural logarithm of the dollar amount.

3.2.2. Independent Variables

3.2.2.1. Country Distance.

We operationalized country distance in line with Ghemawat's (2007) CAGE distance, calculated by Kogut and Singh (1988), and the four dimensions of CAGE distance: economic, geographical, cultural, and administrative distances.

$$CAGE_{D_\zeta} = \sum_{i=1}^{4}((I_{ij} - I_{ik})/V_i)/4 \tag{1}$$

where:

$CAGE_{D_\zeta}$: the country distance measured by CAGE distance between exporting country (herein, Korea) and importing country.
I_{ij}: the exporting country j's (herein, Korea) score for CAGE dimensions i.
I_{ik}: the importing country k's score for the corresponding CAGE dimensions i.
V_i: the variance of the CAGE component i.

3.2.2.2. Cultural Distance.

We operationalized cultural distance (CD) with Hofstede's (1984) cultural index. Then, based on Kogut and Singh's (1988) formula, we combined four cultural dimensions, individualism, uncertainty avoidance, power distance, and masculinity, into the following composite index:

$$CD_k = \sum_{i=1}^{4}((I_{ij} - I_{ik})/V_i)/4 \tag{2}$$

where:

CD_k : the cultural distance measured by Hofstede's (1980) cultural index between exporting country (herein, Korea) and importing country.
I_{ij}: the exporting country j's (herein, Korea) score for Hofstede's cultural dimension i.
I_{ik}: the importing country k's score for the corresponding cultural dimension i.
V_i: the variance of the index score of cultural dimension I.

This paper extended from East Africa, West Africa, and the Arab area into more countries, similar to what Blomkvist and Drogendijk (2013) did. For example, we gave Uzbekistan, Ukraine, and Kazakhstan the same score as Russia. However, we removed Uzbekistan from the dataset as it was missing years in the GEI from 2008 to 2010.

3.2.2.3. Administrative Distance.

We operationalized administrative distance by adopting a measure of World Governance Indicators (WGI). The benefits of this data source are its accessibility and expanded dataset (it includes more than 200 countries), making it one of the most comprehensive databases for studying institutional features in a wide range of studies (e.g., Håkanson & Ambos, 2010; Hutzschenreuter et al., 2014). The WGI provide a country score from –2.5 (weak governance) to 2.5 (strong governance) for all indicators. The dataset comprises six dimensions of governance: voice and accountability (measuring political, civil, and human rights); political stability and lack of violence (measuring the likelihood of violent threats to, or changes in, government, including terrorism); government effectiveness (measuring the competence of the bureaucracy and the quality of public service delivery); regulatory quality (measuring the incidence of market-unfriendly policies); the rule of law (measuring the quality of contract enforcement, the police, and the courts, as well as the likelihood of crime and violence); corruption control (measuring the exercise of public power for private gain, including both petty and grand corruption and state capture). The same formula used to calculate cultural distance was applied to measure administrative distance. We then averaged the yearly index over the sampling period and used it in the statistical analysis.

$$AD_k = \sum_{i=1}^{6}((I_{ij} - I_{ik})/V_i)/6 \tag{3}$$

where:

AD_k: the administrative distance measured by WGI between exporting country (herein, Korea) and importing country.
I_{ij}: the exporting country j's (herein, Korea) score for WGI i.
I_{ik}: the importing country k's score for the corresponding WGI i.
V_i: the variance of the administrative score for WGI i.

3.2.2.4. Geographic Distance.

Along with the previous studies (Buckley et al., 2007; Ojala and Tryvainen, 2007; Malhotra et al., 2009), we calculated geographic distance by the actual distance between the capital city of exporting country j (herein, Korea) and the capital city of importing country i. The distance in kilometers was obtained from the CEPII (The Centre d'Etudes Prospectives et d'Informations Internationales) database (2007), and geographical distance was converted to a natural logarithm to avoid significant variance.

3.2.2.5. Economic Distance.

Economic distance refers to differences that affect cross-border economic activity through economic mechanisms distinct from the cultural, administrative, or geographic ones already considered (Ghemawat, 2007). Herein, economic distance means the economic development gap between the exporting country and importing country. The effects of economic distance, viewed in isolation, are more ambiguous than those of other forms of distance are, making it harder to test for distinct effects (Hutzschenreuter et al., 2016). The measurement for the difference in economic development has been developed in a multitude of different ways. For example, Berry et al. (2010) developed the measure based on various factors, such as GDP per capita, inflation, and export and import amount, with Mahalanobis Distance. Håkanson and Ambos (2010) measured the economic distance with GDP per capita in US dollars. However, individual income levels are regarded as the most crucial economic attribute creating distance between countries (Ghemawat, 2001). In this paper, we measured economic distance by averaging the gap of GDP per capita (in US dollars in 2000) between the exporting country (herein, Korea) and importing country from 2010 to 2018. To this end, we employed the World Development Indicators (WDI) from the Database of the World Bank (2020).

$$ED_k = \log(1 + |{S_i}^2 - {S_j}^2|) \tag{4}$$

where:

ED_k: the economic distance measured by WDI between exporting country (herein, Korea) and importing country.
S_i: GDP per capita of exporting country.
S_j: GDP per capita of importing country.

3.2.3. Moderating Variable

In this study, we used the GEI as a measure for entrepreneurship. GEI refers to entrepreneurship as part of a "national system of entrepreneurship," and thus, entrepreneurship arises in response to embedded institutional interactions between an individual's entrepreneurial attitudes, abilities, and aspirations, facilitating resource allocation through the creation and operation of new ventures (Ács et al., 2014). GEI is the first complex index to address the multidimensional aspects of entrepreneurship quality. It is based on 14 pillars, comprising three sub-indexes, and each pillar includes one individual and one institutional variable. The means of the 14 pillars are equalized to balance the marginal effects of improvements.

Based on the research from Ács et al. (2017), because entrepreneurship depends on recognizing and exploring new business opportunities, the Entrepreneurial Attitude (ATT) Sub-Index measures the potential for business opportunity perception. In addition, institutional factors, such as the size of the market, the level of a population's post-secondary education, the country's business climate, use of the Internet, and cultural attitudes, also affect entrepreneurship development. The constituent factors are opportunity perception, start-up skills, risk acceptance, networking, and cultural support. By contrast, the Entrepreneurial Abilities Sub-Index (ABT) focuses on measuring high-growth-potential start-up activities. Again, the constituent factors are opportunity perception, start-up skills, risk acceptance, networking, and cultural support. Finally, the Entrepreneurial Aspiration (ASP) sub-index comprises the most relevant variables that measure the individual and institutional aspects of market expansion and innovative entrepreneurial development. The constituent factors are product innovation, process innovation, high growth, internationalization, and risk capital. We took the average annual index of importing country j over the sampling period to measure entrepreneurship as a moderating variable.

3.2.4. Control Variables

In line with previous studies (Gibbs et al., 2003; Berry et al., 2010), we controlled five variables to affect e-commerce performance: global production network (L_OFDI); open trade regimes (FTA); mobile phone penetration (L_Mobile); the efficiency of logistics (LPI); and global connectedness distance (GCD) (Oxley and Yeung, 2001; Berry et al., 2010). This shows the ability of resident individuals and firms to interact with other parts of the world, obtain information, and diffuse their activities. Furthermore, following the literature in this area (Berry et al., 2010), we used international tourism expenditures and employed the dimensions as a percentage of GDP, international tourism receipts as a percentage of GDP, and Internet users as a percentage of population. All of the aforementioned data were secured from the WDI Database of World Bank (2020), and Kogut and Singh's (1988) formula for the distance was used herein.

$$GCD_k = \sum_{i=1}^{3}((I_{ij} - I_{ik})/V_i)/3 \tag{5}$$

where:

GCD_k: The global connectedness distance between the exporting country (herein, Korea) and importing country.
I_{ij}: The exporting country j's (herein, Korea) score for GCD i.
I_{ik}: The importing country k's score for GCD i.
V_i: The variance of the score for GCD i.

Table 1. Description of Variables

Dimension	Variable	Component of variable	Years available	Source
E-commerce	E-com	E-commerce export amounts of Korea (USD, log)	2010–2018	ktspi.or.kr
Country Distance	CAGE	CD, AD, GD, ED	2010–018	Blomkvist and Drogendijk (2013)
Cultural Distance	CD	Power distance, uncertainty avoidance, individualism, masculinity	2010–2018	Hofstede Index
Administrative Distance	AD	Voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, rule of law, control of corruption	2010–2018	WGI
Geographic Distance	GD	Distance between the capital of Korea and the capital of the e-commerce export destination	2010–2018	CEPII
Economic Distance	ED	GDP per capita (USD, log)	2010–2018	WDI
Entrepreneurship	GEI	Attitudes Abilities Aspiration	2010–2018	GEDI
Global Production Network	L_OFDI	Outward foreign direct investment (USD, log)	2010–2018	koreaexim.go.kr
Efficiency of Logistics	LPI	Customs, infrastructure, quality, shipment, tracking and tracing, timeliness	2007–2018	WDI
Open Trade Regimes	FTA	FTA status	2010–2018	fta.go.kr
Global Connectedness Distance	GCD	International tourism expenditure, international tourism receipts, internet users	2010–2018	WDI
Mobile Penetration	L_Mobile	Mobile cellular subscriptions	2010–2018	WDI

We measured the number of mobile phone subscribers from the World Bank's WDI to determine mobile phone penetration (L_Mobile), averaged the numbers from 2010 to 2018, and used a logarithm.

An LPI was employed to measure logistics efficiency. We averaged the index, collected six times from 2007 to 2018. A five-point Likert scale was used to survey LPI, comprising customs, infrastructure, international shipment, logistics quality and competence, tracking and tracing, and timeliness. Martí et al. (2014) used LPI as a factor to analyze its impact on the international trade of emerging economies. In line with this study, we used LPI to measure the logistics efficiency of e-commerce exports.

In the global production network, Gibbs et al. (2003) presented theoretical evidence and cases to suggest that global production networks (L_OFDI) and open trade regimes promote e-commerce activities. We operationalized L_OFDI as the size of outward foreign direct investment (OFDI). We obtained and used a logarithm on the average OFDI provided by Korea Exim Bank Statistics for the period 2010–2018.

We measured the open trade regimes of free trade agreements (FTAs) between Korean and importing countries, obtained from the Korean Ministry of Trade, Industry, and Energy (2020), which we used as dummy variables.

4. Result

4.1. Descriptive Statistics and Correlation Matrix

Table 2 and Table 3 present the descriptive statistics, and Table 4 shows the correlation matrix. Europe and North America were the most extensive regions for Korea's e-commerce exports in 2010, and East Asia and Pacific replaced the Western nations for top position in 2013. In terms of CAGE distance, the countries closest to Korea are, in descending order, China, Japan, and Slovenia. Other distances, such as CAGE distance, are illustrated in Table 3.

The diagnostic information from the regression analysis (Table 5) supports the correlation result. We used variance inflation factors (VIF) and determining factors to confirm that multicollinearity problems were unlikely. The highest VIF was 3.09, well below 10 (Hair et al., 2006).

Table 2. The Republic of Korea's E-commerce Exports (Units: US Dollars)

Export Zone	2010	2011	2012	2013	2014	2015	2016	2017	2018
East Asia and Pacific	180,424 (8.77%)	1,307,245 (30.63%)	3,940,759 (38.11%)	11,170,443 (47.95%)	16,795,515 (46.39%)	78,625,070 (78.91%)	102,195,756 (78.81%)	81,038,963 (80.09%)	113,557,528 (86.04%)
Eurasia	35,385 (1.72%)	382,747 (8.97%)	1,474,391 (14.22%)	1,762,726 (7.57%)	2,870,139 (7.93%)	1,227,015 (7.93%)	1,017,074 (0.79%)	728,820 (0.72%)	1,987,170 (1.51%)
Europe and North America	1,788,111 (86.89%)	2,176,541 (50.99%)	4,472,569 (43.14%)	9,299,820 (39.92%)	15,077,780 (41.64%)	18,189,242 (18.26%)	23,506,247 (18.36%)	18,433,594 (18.22%)	15,082,280 (11.43%)
Latin America and the Caribbean	37,232 (1.81%)	248,519 (5.82%)	253,226 (2.44%)	567,503 (2.44%)	509,956 (1.41%)	461,945 (0.46%)	457,558 (0.36%)	424,064 (0.42%)	668,422 (0.51%)
Middle East and North Africa	11,689 (0.57%)	133,362 (3.12%)	177,202 (1.71%)	430,168 (1.85%)	815,104 (2.25%)	962,247 (0.97%)	642,257 (0.50%)	480,703 (0.48%)	565,866 (0.43%)
South Asia	3,604 (0.18%)	13,348 (0.31%)	25,347 (0.24%)	45,002 (0.19%)	98,871 (0.27%)	149,551 (0.15%)	143,661 (0.11%)	66,250 (0.07%)	105,249 (0.08%)
Sub-Saharan Africa	1,485 (0.07%)	6,460 (0.15%)	24,764 (0.24%)	20,691 (0.09%)	39,224 (0.11%)	20,130 (0.02%)	80,457 (0.06%)	16,472 (0.02%)	18,352 (0.01%)

Table 3. CAGE Distance to the Republic of Korea, per factor

Top Five Countries	CD	AD	GD	ED	CAGE
Countries nearest to Republic of Korea	Peru	Latvia	Mainland China	Slovenia	Mainland China
	El Salvador	Spain	Japan	Greece	Japan
	Chile	Lithuania	Hong Kong(China)	Portugal	Slovenia
	Egypt	Poland	Philippines	Bahrain	Hong Kong(China)
	Bulgaria	Croatia	Vietnam	Puerto Rico	Greece
Countries farthest from Republic of Korea	Denmark	Libyan Arab Jamahiriya	Uruguay	Luxembourg	Luxembourg
	Slovakia	Venezuela	Argentina	Norway	Argentina
	U.K	Iraq	Chile	Switzerland	Ecuador
	Sweden	Myanmar	Brazil	Qatar	Peru
	U.S.A	Nigeria	Peru	Denmark	Sierra Leone

4.2. Test of Hypothesis

We ran hierarchical regression analyses to test the hypotheses, wherein there were four different regression models. As F-statistics show, each of the four models was a statistically significant predictor, at $p < .001$. In Model 1, e-commerce export of Korea was regressed on the study's control variables. In Model 2, two CAGE distance (CAGE) variables and entrepreneurship (GEI) were added to Model 1's control variables. In Model 3, interaction terms were added to the variables already present in Model 2. The interaction terms were created by multiplying GEI (the "entrepreneurship" measure) by CAGE distance (CAGE). We also checked for improvements made in the explanatory powers between successive steps by applying the procedure suggested by Cohen and Cohen (1975).

Table 5 presents the results of moderated regression analysis for e-commerce export. Model 1 regressed e-commerce export on the control variables and was significant ($p < .001$), explaining 58%. The global production network ($p < .001$) and efficiency of logistics ($p < .001$) both had positive and significant coefficients. Model 2, which included the control, entrepreneurship, and CAGE distance variables, was also significant ($p < .001$) and explained 65% of e-commerce export variance. The entrepreneurship measure was not statistically significant; however, CAGE distance was negatively associated with e-commerce export ($p < .001$). The third step of the analysis (Table 5) tested moderated regression models. In the regression, we added the interaction term for CAGE distance to variables in Model 2. The analysis was significant ($p < .001$), explaining 66.5% of the e-commerce export variance. The interaction term was also significant and positive ($p < .05$). The entrepreneurship interaction term's addition improved the overall R2 of the model by 1.5% ($p < .001$).

In Model 4, we added four CAGE dimensions, but we removed CAGE distance from the variables in Model 3. We ran the analysis using interaction terms for cultural distance, administrative distance, geographic distance, and economic distance variables. The model was significant, explaining 67% of e-commerce export variance. The interaction term was positive and significant only to cultural distance ($p < .10$) and administrative distance ($p < .10$); however, it added 1% to the explanatory power of Model 3. This improvement was also significant ($p < .001$).

Table 4. Correlation Matrix

Type	Name of Variable	Mean	STD	1	2	3	4	5	6	7	8	9	10	11
CV	L_OFDI	9.99	2.93	1										
	LPI	3.11	0.54	0.39***	1									
	FTA	0.45	0.50	0.35***	0.44***	1								
	GCD	1.50	1.64	−0.19*	−0.27***	−0.31***	1							
	L_Moblie	4.69	0.34	0.20**	0.39***	0.15	−0.32	1						
IV	CD	1.52	1.28	0.31***	0.47***	0.30***	−.023**	0.11	1					
	AD	1.43	1.31	−0.18*	−.045***	−0.27***	0.23**	−0.33***	−0.26**	1				
	GD	9.01	0.53	−0.36***	−0.20**	−0.19*	−0.14	−0.07	−0.19*	−.0.6	1			
	ED	9.64	0.80	0.23**	−0.01	−0.04	0.11	−0.22**	0.24**	0.21**	−0.08	1		
MV	GEI	38.44	18.65	0.36***	0.53***	0.41***	−0.37***	0.20	0.47***	−0.44***	0.04	0.04	1	
DV	e−Com	9.54	2.80	0.60***	0.65***	0.46***	−0.35***	0.40***	0.42***	−0.39***	−0.46***	−0.03	0.47***	1

Note: 1. CV = Control Variable, IV = Independent Variable, MV = Moderating Variable, DV = Dependent Variable
2. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

In summary, the results partially support Hypothesis 1 because CAGE distance is associated with e-commerce export. Even so, each CAGE dimension, such as cultural, administrative, geographic, and economic distance, showed mixed results. Therefore, Hypotheses 1-1 and 1-2 were rejected, but Hypotheses 1-3 and 1-4 were supported. Hypothesis 2 was supported, and Hypothesis 3, which tested the interaction variables, was partially supported. This was also the case with Hypothesis 1; Hypotheses 3-1 and 3-2 were supported, but Hypotheses 3-3 and 3-4 were rejected.

Table 5. Moderated regression results for e-commerce exports of Korea

Variables	Model_1	VIF	Model_2	VIF	Model_3	VIF	Model_4	VIF
L_OFDI	0.354 *** (5.01)	1.25	0.315*** (4.8)	1.32	0.285*** (4.32)	1.36	0.234** (3.24)	1.66
L_MOBILE	1.021 (1.66)	1.27	0.553 (0.97)	1.32	0.414 (0.73)	1.77	0.495 (0.81)	1.59
GCD	−0.177 (−1.41)	1.21	−0.244* (−2.05)	1.29	−0.296* (−2.48)	1.39	−0.299* (−2.46)	1.46
LPI	1.926 *** (4.51)	1.53	1.639*** (3.9)	1.78	1.706*** (4.12)	1.79	1.536*** (3.5)	2.06
FTA	0.661 (1.52)	1.37	0.311 (0.77)	1.44	0.162 (0.4)	1.49	0.28 (0.68)	1.56
GEI			0.0167 (1.42)	1.67	0.00948 (0.79)	1.83	0.00573 (0.43)	2.31
CAGE			−0.0858*** (−4.49)	1.17	−0.0865*** (−4.61)	1.17		
CAGE*GEI					0.00242* (2.06)	1.35		
CD							0.0883 (0.52)	1.78
AD							0.0383 (0.17)	3.09
GD							−1.743 *** (−4.55)	1.5
ED							−0.472 † (−1.77)	1.7
CD*GEI							0.0148 † (1.82)	1.94
AD*GEI							0.0218 † (1.78)	2.51
GD*GEI							0.0174 (0.74)	1.29
ED*GEI							0.013 (0.76)	1.96
F−Value	27.34***		26.46***		25.54***		14.84***	
N	96		96		96		96	
Adj R2	0.58		0.65		0.66		0.67	

Notes. 1. t−values in parentheses

2. †$p < .10$, * $p < .05$, **, $p < .01$, *** $p < .001$

5. Conclusion and Implication

The decision on which foreign market to enter is critical for corporate strategy and successful internationalization. Therefore, this study reflected the country distance based on the CAGE framework of e-commerce derived from technological innovation. With regard to this, we addressed the influence of "distance matter," which is considered a barrier for traditional internationalization and international e-commerce. In addition, we addressed the possibility that "distance matter" could be overcome via entrepreneurship in the context of newly rising e-commerce. Ghemawat (2007) suggested that distance provides a good set of metrics for capturing degrees of difference and similarity between countries, including consideration for the dimensions of the CAGE framework. Johanson and Vahlne (1977) argued that the Uppsala model defined psychic distance as the sum of factors preventing the flow of information; markets and firms would gradually enter other markets that were further away in psychic terms. Our study confirmed that "distance still matters" (Ghemawat, 2001) in the internationalization process.

Among control variables, global production networks and logistics efficiency have positive associations with e-commerce. This result supports the argument that participation in global production networks is an essential driver of e-commerce diffusion. Furthermore, global production networks rely heavily on IT and e-consumers for coordination, and MNCs transfer technology and knowledge to local firms on conducting e-commerce (Gibbs et al., 2003). Moreover, we identify that the efficiency of logistics, denoted by characteristic features such as on-time delivery, tracking, and various logistic infrastructure, is as crucial to e-commerce export as it is to traditional international trade. Last, in Model 4, the distance of global connectedness control variable enables individuals and firms to interact with others, share information, and expand activities further.

In Model 3, CAGE distance is negatively associated with Korea's e-commerce exports as expected in Hypothesis 1, and some CAGE dimensions are not associated with e-commerce exports. Geographic distance and economic distance, while marginal, are negatively associated with e-commerce exports. Clark et al. (2004) argued that transportation costs are a higher barrier in the American market than import tariffs are in Latin American countries. One critical factor affecting transportation cost is the geographic distance separating an importer and an exporter (Leamer, 1974). With all these considerations, exported e-commerce goods must be delivered to the final importer in the final analysis as is the case with traditional exports. Therefore, we identified that geographic distance is still negatively associated with e-commerce exports. Economic distance is also negatively associated with e-commerce exports in what is consistent with Linder's theory of representative demand (1961). From country similarity, the economic proximity between two countries leads to similarity of income and wealth for both countries, which results in similar consumer preferences.

Cultural distance and administrative distance are not associated with e-commerce export, contrary to what previous studies say. Entering firms favor overseas markets with similar cultures (Blomkvist and Drogendijk, 2013; Johanson and Vahlne, 1977; Kogut and Singh, 1988). The result is not consistent with that obtained by Håkanson and Ambos (2010). They pointed out the prevailing suggestion in the existing literature that the more significant the differences in foreign environments the more difficulties for firms to collect, analyze, and correctly interpret information about the country, leading to higher uncertainties and challenges in doing business. We suggest that cultural distance and administrative distance do not influence e-commerce exports as sharing information with other countries becomes easier through the global connectedness of the Internet, making cultural differences negligible. E-commerce also enables a firm to communicate with its customers more efficiently and capture opportunities to seize potential customers in remote regions that traditional methods have difficulties accessing. We submit that these affirmative e-commerce factors are reflected in the results.

Model 3 shows that entrepreneurship in importing countries is not statistically related to e-commerce exports; however, CAGE distance eases negative impacts on e-commerce exports. Model 4 tests the relationship between entrepreneurship and each dimension of CAGE distance; we identified that entrepreneurship positively moderated the relationship between e-commerce exports and cultural and economic distance. Entrepreneurship helps people view the world in a nontraditional way, creating business opportunities and facilitating adaptation to uncertain global environments (Timmons et al., 2004). Entrepreneurship is widely viewed as being concerned with technology; creating new products, services, and processes; and spurring entrepreneurs to challenge and exploit adverse environments. Therefore, the difference of cultural and administrative distance might be positively moderated by entrepreneurship, including identifying business opportunities and EO (Miller, 1983; Lumpkin and Dess, 1996, 2001; Knight, 1997; Chandra et al., 2009). In our study, we provide the theoretical and practical implications as follows.

First, we confirm that a firm at the country level in the internationalization process is more likely to choose an overseas market with a shorter CAGE distance, that is, a foreign market most similar to the domestic market (Sousa and Bradley, 2006; Ghemawat, 2001; Blomkvist and Drogendijk, 2013). E-commerce exports are influenced by distance, especially geographic and economic distance, implying that traditional or established entry barriers might be underestimated because of technological innovation. Most people expect geographic distance not to significantly impact e-commerce, which is primarily conducted in cyberspace. On the contrary, we identify that CAGE distance has a negative relationship with e-commerce export performance. This finding provides a theoretical contribution to the e-commerce export research field.

Second, as entrepreneurship in importing countries increases, the relationship between CAGE distance and e-commerce exports becomes less negative. We suggest that e-commerce might be a unique entry mode backed by current technology innovation and derived from a traditional internationalization model. E-commerce provides options to choose between gradual and rapid internationalization. The following has been suggested.

Opportunity favors the prepared and connected firms. International opportunity discovery requires favorable conditions within the firm to exist in terms of prior international and technical knowledge, intellectual property, openness/access to information sources, including the Internet, and firm characteristics, such as EO. The discovery process did not occur simply through serendipitous encounters with new information from networks or referrals. (Chandra et al. 2009)

In line with this argument, we believe that this study contributes toward expanding the role of EO in the context of country distance and e-commerce.

By better understanding the relationship between e-commerce exports and distance, our study can develop performance-related strategies for e-commerce export managers. For firms, differences between countries are familiar concepts; however, if the cultural or geographic distance is only recognized, they will be seen as being disconnected. Furthermore, if distance is not considered a single framework, the differences between countries may seem to be a mosaic. The more efficiently the differences between countries are recognized the more likely an entity to overcome each distance.

Pre-solving the distance problem can mitigate the negative impact of distance on performance. The results of this study show that geographic distance and economic distance have negative effects. Therefore, to overcome problems associated with geographic distance, firms should take proactive measures to show greater interest in logistics and transportation systems. Similarly, economic distance should explain large and attractive market entry and possible resultant friction. In some cases, the “paradox of distance” may be shown when performance is relatively high in the distance (Evans & Mavondo, 2002). However, because of the uncertainty arising from a distance, the distance paradox arises from more significant market interest and customers. In addition, cultural and institutional distance does not negatively affect performance; however, that does not mean it should be overlooked. On the contrary, cultural distance hinders learning about customers and markets, and institutional distance can lead to risk and uncertainty because of inexperience with rules and regulations. In other words, managers should be careful not to overlook the problem or underestimate differences with foreign markets.

Some of the practical implications are related to Korea-specific factors. In this study, the CAGE distance from Korea to importing countries shows a noticeable difference on a continent-by-continent basis. Along with this finding, Korean firms must consider various options when selecting an overseas market to enter. Firms are also cautious about the country's distance with the virtuality trap (Yamin and Sinkovics, 2006). Because of strong interaction with overseas buyers, e-commerce exports might cause firms to fall into a virtuality trap and assume that they understand the market conditions. Therefore, during overseas market selection, a firm should choose a country with a higher level of entrepreneurship. A firm may also mitigate geographic distance problems by selecting a country with higher logistics efficiency. Total FDI flows into a region or country is also a telling indicator that aids in selecting a target country for e-commerce export.

Although this paper has the aforementioned significant findings, we concede that it has some limitations, and we recommend further research for the field to progress. First, this paper might reflect country-specificity, primarily the Korean context, and some countries were excluded from the samples, which might present some generalization limits of the study. Future research needs to expand to encompass more countries and regions. Second, the study measured variables based in the 2010–2018 period; this measurement period possibly arouses caution as to whether it reflects current distances, particularly cultural distance, and as to whether the impact of management capability on cultural distance is considered. As with previous studies, different input values produce different outputs. Therefore, additional factors influencing distance and other possible distance measurements need to be developed. Third, the effects of the external shock of COVID-19 are still ongoing, which has changed all business and export environments, including e-commerce exports. Therefore, it is still premature to judge whether changes in e-commerce export performance are temporary due to shocks or whether they herald a shift in the export environment. It is, however, definite that follow-up research is needed to focus on the “external impact effect” in the foreseeable future. Fourth, the Hofstede index has previously been added to the fifth dimension, Long-Term versus Short-Term Orientation (LTO), and the sixth dimension, Indulgence Versus Restraint (IVR). However, the study has the limit that the Hofstede index was measured using only four dimensions: Power Distance Index (PDI), Individualism versus Collectivism (IDV), Masculinity versus Femininity (MAS), and Uncertainty avoidance index (UAI). In a future study, the complete Hofstede index should be applied to measure cultural distance. Finally, we took a composite index for the entrepreneurship variable and the efficiency of logistics. However, they could have various other constructs and impose some limits on explaining their impacts on e-commerce.

Notwithstanding some limitations, this paper tries to tackle distant issues related to international trade and business, a once popular but now forgotten research topic. Yet, distance still matters. The challenging question we may need to answer shortly is, “What does distance have to do with us?”

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Appendix. CAGE Distance Scores

We measured the country distance with the CAGE framework, between Korea and importing countries, based on Kogut and Singh (1988). The scores of calculated CAGE distance were converted to the range from 1 to 100 by following Blomkvist and Drogendijk's (2013) formula:

$$X_j^D = \left[\left[(X_j - min_{pd})/R_{pd}\right]99\right] + 1$$

Where:
X_j^D: the converted score of CAGE distance for importing country j.
X_j: the score of CAGE distance before conversion for importing country j.
min_{pd}: the minimum score of CAGE distance before conversion.
R_{pd}: the score range of CAGE distance before conversion.

Country	CAGE Distance	Country	CAGE Distance	Country	CAGE Distance
Mainland China	1.0	Turkey	59.8	Uganda	83.8
Japan	10.4	Croatia	59.8	Australia	83.9
Slovenia	11.6	Sri Lanka	60.4	Madagascar	85.0
Hong Kong (China)	15.3	Singapore	60.8	Panama	85.4
Greece	26.2	Hungary	64.0	Libyan Arab Jamahiriya	86.7
Bahrain	34.4	Romania	64.0	Cameroon	87.2
Philippines	34.4	Iran	64.8	Zambia	87.3
Vietnam	36.7	Italy	65.1	Canada	87.5
Saudi Arabia	41.1	Finland	68.5	Costa Rica	88.2
Thailand	41.6	Ukraine	69.2	South Africa	88.9
Kazakhstan	42.0	Serbia	69.4	Ireland	89.0
Czech Republic	42.7	Lebanon	69.8	El Salvador	89.2
Lao People's Dem. Rep.	43.4	Jordan	70.5	Ghana	89.5
Portugal	44.0	Bulgaria	71.1	Mozambique	90.1
Malaysia	45.1	France	72.0	Colombia	90.2
Oman	45.5	Egypt	73.3	Cote d'Ivoire	90.5
Bangladesh	48.7	Germany	74.3	Denmark	90.7
Estonia	52.1	Belgium	74.8	Guatemala	90.8
Myanmar	52.6	Iraq	75.1	Chile	91.1
India	54.2	Iceland	76.0	United States of America	93.1
Lithuania	54.6	Trinidad and Tobago	77.5	Nigeria	93.3

Country	CAGE Distance	Country	CAGE Distance	Country	CAGE Distance
Indonesia	55.8	Austria	77.9	Uruguay	93.7
Israel	56.6	Qatar	78.6	Venezuela	93.8
Russian Federation	57.1	United Kingdom	78.9	Jamaica	93.8
Poland	57.2	Ethiopia	79.0	Switzerland	93.8
Latvia	57.2	Mexico	80.0	Norway	94.0
United Arab Emirates	57.6	Algeria	80.5	Brazil	94.0
Kuwait	57.8	Netherlands	81.8	Sierra Leone	94.8
Spain	58.6	Sweden	82.0	Peru	95.7
Pakistan	59.1	Morocco	82.2	Ecuador	96.0
Slovakia	59.5	Kenya	82.7	Argentina	98.2
Puerto Rico	59.6	Tanzania	82.8	Luxembourg	100.0

Journal of Korea Trade Vol. 25, No. 4, June 2021, 88-107
https://doi.org/10.35611/jkt.2021.25.4.88
ISSN 1229-828X

Bilateral Trade and Productivity Differences in a Ricardo-Cournot Model*

JKT 25(4)

Received 21 October 2020
Revised 17 May 2021
Accepted 18 June 2021

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Abstract

Purpose – Using a model that highlights Ricardian comparative advantage and Cournot competition, I derive theoretical predictions on how bilateral measures of trade intensity, specialization, and intra-industry are interrelated, and how Ricardian productivity differences affect these measures. We test the predictions using trade and production data, and confirm them.

Design/methodology – A simple two-country general equilibrium model is constructed to derive theory-based bilateral indexes. We then test the relationships among them using panel data for 35 countries and 14 industries between 1996 and 2008.

Findings – Bilateral trade intensity is increasing in specialization, as in the classical trade theory, and in intra-industry trade, as in the new trade theory. However, productivity differences positively affect specialization, and negatively affect intra-industry trade. These effects cancel each other; thus productivity differences have little impact on trade intensity.

Originality/value – This paper provides a comprehensive conceptual framework for understanding the relationship among trade intensity, specialization, intra-industry trade, and productivity differences. We derive theory-consistent measures of specialization, intra-industry trade, and productivity differences. Moreover, we reevaluate the empirical relevance of these variables for the study of gravity equations. This paper is also an effort to capture oligopolistic competition in a general equilibrium framework, interests in which recently resurged.

Keywords: Comparative advantage, Cournot competition, Intra-industry trade, Labor productivity, Specialization

JEL Classifications: F10, F12, F14

1. Introduction

This study explores, both theoretically and empirically, the influence of bilateral productivity differences on trade intensity, specialization, and intra-industry trade. We construct a Ricardian trade model featuring Cournot competition to show that trade intensity is increasing in specialization, as in the classical trade theory, and in intra-industry trade, as in the new trade theory. However, the model predicts that productivity differences between trading partners do not affect trade intensity because they increase specialization and decrease intra-industry trade simultaneously, the two effects canceling each other.

We test the theoretical predictions using trade and production data for 35 countries and 14 industries between 1996 and 2008. Our estimation results largely support our model, although the quantitative effects of our indexes are smaller than their theoretical values. We find that our bilateral indexes of specialization and intra-industry trade are positively correlated with bilateral trade intensity as implied by our model. We also find that our index

* The author is grateful to two anonymous referees for their valuable comments, which substantially improved the paper. However, all remaining errors are mine.

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of productivity differences positively affects specialization, but negatively affects intra-industry. However, productivity differences have no additional explanatory power on trade intensity after the effects of trade costs are controlled for, confirming our theory.

The effect of productivity differences on trade volume is a long-studied topic in Ricardian trade theory. The influence of specialization and intra-industry trade on trade volume has also been intensively studied in the classical and the new trade theory. However, a study investigating the relationship among trade volume, specialization, intra-industry trade, and productivity differences in a single comprehensive framework is rare. This paper does so based on a minimalist general equilibrium model where Cournot competition between a domestic firm and a foreign firm prevails in every industry.

The lack of theoretical generality would look limiting given the remarkable progress of general equilibrium trade theory in the last two decades. Eaton and Kortum (2002) elevated the empirical applicability of the Ricardian model by successfully introducing multiple countries and transportation costs. Anderson and van Wincoop (2003) did so for the monopolistic competition model of Krugman (1997), and Melitz (2003) and Chaney (2008) further amplified the model by incorporating heterogeneous firms. Now researchers can apply their estimation equation from a theory directly to data without apology. However, with the advancement of trade theories mirroring real- world complexity, the literature moved away from trade pattern theory in the classical sense. Bilateral differences or similarities between trading partners in terms of productivities, endowments, or production structure had been a dominant concept for explaining the volume and pattern of bilateral trade. Bilateral indexes measuring differences between trading partners are also frequently used to study business cycle synchronization or optimum currency areas (*e.g.* Clark and Van Wincoop, 2001; Imbs, 2004; Baxter and Kouparitsas, 2005; Duval, Saraf, and Seneviratne, 2016). Now, they are seldom used in the frontier studies of gravity equations because their presence in the estimation equation is hard to justify in a rigorous multi-country model.

The bilateral indexes examined in this study have long and frequently been used in the international trade literature. We measure trade intensity as the ratio of trade volume to the product of partner incomes. The gravity equation theories, from the simple version of Leamer and Stern (1970) to the full-fledged versions of Eaton and Kortum (2002), Anderson and van Wincoop (2003), and Chaney (2008), all focus on expressing this ratio as a function of trade costs. Our index of specialization, which measures the difference between two countries in the industry distribution of value-added shares, has been used by several authors (Krugman, 1991; Clark and van Wincoop, 2001; and Imbs, 2004) because it makes an intuitive sense. However, to our knowledge, it had never been derived from a theory. Our measure of intra-industry trade is a simple transformation of the well-known index by Grubel-Lloyd (1975), which became the standard for measuring the intensity of intra-industry trade. Finally, we measure productivity differences as the difference in the industry distribution of labor productivity relative to the country-wide average. This index captures the classic concept of the Ricardian comparative advantage simply and intuitively. However, as far as we know, it has never been theoretically derived or empirically tested.

We derive all these measures theoretically and show that these measures have clear-cut theoretical relationships. Moreover, we demonstrate their empirical significance in the prediction of trade volume and pattern. We believe that our findings suggest the necessity to expand our model further rather than drop them from the empirical application because a current forefront model cannot justify them.

The work of Costinot, Donaldson, and Komunjer (2012) is an important exception in the recent literature that investigates the empirical significance of bilateral productivity differences in explaining trade pattern. They tested a Ricardian prediction on trade pattern derived from the Eaton and Kortum (2002) model: the ratio between the relative export of a pair of exporters to a third country in one industry and that in another is increasing in the ratio between the relative labor productivities of the pair in the two industries. This proposition is perhaps the strongest Ricardian prediction derivable from a general Ricardian model. However, it is distanced from the conventional notion on the relationship between comparative advantage and trade pattern.

Costinot, Donaldson, and Komunjer (2012) also anticipated some of our results. In a numerical simulation, they found that the complete removal of the Ricardian comparative advantage across all countries would reduce world trade flows only slightly. They attributed the small reduction to an increase in intra-industry trade following the disappearance of comparative advantages. This is consistent with our finding that a reduction in productivity differences has little effect on trade intensity because it decreases specialization and simultaneously increases intra-industry trade. However, the authors neither algebraically derived nor econometrically tested the prediction as we do here.

It seems a great irony that general equilibrium trade theory is being drawn more and more into the atomistic models of perfect and monopolistic competition when a small number of multinational giants increasingly dominate international trade. Recently, interest in incorporating oligopolistic competition in general equilibrium trade theory resurged (Atkeson and Burstein, 2008; Neary, 2010/2016; Head and Spencer, 2017). This paper is an effort to capture oligopolistic competition in a general equilibrium framework. Our model is similar to Neary (2016) in some respects, but we derive different propositions and empirically test them. This study is an extension of Song and Sohn (2012), who used a similar model, but narrowly focused on the determinants of intra-industry trade. Here, we deal with trade volume and pattern in general, and use more reliable data to calculate labor productivity, which determines our key index.

This paper is naturally related to the classic literature testing the influence of Ricardian comparative advantage on bilateral trade (Macdougall, 1951; Stern, 1962; Balassa, 1963; Gohub and Hsieh, 2000). Our study tests different Ricardian predictions that embody the new trade theory, and is more theory-based. Related are the multi-industry versions of the Eaton and Kortum (2002) model (*e.g.* Costinot, Donaldson, and Komunjer, 2012; Levchenko and Zhang, 2012; Caliendo and Parro, 2015; Burstein and Vogel, 2017). These models are based on perfect competition, but they generate intra-industry trade by introducing intra-industry technological heterogeneity across firms. These models have a potential to generate propositions similar to ours.

The remainder of this paper is organized as follows. Section 2 constructs a simple Cournot-Ricardo model. Section 3 presents the empirical results. Section 4 concludes the paper.

2. A Simple Ricardian Model of International Rivalry

The world is composed of two countries, “home” and “foreign”, that produce a continuum of goods indexed over the unit interval $[0,1]$. The countries share an industry classification system in which goods are classified into N industries such that each industry is represented by a subinterval I_n $(n = 1, 2, \dots, N)$, and $\cup_{n=1}^{N} I_n = [0,1]$.

The two countries are populated by consumers with identical Cobb-Douglas tastes. Denoting the expenditure share of good z by $\gamma(z)$, we write the problem of the home consumers as maximizing the following utility function:

$$U = \int_0^1 \gamma(z) \log d(z) \; dz,$$

where $d(z)$ denotes the home consumption of good z and $\int_0^1 \gamma(z)\ dz = 1$. With the industry classification system, the objective function can be rewritten as:

$$U = \sum_{n=1}^{N} \beta_n \log c_n,$$

where $\beta_n = \int_{z\in I_n} \gamma(z)\ dz$ and $\log c_n = \int_{z\in I_n} \frac{\gamma(z)}{\beta_n} \log d(z)\ dz$. Likewise, denoting foreign variables by asterisks, we can express the utility function of the foreign consumers as:

$$\begin{aligned} U^* &= \int_0^1 \gamma(z) \log d^*(z)\ dz \\ &= \sum_{n=1}^{N} \beta_n \log c_n^*, \end{aligned}$$

where $\log c_n^* = \int_{z\in I_n} \frac{\gamma(z)}{\beta_n} \log d^*(z)\ dz$.

We assume that each good is produced by one home firm and one foreign firm. They engage in separate Cournot competition in the home and foreign markets, as in the reciprocal dumping model of Brander (1981) and Brander and Krugman (1983). Firms must incur iceberg-type transportation costs to move goods across the countries, and a firm located in one country has to to produce τ (>1) units of a good to deliver one unit of the good to the other country. Labor is the only factor of production, and it is mobile across industries, but not between countries.

Let $\alpha(z)$ and $\alpha^*(z)$ be the labor productivities of the home and foreign firm producing good z, and $p(z)$ and $p^*(z)$ the home and foreign price of the good. We use Y and Y^* to denote the gross domestic products of the home and foreign country, and w and w^* their wages, respectively. Overall trade is balanced, and in each country, total consumption expenditure is equal to gross domestic product, which we also call income. We can easily derive the following results:

$$d(z) = \frac{\gamma(z)\, Y}{p(z)}, \tag{1}$$

$$d^*(z) = \frac{\gamma(z)\ Y^*}{p^*(z)}, \tag{2}$$

$$p(z) = \frac{w}{\alpha(z)} + \frac{\tau\, w^*}{\alpha^*(z)}, \tag{3}$$

$$p^*(z) = \frac{\tau\, w}{\alpha(z)} + \frac{w^*}{\alpha^*(z)}. \tag{4}$$

Let $s(z)$ denote the home firm's share in the home market for good z, and $s^*(z)$ denote the home (not foreign) firm's share in the foreign market for good z. L and L^* denote home and foreign labor endowments. Then, we can show that

$$s(z) = \frac{\frac{\alpha(z)}{\alpha^*(z)}\frac{L}{L^*}}{\frac{\alpha(z)}{\alpha^*(z)}\frac{L}{L^*}+\frac{1}{\tau}}, \tag{5}$$

$$s^*(z) = \frac{\frac{\alpha(z)}{\alpha^*(z)}\frac{L}{L^*}}{\frac{\alpha(z)}{\alpha^*(z)}\frac{L}{L^*}+\tau}. \tag{6}$$

The proofs for the equations above are in the appendix. (5) and (6) state that the home firm's share, in both the home and foreign market, increases with the home firm's relative productivity $\alpha(z)/\alpha^*(z)$. It also increases with L/L^* because an increase in L/L^* reduces the relative wage w/w^*. Because $\tau > 1$, $s(z)$ is always greater than $s^*(z)$. In addition, an increase in τ raises $s(z)$ and lowers $s^*(z)$, intensifying home bias in sales.

We introduce the following notations to express the link between production pattern and trade pattern in terms of variables observed in industry-level data.

$$s_n = \int_{z \in I_n} \frac{\gamma(z)}{\beta_n} s(z)\, dz, \tag{7}$$

$$\overline{s} = \textstyle\sum_{n=1}^{N} \beta_n\, s_n, \tag{8}$$

$$s_n^* = \int_{z \in I_n} \frac{\gamma(z)}{\beta_n} s^*(z)\, dz, \tag{9}$$

$$\overline{s^*} = \textstyle\sum_{n=1}^{N} \beta_n\, s_n^*\,. \tag{10}$$

In other words, s_n is the home firms' average share in the home markets of industry n, and $\overline{s}$ is the home firms' average share in the home markets of all industries. The weights in each case are given by the markets' relative sizes, which in turn are determined by the expenditure shares. Similarly, s_n^* and $\overline{s^*}$ are the home firms' average shares in the foreign markets. Let Y_n and Y_n^* be home and foreign valued added produced in industry n. Then, $Y = \sum_{n=1}^{N} Y_n$ and $Y^* = \sum_{n=1}^{N} Y_n^*$. The total expenditures of home and foreign consumers on goods of industry n are equal to $\beta_n\, Y$ and $\beta_n\, Y^*$, and the home firms' shares in the home and foreign market are equal to s_n and s_n^*, respectively. Therefore, the following equations must hold.

$$Y_n = s_n\, \beta_n\, Y + s_n^*\, \beta_n\, Y^*, \tag{11}$$

$$Y_n^* = (1 - s_n)\, \beta_n\, Y + (1 - s_n^*)\, \beta_n\, Y^*. \tag{12}$$

Adding both sides of (11) over n, we obtain $Y = \bar{s}\, Y + \overline{s^*}\, Y^*$. Therefore, the share of home GDP in world GDP is given by:

$$\frac{Y}{Y_W} = \frac{\overline{s^*}}{1 - \bar{s} + \overline{s^*}}. \tag{13}$$

where Y_W is equal to $Y + Y^*$. Let X_n and X_n^* be the home and foreign country's exports in industry n. Then, using (13), we obtain

$$X_n = s_n^*\, \beta_n\, Y^* = \frac{s_n^*}{\overline{s^*}}\, \beta_n\, (1 - \overline{s} + \overline{s^*})\, \frac{Y\, Y^*}{Y_W}, \tag{14}$$

$$X_n^* = (1 - s_n)\, \beta_n\, Y = \frac{1 - s_n}{1 - \overline{s}}\, \beta_n\, (1 - \overline{s} + \overline{s^*})\, \frac{Y\, Y^*}{Y_W}. \tag{15}$$

The current study investigates the influence of Ricardian comparative advantage on trade intensity, production specialization, and intra-industry trade. Trade intensity is normalized trade volume. It is frequently measured as the ratio of bilateral trade volume to the sum of partner incomes or as the ratio of bilateral trade volume to the product of partner incomes. The latter method has a more theoretical basis because most gravity equation theories express the latter ratio as a function of trade costs and other variables. The most influential gravity models—those of Eaton and Kortum (2002), Anderson and van Wincoop (2003), and Chaney (2008)—all derive from a multi-country model the gravity equation in the following form.

$$\frac{X_{ij}}{\frac{Y_i Y_j}{Y_W}} = \left(\frac{\tau_{ij}}{\Pi_i P_j}\right)^{1-\theta}. \tag{16}$$

X_{ij} denotes the value of exports from county i to country j, Y_i country i's income, Y_W world income, and τ_{ij} transportation costs from county i to country j. θ represents different parameters in different models. θ is equal to a parameter measuring inter-firm technological heterogeneity in the Ricardian model of Eaton and Kortum (2002) or in the monopolistic competition model of Chaney (2008).[1] It is given by the elasticity of substitution in the demand for differentiated products in the monopolistic competition model of Anderson and Van Wincoop (2003). Π_i and P_j are the complex functions of trade costs, price levels, and incomes involving all trading partners of countries i and j. Their exact form varies between models. The literature calls them "multilateral resistance" terms, following Anderson and Van Wincoop (2003). The right-hand side of (16) becomes equal to 1 in the absence of trade costs in all models.

As in the above literature, we measure trade intensity as the ratio of trade volume to the product of partner incomes (relative to world income). We first show that in our two-country model, trade intensity is determined as

$$TRADE \equiv \frac{X}{Y\,Y^*/Y_W} = \frac{X^*}{Y\,Y^*/Y_W} = 1 - \bar{s} + \bar{s}^*. \tag{17}$$

$X = \sum_{n=1}^{N} X_n$ and $X^* = \sum_{n=1}^{N} X_n^*$. (17) directly follows from (8) and (14). It is strikingly simple compared to (16). Trade intensity depends only on the difference between the average share of home firms in the home market and that in the foreign market, which in turn is increasing in trade costs as we show later. Of course, this is a special result coming from a two-country model with restrictive assumptions.

We measure the degree of bilateral production specialization by the difference in industrial structure:

$$SPEC \equiv \frac{1}{2}\sum_{n=1}^{N}\left|\frac{Y_n}{Y} - \frac{Y_n^*}{Y^*}\right| = \frac{1}{2}\sum_{n=1}^{N}\left|\frac{s_n^*}{\bar{s}^*} - \frac{1-s_n}{1-\bar{s}}\right| \beta_n\,(1 - \bar{s} + \bar{s}^*). \tag{18}$$

The proof for (18) is in the appendix. When the two countries have an identical industry structure, that is, $Y_n/Y = Y_n^*/Y^*$ for every n, *SPEC* takes the minimum value of 0. If complete specialization occurs in the sense that whenever one country produces in an industry, the other country does not produce in the same industry, *SPEC* takes the maximum value of 1. A few authors have used the index to measure the degree of bilateral specialization between two regions. (Krugman, 1991; Clark and van Wincoop, 2001; and Imbs, 2004). Note that $s_n^*/\bar{s}^*$ is the home country's foreign market share in industry n relative to its overall foreign market share. Meanwhile, $(1-s_n)/(1-\bar{s})$ is the foreign country's home market share in industry n relative to its overall home market share. (18) states that the specialization index is increasing in the difference between the two countries in the distribution of overseas market shares.

To measure the intensity of intra-industry trade, we use a transformation of the Grubel-Lloyd (1975) index:

$$IIT \equiv \left(\frac{\sum_{n=1}^{N}|X_n - X_n^*|}{\sum_{n=1}^{N}(X_n + X_n^*)}\right)^{-1} = \left(\frac{1}{2}\sum_{n=1}^{N}\left|\frac{s_n^*}{\bar{s}^*} - \frac{1-s_n}{1-\bar{s}}\right|\beta_n\right)^{-1} \tag{19}$$

[1] Chaney (2008) has an additional term for capturing the fixed costs of exporting.

Note that *IIT* is equal to $1/(1 - \text{the Grubel Lloyd index})$. IIT takes the minimum value of 1 when all trade is inter-industry trade, and it goes to infinity when all trade is intra-industry trade ($X_n = X_n^*$ for every n). (19) is proved in the appendix.

Comparing (17), (18) and (19), we can see that

$$TRADE = SPEC \times IIT. \tag{20}$$

Trade intensity is equal to the product of the degree of production specialization and the intensity of intra-industry trade. This is not a special property of our model. Song (2011) shows that (20) always hold in a world of two countries running balanced trade if transportation costs of iceberg type are the only barrier to trade and consumers have identical Cobb-Douglas preferences. In traditional trade models such as the Ricardian or the Heckscher-Ohlin model where intra-industry trade does not exist, *IIT* is equal to 1. Without intra-industry trade, trade is nothing but the difference between the production and the consumption vector at the industry level, and when trading partners share a common consumption structure, trade intensity is equal to the difference in production structure. By contrast, in the new trade theory, trade intensity can be high or low for a given difference in industrial structure depending on how much two-way trade occurs in identical industries.

To link the three indexes above to the industry distribution of productivities, we define the following variables.

$$\alpha_n = \int_{z \in I_n} \alpha(z) \frac{\gamma(z)}{\beta_n} dz, \tag{21}$$

$$\overline{\alpha} = \sum_{n=1}^{N} \alpha_n \, \beta_n, \tag{22}$$

$$\alpha_n^* = \int_{z \in I_n} \alpha^*(z) \, \frac{\gamma(z)}{\beta_n} dz, \tag{23}$$

$$\overline{\alpha^*} = \sum_{n=1}^{N} \alpha_n^* \, \beta_n. \tag{24}$$

α_n is the average productivity of the home firms in industry n, and $\overline{\alpha}$ is the average productivity of all home firms. Again, the weights are given by the relative sizes of the markets. Similarly, α_n^* and $\overline{\alpha^*}$ are the foreign firms' average productivity in industry n and and that in all industries.

The market shares in (5) and (6) are nonlinear functions of commodity-level productivities. Thus, to express them as functions of industry averages, we linearize (5) and (6) in terms of $\alpha(z)$, $\alpha^*(z)$, and τ at $\alpha(z) = \overline{\alpha}$, $\alpha^*(z) = \overline{\alpha^*}$, and $\tau = 1$. We obtain

$$s(z) \cong \sigma + \sigma(1-\sigma)\left(\frac{\alpha(z)}{\overline{\alpha}} - \frac{\alpha^*(z)}{\overline{\alpha^*}}\right) + \sigma(1-\sigma)(\tau - 1), \tag{25}$$

$$s^*(z) \cong \sigma + \sigma(1-\sigma)\left(\frac{\alpha(z)}{\overline{\alpha}} - \frac{\alpha^*(z)}{\overline{\alpha^*}}\right) - \sigma(1-\sigma)(\tau - 1). \tag{26}$$

The proof is in the appendix. σ is a constant, which can be interpreted as the home firm's market share when $\alpha(z) = \overline{\alpha}$, $\alpha^*(z) = \overline{\alpha^*}$, and $\tau = 1$.

$$\sigma = \frac{\frac{\overline{\alpha}}{\overline{\alpha^*}} \frac{L}{L^*}}{\frac{\overline{\alpha}}{\overline{\alpha^*}} \frac{L}{L^*} + 1} \tag{27}$$

Plugging (25) and (26) into (7) through (10), we obtain

$$s_n \cong \sigma + \sigma(1-\sigma)\left(\frac{\alpha_n}{\overline{\alpha}} - \frac{\alpha_n^*}{\overline{\alpha^*}}\right) + \sigma(1-\sigma)(\tau-1), \tag{28}$$

$$\bar{s} \cong \sigma + \sigma(1-\sigma)(\tau-1), \tag{29}$$

$$s_n^* \cong \sigma + \sigma(1-\sigma)\left(\frac{\alpha_n}{\overline{\alpha}} - \frac{\alpha_n^*}{\overline{\alpha^*}}\right) - \sigma(1-\sigma)(\tau-1), \tag{30}$$

$$\overline{s^*} \cong \sigma - \sigma(1-\sigma)(\tau-1). \tag{31}$$

Finally, we plug these approximations into (17), (18) and (19) to obtain the following equations.

$$TRADE \equiv \frac{X}{Y\,Y^*/Y_W} = 1 - 2\sigma(1-\sigma)(\tau-1), \tag{32}$$

$$SPEC = \frac{1}{2}\sum_{n=1}^{N}\left|\frac{Y_n}{Y} - \frac{Y_n^*}{Y^*}\right| = \big(1 - 2\sigma(1-\sigma)(\tau-1)\big)\,\rho(\tau)\,PRODDIF, \tag{33}$$

$$IIT = \left(\frac{\sum_{n=1}^{N}|X_n - M_n|}{\sum_{n=1}^{N}(X_n + M_n)}\right)^{-1} = (\rho(\tau)\,PRODDIF)^{-1}, \tag{34}$$

where

$$PRODDIF = \frac{1}{2}\sum_{n=1}^{N}\left|\frac{\alpha_n}{\overline{\alpha}} - \frac{\alpha_n^*}{\overline{\alpha^*}}\right|\beta_n, \tag{35}$$

$$\rho(\tau) = \frac{\sigma}{1-\sigma(\tau-1)} + \frac{1-\sigma}{1-(1-\sigma)(\tau-1)}. \tag{36}$$

$PRODDIF$ is our key variable. The essence of the Ricardian trade theory is that productivity differences, or more precisely the difference in the industry distribution of productivities between trading partners, are the driver of trade. *PRODDIF* offers a theory-based measure of this difference. When the mean-differenced productivities of the two countries are similarly distributed across industries, or when the pattern of comparative advantages is weak, *PRODDIF* will be close to zero. As the pattern of comparative advantage becomes stronger, it will increase toward 1. (33) states that the extent of specialization is proportional to this Ricardian measure of productivity differences. Meanwhile, (34) states that the degree of intra-industry trade is inversely proportional to the measure of productivity differences.

However, our result on trade intensity in (32) is non-Ricardian. Trade intensity is not affected by the difference in productivity distribution. Only transportation cost τ affects trade intensity by driving in the wedge between firms' market shares in the two countries. Productivity differences increase specialization, enlarging trade flows, but they decrease intra-industry trade, reducing trade flows. The two effects exactly offset each other because trade intensity is equal to the product of specialization and intra-industry trade.

Finally, we note that $\rho(\tau)$ is increasing in τ. Therefore, IIT is decreasing in τ, as can be seen from (34). However, the effect of τ on *SPEC* is ambiguous. $\big(1 - 2\sigma(1-\sigma)(\tau-1)\big)\,\rho(\tau)$ can increase or decrease with τ in (33).

3. Empirical Results

3.1. Data and Measurements

Our data on bilateral trade and value-added at the industry level are obtained from the World Input-Output Database (WIOD, Release 2013); see Timmer et al. (2015) for details.

The database provides annual data from 1995 to 2011 for 40 countries, including most major industrial countries and some emerging economies. Some data are estimated rather than observed, but the database suits our purpose in that it presents trade and production data in a mutually consistent way. We will restrict our investigation to manufacturing, which the WIOD classifies into 14 industries according to the International Standard Industrial Classification (ISIC) Revision 3. Table 1 presents the description for these industries.

The 14 industry classification of manufacturing may not be fine enough to catch all the major trade and industry structure variations. Our choice was dictated by the availability of consistent data on labor productivity. To obtain internationally comparable data on labor productivity, which is crucial to calculate our key index *PRODDIF*, we have to deflate nominal labor productivities calculated from national sources by international relative prices based on purchasing power parity. The most reliable source for relative producer price indexes at the industry level that we can find is the GGDC Productivity Level Database (2005 Benchmark); see Inklaar and Timmer (2014) for details.[2] The database was constructed as a complement to the WIOD, and thus uses the same industry classification as the WIOD. Following Mano and Castillo (2015), we stretch them to other years using inflation rates in local currencies because only the price indexes for a single year (2005) were provided.

Table 1. Industry Classification

Industry description	**ISIC Rev. 3 Code**
Food , beverages and tobacco	15 to 16
Textiles and textile products	17 to 18
Leather, leather products and footwear	19
Wood, wood products and cork	20
Paper, paper products, printing and publishing	21 to 22
Coke, refined petroleum and nuclear fuel	23
Chemicals and chemical products	24
Rubber and plastics products	25
Other nonmetallic mineral products	26
Basic metals and fabricated metal products	27 to 28
Machinery and equipment n.e.c.	29
Electrical and optical equipment	30 to 33
Transport equipment	34 to 35
Manufacturing n.e.c. and recycling	36 to 37

Source: Timmer et al. (2015).

The labor productivity of industry n in country i in year t is calculated by the following formula.

$$\alpha_{nit} = \frac{Y_{nit}}{L_{nit}} \frac{1}{P_{nit} \quad EX_{i2005} \quad PPP_{ni2005}}. \tag{37}$$

[2] The database matches numerous products in different countries meticulously to control for quality differences. Costinot et al. (2012) also use this database to test the Ricardian prediction from the Eaton and Kortum (2002) model.

For industry n in country i in year t, Y_{nit} is gross value added in current local currency units, L_{nit} is the number of engaged people, P_{nit} is the local price index of gross value added using 2005 as the base year ($P_{ni2005} = 1$). These data come from the Socio Economic Accounts of the WIOD. EX_{i2005} is the nominal exchange rate of local currency units per USD in 2005. PPP_{ni2005} is the relative price level of gross output in year 2005 using US GDP as the numeraire (its price level is equal to 1). It comes from the GGDC Productivity Level Database.[3] The idea is that labor productivity in current local currency units (Y_{nit}/L_{nit}) is converted into constant 2005 local currency units via P_{nit}, then into 2005 USD via EX_{i2005}, and then into 2005 international price units via PPP_{ni2005}.

Our theory comes from a two-country world with balanced trade, but, somewhat uncomfortably, we apply it to data from the multi-country world with unbalanced bilateral trade. To do that, we slightly modify the definition of our indexes.

$$TRADE_{ijt} \equiv \frac{\sqrt{X_{ijt}}\sqrt{X_{jit}}}{Y_{it}\,Y_{jt}/(Y_{it}+Y_{jt})}. \tag{38}$$

Y_{it} is total manufacturing valued added of country i in year t. Bilateral trade is not balanced in the data; hence, we use the geometric average of exports from i to j (X_{ijt}) and exports from j to i (X_{jit}). The other indexes are calculated as:

$$SPEC_{ijt} = \frac{1}{2}\sum_{n=1}^{N}\left|\frac{Y_{nit}}{Y_{it}} - \frac{Y_{njt}}{Y_{jt}}\right|, \tag{39}$$

$$IIT_{ijt} = \left(\frac{\sum_{n=1}^{N}|X_{nijt}-X_{njit}|}{\sum_{n=1}^{N}(X_{nijt}+X_{njit})}\right)^{-1}, \tag{40}$$

$$PRODDIF_{ijt} = \frac{1}{2}\sum_{n=1}^{N}\left|\frac{\alpha_{nit}}{\overline{\alpha_{it}}} - \frac{\alpha_{njt}}{\overline{\alpha_{jt}}}\right|\beta(n). \tag{41}$$

$\beta(n)$ in (41), the expenditure share of industry n, is calculated using the share of industry n in the world output of manufactured goods.

Finally, we capture bilateral transportation cost τ by geographical variables used in the standard gravity equations. Data for distance and dummies for contiguity, common language, colonial ties, and RTAs come from the CEPII gravity dataset (Head, Mayer, and Ries, 2010; Head and Mayer, 2014).

Because structural changes would be slow, we use observations made in the quadrennial years of 1996, 2000, 2004, and 2008 out of the entire sample years from 1995 to 2011.[4] All four indexes above can be obtained for country pairs composed of 34 countries. Most of them are OECD countries, but some non-OECD countries (Bulgaria, Brazil, China, Indonesia, India, Lithuania, and Russia) are also included. Countries covered are listed in the footnote of Table 2. Every index above is identical for country pairs (i, j) and (j, i); thus, we use only one of them. Our panel is almost balanced. We make on average 3.9 observations per country pair for 561 country pairs, totaling 2,209 observations.

Table 2 reports the summary statistics for our indexes. Because trade is almost zero for many country pairs (but it is never exactly zero), the mean of *TRADE* is small. *SPEC* and *PRODDIF* have the mean of 0.25 and 0.24, respectively, out of the possible maximum of 1.

[3] Ideally, we should use the price level of gross value added, but it is not available at the level of disaggregation.

[4] We cannot use most of the data for 2010 and 2011 because we cannot observe labor productivities for many countries.

The mean of *IIT* is approximately 2, which corresponds to the Grubel-Lloyd index equal to 0.5.

Table 2. Summary Statistics for Key Indexes

Variable	Mean	Std. Dev.	Min	Max	Obs.
TRADE	0.07	0.12	0.00	1.34	2,209
SPEC	0.25	0.08	0.06	0.55	2,209
IIT	2.05	1.03	1.00	10.99	2,209
PRODDIF	0.24	0.11	0.04	0.62	2,209

Notes: The indexes are calculated from data on 34 countries (Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Japan, Korea, Latvia, Mexico, Netherlands, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Turkey, UK, USA, Bulgaria, Brazil, China, Indonesia, India, Lithuania, and Russia) observed for the four years 1996, 2000, 2004, and 2008. The industries covered are the 14 manufacturing industries of Table 1.

Sources: WIOD (2013 Release); GGDC Productivity Level Database (2005 Benchmark).

Table 3 presents the correlations among the four indexes. All correlation coefficients are highly significant. *TRADE* is strongly positively correlated with *IIT*. *SPEC* is positively correlated, and *IIT* is negatively correlated with *PRODDIF*, in accordance with our model. The negative correlation between *TRADE* and *SPEC* does not accord well with our model, and neither does the negative correlation between *TRADE* and *PRODDIF*. However, what matters is partial correlations, conditional upon other variables, which we now investigate.

Table 3. Correlations among Key Indexes

	TRADE	*SPEC*	*IIT*	*PRODDIF*
TRADE	1.00			
SPEC	-0.17 ***	1.00		
IIT	0.60 ***	-0.41 ***	1.00	
PRODDIF	-0.13 ***	0.18 ***	-0.26 ***	1.00

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Sources: WIOD (2013 Release); GGDC Productivity Level Database (2005 Benchmark).

3.2. Estimation Results

We start by examining the determinants of trade intensity in Table 4. Taking natural logarithm of (20),

$$\ln TRADE_{ijt} = \ln SPEC_{ijt} + \ln IIT_{ijt}. \tag{42}$$

(42) would not fit the data perfectly because the world is distant from our two-country Ricardo-Cournot model. This study asks how much trace of our simple model we can detect in the data. In regression (1), we regress $\ln TRADE$ on $\ln SPEC$ and $\ln IIT$ without controlling for any other variable. We do not intend to test (42) by running this regression. *TRADE, SPEC* and *IIT* are jointly determined by the influence of many variables, and by relative productivity differences and trade costs even in the narrow context of our model, generating endogeneity problems. We just inspect the partial correlations of *TRADE* with

Table 4. Trade, Specialization, Intra-industry trade, and Productivity Differences

Dependent variable	(1) ln $TRADE$	(2) ln $TRADE$	(3) ln $TRADE$	(4) ln $TRADE$
ln $SPEC$	0.29**	0.28**		0.29**
	(0.13)	(0.12)		(0.12)
ln IIT	2.35***	0.80***		0.80***
	(0.11)	(0.11)		(0.11)
ln $PRODDIFF$			-0.10	-0.06
			(0.07)	(0.07)
ln Distance		-0.81***	-0.91***	-0.80***
		(0.06)	(0.06)	(0.06)
Contiguity		0.58***	0.72***	0.58***
		(0.13)	(0.14)	(0.13)
Common language		0.38***	0.44***	0.37***
		(0.15)	(0.15)	(0.15)
Colony		0.16	0.20	0.16
		(0.17)	(0.18)	(0.17)
RTA		-0.06	-0.00	-0.07
		(0.12)	(0.12)	(0.12)
Fixed Effects		country×year	country×year	country×year
R^2	0.37	0.71	0.69	0.71
Obs.	2,209	2,209	2,209	2,209

Notes: Numbers in parentheses are robust standard errors clustered by country pairs.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

$SPEC$ and IIT to check the usefulness of the latter variables in the least squares sense. In regression (1), we observe significant positive partial correlations, which agree with our model, but the coefficients are quite different from the theoretical values of 1.[5] For example, the coefficient of 0.29 on ln $TRADE$ implies that a 10% increase in the specialization index (say from the sample mean of 0.25 in Table 2 to 0.275) would raise trade intensity by 2.9% (say from the sample mean of 0.07 in Table 2 to 0.072). However, according to equation (42), a 10% increase in the specialization index should raise trade intensity by a full 10%. The coefficient of 2.35 on ln IIT implies that a 10% increase in the intra-industry index (say from the sample mean of 2.05 in Table 2 to 2.255) would raise trade intensity by 23.5% (say from the sample mean of 0.07 in Table 2 to 0.086), not by a 10% as dictated by equation (42). However, we note that the R-squared of 0.37 seems high with just two variables.

In regression (2), we inspect the explanatory powers of bilateral production and trade structure differently. We plug the indexes in the gravity equation to see if they have any additional explanatory power over the standard gravity variables. The log of distance and binary dummies for contiguity, common language, colonial ties, RTAs are geographical variables frequently used to capture the effect of trade costs in gravity equations. Additionally, as has now become standard in the estimation of gravity equations (see Head, Mayer, and Ries, 2014), we also include country dummies to control for the third countries effects or the

[5] Standard errors reported in Table 4 are clustered by country pairs to correct for possible serial correlations among error terms. Without clustering, all the coefficients on ln $SPEC$ in Table 1 are significant at 1%.

"multilateral resistance" of Anderson and van Wincoop (2014). These country dummies can also be regarded as representing the scales of countries (population, land etc.) or country-specific trade barriers. These variables change over time; thus, we introduce country dummies that vary over years (country × year fixed effects).[6] In regression (2), we see that the coefficients for $\ln SPEC$ and $\ln IIT$ are significantly positive, although they are significantly smaller than the theoretical value of 1. Bilateral production and trade structure have extra explanatory power over the theory-based variables that are commonly employed to predict bilateral trade volume.

In regression (3), we test the first prediction of our model. According to equation (32), $\ln TRADE$ should not be systemically influenced by productivity differences after we control for the effects of trade costs because its effects on specialization and intra-industry trade cancel each other. However, it should be negatively affected by trade costs. We capture the effect of trade costs using the same geographical variables as used in regression (2). The estimation result supports our model. The coefficient for $\ln PRODDIF$ is not significantly different from zero, whereas most trade cost variables negatively affect trade intensity. In regression (4), we add $\ln SPEC$ and $\ln IIT$ in the equation. These two variables are endogenous variables, while $\ln PRODDIF$ is an exogenous variable that determines these variables. Thus, potential econometric problems exist. However, by running this regression, we might be able to check if productivity differences influence trade intensity only through specialization and intra-industry trade, but not independently from them, as our theory argues. We find that the coefficients for $\ln SPEC$ and $\ln IIT$ change little from those in regression (2), and the coefficient for $\ln PRODDIF$ is still insignificant. This agrees with our theory.

Table 5. Specialization, Intra-industry trade, and Productivity Differences

Dependent variable	**(5)** **$\ln SPEC$**	**(6)** **$\ln SPEC$**	**(7)** **$\ln IIT$**	**(8)** **$\ln IIT$**
$\ln PRODDIFF$	0.17^{***}	0.12^{***}	-0.16^{***}	-0.09^{***}
	(0.02)	(0.02)	(0.02)	(0.02)
ln Distance	0.02	0.04^{*}	-0.11^{***}	-0.14^{***}
	(0.02)	(0.02)	(0.02)	(0.02)
Contiguity	-0.18^{***}	-0.19^{***}	0.25^{***}	0.25^{***}
	(0.06)	(0.06)	(0.08)	(0.06)
Common language	-0.11^{**}	-0.06	0.23^{***}	0.10^{*}
	(0.05)	(0.05)	(0.06)	(0.05)
Colony	-0.07	-0.08	0.06	0.07
	(0.09)	(0.07)	(0.09)	(0.06)
RTA	0.07^{**}	0.10^{***}	0.11^{***}	0.05
	(0.03)	(0.04)	(0.03)	(0.03)
Fixed Effects	year	country × year	year	country × year
R^2	0.10	0.38	0.35	0.55
Obs.	2,209	2,209	2,209	2,209

Notes: Numbers in parentheses are robust standard errors clustered by country pairs.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

[6] We do not distinguish between export from country *i* to *j* and export from country *j* to *i*. Therefore, we restrict a dummy for country *i* to have the same coefficient when it is an exporter and it is an importer.

We test the other predictions of our model in Table 5. Taking the logarithm of both sides, equation (33) predicts that ln $SPEC$ increases one-to-one with ln $PRODDIF$, but it is ambiguously affected by trade costs. Regression (5) is largely consistent with this prediction. The coefficient for ln $PRODDIF$ is 0.17 and highly significant. In regression (6), we add time-varying country fixed effects. Unlike the case of gravity equations, theoretical justification for including these variables is not straightforward, but they can be thought as representing country-specific trade barriers. ln $PRODDIF$ is still significantly positive, although its coefficient shrinks. The influence of variables representing trade costs is not clear-cut. The negative estimated coefficients on *Contiguity* in regressions (5) and (6) suggest a positive influence of trade costs on specialization. In contrast, the positive coefficient on RTA implies a negative influence, and distance seems to have little effect.

In regressions (7) and (8), we confirm the negative influence of productivity differences on intra-industry trade, supporting equation (33). The estimated coefficients on ln $PRODDIF$ are negative and highly significant. The estimated coefficients on geographical variables are also largely consistent with our theory. The coefficients on *Distance*, *Contiguity*, *Common language* and RTA in regression (7) all imply the negative effects of trade costs on intra-industry trade, supporting equation (34). However, the significance of *Common language* and RTA almost vanishes in regression (8) where we incorporate time-varying country fixed effects.

The estimated coefficients on ln $PRODDIFF$ are all significant at the 1% level. However, their absolute values are much smaller than 1, the value predicted by our theory. The reason is unclear to us. It could be measurement errors that frequently show up in labor productivity statistics. Or, as we mentioned before, our industry classification composed of only 14 industries may be too coarse to catch the variations of productivity distribution across countries and years. However, the main reason is probably the presence of third country effects. The production and trade pattern of two countries trading with each other must be heavily influenced by those of the other countries that two countries trade with. Our two-country model does not capture this influence, and hence its prediction would only be partly reflected in the data.

Table 6. Regressions with Pair Fixed Effects

Dependent variable	(9) ln $TRADE$	(10) ln $TRADE$	(11) ln $SPEC$	(12) ln IIT
ln $SPEC$	0.75^{***}			
	(0.12)			
ln IIT	0.35^{***}			
	(0.08)			
ln $PRODDIF$		0.00	0.04^{***}	-0.05^{***}
		(0.03)	(0.01)	(0.02)
RTA		0.33^{***}	0.05^{***}	0.03
		(0.06)	(0.02)	(0.03)
Fixed Effects	country pair	year country pair	year country pair	year country pair
R^2	0.06	0.29	0.10	0.04
Obs.	2,209	2,209	2,209	2,209

Notes: Numbers in parentheses are robust standard errors clustered by country pairs. All variables in Table 5 that are constant over time are dropped because country pair dummies subsume them. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Finally, in Table 6, we focus on the time series variations of our indexes within country pairs. In all regressions, we introduce country-pair fixed effects. They can be regarded as capturing all time-invariant bilateral trade costs.[7] Regression (9) is the counter part of regression (1). We examine the partial correlations of trade intensity, in this case across time, with specialization and intra-industry trade. They are all highly significant and positive, and their sizes are also large. Over time, trade intensity, specialization and intra-industry trade tend to move together. In regressions (10), (11) and (12), we test equations (31), (32) and (33), respectively. Productivity differences have no effect on trade intensity, a positive effect on specialization and a negative effect on intra-industry trade, all confirming the predictions of our model. However, the estimated effect of $\ln \mathit{PRODDIF}$ becomes even smaller with pair fixed effects.

4. Conclusion

This paper tests propositions regarding how bilateral trade intensity is related to differences between trading partners in production structure and in productivity distribution. These variables had been central in the analysis of bilateral trade flows, but are seldom used in recent studies. We find that bilateral trade intensity is increasing in both specialization and intra-industry trade, but it is not affected by productivity differences. The reason is that productivity differences intensify specialization, but reduce intra-industry trade, the two effects offsetting each other. However, the estimated effects of productivity differences on specialization and intra-industry are much smaller than the values predicted by our model. This is mostly likely due to the presence of third-country effects that our model ignores. We should improve our model to incorporate them.

We believe that our empirical finding is interesting by itself. However, we also believe that this study contributes toward enlarging the applicability of oligopolistic trade models by deriving tractable and testable propositions using a general equilibrium Cournot model. Oligopolistic trade models once occupied a central stage in trade theory when oligopoly played a starring role in the formation of strategic trade policy theory in the 1980s. After that, they faded out and the literature has been dominated by new theories based on perfect and monopolistic competition that assume the world composed of atomistic firms. This transition is ironic because it occurred when a small number of giant multinationals were increasingly dominating international trade.

The relative decline of oligopolistic models may be due to two major reasons: tractability and utility. For tractability, incorporating oligopolistic models into a general equilibrium model and producing testable propositions are very difficult. For utility, oligopolistic models may be superior in terms of descriptive realism, but why should we use messy models when we have alternative models that look unrealistic, but handle most questions more elegantly? This paper bypasses the first hurdle by imposing quite restrictive assumptions. They are difficult to justify at the high level of rigor, but we extract the central features of Cournot oligopoly with maximum tractability, and let them interact with the Ricardian forces of comparative advantage. In our model, trade occurs not because of cost differences or product differentiation. Trade occurs as Cournot competitors try capturing foreign monopoly rents. The mutual penetration of the foreign rival's market in a single industry generates intra-industry trade, and it drives all trade.

[7] We tried regressions that incorporate both pair fixed effects and country-year fixed effects, but we do not report them here because a multi-collinearity problem occurred in our Stata program in this case.

In this setting, the distribution of market shares between international rivals becomes a dominant force for determining trade volume and pattern. Trade volume, relative to the product of trading partners' GDPs, is decreasing in the difference between firms' market shares in the home and foreign market. An increase in trade costs enlarges this difference, and thus decreases trade volume. In other words, our model produces a gravity equation based on international market share rivalry, which is distinct from other gravity theories. Simultaneously, relative productivity between international rivals determines their relative market shares, and this is where Ricardian comparative advantage kicks in. When the pattern of comparative advantage is strong, or when productivity differences between international rivals are on average large, the asymmetry between their market shares is on average high, implying a low level of pure cross-hauling or intra-industry trade. However, net trade is large across industries because in each country, resources move toward industries where domestic firms have larger market shares. This leads to a high level of specialization and inter-industry trade. The two forces exactly offset each other in our model, and comparative advantage does not affect overall trade volume. However, it strongly affects the intensity of intra-industry trade and the degree of production specialization. The exact cancelation may not hold in a more general setting. However, the main mechanism through which the interplay between Cournot competition and Ricardian comparative advantage determines trade volume and pattern would survive many extensions. We also believe that the mechanism newly identified in this study is working in the real world because it is supported by our empirical findings.

Regarding the second reason for the decline of oligopolistic models, this study contributes little, but may serve as a basis for future studies that enhance the usefulness of oligopolistic models. To prove utility, we must demonstrate the usefulness of Cournot models in tacking questions that models based on perfect or monopolistic competition are ill-equipped to handle. Such questions include the effects of trade policies on income distribution because oligopolistic models generate excess profits, the welfare effect of trade policies because they can improve national welfare by profit-shifting, and the effect of competition policies because they constrain oligopolists' behavior. Partial equilibrium models have analyzed these issues, but exploring their interactions with comparative advantage in a general equilibrium setting has a potential to generate interesting results. Although we do not pursue these difficult challenges here, our model may serve as a basis for further extensions to address these issues.

Another aspect of Cournot competition that can be explored in this paper is the effect of trade costs on trade volume in oligopolistic models. Cournot firms consider the effect of their own decision on the market price, and this leads to the behavior called "pricing to the market." This may imply the relationship between trade costs and trade volume quite distinct from those found in models based on perfect or monopolistic competition. Our model implies that the negative effect of trade costs on trade volume intensifies as international rivals become more symmetric in size. Pursuing and testing its general-equilibrium implication should be deferred to a future study.

Finally, this paper treats productivity differences among countries as exogenous variables, as most Ricardian models implicitly assume. However, in the presence of scale economies or endogenous technological change, they may be determined simultaneously with trade flows. Overcoming this problem econometrically or endogenizing productivity differences as in the new literature on the role of institutions in the formation of comparative advantage (*e.g.* Levchenko, 2007; Nunn, 2007; Chor, 2010) should also be left as a future task.

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Appendix

A.1 Proof for equations (3), (4), and (5)

Let w and w^* be the home and foreign wage, respectively. In the home market, the profit maximization of the duopolists implies that

$$p(z)\big(1-s(z)\big)=\frac{w}{\alpha(z)}, \tag{A1}$$
$$p(z)s(z)=\frac{\tau w^*}{\alpha^*(z)}. \tag{A2}$$

From these equations, we obtain (3). (4) is similarly derived. By plugging (3) into (A2), we can calculate that

$$s(z)=\frac{\frac{\tau w^*}{\alpha^*(z)}}{\frac{w}{\alpha(z)}+\frac{\tau w^*}{\alpha^*(z)}}. \tag{A3}$$
$$s^*(z)=\frac{\frac{w^*}{\alpha^*(z)}}{\frac{\tau w}{\alpha(z)}+\frac{w^*}{\alpha^*(z)}}. \tag{A4}$$

The total income of home workers must be equal to the total employment of the home firms times w. Therefore,

$$\begin{aligned} w\,L &= \int_0^1 \Big[s(z)\frac{w}{\alpha(z)}\,d(z)+s^*(z)\frac{\tau w}{\alpha(z)}\,d^*(z)\Big]\,dz\,,\\ &= \int_0^1\Big[s(z)\frac{\frac{w}{\alpha(z)}}{\frac{w}{\alpha(z)}+\frac{\tau w^*}{\alpha^*(z)}}\,\gamma(z)\,Y+s^*(z)\frac{\frac{\tau w}{\alpha(z)}}{\frac{\tau w}{\alpha(z)}+\frac{w^*}{\alpha^*(z)}}\,\gamma(z)\,Y^*\Big]\,dz.\\ &= \int_0^1\big[s(z)(1-s(z))\,\gamma(z)\,Y+s^*(z)(1-s^*(z))\,\gamma(z)\,Y^*\big]\,dz. \end{aligned} \tag{A5}$$

Likewise,

$$\begin{aligned} w^*\,L^* &= \int_0^1 \Big[(1-s(z))\frac{\tau w^*}{\alpha^*(z)}\,d(z)+(1-s^*(z))\frac{w^*}{\alpha^*(z)}\,d^*(z)\Big]\,dz\,,\\ &= \int_0^1\big[(1-s(z))s(z)\,\gamma(z)\,Y+(1-s^*(z))s^*(z)\,\gamma(z)\;Y^*\big]\,dz. \end{aligned} \tag{A6}$$

Therefore, $w\,L=w^*L^*$. Plugging this relationship into (A3) and (A4) and reshuffling terms, we obtain (5) and (6).

A.2 Proofs for equations (18) and (19)

(18) follows from (11), (12), (13), and (16).

$$\begin{aligned} &\sum_{n=1}^{N}\left|\frac{Y_n}{Y}-\frac{Y_n^*}{Y^*}\right| = \sum_{n=1}^{N}\left|\Big(s_n\beta_n+s_n^*\beta_n\frac{1-\bar{s}}{\overline{s^*}}\Big)-\Big((1-s_n)\beta_n\frac{\overline{s^*}}{1-\bar{s}}+(1-s_n^*)\beta_n\Big)\right|\\ &=\sum_{n=1}^{N}\left|\Big(s_n+s_n^*\frac{1-\bar{s}}{\overline{s^*}}\Big)-\Big((1-s_n)\frac{\overline{s^*}}{1-\bar{s}}+(1-s_n^*)\Big)\right|\,\beta_n \end{aligned}$$

$$= \sum_{n=1}^{N} \left| \frac{s_n^*}{\overline{s^*}} - \frac{1-s_n}{1-\overline{s}} \right| \beta_n \left(1 - \overline{s} + \overline{s^*}\right). \tag{A7}$$

(19) can be similarly proved using (14), (15), and (16).

$$\frac{\sum_{n=1}^{N} |X_n - X_n^*|}{\sum_{n=1}^{N} (X_n + X_n^*)} = \frac{\sum_{n=1}^{N} \left| \frac{s_n^*}{\overline{s^*}} - \frac{1-s_n}{1-\overline{s}} \right| \beta_n \left(1-\overline{s}+\overline{s^*}\right) \frac{Y\,Y^*}{Y_W}}{2\left(1-\overline{s}+\overline{s^*}\right) \frac{Y\,Y^*}{Y_W}} = \frac{1}{2} \sum_{n=1}^{N} \left| \frac{s_n^*}{\overline{s^*}} - \frac{1-s_n}{1-\overline{s}} \right| \beta_n \,. \tag{A8}$$

A.3 Proofs for equations (25) and (26)

(5) can be rewritten as:

$$\begin{aligned}
s &= \frac{\alpha\, L}{\alpha\, L + \frac{1}{\tau}\alpha^*\, L^*} = f(\alpha, \alpha^*, \tau) \\
&\cong f(\overline{\alpha}, \overline{\alpha^*}, 1) + f_\alpha(\overline{\alpha}, \overline{\alpha^*}, 1)(\alpha - \overline{\alpha}) + f_{\alpha^*}(\overline{\alpha}, \overline{\alpha^*}, 1)(\alpha^* - \overline{\alpha^*}) + f_\tau(\overline{\alpha}, \overline{\alpha^*}, 1)(\tau - 1) \\
&= \sigma + \sigma(1-\sigma)\left(\frac{\alpha}{\overline{\alpha}} - 1\right) - \sigma(1-\sigma)\left(\frac{\alpha^*}{\overline{\alpha^*}} - 1\right) + \sigma(1-\sigma)(\tau - 1).
\end{aligned} \tag{A9}$$

Similarly, (6) can be approximated by

$$s^* = \frac{\alpha\, L}{\alpha\, L + \tau\, \alpha^*\, L^*} \cong \sigma + \sigma(1-\sigma)\left(\frac{\alpha}{\overline{\alpha}} - 1\right) - \sigma(1-\sigma)\left(\frac{\alpha^*}{\overline{\alpha^*}} - 1\right) - \sigma(1-\sigma)(\tau - 1).$$

Journal of Korea Trade Vol. 25, No. 4, June 2021, 108-127
https://doi.org/10.35611/jkt.2021.25.4.108
ISSN 1229-828X

JKT 25(4)

Received 8 April 2021
Revised 25 May 2021
Accepted 18 June 2021

The Impact of the Exchange of Sustainable Technological HR Innovation Knowledge within *Chaebols* on the Performance of Global Subsidiaries

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Abstract

Purpose – On the basis of knowledge transfer theory, we empirically explored how three types of human resource (HR) innovation knowledge exchange within a *Chaebol* drive the global subsidiary performance of the headquarters (HQ) of a *Chaebol*'s globally affiliated companies.

Design/methodology – Using a sample of 176 Korean HQ firms of the top 53 *Chaebols* and 1,061 of their foreign manufacturing subsidiaries (n = 1,061), we tested the relationship between the exchange of explorative and exploitative sustainable HR innovation knowledge among HQ firms of *Chaebols*, their subsequent transfer of technical HR knowledge via technical schemas, and the subsequent impact on the global subsidiary performance.

Findings – The *Chaebols*' decisions about the three strategic knowledge management options (i.e., the degree of exchange of explorative and exploitative technological HR innovation knowledge and the extent of HQ-subsidiary HR knowledge transfer) have highly significant relationships with the global subsidiary performance. The results help explains the conditions under which the explorative versus exchange of exploitative sustainable HR innovation knowledge pays off by showing the moderating role of the degree of HQ-to-subsidiary technical HR knowledge transfer, at least in the case of the *Chaebol* as one representative type of the emerging-market business groups.

Originality/value – As the first of its kind in the field of sustainable HR innovation knowledge management at the business group level, the present study makes a clear contribution in demonstrating how the performance of *Chaebols*' manufacturing subsidiaries depends greatly on their strategy for management of knowledge, as reflected in the choices they make about sharing both explorative and exploitative sustainable HR innovation knowledge among HQ firms and the subsequent transfer of HQ's sustainable HR innovation knowledge to the foreign subsidiaries.

Keywords: Explorative and Exploitative Exchange of Sustainable Human Resource Innovation Knowledge, Foreign Subsidiary Performance, Headquarters-to-Subsidiary Technical Human Resource Knowledge Transfer, Korean Chaebols

JEL Classifications: C31, F23, O15, Q56

1. Introduction

This research is concerned with the patterns of the exchange of sustainable technology human resource (HR) innovation knowledge and the transfer of technical HR knowledge among member firms of a *Chaebol*, i.e., a large Korean business group of sister group-affiliated companies (GACs) that are clustered under a single administrative control tower

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and financial controlling entity and are frequently run by one family and cross-shareholdings (Lee et al., 2010). The study further explores the impact of these patterns on the performance of the *Chaebols'* subsidiaries. At present, the transfer of sustainable HR innovation knowledge in multifaceted firms is becoming increasingly critical in organizations (Muñoz-Pascual et al., 2020). Those that are able to transfer sustainable HR innovation knowledge effectively from one unit to another are more productive and more likely to survive than those that are less adept. For example, previous studies suggest that multinational corporations (MNCs) may survive and prosper because of their ability to transfer and exploit sustainable HR innovation knowledge more effectively and efficiently in the intra-organizational context than through the external market mechanism (Lee et al., 2014; Lee et al., 2014; Lee et al., 2020).

Sustainable technological HR innovation knowledge refers to sustainable (environmental) innovation technology and know-how that are based on networked human-based innovative knowledge and skills (Adams et al., 2016; Cillo et al., 2019). In this vein, successful sustainable HR innovation knowledge transfer is difficult to achieve. However, organizations can realize superior performance by attaining sustainable knowledge transfer (Muñoz-Pascual et al., 2020). The efficacy and efficiency of the exchange of sustainable HR innovation knowledge is crucial within complex organizations such as *Chaebols*, especially in the recent decade, because the phenomena of sustainable HR innovation knowledge transfer among learning units have become important drivers of value creation.

Sustainable HR innovation knowledge flows occur among units of diversified domestic firms as well as among units of diversified MNCs (c.f. Adams et al., 2016; Argote et al., 2000; Cillo et al., 2019; Lee et al., 2010). Some *Chaebols* have the same HR innovation knowledge exchange patterns as diversified domestic firms, while other *Chaebols* have the same HR innovation knowledge exchange systems as the more complex systems of diversified MNCs (c.f. Cillo et al., 2019; Lee et al., 2010; Lee et al., 2014). We view HR innovation knowledge exchanges in the internationally diversified *Chaebol* as a natural extension of the sustainable HR innovation knowledge transfers that occur among units in the domestic *Chaebol*.

As several international business scholars have suggested, knowledge transfers within an MNC take place in the context of an intra-organizational "network" of different units (Buckley and Casson, 1976; Gupta and Govindarajan, 2000). A similar pattern of networking of learning members occurs in the intra-*Chaebol* context. Hence, understanding the processes by which these attributes translate into rents calls for finer-grained analyses that focus on networked knowledge exchange among *Chaebol* headquarter (HQ) units and their subsidiaries (Lee et al., 2020).

Within the *Chaebols*, diverse types of business group-level knowledge-creation and knowledge-seeking activities have become a critical organizational strategy. In the face of competition from the sophisticated technologies and managerial strategies of American, European, and Japanese competitors, *Chaebol* groups have pursued the intense exchange of sustainable technological HR innovation knowledge among HQ units, accompanied by deliberate HR knowledge transfer from the HQ unit to its manufacturing subsidiaries (c.f. Adams et al., 2016; Lee et al., 2020). As a result, an intertwined and well-protected organizational learning network has evolved as a way of, first, syndicating sustainable technological HR innovation knowledge across HQ units of the *Chaebol*, second, amalgamating technological HR innovation knowledge within each HQ unit, and, third, transferring this amalgamated knowledge from the HQ firm to its subsidiaries. We believe that these networked patterns of knowledge exchange among the HQ units of the *Chaebol* and the subsequent transfer of knowledge to their foreign manufacturing subsidiaries lead to the creation of sustainable competitive advantages that, in turn, create rent streams and enhance the global performance of GACs within the group.

The unique characteristics of these GACs and their subsidiaries have been the subject of considerable scholarly attention. Management scholars have studied the *Chaebol* phenomenon using various lenses and with different levels of granularity. *Chaebol* literature has four main streams, each explaining some facet of our phenomenon of interest: sociology, political economics, transaction costs theory, and the resource-based view of the firm. For instance, Granovetter (1994) used the sociological perspective to depict the *Chaebols* as networks of interconnected member firms, unified in purpose and coordinated in decisions by the norms and codes of behavior among them. This sociological perspective supports our networked HR knowledge transfer argument. A political economics lens (Ghemawat and Khanna, 1998) proposes why *Chaebols* would pursue intra-group sustainable HR innovation knowledge exchange so extensively. As we see it, closely tied interconnected HR innovation knowledge exchange among learning members within the group creates rents for that group. Next, transaction-cost theory (Khanna and Rivkin, 2001) can explain why *Chaebols* should focus on intra-group HR innovation knowledge exchange, that is, to overcome the market imperfections and high transaction costs in less-developed markets. Finally, the resource-based view has been used to explain *Chaebol* performance. Chang and Hong's (2000) empirical analysis argued that *Chaebols* create value through the vertical sharing of intangible and tangible resources at the group level, thereby creating idiosyncratic value.

Despite the scholastic attention on the *Chaebol* phenomenon, no study has been conducted on the management of sustainable HR innovation knowledge at the business group level to date. Hence, the present study makes a clear contribution by determining that the performance of *Chaebols*' manufacturing subsidiaries depends largely on their strategy for the management of knowledge. This dependence is reflected in the choices these businesses make about sharing their explorative and exploitative sustainable HR innovation knowledge among HQ firms and the subsequent transfer of HQ's sustainable HR innovation knowledge to foreign subsidiaries.

The purpose of this study is to explore the knowledge transfers among *Chaebol* units, specifically sustainable HR innovation knowledge-exchange processes among Korean HQ firms belonging to *Chaebols*, the transfer of HR knowledge from HQ units to their respective foreign manufacturing subsidiaries, and the impact of this HR knowledge transfer on the performance of the foreign subsidiaries. Therefore, we explore the following research questions:

1) What are the patterns of the networked exchange of sustainable technological HR innovation knowledge among the HQ firms of the *Chaebol*, and how are they related to the performance of their foreign manufacturing subsidiaries?
2) What are the patterns of the deliberate transfer of technical HR knowledge by HQ firms to their foreign manufacturing subsidiaries, and how are they related to the performance of the foreign subsidiaries?

2. Theoretical Background and Hypotheses

March (1991) categorized organizational learning strategies as exploratory or exploitative. Moreover, the researcher posited the importance of maintaining an appropriate balance between these two approaches, in which a firm can pursue ecological learning about its environment. Exploration and exploitation require various structures, processes, and capabilities. Furthermore, they have differing impacts on the organizational performance. The self-reinforcing nature of excessive exploitative learning may cause core capabilities to be changed into core rigidities in the face of environmental changes. To counter an excessive focus on exploitation, which results in organizational myopia and competency traps, business groups must undertake exploratory learning (Ghemawat and Costa, 1993; Holmqvist, 2004; Leonard-Barton, 1995; Levitt and March, 1988; Winter and Szulanski, 2001). However, focusing predominately on explorative learning sacrifices the short-term performance for this long-term adaptiveness.

2.1. Knowledge Exchange among HQ Units and Their Manufacturing Subsidiaries' Performance

Building on March's (1991) study, He and Wong (2004) investigated the explorative and exploitative technological innovations at the firm level. Furthermore, Jansen et al. (2005) researched explorative and exploitative innovations at the multi-unit level of diversified firms. These studies showed that in a diversified firm, technological innovations evolve via explorative and exploitative knowledge flows across—with subsequent diffusion within—the units of a multi-unit organization. Thus, both types of innovation knowledge exchange among HQ firms lead to the creation of idiosyncratic and heterogeneous resources (Ahuja and Lampert, 2001). According to He and Wong (2004), the exchanges will have differing impacts on firm performance. If we examine HR technology management and sustainability in the *Chaebol* context, technological knowledge exchange should similarly lead to both explorative and exploitative sustainable HR innovations. In this sense, the general objective of the exchange of exploitative sustainable HR innovation knowledge among GACs is to improve the eco-efficient productivity and quality of operating functions and reduce costs through improved environmental processes. Meanwhile, the general goals of the exchange of explorative sustainable HR innovation knowledge among peer GACs are to enter new environmental technology fields and introduce new generations of eco-efficient products.

Explorative innovations lie as the core factor of entrepreneurial activities and wealth creation. They serve as the fundamental elements of novel technological innovation trajectories and paradigms. Moreover, they are a crucial part of the creative destruction processes, in which the extant techniques and approaches can be replaced by novel innovative technologies and products. Such exploratory innovations help units counter the obsolescence of products and services. Large firms that are successful at exploratory learning and knowledge exchange are able to generate significant technological breakthroughs and reinvent themselves while maintaining technological parity or leadership in their industries, thus leading to a higher level of performance (Barney, 1991; Wernerfelt, 1984).

To extend this logic to *Chaebols*, these firms need the exchange of explorative sustainable technological HR knowledge among HQ units if they are to reinvent themselves continually and retain technological leadership in their industries. As a *Chaebol*'s GACs share their explorative sustainable HR innovations with peer GACs within their group, the exchange builds shared and syndicated group-level sustainable HR knowledge stocks and absorptive capacity. As these shared and intertwined sustainable HR knowledge assets are transferred to GACs' foreign manufacturing subsidiaries, the exchange has the potential to enhance the subsidiaries' sustainable competitiveness, thus leading them to perform at a higher level than their local competitors. Therefore, the exchange of explorative sustainable HR knowledge among the *Chaebol*'s HQ firms generates innovative competencies for the GACs, which, on absorption, can be converted to new sustainable competitive advantages by the foreign manufacturing subsidiaries and trigger enhanced performance. Hence:

Hypothesis 1 (H1). *The more extensive the sharing of* ***explorative*** *sustainable technological HR innovation knowledge among HQ units of the focal GAC is, the more likely the performance of the foreign manufacturing subsidiaries of that GAC is to increase.*

However, scholars have also argued that increasing exploration will decrease long-term performance. March (2006) argued that “ventures in more complex explorations seem often to lead to huge mistakes and thus unlikely to be sustained by adaptive processes.” Empirical studies also show that exploration-oriented corporate venture units have a high level of correlation with negative longitudinal performance (Hill and Birkinshaw, 2008).

The complexities of the *Chaebol* structure accentuate this problem (Lee et al., 2010; Lee et al., 2014), especially in the context of its technological management and sustainability. In the *Chaebol* context, the exchange of explorative sustainable HR innovation knowledge may be considerably delayed given the multiplicity of interactions among HQ units and the patterns of interactions with HQ subsidiaries. Enhancing the performance of *Chaebol* firms through explorative sustainable HR innovation knowledge may require a long-term horizon. Hence:

Alternative Hypothesis 1A (H1A). *The more extensive the sharing of* ***explorative*** *sustainable technological HR innovation knowledge among HQ units of the focal GAC is, the more likely the performance of foreign manufacturing subsidiaries of that GAC is to decrease.*

Exploitative sustainable HR innovation knowledge exchange can be deployed to enhance the core competencies of GACs, which can, in turn, boost the competencies and performance of their subsidiaries in the short term. Consequently:

Hypothesis 2 (H2). *The performance of the foreign manufacturing subsidiaries of a focal GAC is more likely to_increase with the more extensive exchange of* ***exploitative*** *sustainable technological HR innovation knowledge among the focal GAC and other HQ units of GACs within its Chaebol.*

2.2. Transfer of Technical HR Knowledge from HQ Unit to Manufacturing Subsidiary

In the international business arena, the transfer of firm-specific resources, especially knowledge, has been posited as a key success factor for MNCs (Kogut and Zander, 1993). Prior research has also supported the theory that a positive association exists between knowledge transfer from parents to foreign subsidiaries and the performance of those subsidiaries (Lyles and Salk, 1996).

Such transfers take place in two broad formats. First, informal, “osmotic” transfer takes place through being absorbed during the myriad of constant interactions between members of GAC HQ units and their subsidiaries (which was not focused in this study). Second, through deliberate transfers of documents, guidelines, policies, interventions, and directives from the HQ, technical “schemas,” such as product designs, process designs, best practices, and management processes, are conveyed to the subsidiaries (Lee et al., 2010). This study focuses on the deliberate transfer of such technical schemas, especially in the context of technological management and sustainability within *Chaebols*.

Galbraith (1990) reported that numerous firms find intra-firm knowledge transfer much more difficult than expected. Therefore, knowledge assets in the form of organizational practices and technologies are important for MNC success; however, they often do not transfer easily, as knowledge assets can be “sticky” (Jensen and Szulanski, 2004; Szulanski, 1996). In addition to stickiness, the tacitness of knowledge also prevents knowledge transfer within MNCs (Kogut and Zander, 1993). In the case of foreign subsidiaries, the liability of foreignness may further dampen the transfer of knowledge to subsidiaries (Zaheer, 1995).

The flow of knowledge from HQ to manufacturing subsidiaries is by no means guaranteed, and obstacles, such as tacitness, stickiness, and foreignness, need to be overcome by deliberate knowledge transfer. In reality, within the *Chaebol*, this knowledge transfer can occur through the sharing of globally networked human-based innovative knowledge/skills (e.g., sharing of innovative knowledge/skills among parent-country nationals (PCNs)/host-country nationals (HCNs) and transnational teams) between HQ and manufacturing subsidiaries, especially in the vein of sustainable, environmental technology management (Lee et al., 2014; Lee et al., 2020). To the extent that firms are able to overcome these obstacles, the subsidiaries will have new insights to develop competencies in sustainable HR technology management that will boost performance. Thus:

Hypothesis 3 (H3). *The greater the degree of technical HR knowledge transfer between the HQ unit of a focal GAC and its foreign manufacturing subsidiaries (to reduce the HR knowledge transfer barriers) is, the better the performance of that focal GAC's subsidiaries becomes.*

2.3. Moderating Effect of Transfer of HR Knowledge to Subsidiaries

The long-term prosperity of firms operating in cross-border environments seems increasingly predicated on their ability to identify and transfer HR knowledge assets so that the firm can properly exploit those assets (Lee et al., 2020; Teece et al., 1997; Zander and Kogut, 1995). This scenario is even more relevant for MNCs, including multinational GACs, where technology and corporate know-how are frequently transferred across borders, either between the parent firm and its subsidiaries or among subsidiaries through the sharing of globally networked human-based innovative knowledge and skills (Lee et al., 2014). In this respect, the issue of the transfer of HR knowledge assets takes on greater importance, with some scholars placing the leverage of knowledge across borders at the center of the theory of the MNC (Winter, 1995).

Thus, we argue that HR knowledge transfer is a moderating variable. If sustainable technological HR innovation knowledge cannot flow into foreign manufacturing subsidiaries effectively and efficiently from the GAC HQ, the opportunities for exploiting this HR knowledge will be inhibited. The performance of the foreign subsidiaries will be enhanced only if GACs can overcome the barriers to the transfer of explorative and exploitative sustainable HR innovation knowledge to foreign subsidiaries. Accordingly, we predict that:

Hypothesis 4a (H4a). *The degree of HQ's HR knowledge transfer to manufacturing subsidiaries (to reduce the barriers) positively moderates the degree to which the exchange of* ***explorative*** *sustainable technological HR innovation knowledge among HQ units affects subsidiary performance.*

Hypothesis 4b (H4b). *The degree of HQ's HR knowledge transfer to manufacturing subsidiaries (to reduce the barriers) positively moderates the degree to which the exchange of* ***exploitative*** *sustainable technological HR innovation knowledge among HQ units affects subsidiary performance.*

From the theoretical background and hypotheses above, we created a research model (shown in Fig. 1, which displays the HR knowledge exchanges and transfer pattern we discussed above, and Fig. 2, which shows the signs of the expected relationships, including interactions) for the effects of the exchange of explorative and exploitative sustainable HR innovation knowledge among GACs within the *Chaebol* and its impact on foreign manufacturing subsidiary performance, as moderated by the HQ unit transfer of HR knowledge to the subsidiaries.

Fig. 1. Depiction of the basic variables in the study

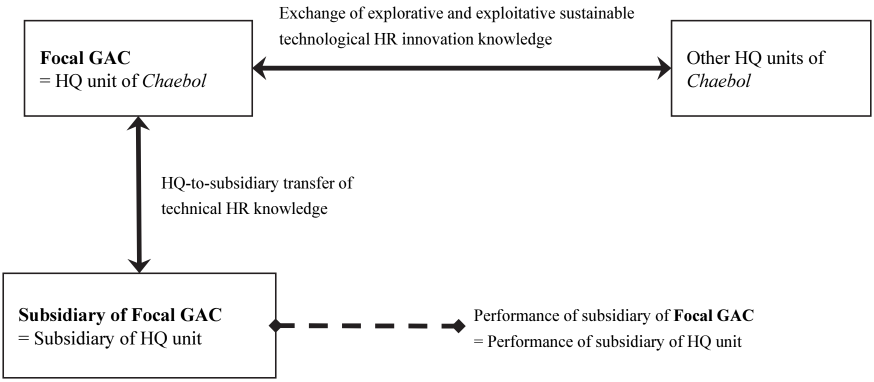
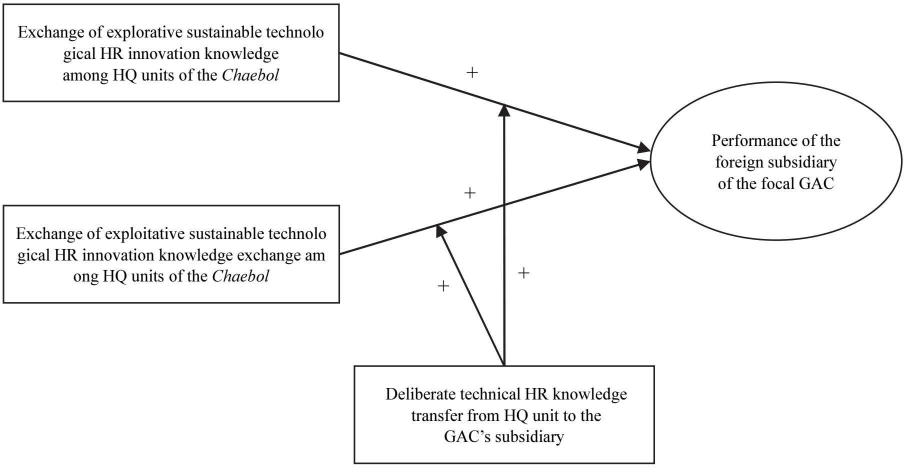


Fig. 2. Research model of explorative vs. exploitative sustainable technological HR innovation knowledge sharing within the *Chaebol* and its impact on subsidiary performance



3. Methods

3.1. Research Design and Methodology

We selected the survey method as our research design based on detailed, face-to-face, structured interviews with senior executives/directors and high-ranking managers in South Korea's 25 largest *Chaebol* firms and their foreign subsidiaries. With the support of a former high-ranking member of the South Korean government, we were able to conduct our interviews with the support of current senior Korean government officials, thus leading to a conspicuous 89 percent response rate from senior managers of all major *Chaebols* and their foreign subsidiaries.

3.2. Selection of Sample

Our sample consisted of 176 manufacturing GACs in 53 Korean business groups that had undertaken foreign direct investments (FDIs), together with their 1,061 foreign manufacturing subsidiaries. We collected these data through the two waves of our survey with a time gap of at least six months to nullify the risk of common method bias and reverse causality (Podsakoff et al., 2003). The first wave of our survey was conducted for seven months from December 2016 to June 2017, while the second wave of our survey was conducted for six months from January to June 2018. In line with these two waves of surveys, we used the first wave of our survey data to measure independent and moderating variables. Meanwhile, we used the second wave of survey data to measure a dependent variable. We used the survey data only for our main variables, i.e., independent, moderating, and dependent variables. However, we used the secondary data with various sources for other control variables. Specifically, we collected the financial and accounting information for MNEs from KISVALUE and the Korean FDI information from the Korean Ministry of Economy and Finance, Korea Trade Investment Promotion Agency (KOTRA), and the Financial Supervisory Service's Data Analysis, Retrieval, and Transfer System. Our sample list of 53 Korean business groups included all *Chaebols* that undertook FDIs and were listed in the Korea Fair Trade Commission (KFTC) list of the largest Korean business groups as of 2016. Among the 53 sample business groups, 38 business groups were under the obligatory auditing by the KFTC on cross-subsidizations. These 53 *Chaebols* had a total of 176 HQ businesses, whose sustainable HR innovation knowledge-exchange activity was the focus of our study.

Drawing from the previous literature (Demmerling, 2014; Ellen et al., 2006; Gupta and Govindarajan, 1991a; He and Wong, 2004; Lee et al., 2016; Lee et al., 2010; Lee et al., 2014; Lee et al., 2020), we developed a structured interview-based questionnaire. Our questionnaire was pretested for the face and construct validities with 29 senior executives of the top 25 *Chaebol* companies in the largest Korean business groups. We interviewed these executives and had them identify what they regarded as the most critical parameters of sustainable technological HR innovation management related to the performance of their firms' foreign manufacturing subsidiaries. Their responses showed a very close correspondence between their perceptions of the important technological HR innovation management factors and those found in the existing literature, which were incorporated in the present study.

To maximize our data capture, following prior studies (Lee et al., 2010; Lee et al., 2020), we applied three steps: 1) a face-to-face visit to the respondents at their companies, 2) a short interview with each respondent explaining our project, and 3) direct collection of the complete questionnaire from each respondent. The face-to-face visits to our respondents augmented a response rate close to 90 percent. We visited all 198 firms that were involved in the population. Altogether, we received 176 completed questionnaires, thus representing an 89 percent response rate. Our sample included 176 firms, each from one of 53 Korean business groups, and responses regarding their 1,061 foreign manufacturing subsidiaries. All respondents were members of the top management teams (TMTs) of their respective firms, holding positions such as senior HR managers and chief technical officers (CTOs). Even if we contacted only the TMT members of the *Chaebol* firms, we were able to collect foreign subsidiary-level data, including HQ-subsidiary HR knowledge transfer and subsidiary performance. Senior managers who had experience working in host countries or regions helped our TMT respondents answer our questionnaire items.

To check the non-response bias, we used KISValue and KISLINE, which were reliable public databases compiled by the Korea Information Service (KIS). From these KIS databases, we were able to obtain secondary data with which to compare our respondents to the original population sample with respect to key firm characteristics, such as R&D intensity and total assets, and subsidiary characteristics, such as total investment and age. The mean difference between the respondent group and the non-respondent group regarding those important characteristics of firms and subsidiaries was examined using an unpaired *t*-test. The results demonstrated that all *t* statistics were not significant. Furthermore, Kolmogorow-Smirnov's *D* (the maximum deviation of the frequency distribution of those two samples) was computed to examine whether the two groups were drawn from the same distribution. The test result indicated that all *D* statistics for the above firm and subsidiary characteristics were non-significant. On the basis of these tests, we concluded that the non-response bias was non-significant.

3.3. Variables and Measurement

3.3.1. Dependent Variable

Given the characteristic of a multidimensional construct, a foreign subsidiary's performance should include not only financial measurements but also strategic criteria, e.g., competitive position in the target host market (Dunning, 1988; Lee et al., 2014). Thus, as a continuous variable, the subsidiaries' performance over the previous three years was measured using four items that other scholars have previously applied (e.g., Lee et al., 2014; Luo and Peng, 1999) to their research on the performance of MNCs' subsidiaries. These four items (item factor loadings are in brackets) were 1) after-tax return on assets (ROA) [0.73], 2) after-tax return on investment (ROI) [0.95], 3) sales growth rate [0.94], and 4) competitive position [0.93]. Principal component analysis showed that all items loaded on a single factor with an eigenvalue of 3.68. Moreover, the internal reliability was very high ($\alpha = 0.89$).

Following prior studies (e.g., Lee et al., 2010), respondents rated the performance of a foreign subsidiary on the basis of a five-point Likert scale. The items compared each foreign subsidiary's performance with its major competitors in its local industry of the host market, with 1 being the lowest 20% and 5 being the highest 20% in the industry.

Although foreign subsidiary performance can be measured by three different dimensions, i.e., financial, objective, and perceptual judgements, prior literature suggested that using subjective measures of firm performance relative to competitors is particularly useful in researching emerging market businesses and that these measurements correlate with objective measures with a high degree of reliability (Chandler and Hanks, 1993). We used three-year average estimates to minimize the influence of short-term performance variations and to manage the longer-term effects of sustainable HR innovation knowledge sharing within *Chaebols*.

3.3.2. Independent Variables

Our measurements for the two types of exchange of sustainable technological HR innovation knowledge among GACs within a *Chaebol* were derived from the published work by reputed scholars (Demmerling, 2014; Ellen et al., 2006; Gupta and Govindarajan, 1991a; He and Wong, 2004; Lee et al., 2016; Lee et al., 2010; Lee et al., 2014; Lee et al., 2020). As we needed to apply these scholars' measurements to our study at the level of the intra-group exchange of sustainable HR innovation knowledge among units, we modified their questionnaire items.

A focal GAC's explorative sustainable technological HR innovation knowledge sharing with sister GACs within a *Chaebol* was measured by a four-item scale. We asked TMT respondents to score the extent of the exchange of explorative sustainable technological HR innovation knowledge with the question, "Over the last five years, for the items below, to what degree has your company given or taken technology/know-how to/from other manufacturing group-affiliated companies within your business group through the sharing of networked human-based innovative knowledge/skills?"

Four items were scaled as follows: "We have provided or received environmental innovation technology/know-how to/from other manufacturing group-affiliated companies for 1) introducing the next generations of eco-efficient products [0.92], 2) opening up new product markets through new environmental technologies [0.70], 3) entering new environmental technology fields with a long-term perspective [0.82], and 4) extending the product range through researching basic or fundamental environmental technologies [0.93]." The numbers in brackets demonstrate the factor loadings. All items loaded on a single factor with an eigenvalue of 1.05. In addition, the internal reliability was high ($\alpha = 0.86$).

A focal GAC's exchange of exploitative sustainable technological HR innovation knowledge with sister GACs within the *Chaebol* was assessed with the question, "Over the last five years, for the items below, to what degree has your company given or taken technology/know-how to/from other manufacturing group-affiliated companies within your group through the sharing of networked human-based innovative knowledge/skills?"

Four items were scaled as follows: "We have provided or received environmental innovation technology/know-how to/from other manufacturing group-affiliated companies to 1) improve existing eco-efficient product quality [0.82], 2) improve eco-efficient production flexibility [0.88], 3) reduce production cost by incrementally decreasing environmental emissions [0.94], 4) improve yield through enhanced environmental processes [0.91], and 5) reduce material consumption through improved environmental processes [0.78]." All items loaded on a single factor with an eigenvalue of 6.98. Moreover, the internal reliability was very high ($\alpha = 0.90$).

We decided on a five-year period, as prior research has demonstrated that innovation strategy tends to be stable across a number of years (Cao et al., 2009; He and Wong, 2004). While the firms in our sample were of different ages, all were more than five years old. Hence, we could reasonably presume that most of them had been pursuing a stable innovation knowledge-management strategy for five years or longer. After obtaining the post-interview feedback from the pre-test of the 29 executives at the top 25 *Chaebol* firms, we concluded that the five-year time span was a reasonable duration for our study.

3.3.3. Moderating Variable

Our measurement for HR knowledge transfer between a parent company and its foreign manufacturing subsidiary was adapted from prior studies (Demmerling, 2014; Ellen et al., 2006; Gupta and Govindarajan, 1991a; Lee et al., 2016; Lee et al., 2010; Lee et al., 2014). Following the existing research, we focused on the transfer of technical HR knowledge in the form of human-based schemas, such as technical design and procedures. Data on technical HR knowledge transfer between an HQ unit of the GAC and its foreign subsidiaries over the last five years were gathered on four items as follows: 1) eco-efficient product designs [0.85], 2) eco-efficient manufacturing process designs [0.93], 3) environmental management systems [0.76], and 4) environmental managerial practices [0.79]. All items loaded on a single factor with an eigenvalue of 2.58. In addition, the internal reliability was high ($\alpha = 0.85$). For each item, the respondent was asked to indicate on a seven-point Likert scale (ranging from "not at all" to "a very great deal") the degree to which the parent company engaged in transfers of HR knowledge and know-how to the foreign subsidiary.

3.3.4. Control Variables

We also controlled for other variables that may affect a foreign subsidiary's performance: 1) a GAC's technological knowledge capability base and size; 2) a GAC's foreign subsidiary's age, size, ownership, entry market size, and cultural distance; and 3) firm and industry dummies.

Moreover, according to existing literature (e.g., Buckley and Casson, 1976; Lee et al., 2014), R&D intensity has been recognized as one of the key determinants of MNCs. Intensive R&D activities create intangible assets that generate technological knowledge-based capabilities and can contribute to higher financial performance. When an MNC enters a host country by establishing a foreign subsidiary, the subsidiary becomes the MNC's overseas agent for exploiting its knowledge asset advantages in that host market. These advantages offer the foreign subsidiary with a superior competitive position in the local market, particularly when the parent company is committed to developing a strong position in the host market (Rugman, 1982). Empirical evidence supports this discussion. Mishra and Gobeli (1998) found a positive association between an MNC's possession of intangible assets and its subsidiaries' market value. Hence, we selected a parent company's R&D intensity as a control variable to demonstrate the parent company's technological knowledge base. The average R&D intensity of the previous five years was selected to minimize the influence of short-term R&D variations. The data for the R&D were obtained from the KISValue database. This database is a reliable and popular source of financial data in analyzing the R&D intensity of *Chaebols* (e.g., Chang and Hong, 2000; Lee et al., 2020).

Following prior studies, we also used other control variables, such as GAC size and foreign subsidiary size and age. The measurements of these control variables followed standard practice, with size defined as the total assets. Age was the number of years since the establishment of the subsidiary. A dummy variable was used to measure a subsidiary's ownership mode: a value of 1 was assigned if a Korean parent company owned 95 percent or more of equity; 0 was assigned otherwise. The 95-percent cut-off point has been commonly used in prior studies on partial and full ownership (Hennart, 1991; Gaur et al., 2019). In addition, a foreign subsidiary's entry market size was measured by a host country's GDP per capita. To measure the degree of each subsidiary's cultural distance from HQ, we used Kogut and Singh's (1988) cultural composite index by computing the cultural distance between home (Korea) and host countries on the basis of Hofstede's (1980) four cultural dimensions (i.e., individualism vs. collectivism, power distance, uncertainty avoidance, and masculinity vs. femininity). Furthermore, we controlled for parent firm dummies. On the basis of foreign subsidiaries' local industries in host countries, we also controlled for the industry dummies according to two digits of the Korean Standard Industrial Classification (KSIC) codes.

4. Empirical Results

4.1. Validity Checks

Discriminant validity was established through exploratory and confirmatory factor analyses to verify the distinctiveness of the constructs in this study using all the items from all of the scales. The exploratory factor analysis replicated the intended four-factor structure (including the exchange of explorative and exploitative sustainable HR innovation know-ledge, HQ-to-subsidiary HR knowledge transfer, and foreign subsidiary performance) to be used in tests of hypotheses. Items loaded on the intended factors, all of which had eigenvalues greater than 1 that supported our four-factor model. Given that this study is based on a survey, common method bias may emerge. Hence, to nullify such bias, we first collected separate responses with a time lag between answering independent/moderating variables and answering a dependent variable by conducting two waves of surveys by following Podsakoff et al.'s (2003) procedural remedy. Second, we used different sources for control variables by collecting the archival data. Finally, we conducted Harman's one-factor test (Podsakoff and Organ, 1986), in which common method bias was indicated by the emergence of a single factor that explains a dominant portion of the variance in a factor analysis. The results of the one-factor test revealed that the largest factor accounted for only 29.5 percent of 72.4 percent explainable variances, thus indicating an absence of common method variance.

We used confirmatory factor analysis (Wang and Ahmed, 2004) using AMOS 21 to compare the proposed four-factor model with alternative five-factor models. Absolute fit indexes for the proposed four-factor model were acceptable (χ^2 = 504.73, df = 112, p < .001, GFI = .92, CFI = .94, IFI = .93, RMSEA = .05), and these fit indexes were superior to those for alternative models. All of these results indicated that our four-factor model provided better fit to the data than plausible rival specifications. Moreover, these results revealed that the four scales represented constructs that were not only theoretically but also empirically distinguishable.

4.2. Results

Table 1 presents descriptive statistics and correlation matrix for variables. In addition, to make a diagnosis on any potential multicollinearity among variables, we checked the variance inflation factor (VIF) for each variable; the excess of 10 cut-off limitations signified a multicollinearity problem (Menard, 1995). Our results indicated that the VIFs associated with our variables did not exceed 3.5. Thus, we concluded that our sample had no concern regarding multicollinearity.

Table 1. Descriptive statistics and correlation matrix[a]

Variable	Mean	St. dev.	1	2	3	4	5	6	7	8	9	10
1. Subsidiary performance	3.54	0.89										
2. Exploration exchange	4.39	1.42	-0.15**									
3. Exploitation exchange	4.22	1.54	0.13**	0.10**								
4. HQ-subsidiary transfer	5.25	1.17	0.22**	0.12**	-0.00							
5. R&D intensity	0.05	0.07	0.23**	0.01	-0.04	0.03						
6. Parent size	24.76	1.70	0.40**	0.24**	0.10**	0.25**	0.22**					
7. Subsidiary size	10.64	1.97	0.11**	0.10**	0.07*	0.07*	0.06	0.09**				
8. Ownership dummy	0.45	0.50	-0.04	-0.02	0.03	-0.07*	0.07*	-0.05	0.13**			
9. Subsidiary age	9.65	5.02	0.04	0.02	0.02	0.05	0.04	0.16**	0.09**	-0.14**		
10. Host's GDP per capita	9.55	13.54	-0.07*	-0.03	-0.03	-0.04	0.03	0.04	0.06	0.12**	-0.00	
11. Cultural distance	1.81	0.84	-0.05	-0.07	-0.05	-0.05	0.02	-0.00	-0.03	0.04	-0.10**	0.50**

[a] n = 1,061. **p<0.01, *p<0.05 (2-tailed).

We carried out multiple regression analyses to investigate the effects of the explorative versus exchange of exploitative sustainable technological HR innovation knowledge on subsidiary performance. Given the relatively high correlation between the exchange of explorative sustainable HR innovation knowledge and HQ-subsidiary HR knowledge transfer, we used centered data to avoid a multicollinearity issue, following Aiken and West's (1991) method of a centered regression analysis. Table 2 shows the results of our multiple regression analyses.

Models A, B, and C of Table 2 all supported Alternative Hypothesis 1A: the exchange of explorative sustainable HR innovation knowledge within the *Chaebol* is negatively and significantly related to subsidiary performance. Therefore, Hypothesis 1 was rejected because of the delay factor, as discussed in the literature (Lee et al., 2020; March, 1991), between the generation of explorative sustainable HR innovation knowledge at HQ and its manifestation in a format that increased subsidiary performance. Furthermore, Models A, B, and C supported Hypothesis 2: the exchange of exploitative sustainable HR innovation knowledge among GAC units is positively and significantly related to enhanced subsidiary performance.

Next, the coefficients for the HQ-subsidiary HR knowledge transfer of the schema in Models B and C were both positively and significantly related with subsidiary performance. This outcome supported Hypothesis 3, which posited that increasing technical HR knowledge transfer through technical schemas is beneficial.

The interaction term between the exchange of explorative sustainable HR innovation knowledge and HQ-to-subsidiary HR knowledge transfer had a positive coefficient, as predicted in Hypothesis 4a. However, the interaction term between the exchange of exploitative sustainable HR innovation knowledge exchange and HQ-to-subsidiary knowledge transfer was negative, which was opposite to the prediction of Hypothesis 3b. How can we reconcile this unexpected result? We discuss this issue in the discussion section below.

Table 2. Regression analyses for sustainable HR innovation knowledge on *Chaebols*' foreign subsidiary performance[a]

Variable	Model A	Model B	Model C
Constant	-1.50***	-1.17***	-1.18***
	(0.34)	(0.35)	(0.35)
Exploration exchange	-0.09*	-0.15***	-0.16***
	(0.04)	(0.04)	(0.04)
Exploitation exchange	0.12***	0.14***	0.13***
	(0.03)	(0.03)	(0.03)
HQ-sub transfer		0.11***	0.11***
		(0.02)	(0.02)
Exploration × HQ-subsidiary transfer			0.07***
			(0.02)
Exploitation × HQ-subsidiary transfer			-0.06***
			(0.02)
R&D	1.30***	1.30***	1.37***
	(0.37)	(0.36)	(0.36)
Parent company size	0.23***	0.21***	0.21***
	(0.02)	(0.02)	(0.02)
Subsidiary size	0.02	0.02	0.02
	(0.01)	(0.01)	(0.01)
Ownership	-0.03	-0.02	-0.01
	(0.05)	(0.05)	(0.05)
Subsidiary age	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)
Host country's GDP per capita	-0.008***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)
Cultural distance	-0.05	-0.05	-0.06
	(0.04)	(0.04)	(0.04)
Adjusted R^2	.36	.41	.49
Model *F*	27.44***	34.10***	43.08***

[a] n = 1,061. Unstandardized regression coefficients and standard errors (in parentheses) are shown. Firm- and industry-fixed effects are included but not reported.

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, †$p < 0.10$.

Regarding Hypotheses 4a and 4b, Model C tests the moderating effect of HQ-to-subsidiary HR knowledge transfer on the relationship between sustainable HR innovation knowledge-exchange activities and subsidiary performance. In Model C, the interaction term between the exchange of *explorative* sustainable technological HR innovation knowledge and HQ-to-subsidiary HR knowledge transfer is positively and significantly related to subsidiary performance. In contrast, the interaction term between the exchange of *exploitative* sustainable technological HR innovation knowledge and HQ-to-subsidiary HR knowledge transfer is negatively and significantly related to subsidiary performance. Therefore, Hypothesis 3a is supported, whereas Hypothesis 3b is not supported.

In addition, Table 2 reports the following results concerning control variables. First, in all models, the parent company's R&D intensity and the parent company's size were found to have a significant and positive relationship with foreign subsidiary performance. Second, subsidiary size, ownership, and age and cultural distance are insignificantly related to subsidiary performance. Finally, the host country's GDP per capita is negatively and significantly related to foreign subsidiary performance in all models, thus suggesting that the FDI by the *Chaebol*'s HQ unit is more likely to be successful in target host countries with lower levels of GDP per capita, such as emerging markets like China.

5. Discussion

5.1. Theoretical and Empirical Implications

In general, the results fit the theory but with two exceptions. First, a negative relationship exists between the exchange of explorative sustainable HR innovation knowledge and subsidiary performance supporting Hypothesis 1A, as opposed to the positive relation forecasted by Hypothesis 1. Second, a negative interaction term exists for the exchange of exploitative sustainable HR innovation knowledge and HQ transfer of technical HR knowledge. We discuss each in turn.

First, the negative effects of the exchange of explorative sustainable HR innovation knowledge are an interesting exception. This result provides the contention in the literature that the exchange of exploitative sustainable HR innovation knowledge pays off while the exchange of explorative sustainable HR innovation knowledge does not (Lee et al., 2010; March, 1991). Alternative Hypothesis 1A is supported, presumably because explorative sustainable technology takes time to flow to subsidiaries. In the case of *Chaebols*, knowledge first needs to be developed "at home," as described in the conventional Vernon product life cycle theory (Collis and Montgomery, 1998). Moreover, if a firm is creating and conducting cutting-edge products, processes, and technology development (Park, 2010; Xiao, Lew and Park, 2021), it will first manufacture those products in the HQ in Korea before passing them along to the subsidiary. All of these steps would take longer than the five-year horizon of the study. Furthermore, passing them along could initially cause *mishaps* in the subsidiary's performance because it would initially have higher costs and lower efficiency as it copes with the more complicated product lines (Collis and Montgomery, 1998).

Second, the negative interaction effect of the exchange of exploitative sustainable HR innovation knowledge exchange and HQ technical HR knowledge transfer is also another interesting exception. The explanation for this second exception lies in the nature of the HR knowledge that cumulates over time in the HQ unit after sustained HR knowledge exchange activity with other HQ units. In the *Chaebol* case, exchanges of technological HR knowledge among GAC HQ units over time lead to a reservoir of technological HR knowledge in each

HQ unit, from which the subsidiaries derive insight through technological HR knowledge transfer.

The content of the knowledge reservoir that develops in the HQ units is deeply influenced by the nature of HR knowledge shared with other HQ units within the *Chaebol*. Given that technological HR knowledge has two major types, namely, explorative and exploitative, the emergent knowledge reservoir will contain levels of each type relying on the degree of sharing of each type. Conceptually, we can consider the reservoir in terms of the "concentration" of the HR knowledge type. Thus, if much effort goes into sharing only explorative (or exploitative) HR knowledge, the reservoir will become increasingly concentrated with explorative HR knowledge (or exploitative) content. Meanwhile, if much effort is expended on sharing both explorative *and* exploitative HR knowledge, the reservoir will have a highly concentrated knowledge *mix*. If little effort is expended on both types, the knowledge reservoir will be a diluted mix of both types.

Once the GAC HQ establishes the reservoir, it can then decide the degree to which it will transmit schemas to the relevant subsidiary. The nature of the reservoir knowledge directly affects the value to the subsidiary of the schema being transferred. The value of the schema is driven by two components. The first one is the "applicability" or the degree to which a schema matches the subsidiary's local competitive environment. The second one is the "adaptability" or extent of efforts needed for the schema to be adapted to fit the local environment.

First, we discuss e*xplorative reservoirs*. Highly explorative reservoirs have coarse-grained, sticky knowledge (Jensen and Szulanski, 2004). The disadvantage is that schemas that are coarse grained are not easily "translated" into routines by the subsidiary. However, the advantage is that these schemas have a more comprehensive application bandwidth and are thus more adaptable for the subsidiary. The translation problem entails delays and expenses (Lee et al., 2010). This issue leads to a negative impact on performance and a need for the GAC HQ to provide assistance with translation. Augmented technical HR transfer effort by HQ will attenuate the negative impact and enhance performance. In sum, intense explorative HR knowledge exchange will be accompanied by decreased subsidiary performance, which is ameliorated by invigorated HQ transfer.

Second, we discuss *exploitative reservoirs.* Highly exploitative reservoirs have schemas that are less sticky and are fine grained. Therefore, the subsidiary can easily be adopting these schemas. However, each schema has the disadvantage of having tapered application bandwidth. Subsidiaries should inevitably compete in their own local environments. Therefore, this scenario cannot guarantee that fine-grained exploitative technological schemas transferred by the GAC HQ will fit the prerequisites of the subsidiary's local surrounding. If the subsidiary can select from the pool of exploitative schemas at the GAC HQ, it can rapidly adopt and adapt the most suitable schema and reap early benefits. Yet, the more extensively HQ transfers densely exploitative schemas, the more the subsidiary will find itself struggling with disentangling and force fitting schemas that do not fit their local surrounding. Thus, the numerous transfers of exploitative schemas that HQ makes will bring about processing overload, which is deleterious. In sum, the subsidiary will derive early and rapid performance benefit if schema transfer is restricted. However, as GAC HQ transfer increases, the performance can suffer.

5.2. Practical Implications

The present study has four strategic implications for knowledge management. The first one is our result indicating that exploration is not rewarded in subsidiary performance in the short term (Yoo et al., 2019; Yu and Kim, 2020) and that an explorative strategy requires extensive technical HR knowledge transfer from HQ. This finding may also extend to non-Korean multidivisional and multinational firms.

The second implication is for those *Chaebols* that have elected to eschew the intense exchange of explorative HR knowledge. These firms benefit most by aggressively pursuing exploitative HR knowledge exchange among HQ units. Moreover, they can benefit by transferring only limited HQ schemas so that the subsidiaries can select, adapt, and adopt schemas that rapidly fit their local environments and deliver good short-term performance with minimal distraction. They, too, need to be concerned about long-term vulnerability to explorative HR knowledge exchange.

The third managerial implication is for those successful *Chaebols* that have elected to shift to combine highly exploitative HR knowledge exchange with highly explorative HR knowledge exchange (mostly sought by large and mature *Chaebols*). Their first challenge is to ensure that attention to highly exploitative HR knowledge exchange is maintained despite the distraction. The second is to maintain a sufficiently high level of HQ HR knowledge transfer.

Last but not least, the dilemma of low subsidiary performance payoff for exploration remains. If they are to survive in the long run, managers have to wrestle with abandoning the comforting world of rapid payoff from exploitative HR knowledge exchange with minimal HQ transfer. Furthermore, they must enter the painful world of explorative HR knowledge exchange with its attendant delays in subsidiary performance payoff as well as the cost of delivering high effort in HQ transfer.

5.3. Limitations and Future Research

The above results suggest at least three directions for future research along with certain limitations. First, given that organizational learning at the *Chaebol* level takes place over time, we should further test our research model using a longitudinal design. With a longitudinal study, we should be able to unfold the evolution of learning from HR knowledge exchange among HQ units of the *Chaebols* and better assess the impact of this learning on the HQ transfer of HR knowledge by overcoming the limitation of a cross-sectional study.

Second, although we understand the value of conducting quantitative research, we also find the merits in conducting multiple case studies, through massive in-depth interviews with TMT members in leading *Chaebols,* to begin to reveal the actual organizational learning mechanisms and their impact on the subsidiary's performance.

Third, we collected the data for our main variables through a survey. However, knowledge exchange and transfer can be measured by patent data or other archival data. In addition, given the effect of innovation knowledge diffusion, this study may need to differentiate the short- and long-term performances (e.g., ROA and ROI) of subsidiaries. Nevertheless, the issue of data availability emerged for the variables of some portions of our sample *Chaebol* GACs. Furthermore, if scholars can use patent data or other archival data in future research to analyze our research model, the results can have different implications. We were not able to use these alternative measurements for our variables. Thus, we encourage such measurements for our constructs in future research.

Finally, given that we used *Chaebol* GACs as our sample, generalization may occur in the transfer of knowledge due to the unique characteristics and differentiations of the *Chaebol*. Nevertheless, the *Chaebol* has been categorized as one of the prevalent business groups across the globe (Chang and Hong, 2000; Lee et al., 2010; Lee et al., 2020). Hence, we believe that our findings can be applied to the broad category of business groups that have existed in both developed and developing countries.

6. Conclusion

This study makes it clear that the performance of *Chaebol* subsidiaries depends substantially on the management of sustainable HR innovation knowledge, as reflected in the choices about the exchanges of both exploitative and explorative sustainable HR innovation knowledge among HQ firms and the subsequent transfer of technical HR knowledge from HQ to the subsidiaries. The *Chaebols*' choices about these three HR knowledge management variables have very high correlations with subsidiary performance. Relying on whether the *Chaebol* opts to seek the exchange of explorative sustainable HR innovation knowledge among units excessively, three major strategic choices appear to yield good performance results as follows.

First, a low exploration strategy practices extensive exploitative exchange, but the extensive transfer from HQ is *deleterious*. This scenario yields short-term benefits. Second, a high exploration strategy pursues extensive explorative exchange, and extensive HQ transfer is *highly beneficial*. This scenario does not deliver short-term benefits. Third, an ambidextrous strategy pursues both explorative and exploitative exchanges. The benefits of increased HQ technical transfers are *modest* but real, and short-term performance is good but modest.

The contribution of the study at its core is the evidence that the subsidiary performance relies not only on the choice of the degrees of exploitative and explorative technology exchanges at the HQ level. It also depends on the correct *combination* of the degrees of both types of exchanges with the extent to which HQ undertakes technical schema transfer to the subsidiary.

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Journal of Korea Trade Vol. 25, No. 4, June 2021, 128-145
https://doi.org/10.35611/jkt.2021.25.4.128
ISSN 1229-828X

Imitation, Technology, and Firm Performance: The Korean Firms Case in China

JKT 25(4)

Received 27 November 2020
Revised 10 January 2021
Accepted 18 June 2021

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Abstract

Purpose – The main purpose of this study is thus to investigate the contingent effect of imitation strategies on firm performance in transition economies such as China, focusing on pure and creative imitation.

Design/methodology – We conducted a survey targeting department heads of each company who have more than 10 years work experiences. We assessed that the ability to gain trust and to access information from high-ranking informants would be greater if the firms were from the same country – Korea – as the lead researcher. A total of 200 highly reliable samples were obtained, which could effectively explain the nine variables set in the study. Relevant hypotheses were tested using a hierarchical linear model (HLM).

Findings – The findings suggest that SMEs' technology level also had a positive impact on performance. Firms with better technology had a positive impact on performance, irrespective of pure or creative imitation. This reflects the cases where many Korean SMEs entering China without high technology level lose their competitiveness due to Chinese firms' technology catch-up within a short period of time.

Originality/value – SMEs that lack technology and know-how need to focus on pure imitation strategies. It is possible that SMEs can perform creative imitation, but it seems difficult under the current circumstances. Therefore, SMEs with limitations in technology and know-how should maintain their competitive advantage for a while, by maintaining their pure imitation strategy.

Keywords: Imitation, Technology, Firm Performance, China, Korean Firms
JEL Classifications: F14, F23, M16

1. Introduction

Why do firms imitate each other? Many scholars have investigated firms' imitation strategies for a long time (e.g., Lee and Zhou, 2012; Shenkar, 2010). Firms naturally and unconsciously imitate each other in the process of developing new products and in the adoption of managerial methods and organizational forms (Liberman and Asaba, 2006). Imitation is an effective tool for firms to enhance their performance in the short run. Firms can gain knowledge and know-how via imitation, which prevent them from being left behind their competitors (Song, 2015). Shenkar (2010b) demonstrated that as much as 98% of the value created by innovation accrues not to the innovators but to the copycats. However, firms may not always succeed by adopting imitation strategies to enter transitional economies like

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China. The key to the imitation strategy of a firm is how adaptively and efficiently the competitor firm's developed product or selected strategy is applied to the firm. Academic researchers and experts seem to have no theory other than the one that the imitation strategy is necessary for firms to gain competitive advantage (Zhou, 2006; Lee and Zhou, 2012). IBM, Samsung, and many other firms that have gained reputation worldwide chose the imitation strategy for growth in the initial stage (Lee et al., 2016; Hitt et al., 2019). From the fact that they chose the imitation strategy for growth and achieved stellar success, we can conclude that imitation could be an effective strategy for a firm to grow beyond being a simple copy tool.

Even though firms imitate the actions of other firms, not all firms are equally susceptible to imitative pressures and not all firms exert a similar imitative influence (Gimeno et al., 2005). Even though imitation is a prevailing phenomenon in the transition economies such as China, imitation strategy has received limited attention from scholars until recently (Shenkar, 2010b; Lee and Zhou, 2012). It is true that counterfeiting opportunities are increasing in countries such as China, where MNCs entering developing countries need to create joint ventures with local firms (Yang and Clarke, 2004). In China, imitation and theft of intellectual property does not require high-tech or skilled labor, but only cheap labor supply (Lai and Zaichkowsky, 1999). Since technology is not sufficiently mature yet, imitation is quite common in many Chinese industries, which contributes significantly to the country's economy (Lee and Zhou, 2012). Therefore, China provides a perfect setting for our research. It is interesting that many Chinese companies, as a latecomer, begin with imitation for their economic growth, but later develop into the innovation stage using the technology chase strategy (Song, 2015). In contrast, other East Asian countries such as South Korea acquired technology from abroad and actively implemented FDI attraction strategies in order to achieve rapid growth in the short run (Freeman and Sote, 1997).

Previous research (e.g., Luo, Sun and Wang, 2011; Lee and Zhou, 2012; Shenkar, 2010; Lee et al., 2016) has classified imitation into two types: 1) pure imitation, which refers to the practices that companies launch new products as replications of competitors' existing products, and 2) creative imitation, which refers to the practices that companies adapt the features of their competitors' original products and adds new features to its own products. Many Chinese firms started with purely imitating others, but later turned into creative imitation. For example, founded in 1984 in Qingdao, China, Haier was the first firm to manufacture refrigerators after receiving technology transfer from Germany (Frynas et al, 2018). At the beginning of its business, Haier adopted a strategy to imitate the superior technology of other firms. Initially, it produced refrigerators with a focus on the Southeast Asian market, including Malaysia and the Philippines (Liu and Li, 2002). Subsequently, Haier also manufactured computers, LCDs, and other electronic products. By diversifying its business portfolio, it turned to creative imitation rather than pure imitation, and became a representative firm in China. Established in 2010, Xiaomi entered the smartphone market dominated by Apple and Samsung as a latecomer. At the early stage, Xiaomi only launched low-priced smartphones, a tablet Mi-Pad and a wristband-type wearable Mi-Band by imitating the products of the market leaders, such as Apple. In addition, Xiaomi also followed Apple's marketing strategy of selling only one or two representative products annually as well as Toyota's just-in-time production method. As Xiaomi increase their sales and customer base, they begin to develop their own products that go beyond pure imitation (Lee et al., 2016). By the end of 2018, Xiaomi acquired 7.6% of the global smartphone market and ranked No. 4.

The status of creative imitation in China can also be reflected by the number of registration of intellectual property rights (IPRs). While it is true that China potentially has a very serious moral hazard in imitating the brands and product technology without registered IPR for both domestic and foreign firms, an increasing number of firms, including those multinational firms worldwide, have come forward to apply for and register IPRs to the Chinese government. The number of patent applications in China increased from 173,327 in 2005 to 928,177 in 2014 and that of utility model applications increased from 139,566 in 2005 to 818,511 in 2014. In addition, the number of design right applications increased from 163,371 in 2005 to 514,555 in 2014 (China Intellectual Property Office, 2014). Those statistics clearly demonstrates that some of the large Chinese firms have naturally transformed their strategies from pure imitation to innovative imitation. However, on the other hand, most Chinese firms still stick to the pure imitation. A possible reason could be that pure imitation enables firms to increase their performance as well as competitiveness without significant financial investment in the mid and long term (Lee and Zhou, 2012).

Although considerable research has been conducted to examine the motivation of firms to adopt imitation strategy, but empirical research on the impact of imitation on the performance of firms is still limited (e.g., Ethiraj and Zhu, 2008), especially on the different impacts of different types of imitation. The main purpose of this study is thus to investigate the contingent effect of imitation strategies on firm performance in transition economies such as China, focusing on pure and creative imitation as suggested by Lee and Zhou (2012). Further, we also look at the environmental variables that affect the performance of imitation-driven firms, such as technology capability, competitive intensity, and imitation capability on firm performance. These environmental variables are frequently encountered in environmental uncertainty and environmental uncertainty promotes imitation as well as causes the likelihood of undesirable outcomes (Liberman and Asaba, 2004). Moreover, unlike previous studies such as Zhou (2006) and Lee and Zhou (2012) focusing on how pure and creative imitation affects the performance of domestic firms in China, this study empirically analyzes the impact of the two types of imitation strategies on the performance of foreign firms, namely Korean SMEs in China. This study intends to extend existing theories on the impact of pure and creative imitation on firm performance as well as to suggest managerial implications that help firms to do business.

2. Theoretical Development

2.1. Imitation

Imitation is a widely-used term and found in many contexts. It is important that we clarify how we use it here. At the most macro-level, imitation can resemble adoption – commencing to use processes in use elsewhere – and, at another level something as small as a cigarette can simply be counterfeited. So, in the motor vehicles sector the dominant mode of production was Fordism (or Taylorism) where the Division of Labour and task simplification reflected available labour skills and low costs of resources. In Japan Fordism would be far less feasible and so production there gave rise to robotics, flexibility and Just in Time. To choose to produce vehicles by either mode of production today would reflect adaptation/ adoption rather than imitation. At the other extreme, imitation could come close to the risk of counterfeiting – depending on the strength of protection that innovators gain from Patent Laws. Game-playing is possible with patents as a successful company may find that its key elements attract speculative patents based on very similar characteristics. In the long run this can stifle innovation and resemble speculators who register internet domain names in the hope that they may one day be valuable. Also, innovators (with both Patents and with internet domain names) need to keep themselves updated as the story of Esso/Exxon demonstrated. In the realm of products, the ways in which imitation can be damaging to an innovator has long been found in the work of Dobson (see Dobson 1998). Dobson (1998) argues that rivals who produce products that closely resemble the market leader can easily confuse the consumer. This is close to, but not the same as, producing a fake version of the market leader. Fake versions (high value goods such as perfume and Rolex watches attract fakes) risk legal action for copycatting/ passing-off an item and selling it as something that it is not. Much depends on proving that the consumer was misled – some even like to wear fake Rolex watches.

Imitation, as we use here, is one of the most effective strategies when firms encounter uncertainty (Liberman and Asaba, 2006). The information quality of the innovator's product becomes poor and the possibility of using such information to develop a superior product is relatively limited when uncertainty is high (Ethiraj and Zhu, 2008). Ethiraj and Zhu (2008) argued that if uncertainty is low, the quality of information increases and that imitation can be used to develop superior imitative products. It is clear that imitation is a very useful tool for successful business execution of firms that lack technology. Imitation can be classified into several levels. Ding *et al.* (2011) divided imitation into four stages in the research on R&D policy of the Chinese drug industry as follows: (i) Pure imitation; (ii) Innovative imitation; (iii) Imitative innovation; and (iv) Independent Innovation. In terms of resource-based and enterprise capabilities, enterprises' R&D investment and activities, generally measured by their R&D concentration, can be recognized as unique resources and capabilities, which are considered one of the key determinants of successful innovation (Posen et al., 2013; Posen and Martignoni, 2018).

Firms try to imitate each other in order to maintain their relative positions and neutralize the aggressive actions of the rivals (Lieberman and Asaba, 2006; Chen and Ma, 2017). Imitation is excellent in terms of its value and use as a strategy (Porter, 1985; Miner and Rahavan, 1999). Shenkar (2010) pointed out that imitation is largely underestimated in practice and that imitation can outperform innovation in many cases. A good imitator does not passively copy the idea, but creatively leverage the value of the idea by enhancing the quality or reducing cost of the original product (Shenkar, 2010). New ventures seeking creative imitation have technology capabilities in the local market of the emerging market. Park and Bae (2004) argued that as a strategic change was important for venture firms to enter developing countries and succeed, they need to make good use of creative imitation in order to succeed in internationalization, and that the main methods are (i) to practice creative imitation in the local market; and (ii) to make some transition of creative imitation in order to become a major player in the global market. It is thus believed that creative imitation exerts a stronger impact on firm performance than pure imitation.

However, some research results suggest a different view. By an empirical analysis of top and middle managers of 192 firms in China, Lee and Zhou (2012) demonstrated that pure imitation can help companies to gain market share in the short run. Companies that adopt pure imitation launch new products that are similar and functionally identical to their major rivals' products (Lee and Zhou, 2012), which may reduce the risks that consumers encounter when making purchase decisions (Van Horen and Pieters, 2012). In other words, a purely-imitated product is more likely to be accepted in the market. Hence, companies that adopt the pure imitation strategy are more likely to penetrate the market and increase their sales rapidly. On the other hand, although a creative imitation might not be quickly accepted by the market due to the uncertainly involved with the added new features (Zhou and Nakamoto, 2007), it may eventually evolve into a more innovative product that are unique in the market. Companies are thus able to charge a higher price and gain additional customers. In the long run, the advantages of creative imitation will be reflected on the firm's financial performance, such as ROA (Liberman and Montgomery, 1988; Zhou, 2006; Lee and Zhou, 2007; Wang et al., 2018). Lee and Zhou (2007) argued that both positivity and creativity influence financial performance differently and argued that creative imitation in particular appears to have greater impact on financial performance compared to pure imitation.

In summary, we expect that the pure imitation strategy exerts a stronger effect on the market performance, such as sales, while the creative imitation strategy will impact the firms' financial performance more. We adopted the research results of Liberman and Montgomery (1998), Zhou (2006), and Lee and Zhou (2007), Wang et al., (2018), and Moon and Acquaah (2020) to measure the hypotheses of pure and creative imitation. Pure imitation has a stronger positive impact on firm sales than creative imitation. Therefore, we hypotheses:

H1. Pure imitation has a stronger positive impact on firm ROA than creative imitation
H2. Creative imitation has a stronger positive impact on firm ROA than pure imitation

2.2. Technology Capability

R&D investment has received significant attention from researchers as a key indicator of the overall level of innovation in companies (Xin et al., 2019). R&D investment is also used as a source of competitive advantage and technological advantage for better performance of the firm (James and McGuire, 2016; Ruiqi et al., 2017). A firms' technology capability refers to its acquired technological advantages and R&D investment. Technology-driven firms are more active in acquiring new technologies to develop new products that would reflect the changing needs of their customers (Berman and Hagan, 2006). In terms of resource-based and enterprise capabilities, enterprises' R&D investment and activities, generally measured by their R&D concentration, can be recognized as unique resources and capabilities, which are considered one of the key determinants of successful innovation (Anzola-Román et al., 2018). Numerous studies showed that there were positive relationships between R&D investment and firm performance (Branch, 1974; Cuneo and Mariresse, 1984; Griliches, 1980; Hirschey and Weygandt, 1985; Hall and Bagchi-Sen, 2002). For example, Tubbs (2007) showed the higher the R&D intensity, the higher the sales and operating profits. In general, companies with a stronger technology capability are more likely to succeed in innovation (Kraasnikov and Jayachandran, 2008), which lead to superior firm performance (e.g., Song et al., 2005; Zhou et al., 2013). With a stronger technology capability, companies that adopt imitation strategies are more likely to invest in R&D and are more able to develop similar products as their competitors, and the imitated products are likely perform better in terms of functionality, as compared to companies with a weaker technology capability (e.g., Huang et al., 2010; Schewe, 1996), especially for the SMEs (Amin and Thrift, 1994). Ince et al., (2016) also argued that technology's "absorptive capacity" has a positive impact on technological innovation capability. Huang et al., (2010) argued that the core technological capacity of an imitative firm would certainly perform well in the industry. Wei et al., (2005) demonstrated that the performance of technological innovation is also determined by the core technological capacity. The imitation of technological innovation by enterprises is challenging, therefore, companies argue that it is strengthened by continuous indivisibility and organizational learning. Lestari and Ardianti, (2019), argued that technological capabilities must be well managed to achieve superior firm performance in a highly competitive market. Hitt et al., (2019) argued that diversification reduces the risk of R&D investments and creates the potential for entities to achieve higher returns on innovation. Thus, we have adopted the findings of Wei et al., (2005), Huang et al., (2010), Ince et al., (2016), and Lestari and Ardianti, (2019) to measure the hypotheses of technology capability. Therefore, we predict the positive effects of imitation, both pure and creative imitation, will be more pronounced when a firm has a stronger technology capability:

H3. The stronger the firm's technology capability, the stronger the positive impact of imitation on firm performance, irrespective of pure or creative imitation.

2.3. Competitive Intensity

Competitive intensity is defined as the degree of competition that firms encounter within the industry (Zhou, 2006). In a highly competitive environment, companies encounter pressure from a variety of sources, such as intensive price wars, high advertising investment, more product alternatives, and added services (Porter, 1980; Porter et al., 1985). As a result, companies also have a stronger motivation to reduce cost to gain competitive advantages (Gatignon and Xuereb, 1997; Porter et al., 1985), which may enhance their performance (Cadogan et al., 2003; Zhou, 2006; He and Nie, 2008). In comparison to companies that develop purely new products, which usually requires high investments in terms of R&D and marketing communication (Cooper, 1984a), companies that adopt an imitation strategy can reduce costs in new product development as they can easily copy the product from their competitors. Moreover, since existing products have already been on the market for a certain period of time, consumers may have already gained sufficient knowledge about such products. This is likely to make it easier for an imitated product to be accepted by the market, which further reduces the marketing efforts in educating consumers about the new products (e.g., Day and Wensley, 1988). Jaworski and Kohli (1993) addressed the importance of environmental factors in the relationship between market orientation and business performance. In contrast to the argument that the company's performance would be better (Huston, 1986) in the absence of competition, in a high competition situation, customers claimed that it might be detrimental to the entity as there were several options in purchasing the products they want and need (Kohli and Jaworski, 1990). Competitive intensity is a form of challenge for new ventures, and in an empirical analysis of 146 new entities in the United States, it argued that increasing competitive intensity reduces positive marketing capabilities in terms of performance (Zhang et al., 2020).

Ng'ang's et al. (2016) argued that competitive intensity plays a role in controlling the relationship between customer orientation and hotel performance in a survey of 330 managers using Resource-Based View (RBV). Zhang et al. (2019) conducted empirical analyses of 146 U.S. new ventures, arguing that increasing competitive strength reduces the positive effects of venture firms' marketing capabilities. In all, we predict that, as competition intensifies, the positive effect of imitation strategy on firm performance will increase. we adopted the research results of Cooper, (1984a); Day and Wensley, (1988), Jaworski and Kohli (1993), Zhou (2006), Ng'ang's et al., (2016), and Zhang et al., (2019) to measure the hypotheses of competitive Intensity. Therefore, we hypotheses:

H4. The stronger the competitive intensity, the stronger the positive impact on firm perfor mance, irrespective of pure or creative imitation.

2.4. Imitation Capability

Imitation capability has long been identified as a learning activity (Mukoyama, 2003). Mukoyama (2003) emphasized that many firms initiate business with imitation strategy and develop new technology based on the knowledge learned from other firms. Imitating capability is borrowing ideas from other companies and tying them together with one's creativity (Otuya, 2018). It is commonly believed that Samsung Electronics has become the world's leading semiconductor firm producing semiconductors independently after imitating and acquiring the technology of Japanese semiconductor firms in the early 1980s. Luo *et al.*,

(2011) proposed imitation capability after classifying it into combinative capability, hardship-surviving capability, absorptive capability, intelligence capability, and networking capability. In particular, Luo *et al.*, (2011) and Song (2015) asserted that absorptive capability shows an emerging economy copycats' distinctive ability to apply new knowledge. The stronger the imitation capability, the stronger the positive impact on firm performance. Latecomers use the imitation capability to access the technological frontier, which argues that companies' strategies should shift from imitation to innovation (Kim, 1997). Xia et al. (2018) argued that there was a mediating effect of imitation between foreign competition and local firm's innovation performance for UK companies. Finally, Houet et al. (2019) argued in a study of 143 Chinese venture firms that competition intensity plays a modification role between entrepreneurial orientation and firm performance. Wu et al. (2019) argued that imitation strategies are positively linked to innovation, and that imitation capabilities can be used as a process to reduce financial capital and technological obstacles typical of small businesses. We adopted the research results of Kim (1997), Mukoyama (2003), Luo et al., (2011), Xia et al., (2018), and Hou et al., (2019) to measure the hypotheses of the imitation capability. Therefore, the following hypothesis is set.

H5. The stronger the imitation capability, the stronger the positive impact on firm performance, irrespective of pure or creative imitation.

3. Method and Data

Experiencing limited growth in Korea, Korean firms began to invest overseas since the early 1990s. Subsequently, major global players such as LG, Samsung, and Hyundai began to emerge in Korea. They invested overseas based on the benefits gained from the domestic market thanks to the Korean government's active export promotion policy. As mentioned by Goldstein *et al.*, (2006), they were becoming "Second-Wave MNEs." It is also true that SMEs have tried to advance overseas through linkage with the advancement of MNCs and achieved success. However, most Korean SMEs have entered other developing countries such as China by their own investment or joint venture investment rather than advancing through linkage with MNCs. These SMEs did not enter the overseas market with competitiveness in specific fields, such as capital, know-how, technology, and management ability, but advanced overseas due to the aggravated business environment such as strikes and a wage increase. Therefore, Korean SMEs that do not have competitiveness come to use the strategy of pure imitation of local and foreign firms' technology even after they enter China. Of course, some firms go beyond pure imitation, conduct business based on innovative imitation strategies, and successfully soft-land in China. However, most Korean SMEs are doing business in China without competitive advantage. According to Korea's import and export statistics (2015), investment in China reached 5.4 billion USD in 2007 when SMEs advanced to China, but declined from 2009 up to 3 billion dollars in 2014. In 2014, the number of SMEs' investment projects out of Korea's investment projects in China was 461,000 (48%) and the amount of investment was 460 million USD. These results verify the fact that Korean SMEs have lost their competitiveness because of intensified competition with local and foreign firms after entering China to take advantage of cheap labor costs. Korea, then, is a significant player in the SME sector of China and, as we shall see, there are further good reasons for us to select Korean firms for study. Note that our interest lies only in operational factors: we do not discuss any changes in the wider political landscape that may, in some cases, have an impact.

This study uses theoretical models presented by Liberman and Asaba (2006) and Delios *et al.* (2008) to reinforce the theoretical background. First, the study applies information-based theories that firms imitate other firms because they have superior information than their own. For this reason, firms with superior technology are expected to exhibit better performance. This study uses technology capacity as a control variable to determine how this variable affects the management performance of copycat companies. Second, rivalry-based theories, which suggest that firms' imitation strategies limit rivalry or competitive parity depending on the degree of competition, are applied. Therefore, this study aims to investigate the impact of competitive intensity on performance. Competitive intensity is used as a control variable to determine how it affects the management performance of copycat companies. The imitation capability was established by referring to Kim (1997) and Mukoyama (2003), Luo et al., (2011), and Moon and Acquaah, 2020). Despite the existence of various environmental factors, we selected only three control variables, taking the aforementioned existing theories such as information-based theories and China's special competitive environmental factors into account. As China is a developing country where domestic and foreign companies compete fiercely, it is considered an environment where small and medium-sized enterprises with weak competitiveness have no choice but to consider the importance of technology, the strength of competition, and the ability to imitate it first.

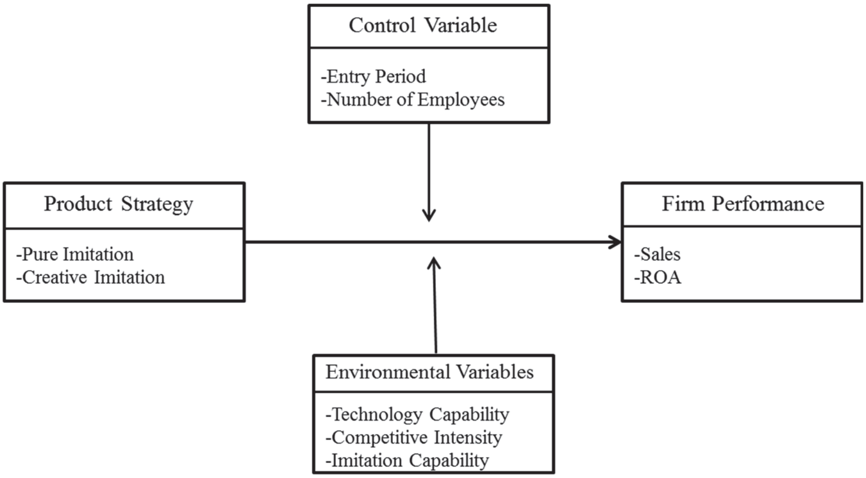
For the empirical analysis, an initial survey of Korean firms conducting business for more than 10 years in China was performed by e-mail and telephone, through specialized research firms. We conducted a survey targeting department heads of each company who have more than 10 years work experiences. We assessed that the ability to gain trust and to access information from high-ranking informants would be greater if the firms were from the same country – Korea – as the lead researcher. The department heads answered the questions regarding imitation strategy, technology capability, and competitive intensity of corporate strategy. The department heads had worked for their firms for 12.5 years. We measured the degree of satisfaction using a five-point scale (1=strongly negative and 5=strongly positive) that measured their thinking about the survey questions. From September 15 to 25, 2018, 120 samples were obtained, representing a response rate of 50% (120 of 240 firms).

Table 1. Demographics Characteristics

Division		Frequency	Ratio(%)
Form of Investment	Joint ventures	76	38
	Wholly owned	124	62
Industry Segment	Industrial products	128	64
	Electric products	26	13
	Machinery	16	8
	The others	30	15
Area	Shanghai City	76	38
	Shandong City	52	26
	Weihai City	44	22
	Yantai City	28	14

Considering the relatively large number of variables set in this study, a second questionnaire survey was conducted for 6 days from October 2 to 7, 2018 and additional 80 samples were obtained, representing a response rate of 66.6% (80 of 120 firms). Finally, a total of 200 highly reliable samples were obtained, which could effectively explain the nine variables set in the study. Of the 200 firms, 100% were small or medium sized, with 300 or fewer employees, and 62% had annual sales revenues of less than US$ 9 million. 38% were joint ventures and 62% were wholly owned companies. Among surveyed firms, the largest industry segment was industrial products (64%), followed by electric products (13%), machinery (8%), and the others (15%). Also, the data were collected in four cities (Shanghai City 38%, Shandong City 26%, Weihai City 22%, Yantai City 14%), each of which has more than 1,000,000 citizens.

Fig. 1. Research Model



Pure imitation and creative imitation represent a very effective product strategy when a firm replicates a competitive corporate's product. So, we measured firm's imitation performance using these variables based on previous studies (Schnaars, 1994; Lee and Zhou, 2012; Posen, 2013; Posen and Martignoni, 2018; Moon and Acquaah, 2020). And we considered technology capability, competitive intensity and imitation capability as environmental variables. Technology capability such as R&D investment is adapted since it has a critical role to firm's performance based on previous researches (Hall and Bagchi-Sen, 2002; Foster, 2003; Hitt et al., 2019). Competitive intensity represents the degree of competition that a firm faces in the industry, so we adapted this variable based on previous researches (Jaworski and Kohli, 1993; Zhou, 2006; Zhang et al., 2020). Imitation capability reflects useful corporate strategy to get competitiveness through a firm's imitation and acquisition based on previous researches (Kim, 1997; Mukoyama, 2003; Luo et al.,2011). Finally, we adapted firm performance from the previous studies (Kogut and singh, 1998; Lee and Zhou, 2012). Firm performance is usually measured by the return on investment, the ordinary return, the operating profit, the profit margin, and so on (Jacobson, 1987; Ho and Wu, 2006; Hatem, 2014). Kogut and Singh (1998) argued that firm performance and R&D intensity were highly correlated and that a firm's R&D expenditure ratio had a positive impact on performance. Lee and Zhou (2012) used market share and ROA as key indicators to empirically analyze the impact of product imitation strategies (creative and pure) on firm performance. Zhou et al., (2013) also asserted that ROA to indicate firm performance because ROA, as a widely used firm performance measure, is not affected by the firms' decisions in equity evaluations. Based on the above, this study uses ROA and profit margins (for the last three years) as financial indicators to measure firm performance. We divided firm performance into two dependent variables. Sales represent sales performance and three year lagged ROA represents to seize financial performance. We acquired the data on ROA from 2015 in 2017 when the data were completed available through the survey. We controlled Entry Period and Numbers of Employees as control variables. We measured entry period by the timing to enter Chinese market and number of employees as the number of locally employed employees in China. We used Korean firm's entry period to measure business experience in China since firms that have long business period could have a good performance, and we measured the number of employees as the firm size since the larger firms that have more employees have more management know-how and competitiveness.

4. Analysis and results

Relevant hypotheses were tested using a hierarchical linear model (HLM). Table 1 shows the results. As a result of verifying through VIF, all of the multicollinearity that can occur among the explanatory variables appears to be less than five. Therefore, it can be seen that the control of the multicollinearity among the independent variables is effective. For financial performance, the sales and ROA are used as dependent variables in this study. Six models were constructed for each independent variable. First, Model 1 was constructed to see how control variables affect the sales, i.e., the dependent variable. Model 2 was built by adding the impact of product strategies and environmental variables on the sales, i.e., the dependent variable. Model 3 was constructed by adding interaction terms between product strategies and environmental variables. Finally, Models4 to 6 were constructed with ROA set as the dependent variable in the same way as Models1 to 3, in which sales were set as the dependent variable.

Table 2. Descriptive statistics of the constructs

Construct	1sale	2ROA	3PURE	4CRE	5TECH	6COMP	7ENTRY	8EMPL	9IMAT
1. Sale	1.00								
2. ROA	0.65***	1.00							
3. pure	0.41***		1.00						
Imitation		0.57***	0.85***						
4. Creative	0.37***			1.00					
Imitation		0.56***	0.20						
5. Technology	0.42***		0.02	0.24	1.00				
6. Competitive	-0.23	0.39***		-0.03	-0.13	1.00			
Intensity		-0.11	0.66***						
7. Entry Period	0.58***		0.38***	0.62***	0.44***	-0.20	1.00		
8. Firm	0.87***	0.55***		0.32***	0.34***	0.52***	0.52***	1.00	
Employee			-0.04						
9. Imitation	-0.01	0.53***		-0.00	-0.07	0.07	0.01	0.07	1.00
Capability	6218		3.33						
Mean	13072	-0.11	1.26	3.82	3.03	3.02	10.44	27.96	
Standard		5.44		1.18	1.29	1.46	6.64	45.20	3.41
deviation		4.44							1.16

Notes: sample size=200, $*p<0.01$, $**p<0.05$, $***p<0.001$.

In the estimation result, the coefficient of determination was 0.7842 in Table1. In other words, 78% was explained by the change of factors considered in the regression model. The sign and significance of coefficient estimates were considered to accurately reflect the changes in sales. In particular, the coefficient estimate of the entry period had a significant positive (+) sign, indicating that the longer the business history, the greater the firm sales. The number of employees had a significant positive sign (+), indicating that the greater the number of employees, the higher the firm sales.

The coefficient of determination was 0.3359 in Model 2. In other words, 34% is explained by the change of factors considered in the regression model. The sign and significance of coefficient estimates were considered to accurately reflect the sales changes. In addition, the coefficient of determination was 0.4291 in Model 5. In other words, 43% is explained by the change of factors considered in the regression model. Thus, the sign and significance of the coefficient estimates were considered to accurately reflect the ROA changes. The coefficient estimate of pure imitation had a significant positive (+) sign in Model 2, indicating that pure imitation had a positive impact on firm sales. On the other hand, the coefficient estimate of creative imitation had an in significant negative (-) sign, indicating that creative imitation did not have a positive impact on firm sales. Creative imitation was not statistically significant. As a result of comparing the T-test values, pure imitation was estimated to be 2.52 and creative imitation was estimated to be -0.42. Therefore, it was confirmed that pure imitation had a stronger impact on the sales than creative imitation. Therefore, Hypothesis 1 was supported. On the contrary, Hypothesis 2 was not supported because creative imitation had no significant impact on sales.

The coefficient estimate of technology capability had a significant positive (+) sign in Model 2, indicating that technology capability had a positive impact on firm sales. The coefficient estimate of technology capability had a significant positive (+) sign in Model 5, indicating that technology capability had a positive impact on ROA as in Model 2. The result of testing Hypothesis 3 showed that the better the firm's technology capability, the stronger the positive impact on firm performance, irrespective of pure or creative imitation. Therefore, Hypothesis 3 was supported. On the other hand, the coefficient estimate of competitive intensity had an in significant negative (-) sign, indicating that competitive intensity had no positive impact on firm sales. Therefore, Hypothesis 4 was rejected. Imitation capability was estimated to have a positive (+) sign in Model 2, indicating that imitation capability had a positive impact on sales. However, it was not statistically significant. Therefore, Hypothesis 5 was rejected.

The results of the analysis on moderation of environmental variables in the impact of pure and creative imitation on the sales and ROA were as shown in Models 3 and 6. It was observed that pure imitation had a significant positive (+) impact on sales through its interaction with technology capability in Model 3, indicating that there was a moderation effect. Moreover, pure imitation had an insignificant negative (-) impact on sales through its interaction with competitive intensity. On the other hand, creative imitation had a significant positive (+) impact on sales only through its interaction with competitive intensity. Furthermore, pure imitation had a significant positive (+) impact on ROA through its interaction with competitive intensity in Model 6, indicating that there was a moderation effect.

Table 3. Model 1

Variable	Estimate	t-value	Approx. Pr> (t)
Intercept	-3814	-3.30	0.0014
Entry	360	-3.30	0.0013
Emp	224	14.01	0.0001
Dependent variable: sales; R-Square: 0.7842			

Table 4. Model 2

Variable	Estimate	t-value	Pr> (t)
Intercept	-11444	-1.96	0.0535
Pure Imitation	4303	2.52	0.0133
Creative Imitation	-760	-0.42	0.6790
Technology Capability	3346	3.78	0.0003
Competitive Intensity	-1854	-2.42	0.0172
Imitation Capability	492	0.52	0.6061
Dependent variable: sales; R-Square = 0.3359 F = 11.95			

Table 5. Model 3

Variable	Estimate	t-value	Pr> (t)
Intercept	-2949	-1.06	0.2926
Technology capability × pure imitation	2468	2.47	0.0155
Technology capability × creative imitation	-1213	-1.32	0.1900
Competitive intensity × pure imitation	-2639	-2.72	0.0077
Competitive intensity × creative imitation	1765	2.07	0.0413
Imitation capability × pure imitation	1279	1.30	0.1963
Imitation capability × creative imitation	-775	-0.86	0.3904
Dependent variable: sales; R-Square = 0.4376 F = 12.06			

Table 6. Model 4

Variable	Estimate	t-value	Approx.Pr>(t)
Intercept	1.8602	2.82	0.0059
Entry	0.2538	4.08	0.0001
Emp	0.0333	3.64	0.0004
Dependent variable: ROA; R-Square = 0.3924			

Table 7. Model 5

Variable	Estimate	t-value	Pr> (t)
Intercept	-2.47226	-1.35	0.1810
Pure Imitation	1.32888	2.49	0.0146
Creative Imitation	0.64716	1.13	0.2624
Technology Capability	0.89755	3.24	0.0017
Competitive Intensity	-0.24126	-1.01	0.3166
Imitation Capability	-0.28780	-0.96	0.3371
Dependent variable: ROA; R-Square = 0.4367 F = 14.58			

Table 8. Model 6

Variable	Estimate	t-value	Pr> (t)
Intercept	-2948	-1.06	0.2926
Technology capability × pure imitation	2468	2.47	0.0155
Technology capability × creative imitation	-1212	-1.32	0.1900
Competitive intensity × pure imitation	-2639	-2.72	0.0077
Competitive intensity × creative imitation	1764	2.07	0.0413
Imitation capability × pure imitation	1278	1.30	0.1963
Imitation capability × creative imitation	-775	-0.86	0.3904
Dependent variable: ROA, R-Square = 0.4376 F = 12.06			

5. Discussion and Conclusions

Different from Lee and Zhou (2012), this study concluded that pure imitation, rather than creative imitation, had a stronger positive impact. In other words, this study concluded that pure imitation had a stronger positive impact on firm performance than creative imitation. Lee and Zhou (2012) argued that unlike in developed countries, imitation strategies in transition economies such as China played an important role in market share and performance as core strategies of firms. However, through a further empirical analysis in transition economies, such as China, it was found that not all creative imitation strategies had a positive impact on firm performance. Because the empirical analysis focused on foreign SMEs in China, some results might be different. However, the reason the study concluded that pure imitation had a stronger positive impact on financial performance than creative imitation was because the foreign SMEs in China were influenced by the external environment, such as changes in the Chinese government policy, and because their technology level was low.

In addition to Lee and Zhou (2012), few previous studies empirically analyzed the impact of pure and creative imitation on firm performance. Nevertheless, empirical research on how useful the imitation strategy is in developing economies and whether it has a positive impact on firm performance is still lacking. We confirm in several papers that imitation strategies are still very useful, especially those that are very necessary for survival and development for later companies with weak skills (Valdani and Arbore, 2007; Lee et al., 2016; Tsolakidis et al., 2020). Therefore, this study attempts to empirically analyze the impact of pure and creative imitation strategies on firm performance through their interaction with environmental variables composed of technology capability, competitive intensity, and imitation capability to fill the gap in the literature.

The findings suggest that SMEs' technology level also had a positive impact on performance. Firms with better technology had a positive impact on performance, irrespective of pure or creative imitation. This reflects the cases where many Korean SMEs entering China without high technology level lose their competitiveness due to Chinese firms' technology catch-up within a short period of time. Therefore, foreign SMEs can maintain their competitiveness if only they enter China with definitely better technology level compared to the local firms. However, it can be argued that this is also a short-term basis and that continuous technology innovation is required.

It must be a huge challenge for SMEs to conduct business in transition economies such as China. While the business difficulties experienced by Western and Asian firms may be different, it seems clear that Asian firms have a competitive advantage in terms of China's labor policy changes, personnel management, and so on. However, the difficulty commonly experienced by all foreign firms conducting business in China is that Chinese firms adopt imitation strategy very broadly and catch up with the latest technology quickly. Therefore, foreign SMEs with medium- and low-level technology entering China to conduct business are likely to lose their short-lived competitiveness and eventually withdraw from China. Therefore, foreign SMEs entering China should constantly strive for technology innovation.

In addition, SMEs that lack technology and know-how need to focus on pure imitation strategies. It is possible that SMEs can perform creative imitation, but it seems difficult under the current circumstances. Therefore, SMEs with limitations in technology and know-how should maintain their competitive advantage for a while, by maintaining their pure imitation strategy. If their technology is caught up by Chinese firms, it would be advisable for them to look for new business opportunities in a third region where labor and other costs are comparatively low. Otherwise, these SMEs will eventually fail.

6. Implications

For firms that lack financial resources and technology development skills, imitation strategy is one of the most important growth strategies. Through an empirical analysis, this study found that pure imitation plays a very important role in the growth of foreign SMEs in China. This study provides theoretical implications from several perspectives. First, although imitation strategies are attracting attention in the literature, only a few studies such as Lee and Zhou (2012) empirically measured which imitation between pure or creative had a significant impact on firm performance. In order to compete with foreign firms in the emerging market, local firms grow through learning and imitation strategies. As Zhou (2006) argued, it is true that firms' new products with innovation strategy are more successful than those with imitation strategy. However, for CEOs of SMEs with no technology innovation ability, imitation is a very suitable strategy that provides the foundation for their growth, such as financial resources and technology ability (Efendi et al., 2020). This study demonstrated empirically that imitation strategy was one of the product strategies for firms to easily choose, especially for SMEs, and that choosing pure imitation rather than creative imitation led to better firm performance. There was lack of research on which imitation between pure or creative had a significant impact on firm performance.

The theoretical contribution of this study is that it shows that pure imitation has a stronger impact on firm performance. Second, pure imitation only had a statistically significant positive impact on firm performance among imitation strategies in this study, unlike the findings of Zhou (2012). In other words, creative imitation is not very easy for SMEs to choose in the emerging market like China. Firms must focus on enhancing performance by choosing pure imitation which allows them to copy other firms easily without much financial investment. These results are contrary to papers that claim that creative imitation is one of the most useful management strategies for companies and is also very effective in improving their business performance (Lee et al., 2016; Wang et al., 2019). In addition, pure imitation had a positive impact on firm performance through its interaction with the environment variables such as technology capability and competitive intensity. As a result of verifying the interaction effects between environmental variables and pure and creative imitation variables, the pure and creative imitation strategies showed similar results as the empirical analysis results above. Unlike the predictions, imitation capability was not statistically significant. In general, the better the imitation capability, the better the firm performance. However, different results were obtained in this analysis. It can be seen that imitation strategy alone had its limitations, as it was not long before Chinese firms caught up with foreign firms' low technology level, even though the latter had strong performance for a certain period of time after entering China.

7. Limitations

This study solely focused on Korean SMEs for empirical analysis. Therefore, there is a limit to the general application of this study to SMEs from other countries that have entered China. The theoretical and practical implications suggested in this study are also derived from Korean SMEs that have entered China. More sophisticated results could be obtained about how much more impact imitation had on the foreign investment firm performance if more variables were considered, such as the Chinese government's frequent policy changes and the Chinese economy's uncertainty in addition to the environmental variables. Future research must consider these points.

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Journal of Korea Trade Vol. 25, No. 4, June 2021, 146-163
https://doi.org/10.35611/jkt.2021.25.4.146
ISSN 1229-828X

China Shocks to Korea's ICT Exports

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JKT 25(4)

Received 11 September 2020
Revised 13 June 2021
Accepted 18 June 2021

Abstract

Purpose – This paper examines China's impact on Korea's ICT exports considering the direct competition channel, the production shift channel, and the indirect demand channel at once. This paper also takes China's economic rebalancing into account and discusses whether it makes any differences in the effect of the three channels.

Design/methodology – To quantify the effect of the three channels, I constructed a linear panel regression model and estimated it with various estimation methods including the system GMM. China's exports toward the same destination as Korea's exports, Korea's exports toward China, and the third countries' exports toward China respectively reflect the three channels. China's GVC indicators are included as well to evaluate the effect of further China's economic rebalancing. Since the present paper has a greater interest in the effect of China rather than the determinant of bilateral trade, a (fixed effect) panel model becomes more appropriate than the gravity model because time-invariant variables in the gravity model, such as the distance and the language, are eliminated during the estimation process.

Findings – The estimation results indicate that Chinese ICT exports are complementary to Korea's ICT exports in general. However, when markets are considered in subgroups, China's ICT exports could have a negative effect in the long run, especially for SITC75 and SITC76 markets, implying a possible competitive threat of China. The production shift effect turns significant during China's economic rebalancing in the markets for the advanced economies and the SITC76 product. China's indirect demand channel is also in effect significantly for the advanced economy and SITC75 commodities during China's economic rebalancing periods. In addition, this paper shows that China's transition toward upstream in the global value chain could have a positive impact on Korea's ICT exports, especially at the Asian market.

Originality/value – The contribution of this paper is threefold. First, it focuses on the ICT industry for which Korea increasingly depends on China and China becomes a global hub of the GVC. Second, this paper quantitatively studies three channels in a model in contrast to the literature which mostly examines those channels separately and pays less attention to the GVC aspect. Third, by utilizing relatively recent data from the period of 2001-2017, this paper discusses whether China's economic rebalancing affects the three channels.

Keywords: Dynamic Panel Regression, Global Value Chains, Korea's ICT Exports
JEL Classifications: C13, C23, F14, F62

1. Introduction

1.1. China's Growth in the Export market and its Spillover Effect on the ICT Sector

Since it acceded to the WTO, China's exports have shown astonishing growth, now accounting for 12.8% of global merchandise exports and 29.5% of global ICT exports in 2017 compared to merely 4.3% and 6.1%, respectively, in 2001 (UN Comtrade Data).[1] Such im-

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pressive export growth has occurred not only in terms of trade volume (and market share) but also in variety (and sophistication), such that Chinese export similarity with OECD countries has grown substantially.[2]

China is exceptional in light of the empirical evidence of a strong positive relationship between export sophistication and income-per-capita (Schott, 2004; Rodrik, 2006; Hummels and Klenow, 2005; Hausmann et al., 2007; Henn et al., 2017). The growing similarity and sophistication of Chinese exports may imply that China can compete with more advanced economies mimicking Korea.[3] Edwards and Lawrence (2010) also noted that newly industrialized Asian economies (NIEs) including Korea face a rising similarity with China in terms of both export variety and value to the US in that their export prices are significantly discounted as those of China. Korea's market share of global ICT export has been very stagnant growing from 4.5% in 2001, which is almost the same as China's share, to 6.9% in 2017 which is merely about one-fifth of China's share.

Accordingly, many researchers and policymakers have concerned themselves with the competitive threat of China in third markets and a large body of research has studied the displacement effect of China's exports on its competitors. Most studies found that the Chinese exports have negatively affected the exports of other developing countries (Hanson and Robertson, 2008; Giovannetti and Sanfilippo, 2009; Wood and Mayer, 2011; Edwards and Jenkins, 2014; Busse et al., 2016).

The literature also shows that countries specialized in high-tech products can still be considered relatively safe from the competition with China despite China's impressive export specialization (Schott, 2008; Hallak and Schott, 2011). This is because China's exports are mostly performed by foreign-funded enterprises and most domestic firms just assemble the imported parts and components from advanced economies (Xing, 2014; Lovely and Huang, 2018). Many industrialized countries were shifting their manufacturing and assembly facilities to China via their FDI to China (Dollar, 2019).[4]

As Haddad (2007) noted, China has quickly become a hub of production networks in East Asia since 2001, and this gives rise to a triangular trade in the area. For instance, East Asian countries export a high share of parts for the ICT product to China and China exports the finished products to the EU and US. This trade pattern has thus contributed to the complementarity between the production structures and the development paths of countries in the region. Accordingly, the share of intra-regional GVC activities increased in Asia from 2000 to 2017 so that the East Asian countries' dependency on China has grown more and more (Dollar, 2019). On the other hand, in North America and Europe, the share of inter-regional production sharing activities increased, especially their GVC linkages with "Factory Asia" reflecting inter-connectedness with China.[5] Consequently, China became an increa-

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[1] Aslam et al. (2017) also shows that China's value-added contribution of world output also has increased substantially from 0.3% in 1990 to 2.0% in 2013, representing a 5-fold increase.

[2] China's export similarity with the OECD increases substantially, and far more than for any other US trading partner, over the period of 1972-2005. The export similarity index (ESI) of Schott (2008) increases from 0.05 to 0.21 for China and 0.11 to 0.33 for Korea over the sample period.

[3] Korea competed with other developing countries during the 1980s and 1990s (Faini et al., 1992; Muscatelli et al., 1994) and it currently competes with industrialized economies especially in high-tech products.

[4] China was the world's second-largest source and second-largest recipient of FDI between 2015 and 2017.

[5] China replaced Japan and part of the US position and became the second-largest supply hub in terms of both the magnitude of its value-added exports and the number of strong linkages to other countries.

singly important supply and demand hub in GVC, and thus production and final demand from third countries have had a significant impact on trade with China.

Even in the ICT sector, China became the largest regional hub for the traditional trade and GVC networks in 2017 reflecting the so-called industrial hollowing out in the US and Japan's ICT sectors, accompanied by large-scale FDI from these countries to China (Dollar, 2019). This implies multinational firms in these countries have shifted their production stages or facilities to China, and consequently their direct exports to third countries decrease when other things being equal. Two-thirds of all ICT intermediate imports of China, coming from other countries in Factory Asia, are used as inputs into Chinese exports.

Therefore, even as it has fostered rivalries for market share abroad, ICT exports of East Asian countries could be positively affected by China's development in export volume and variety.

1.2. China's Economic Rebalancing and Its Spillover Effect

On the other hand, China has suffered from the high investment share of GDP and large current account surplus, so-called 'twin surpluses.' To prevent from potential negative consequences of the imbalances[6] and to achieve sustainable growth, the Chinese government is striving to transform its economy from an 'export'- and 'investment'-oriented economy toward a 'domestic'- and 'consumption'- driven economy (Dieppe et al., 2018; Mano, 2016; Kelly, 2014).[7] China's such economic rebalancing would result in slower but sustainable growth, and thus lower import demand, especially for the intermediate goods. It also would lead to a larger services sector compared to the manufacturing sector and faster growth of the high-tech industry. In addition, the lower demand for imported intermediate goods and greater demand for domestically produced intermediate goods in China may also reduce backward GVC activities due to the deepening of the domestic division of labor and the lengthening of domestic value chains. In fact, as Mano (2016) noted, the investment and manufacturing share of China's gross value-added decreased since 2011, and the high-tech industry value-added share increased.[8] Moreover, the Global Value Chain (GVC) indicators reveal the changes in GVC activities of China as in Figure 1. China's foreign value-added share of its gross export (hereafter FVA) began to decrease in 2011[9], while its indirect value-added share of its gross exports (hereafter DVX) continued to increase; consequently, the GVC position (GVCPO) begins to sharply increase since then; the magnitude of decrease in FVA is larger and thus GVC participation rate (GVCPA) decrease significantly.[10]

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[6] The heightened investment share induced by rising indebtedness raised concerns of financial vulnerabilities, especially for State-owned enterprises.

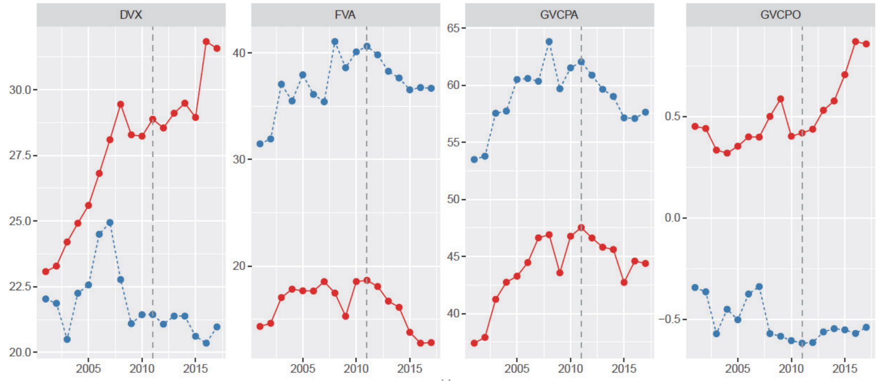
[7] The National People's Congress of the People's Republic of China in 2011 and the Third Plenum of the Chinese Communist Party in 2013 clearly emphasized their need for structural reforms.

[8] The Chinese government has announced a plan to expand domestic supply for semiconductors to 80 percent of domestic demand by 2030 from 33 percent in 2016. However, despite soared R&D expenditure, China still depends on imports of some core technologies, such as semiconductors and optical devices, as well as intellectual property (IP) from abroad. (Woetzel, 2019).

[9] According to OECD 2018 TiVA analysis, China's FVA has declined to lower than OECD and G20 averages even in the ICT sector, which is not only the largest export industry but also the highest imported intermediate use sector for exports.

[10] Countries with a larger GVC position index are relatively more upstream, i.e., they contribute more value-added to other countries' exports than other counties contribute to theirs.

Fig. 1. Trends in Global Value Chain for Korea (dashed blue) and China (red)



Note: FVA is also referred to as a measure of 'backward participation', given that it measures imported intermediate inputs that are used to generate output for export. DVX is a measure of 'forward participation', i.e. it measures exports of intermediate goods that are used as inputs for the production of exports of other countries. (Aslam et al., 2017).

Source: Author's calculation based on Eora MRIO tables following Koopman et al. (2014).

This implies that China's role as a hub in the global production network is shrinking, and its demand for domestic intermediate goods is growing as it moves up the value chain. The lower import demand and change in import demand composition could negatively affect East Asian countries, which are deeply involved in the triangular trade with China.[11] In that sense, Korea's ICT exports must be largely affected by China's economic rebalancing. This is because China's economic transformation is most pronounced in the ICT-relevant sectors and Korea is one of the top ICT trading partners for China.[12] For Korea, the share of China in its ICT export was only 9.2% in 2001 and reached 48.1% in 2017.

As for the topic of China's development in the export market, a lot of papers have tried to analyze the effect of China's economic rebalancing. Those researches investigate the effect concerning changes in industrial composition and lower GDP growth of China, based on various models.[13] Taken together, these studies showed that the consequences of China's economic rebalancing vary over countries and sectors depending on the degree of trade, financial, commodity linkages, and policy response and that the successful transition of China could have a positive effect in the long run by reduced uncertainty and sustainable growth trajectory. However, Hong et al. (2017) and Mano (2016) found that Korea's income and

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[11] Hong et al. (2017) and Bussière et al. (2013) showed that China's economic rebalancing induced changes in China's import demand composition and the changes significantly affect world trade dynamics respectively.

[12] The TiVA 2018 reports by country indicate that China is the top trading partner for Korea and Korea is a top 5 trading partner for China in terms of both gross and value-added exports and imports. In addition, 'ICT and electronics' is the industry for both Korea and China with the highest imported intermediate inputs used for exports and the greatest source of domestic value added content of exports.

[13] Among others, Sznajdersak and Kapuscinski (2020) and Blagrave and Vesperoni (2018) used the (G)VAR model, Aasaavari et al. (2020) used the CGE model, Dieppe et al., 2018 used the ECB-Global model, Mano 2016 used calibrated the Ricardian trade model, Dizioli et al. (2016) and Anderson et al. (2015) used IMF's Flexible System of Global Models, and Hong et al. (2017) used the VAR and panel regressions model.

exports would be negatively affected both cases when China's preference moves for consumption away from investment and when China moves up the value chain into higher-tech industries in the short-run. However, their analysis is performed on a country level and is thus silent on how Korea's ICT exports are affected. As noted above, despite government efforts, China still heavily depends on imports of core technologies such as semiconductors, and hence, China's economic rebalancing could have differently affected the ICT industry.

1.3. Three Channels through which China can Affect Korea's ICT Exports

While investigating how China's rapid export growth and its recent economic rebalancing affect Korea's ICT exports to third countries, this paper focuses on the trade channel considering their influence on global value chains. This is because, as the literature noted (Sznajdersak and Kapuscinski, 2020; Dieppe et al., 2018 among others), not only is the trade linkage the most significant and powerful transmission channel of China's development and economic rebalancing, but the financial and commodity prices link between Korea's ICT industry and China is very limited.[14]

Even in the trade channel, there could be many different propagation mechanisms. However, the literature mostly has focused on the competition between China and the countries interested. I derive three channels among others from the literature mentioned above: 1) the direct competition channel, 2) the production shift (or capacity) channel, 3) the indirect demand channel.

The first channel is supposed to capture the competition between Korea and China in a certain market. China's ICT exports of the same product category to the same destination can either crowd out (or complement) Korea's ICT exports depending on its quality and partners' industrial structure. When China's ICT exports have negatively associated with Korea's ICT exports holding other factors being equal, we can take the results as evidence of competition between the two countries. In the opposite case, ICT exports of the two countries could be complementary.

The second channel is related to China's position in the global value chain and its internal restructuring.[15] As China became a hub of the production network, Korean multinational firms may have relocated some of their production stages to China from third-world countries, or the opposite could be the case because of increased wages and the recent economic rebalancing of China. If China is alike any other countries, not having any special role in the GVC, then Korea's ICT exports to China should move along with its exports to third-world countries reflecting Korea's ICT production capacity. However, when Korea's ICT exports to third-world countries are negatively related to its exports to China, it could be evidence of a production shift.

The third channel is related to complex global value chains and captures the case; for example, when a greater import demand due to China's economic growth or stronger connectivity of the third-world countries with China raises third countries' exports. Hence, the demand of these countries for Korea's ICT intermediates increases as well. Thus, when

[14] I also do not directly consider the government policy response to China's economic rebalancing because government policy reactions could hardly be identified and because those effects, if existing, would appear with many year lags.

[15] Hong et al. (2017) estimates the spillover effect of China's rebalancing and argues that countries closely integrated into China through the GVC such as Korea and Taiwan, that are, therefore, exposed heavily to China's investment demand will be most adversely affected. However, they also mentioned that the spillover effect would be positive as China's economic growth becomes more sustainable in the medium term.

Korea's ICT exports to third-world countries increase while the destination country's exports to China increase, it is considered as the 'indirect demand effect'.

This paper examines China's impact on Korea's ICT exports considering all three of these channels. It also investigates whether there are any changes in the effect of the three channels during the period of China's economic rebalancing. The research utilizes relatively recent data compared to the literature covering the period of 2001-2017, which allows for a discussion of the role of China's economic rebalancing on the three channels. This is the first paper that quantitatively studies the effect of all three channels in a model considering China's economic rebalancing.

To this end, a dynamic panel model is constructed and estimated using various estimation methods including the system GMM method. Only the data of the top 20 importing countries of Korea's ICT products for each year is considered. There are 29 countries in total accounting for about 90% of Korea's total ICT exports, on average, over the sample periods.

The results show that China's ICT exports have been complementary to Korea's ICT exports in general as is in the literature. However, when markets are considered in subgroups, China's ICT exports could have a negative effect in the long run.[16] The production shift effect turns significant during China's economic rebalancing only in the markets for the advanced economies and SITC76 product (such as telecommunication apparatus) in that the relationship between Korea's ICT exports to third-world countries and China is negative and significant. Although for the other markets and periods, Korea's ICT exports to China have a positive relationship with its exports to third-world countries in general, this relationship has loosened during the CER periods. China's indirect demand channel is in effect significantly for the advanced economy and SITC75 (such as office machines) commodities during China's economic transition periods. Furthermore, China's forward GVC participation (DVX) and backward GVC participation (FVA) are positively and negatively associated with Korea's ICT exports to third-world countries respectively during the rebalancing periods. Therefore, China's transition toward further upstream in the value chain could support Korea's ICT exports to third-world countries.[17] The main findings described above emphasize that China's economic rebalancing induces significant changes in the relationship between China and Korea's ICT exports.

The remainder of the paper is structured as follows. Section 2 explains the model and variables employed in the empirical analysis. The main results as well as various robustness checks and limitations are discussed in Section 3. In section 4, selective papers close to the present paper are discussed and the contribution is emphasized. Finally, Section 5 concludes the paper.

2. Model and Estimation

2.1. Model and Variables

Most empirical studies on China's competitive threat used an augmented gravity model and OLS estimation because of its strong empirical performance and theoretical derivation. However, given the substantial heterogeneity of trading partners and export products, OLS estimates are easily biased due to omitted variables (individual effect). Moreover, given that

[16] As I explained later, China's ICT exports can crowd out Korea's ICT exports for the Middle East and late-joining EU countries and markets for office machines, automatic data processing machines (SITC75), and telecommunication and sound recording apparatus (SITC76).

[17] Considering again that China's economic rebalancing induces greater DVX and lower FVA.

the present paper has a greater interest in the effect of China rather than the determinant of bilateral trade, a (fixed effect) panel model becomes more appropriate because time-invariant variables in the gravity model, such as the distance and the language, are eliminated during the estimation process. This paper considers a dynamic model for three reasons. First, the paper examines not only the contemporaneous impact but also the long-run (permanent) impact of China, and second, the static versions of the model tend not to pass diagnostic tests for 'cross-sectional dependency', 'serial correlation', and 'heteroskedasticity'. Finally, the omitted variables problem can be solved by using a dynamic model, as a lagged dependent variable is used as an instrument.

Therefore, to quantify the effect of the three channels described above, the paper constructs a linear panel regression model, as follows.

$$RXK_{ijt} \sim RXK_{ijt-1} + \Upsilon_{ijt} + CER \times \Upsilon_{ijt} + \mu_t \tag{1}$$

where CER is a dummy variable for the period of China's economic rebalancing, and it is assigned one for the year 2011 and after. $RXK_{\{i,j,t\}}$ is Korea's ICT exports of 'j' sector to country 'i' at time 't'. The variable μ_t is time dummies and $\Gamma_{i,j,t}$ are explanatory variables defined as follows.

$$\begin{aligned}\Upsilon_{ijt} = \; & \underbrace{RXC_{ijt} + RXC_{ijt-1}}_{\text{Direct Competition}} + \underbrace{RXK2C_{jt}}_{\text{Production Capacity}} + \underbrace{RX2C_{jt} + RX2CT_t}_{\text{Indirect Demand}} + \\ & \underbrace{LCDVX_t + LCFVA_t}_{\text{China's Transition}} + \underbrace{EndUse.I_{it} + EndUse.K_{it} + EndUse.C_{it}}_{\text{Import Demand Composition}} + \\ & \underbrace{RFD_{ijt} + ODI_{it} + ODI.ict_{it} + ER_{it} + WTV_t}_{\text{Traditional Variables}}\end{aligned} \tag{2}$$

China's ICT export to third-world countries (RXC), Korea's ICT export to China (RXK2C), and third countries' ICT export to China (RX2C) are included to capture the first, the second, and the third channel, respectively. If there is a crowding-out effect of China's exports, the coefficient of RXC would have a negative sign. RXK2C captures the ICT production capacity of Korea (if positive), or it would reflect the production shift effect (if negative). The negative coefficient of this variable would imply that Korean firms relocate some of their production stages from third-world countries to China; thus, even with greater production capacity, Korea's ICT exports to third-world markets might decrease. LCDVX and LCFVA are a log of indicators of China's forward (DVX) and backward (FVA) linkages in global value chains, respectively, and accordingly reflect China's transition towards upstream in GVC. The end-use share of total imports of the destination country is considered to capture the industrial structure of Korea's trading partner. These variables are considered because, as mentioned earlier, the composition of demand affects a country's import demand, and thus partners' exports. In addition, total and ICT overseas direct investment of Korea to third countries (ODI and ODI.ICT) are considered to investigate the intrafirm trade of multinational firms. Multinational firms have invested in local subsidiaries, especially in Asia, to procure intermediate inputs that lower production costs. Therefore, exports tend to increase in this case as (ICT) ODI increases. Finally, conventional variables are included such as exchange rate (ER), Real Foreign demand (RFD), and world trade volume (WTV), into the model to control for price competitiveness, import demand, and global trade environment, respectively. The detailed explanations of the variables are in Table 1.

Table 1. DATA Description and Sources

Variables	Description	Source
$RXK_{i,j,t}$	Log of Real Korea's Exports of commodity j to country i at year t	UN Comtrade[a]
$RXC_{i,j,t}$	Log of Real China's Exports of commodity j to country i at year t	UN Comtrade
$RX2C_{i,j,t}$	Log of Real Country i's exports to China for commodity i at year t	UN Comtrade
$RX2CT_{i,t}$	Log of Real Country i's total ICT exports to China at year t	UN Comtrade
$RXK2C_{j,t}$	Log of Real Korea's Exports to China for commodity j at year t	UN Comtrade
$LCDVX_t$[1]	Log of China's Indirect Value Added ratio to total Exports at year t	Eora MRIO Tables[b]
$LCFVA_t$	Log of China's Foreign Value Added Share in total Exports at year t	Eora MRIO Tables
$RFD_{i,j,t}$	Log of Real ICT imports from World for Country i's, commodity j at year t	UN Comtrade
$EndUse.TI_{i,t}$	Log of Intermediate End-use share of country i at year t	OECD[c]
$EndUse.TK_{i,t}$	Log of Capital Goods End-use share of country i at year t	OECD
$EndUse.TC_{i,t}$	Log of Final Consumption Goods End-use share of country i at year t	OECD
$ODIT_{i,t}$	Log of Korea's real cumulative Total Oversea Direct Investment to Country i at year t	Korea Open DATA Portal[d]
$ODI.ICT_{i,t}$	Log of Korea's real cumulative ICT Oversea Direct Investment to Country i at year t	Korea Open DATA Portal
$ER_{i,t}$	Log of scaled exchange rate for country i in terms of Korea won at year t	IMF[e]
WTV_t	Log of World Trade Volume index(2010=100) at year t	CPB World Trade Monitor[f]

[1] DVX(indirect value added exports), i.e., the share of a country's value added exports embodied as intermediate inputs in other countries' exports, which captures the contribution of the domestic sector to the exports of other countries, thus indicating the extent of GVC participation for relatively upstream sectors.
[b] Eora MRIO database(https://worldmrio.com/eora/)
[c] OECD.Stat Bilateral Trade in Goods by Industry and End-use (BTDIxE), ISIC Rev.4 (https://stats.oecd.org/index.aspx?queryid=64755)
[d] The Export-Import Bank of Korea collects the Oversea Direct Investment(ODI) data and reports via Korea Open DATA potal (https://www.data.go.kr/dataset/3040164/fileData.do)
[e] IMF Exchange Rate Archives by Month (https://www.imf.org/external/np/fin/data/param_rms_mth.aspx)
[f] CPB World Trade Monitor (https://www.cpb.nl/en/worldtrademonitor)

2.2. DATA

First, ICT is defined as exports such as the 3-digit SITC of the UN Comtrade database under SITC75 (Office machine and automatic data processing machine), SITC76 (Telecommunication and sound recording apparatus), and SITC77 (Electrical machinery, apparatus, and appliances, n.e.s) categories. [18] Data only after 2001 is considered because China's WTO membership and consequently Information Technology Agreement (ITA) is in effect as of 2001. Based on the ITA, members are allowed to trade ICT goods with practically no tariffs and regulations. As mentioned above, only the top 20 export destinations for each year over the sample period are considered, which total 29 countries. The sum of those countries' ICT imports accounts, on average, for approximately 92% of the total ICT exports of Korea when exports to China are included, and approximately 61% when it is excluded. In addition, the value of global import of a country for each commodity is referred as the country's import demand.

Eora Multi-Region Input-Output (MRIO) tables are used to obtain GVC indicators for China, such as DVX and FVA. Data for each of the end-use share (intermediate goods, final consumption goods, and capital goods) of the importing country is obtained from the OECD STAN Bilateral trade database. Exchange rates of importing countries in Korean won are computed based on Domestic Currency per U.S. Dollar (period average) of the IMF Exchange Rate Archives by month. The annual average of the exchange rate is taken and normalized by its standard deviation. The world trade volume index is obtained from the CPB world trade monitor. The data for Korea's total and ICT overseas direct investment from the export-import bank of Korea is collected. All the nominal variables except for the exchange rate are transformed into real variables using the GDP implicit price deflator in the United States.

Finally, the natural log is taken for all the variables so that the estimated coefficient can be interpreted as an elasticity.

[18] ICT exports thus cover 12 commodity codes which are SITC 751, 752, 759, 761, 762, 763, 764, 772, 773, 775, 776, 778

2.3. Estimation Methodology

As mentioned above, the OLS estimates of a gravity model are susceptible to endogeneity problems. Accordingly, many papers adopt instrument variables (IVs) and estimate the corresponding model using a two-stage least squares method to attain consistency. For example, Eichengreen et al. (2007), Greenaway et al. (2008), and more recently Pham et al. (2017) used the distance between China and the importing country and/or China's GDP to avoid the potential endogeneity of China's exports. However, this distance seems not to be a good IV to discuss China's impact on Korea's ICT exports. This is because the distance between Korea and China is not far enough to explain the difference in exports of the two countries to third-world countries; moreover, the constant distance cannot capture the variations in exports over time. China's GDP could also be endogenous considering global value chains. For example, an increase in China's GDP implies a rise in demand for third countries' ICT exports, which can in turn raise ICT imports from Korea as intermediate inputs. Given the lack of external instruments, the only available instrumental variable is often the lagged dependent one. However, a lagged dependent variable is not an efficient instrument for two reasons. First, this variable does not account for the correlation introduced into the errors by first-differencing, and second, there are further valid instruments available. Therefore, the (two-step) system GMM method is considered to estimate equation (1), a dynamic linear panel model.[19] The Sargan-Hansen test and the second-order error serial correlation test are conducted to determine the validity of instruments and consistency, respectively.[20]

3. Estimation Results

Tables 2 and 3 report the estimation results with robust errors.[21] The second column shows estimation results on the full sample, and the third through the sixth columns are the estimation results on the regional subsamples, and the seventh through ninth column shows the estimation results by product category.[22] Table 2 mostly describes the variables related to the three channels and China's economic rebalancing, and Table 3 mostly describes the variables usually considered in the literature.

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[19] I prefer the system GMM to the first-differenced GMM in light of Bond et al. (2001). He pointed out that when the first-differenced GMM estimate for the lagged dependent variable lies below the corresponding 'within group' estimate, the GMM estimates are seriously biased due to weak instruments. The estimation results of all considered models are reported in Table 6. Various diagnostic tests support the system GMM.

[20] For the validity of instruments, the Sargan-Hansen test should not be rejected. However, the Sargan-Hansen test is sensitive to the number of instruments so the p-value of this test with instruments that are too large tends to be very high, leading to non-rejection of the validity of moment conditions, when the same test is performed on models that are more parsimonious in terms of the instruments; thus, this situation can potentially lead to opposite conclusions. Hence, I considered collapsed instruments (a much lower number of moments of conditions) as well. For consistency, innovations should not be serially correlated. This consequently means that the first-order covariance between $\Delta\varepsilon_{i,t}$ and $\Delta\varepsilon_{i,t-1}$ should be negative and statistically significant and the second-order covariance should be insignificant.

[21] I report the estimation results only if the estimated coefficients are significant in at least one of the eight estimations

[22] In GMM estimation, if the innovations are heteroskedastic and/or correlated, the variance-covariance matrix of coefficients is inconsistent. Thus, I use the robust estimation of the Coefficients' covariance

Table 2. System GMM Estimation by Market and Commodity Code

Dependent variable:RXK	ALL	Advanced	ASIA	Emerging	ME+EU28	SITC75	SITC76	SITC77
lag(RXK, 1)	0.807***	0.802***	0.590***	0.815***	0.813***	0.456***	0.849***	0.840***
	(0.026)	(0.049)	(0.098)	(0.114)	(0.087)	(0.085)	(0.054)	(0.053)
RXC	0.871***	0.968***	0.572*	1.015***	0.648**	0.322	0.538	0.940***
	(0.098)	(0.158)	(0.305)	(0.271)	(0.303)	(0.219)	(0.349)	(0.147)
lag(RXC,1)	−0.800***	−0.855***	−0.440**	−0.889***	−0.694***	−0.489***	−0.696***	−0.801***
	(0.084)	(0.164)	(0.207)	(0.255)	(0.252)	(0.147)	(0.239)	(0.104)
RXK2C	0.052***	0.049**	0.085**	0.105***	0.024	0.014	0.057***	0.043**
	(0.010)	(0.021)	(0.034)	(0.023)	(0.018)	(0.047)	(0.019)	(0.019)
RX2CT	−0.003	0.070	−0.042	0.036	−0.065*	0.072*	0.013	−0.009
	(0.012)	(0.045)	(0.061)	(0.138)	(0.038)	(0.037)	(0.022)	(0.021)
CER:lag(RXC, 1)	0.159	0.294	−0.580	0.014	−0.262	0.008	0.491*	0.142
	(0.117)	(0.187)	(0.360)	(0.416)	(0.370)	(0.153)	(0.254)	(0.252)
CER:RXK2C	−0.042***	−0.052**	−0.066	−0.101***	0.004	−0.021	−0.075***	0.008
	(0.011)	(0.021)	(0.041)	(0.032)	(0.028)	(0.058)	(0.021)	(0.025)
CER:RX2C	0.017	0.062**	0.065	−0.015	0.013	0.069*	0.003	0.012
	(0.012)	(0.026)	(0.043)	(0.032)	(0.042)	(0.036)	(0.026)	(0.018)
CER:RX2CT	−0.018	−0.065	−0.067	0.100	0.089	−0.096*	−0.026	−0.017
	(0.015)	(0.052)	(0.150)	(0.253)	(0.080)	(0.050)	(0.036)	(0.032)
LCFVA	0.265	0.583	−0.264	−0.440	0.772	0.244	1.269**	0.221
	(0.274)	(0.485)	(0.449)	(0.984)	(0.767)	(0.550)	(0.559)	(0.376)
CER:LCDVX	1.234*	0.635	2.796*	2.675	−1.249	3.509**	−0.145	0.673
	(0.714)	(1.121)	(1.665)	(2.131)	(2.030)	(1.403)	(1.372)	(1.225)
CER:LCFVA	−0.006	−0.133	−1.497*	−0.767	−0.353	0.940	−1.198*	−0.234
	(0.385)	(0.581)	(0.772)	(1.854)	(0.967)	(0.859)	(0.627)	(0.556)
EndUse.TI	0.095	−0.070	0.541*	0.119	−0.427	0.103	−0.079	−0.058
	(0.097)	(0.287)	(0.326)	(0.454)	(0.480)	(0.295)	(0.223)	(0.168)
EndUse.TK	0.097	0.378**	−0.401	−0.365	0.018	0.435	0.280*	0.002
	(0.066)	(0.154)	(0.257)	(0.623)	(0.332)	(0.270)	(0.153)	(0.077)
CER:EndUse.TI	−0.153	−0.063	−1.907*	0.107	0.393	−0.278	−0.006	0.145
	(0.102)	(0.375)	(1.022)	(1.290)	(0.575)	(0.309)	(0.260)	(0.172)
CER:EndUse.TK	−0.040	−0.359**	0.534	−0.301	0.022	−0.329	−0.167	0.051
	(0.072)	(0.177)	(0.407)	(1.447)	(0.689)	(0.302)	(0.172)	(0.099)
CER:EndUse.TC	−0.143***	0.142	−0.789	0.240	−0.198	−0.078	−0.112	0.026
	(0.050)	(0.244)	(0.493)	(0.975)	(0.303)	(0.220)	(0.127)	(0.106)
Observations	360	156	72	48	84	90	120	150
Sargan Test	300.7898	61.63304	37.85583	13.39164	42.06652	63.7471	59.88199	66.95485
AR(1) Test	−5.783***	−3.772***	−2.508**	−3.139***	−3.025***	−2.781***	−3.579***	−6.440***
AR(2) Test	0.901	−0.045	0.883	0.713	0.670	0.784	0.812	-1.031
Wald χ^2	1594280***	1036767***	260035.2***	949883.3***	458770.9***	219597.1***	875225.8***	1903313***

Note: *p<0.1; **p<0.05; ***p<0.01

3.1. Full Sample Estimation Results

The estimation results indicate that there is no crowding-out effect of Chinese exports as RXC is positively associated with RXK but this complementary relationship becomes much weaker in the long run. More specifically, a 10% increase in RXC leads to an 8.71% increase of RXK contemporaneously and 3.68% permanently. The positive coefficient to RXC might imply that ICT products produced in China and Korea were used jointly in assembly operations in third countries. In addition, there is no strong evidence on the production shift channel. Korea's ICT exports to China are positively related to its export to third countries implying that RXK2C captures the export capacity of Korea. When Korea's exports to China increase by 10%, Korea's exports to third-world countries rises by 0.52% contemporaneously, and 2.69% permanently. The third-world countries export to China is negatively related to Korea's ICT exports but the coefficient is very small and statistically insignificant. Therefore, the indirect demand channel is not in effect on average over all sample periods.

Surprisingly, China's GVC indicators, such as the foreign value-added share of China's gross exports (LCFVA) and China's forward GVC participation (LCDVX), do not have a significant effect on Korea's ICT export on average over all the sample periods.

The end-use of imported goods of the importing country reflects their import demand composition. Intermediate goods share, capital goods share, and final consumption goods share are considered, but none of those variables are statistically significant in general.

The foreign import demand has a positive effect on exports as in the literature of the gravity model although the magnitude is much smaller. A 10% increase in foreign import demand results in a 1.05% and 5.44% increase of Korea's ICT exports in the short-run and long-run respectively. Korea's total overseas direct investment also has a positive relationship with Korea's ICT exports to the corresponding countries even though its magnitude is very small. On the other hand, Korea's overseas direct investment in ICT industry does not have a significant effect on its exports.

As mentioned earlier, China's economic rebalancing (CER) may change the relationship between Korea's ICT exports to third-world countries and the variables considered. To identify the change, the CER dummy and the intersection term are introduced with major variables.

Among the three channels, only the second channel is significantly affected by China's economic rebalancing, that is production shift (production capacity) channels become very weak as a 10% increase in RXK2C leads to a 0.1% increase in Korea's ICT exports to third-world countries contemporaneously, and a 0.5% increase permanently.

China's forward GVC participation also becomes significant during the CER period, and a 10% increase in China's DVX ratio (LCDVX) is associated with 12.34% greater Korea's ICT exports to third-world countries. Therefore, China's economic rebalancing seems to positively affect Korea's ICT exports to third-world countries on average, because it is associated with higher LCDVX and lower LCFVA as shown in Fig. 1. In addition, the final consumption goods end-use share of importing country becomes significant with a negative sign during the CER period, although it is very inelastic; the corresponding elasticity is -0.143.

The exchange rate turns significant as well during the CER periods and negative; when the Korean won cheaper, Korea exports more ICT products.[23] This may imply that Korea's ICT exports are in price competition during the CER period, in contrast to the previous period. The effect of Korea's total overseas direct investment (ODIT) remains positive but a little bit weaker during the CER as the corresponding coefficient decreases from 0.013 to 0.0105. Korea's ICT overseas direct investment (ODI.ICT) to destination countries has positively affected Korea's ICT exports and is statistically significant during the CER, even though it is very inelastic. Thus, we can conjecture, since 2011, Korea's ICT multinational firms are more vertically integrated on average and their investments have a positive spillover effect on Korea's domestic exporting firms.[24]

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[23] The exchange rates are normalized by the corresponding standard deviations, the estimated elasticity should be interpreted with caution.

[24] At the firm-level decision-making problem, there is a trade-off between foreign investment (fixed costs) and exports (variable costs). Foreign investment tends to be complementary to exports if multinational enterprises are vertically integrated.

Table 3. System GMM Estimation by Market and Commodity Code (Continued)

Dependent variable:RXK	ALL	Advanced	ASIA	Emerging	ME+EU28	SITC75	SITC76	SITC77
RFD	0.105*	0.079	0.343	−0.094	0.301*	0.722***	0.303*	0.047
	(0.056)	(0.089)	(0.214)	(0.218)	(0.174)	(0.195)	(0.173)	(0.098)
ODIT	0.013*	0.018	0.087	0.028	0.009	0.003	0.022	0.014
	(0.007)	(0.012)	(0.068)	(0.029)	(0.032)	(0.022)	(0.014)	(0.011)
ER	−0.051	0.104	−0.730***	−0.879	0.046	−0.096	−0.113	−0.001
	(0.078)	(0.154)	(0.252)	(0.600)	(0.200)	(0.199)	(0.185)	(0.122)
CER:ODIT	−0.025*	−0.013	−0.152*	−0.017	0.033	−0.046	−0.041	−0.020
	(0.013)	(0.025)	(0.085)	(0.186)	(0.104)	(0.035)	(0.030)	(0.021)
CER:ODI.ICT	0.014*	0.009	0.120**	0.060	−0.060	0.036	0.013	0.008
	(0.007)	(0.014)	(0.059)	(0.308)	(0.051)	(0.031)	(0.017)	(0.011)
CER:ER	−0.164*	−0.476	1.920**	0.206	−0.357*	−0.151	−0.154	−0.281**
	(0.100)	(0.292)	(0.780)	(1.023)	(0.194)	(0.410)	(0.207)	(0.122)
CER:WTV	0.432	1.273	−5.242***	−3.221	1.732	2.897	−0.856	0.330
	(0.905)	(1.161)	(1.906)	(3.162)	(2.836)	(2.388)	(1.595)	(1.329)
CER	−5.212	−7.214	41.828***	13.393	−7.807	−29.822*	13.208	−4.423
	(6.676)	(8.555)	(15.528)	(24.999)	(18.517)	(17.467)	(11.313)	(9.739)
Observations	360	156	72	48	84	90	120	150
Sargan Test	300.7898	61.63304	37.85583	13.39164	42.06652	63.7471	59.88199	66.95485
AR(1) Test	−5.783***	−3.772***	−2.508**	−3.139***	−3.025***	−2.781***	−3.579***	−6.440***
AR(2) Test	0.901	−0.045	0.883	0.713	0.670	0.784	0.812	-1.031
Wald χ^2	1594280***	1036767***	260035.2***	949883.3***	458770.9***	219597.1***	875225.8***	1903313***

Note: *p<0.1; **p<0.05; ***p<0.01

3.2. Estimation Results by Market and Product Category

Next, the impact of China on Korea's ICT exports varies across major markets and product categories are identified. In doing so, the same model is estimated separately for four groups of countries (Advanced, Asia, Emerging, and the Middle East plus relatively late-joining EU countries (hereafter ME+EU28)) and three groups of production categories (SITC 75, 76, and 77).[25]

The estimation results show that ICT exports of China and Korea are complementary for all regional submarkets in both the short run and long run. The contemporaneous complementary effect is the strongest (1.015) in markets for emerging economies and the weakest (0.572) for Asian countries and those effects are substantially decrease in the long-run. Exceptionally, in the markets for Middle East countries and lately joined member states of EU (ME+EU28), China's ICT exports crowd out Korea's ICT exports in the long run. A 10% increase in China's ICT exports induces about 2.5% lower Korea's ICT exports permanently.

When considering markets by product, the complementarity exists only in the market for SITC 77 (electrical machinery, apparatus, and appliances) products and the estimated contemporaneous (and permanent) elasticity of Korea's ICT export regarding China's ICT

[25] Advanced countries consist of Australia, Canada, Japan, USA, Germany, Spain, Finland, France, United Kingdom, Ireland, Italy, Sweden; Asian countries consist of Hong Kong, Malaysia, Philippines, Thailand, Vietnam, Singapore; emerging countries consist of Brazil, India, Russia, Mexico; and Middle East & EU28 countries consist of United Arab Emirates, Turkey, Saudi Arabia, Czech Republic, Hungary, Poland, and Slovak Republic.

export for this market is 0.94 (0.867). However, in the markets for SITC 75 (office machines and automatic data processing machines) and SITC76 (telecommunications and sound-recording and reproducing apparatus and equipment), China's ICT exports are negatively associated with Korea's ICT exports in the long run, implying a possible competitive threat of China. The competition with China is quite intense in the market for SITC 76 products. Specifically, a 10% increase in China's ICT exports induces a permanent decrease in Korea's ICT export by 3.1% and 10.4% in markets for SITC 75 and SITC 76 products respectively. Given expanding market share of Chinese smartphone producers especially in the EURO area, the estimation results can easily be accepted.

The production capacity channel is statistically significant for all regional and commodity subgroups except for markets for ME+EU28 and SITC75, and oppositely, the indirect demand channel is in effect only in those markets. However, importing countries' exports to China is negatively related to Korea's ICT exports in ME+EU28 and the ASIA market even though it is statistically significant only for the former market. Although many factors including their role in the supply chain of the ICT industry could explain the negative relationship, I would leave the further discussion for the following research.

China's backward GVC participation has a positive effect on Korea's ICT export to third-world countries in SITC 76 market. A 10% higher foreign value-added share in gross ICT export of China (LCFVA) leads to a 12.7% greater Korea's ICT exports contemporaneously. On the other hand, the demand composition of importing country turns into a significant factor for Korea's ICT exports in advanced economies and the Asian market regionally, and SITC 76 product market. For advanced economies and SITC 76 commodity markets, a greater capital good end-use share leads to a higher Korea's ICT exports, and, for Asian markets, the intermediate good end-use share is positively associated with Korea's ICT exports. Interestingly, foreign demand has a positive effect only in the markets for ME+EU28, SITC75, and SITC76. Total overseas direct investment is statistically not significant for all submarkets in contrast to the results of full sample estimation.

Again, China's economic rebalancing induces a structural change in the three channels through which China affects Korea's ICT exports for the regional and commodity sub-markets. The complementarity of ICT export between China and Korea has become much stronger in the market for SITC76 products. Specifically, a 10% increase in China's ICT exports for this market permanently reduces Korea's ICT exports by 10.4% before the CER period, but it increases by about 22% during the CER. Moreover, the production shift effect takes place in the markets for advanced economies and SITC76 during the CER period. For instance, a 10% increase in Korea's ICT exports to China (RXK2C) leads to a 0.03% (0.25% in the long-run) decrease of its exports to third countries during the CER period in the advanced economy market. Even though the effect of RXK2C remains positive for other markets, they are substantially reduced in magnitude. During the CER period, the indirect demand channel becomes in effect for the advanced economies. This implies that the advanced economies procure Korea's ICT products for their exports to China. In other words, when China's import demand for the ICT products of advanced economies increases, Korea's ICT exports increase because of complex global value chains. The indirect demand effect of China exists only for SITC 75 again in the CER periods.

Furthermore, China's forward GVC participation becomes significant during the CER period for the Asia and SITC75 markets. The estimation results for the Asian market show that Korea's ICT exports have been positively related to China's DVX share and negatively related to its FVA share of China's exports. Noting again that China's FVA share of total exports has fallen, and its DVX share has risen since 2011, the estimation results, in turn, imply that China's transition towards upstream in the global value chain could have a positive effect on Korea's ICT exports, especially in the Asian market. Such a positive effect might also exist for SITC 75 products, for which China's DVX share elasticity of Korean ICT exports is 3.509 since 2011. On the other hand, for SITC 76 products, the effect of China's FVA share remains positive (0.071) and significant (at 10%) even since 2011; thus, Korea's ICT exports could be negatively affected by China's structural change for SITC 76 product market.

The effect of the demand composition also changed during the CER period in the Asian market. The intermediate goods end-use share of the importing countries had a positive effect, but its effect turns negative (-0.649) during CER periods. This result may indicate that either the comparative advantage of Korea's ICT products in the Asian markets is not present for intermediate goods or that Korea's intermediate goods are mainly heading to China and assembled into final goods. Even though the effect of capital goods end-use share remains positive for advanced markets, it becomes very small (0.019) in the CER period. Additionally, the coefficient of exchange rate changes its sign into positive for the Asian market during the CER period. This might imply that price competitiveness becomes an unimportant factor for Korea's ICT exports in the Asian market during the CER periods. The effect of total and ICT overseas direct investment has become significant for the Asian market. The elasticity of Korea's ICT export regarding ICT ODI to the corresponding country is 0.12 and statistically significant, and which would again imply that Korea's ICT industry is vertically integrated during the CER period.

4. Discussion

There is a relatively smaller number of studies from which we can draw some empirical evidence for the impact of China on Korea. In this section, we consider the estimation results from the selected studies which used similar empirical method for Korea's ICT industry and discuss what causes the difference between the results obtained in this paper and the results of these other studies.

First, Eichengreen et al. (2007) discuss the direct competition effect and the indirect demand effect separately using data covering the period of 1990-2003. Their model is a gravity model with country-pair and time-fixed effects. They found that China's exports did not crowd out the exports of other Asian countries for technology-intensive consumer goods and capital goods. In addition, China's exports of intermediates continue to be positively associated with other Asian countries' exports of intermediates. Therefore, China's competitive threat does not exist on Korea's ICT exports. On the other hand, Greenaway et al. (2008) estimated almost the same model as Eichengreen et al. (2007) based on the data from the same period. However, they found evidence of a displacement effect, which is more pronounced for high-income Asian exporters such as Korea, Singapore, and Japan. This discrepancy can be attributed to the individual- and time-fixed effects which are not considered in Greenaway et al. (2008). However, both studies concluded that, because of China's import demand, the net effect of China would be positive for high-income Asian countries, including Korea.

Both studies, however, have limitations in comparison to this paper. First, they consider only the direct competition channel and not the global value chains and, thus, exclude the triangular trade of Asian countries. At best, they discussed the effect of the production shift channel separately and combine it with the direct competition channel in a counterfactual experiment. Second, as mentioned above, utilizing the distance between China and the importing countries would not be a good choice, as noted by Eichengreen et al. (2007), thus the GMM method would be a more appropriate estimation strategy. Third, their data spans the period of 1990-2003; hence, it does not reflect structural changes in domestic and the global trade environment arising from China's economic rebalancing.

Recently, Pham et al. (2017) studied the competition effects of Chinese high-tech exports from the demand side with relatively recent data spanning the period of 1992-2013. Their model is a static gravity model with exporter fixed effects that adopts the same IVs to mitigate the biases induced by the endogeneity of China's exports. According to their estimation results, for the East Asian country group, which includes Korea, and ICT relevant products (computer-office machinery and electronics-telecommunications), Chinese exports are complementary to their exports. They also found that the complementarity in ICT exports for EA countries becomes stronger after 2009. This result is inconsistent with the results of the present paper in which such complementarity is mostly not changed before and after the CER period. A plausible explanation for this discrepancy is that their model did not consider some structural breaks arising from China's accession to the WTO in 2001 and the trade collapse in 2009. They also did not consider the global value chains and, hence, the production shift effects and China's economic rebalancing since 2011.

The three channels discussed in previous sections are also mentioned in Haddad (2007), among others. She showed that China's export growth negatively affected Korea's ICT export growth based on OLS estimation results. She also articulated that because Korea's ICT exports to China have grown substantially during the same sample periods, the negative effect should be attributed to the triangular trade among East Asian countries, rather than the competition between the two countries. However, she did not quantify China's competitive threats controlling the production shift effect in a model. To the best of my knowledge, this is the first paper that incorporates the variables capturing three channels within a model and discusses the effect of China's economic restructuring.

5. Conclusion

In this paper, we examine China's impact on Korea's ICT exports with a dynamic panel regression model considering the direct competition effect, the production shift effect, and finally, the indirect demand effect simultaneously. The first channel investigates whether China's ICT exports crowd out or complement Korea's ICT exports to third-world countries. The second channel evaluates indirectly whether Korean multinational firms relocated some of their production stages to China from third-world countries and, thus, whether they reduce their exports to third-world countries. Finally, the third channel tests the indirect impact of China's demand through complex global value chains.

To estimate the model, we utilize relatively recent data for the period of 2001-2017, and this allows a discussion of a possible structural break arising from China's economic rebalancing. The paper only considers the data for the top 20 importing countries of Korea's ICT products for each year, which cover approximately 90% of Korea's total ICT exports.

The system GMM results using a full sample show that China's ICT exports have been complementary to Korea's ICT exports contemporaneously, as indicated in the literature, but this complementary relationship becomes much weaker in the long-run. In addition, there is no strong evidence on the production shift channel. Korea's ICT exports to China are positively related to its export to third-world countries, however, the link becomes very loose during China's economic rebalancing. The indirect demand channel is not significant over all the sample periods. Surprisingly, China's FVA share does not have a significant effect on Korea's ICT export. Instead, Korea's ICT exports are more associated with China's DVX ratio in the CER period.

We also estimate the model with subsamples classified by region and product category. China's ICT exports are again complementary for all regional markets considered contemporaneously. The complementary effect is the strongest in emerging economies and the weakest in Asian countries regionally. Surprisingly, however, the positive relationship exists only in the market for STIC 77 among production categories. However, the permanent effect of China's ICT exports is negative in the markets for ME+EU28 countries and SITC75 and SITC76 implying a possible competitive threat of China. Korea's ICT exports are positively related to its exports to third-world countries except for ME+EU28 (production capacity), and its relationship has become much weaker since 2011 for the advanced and the emerging economy. For SITC 76 product, the relationship turns negative during the CER periods implying a production shift effect. The indirect demand channel is in effect only for the advanced economies during the CER periods. This means that when China's import demand for the ICT products of advanced economies increases, Korea's ICT exports increase because of complex global value chains. The indirect demand effect of China exists only for SITC 75 again in the CER periods.

Furthermore, the paper finds that Korea's ICT exports have been positively related to China's transition towards upstream in the global value chain, especially for the Asian market during the CER periods. On the other hand, for SITC 76 products, the effect of China's FVA share remains positive and significant even since 2011; thus, Korea's ICT exports could be negatively affected by China's structural change.

In sum, the paper finds that the three channels described above are valid, and China's economic rebalancing induces significant changes in the effectiveness of the channels. This is hardly identified in the empirical literature.

This paper also has some limitations in that the three channels are not exhaustive and the present paper does not discuss the interactive effect of the channels. As mentioned above, importing countries of Korea's ICT exports could respond to China's economic rebalancing so that endogenous effects of the variables could be important. In addition, the effect of each channel could be heterogeneous depending on the degree of other channels. For example, the complimentary effect could also depend on Korea's ICT export to China for some reasons. Although this endogenous and heterogeneous effect would not make any critical changes for the results of the present paper, it is important to understand this issue for policy implications. Therefore, I think, to study this issue combining the three channels with a general equilibrium model or VAR model could be worthwhile for future research.

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