ESSAYS IN INTERNATIONAL TRADE

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ABSTRACT

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My doctoral dissertation consists of three independent empirical papers on International Trade in East Asia. The first chapter studies how the recent trade conflict between Japan and Korea has changed the bilateral trade between the two countries. The second chapter studies the role of Multinational Enterprises' outward foreign direct investment on the employment volatility of domestic workers. The third chapter studies how the surge of China in the global economy has changed the technology innovation of Taiwanese firms through export channels.

Chapter 1 studies the impact of the Japan-Korea trade dispute during the second half of 2019. We employ synthetic control methods (SCM), a modern econometric tool developed in the policy evaluation literature, to empirically address our research topic. Our baseline SCM results imply an 8.37%-10.64% decrease in Japanese exports to Korea for the six months after the trade dispute. We find little evidence that the trade dispute changed Japanese imports from Korea. We also observe heterogeneous negative effects across products by their attributes. Within groups of products mainly used for production input, Japanese exports of differentiated products changed more than exports of homogeneous goods, which can be understood as the supply-side effect of the trade dispute to the Korean economy. From the Korean consumer boycott which is the demand-side event of the trade dispute, the negative effects are obvious for boycotted foods and vehicles but not for other boycotted items. In the recent era of rising political challenges against the free trade regime, new empirical evidence from this paper elucidates how political tensions may change the patterns of international trade.

Chapter 2 examines the role of the outward foreign direct investment (FDI) behaviors of multinational enterprises (MNEs) on the firm-level employment volatility of domestic workers. We merged firm-level data and industry-level outward FDI data from Korea to study how different types of out-

ward FDI by Korean MNEs have disproportionately affected the employment volatility of domestic workers in different tasks. Korean MNEs' outward FDI is strongly associated with an increase in domestic workers' employment volatility. The relationship is stronger for manufacturing firms than non-manufacturing firms. The difference-in-differences (DD) model after proper matching reveals that FDI in pursuit of market access weakly raises the employment volatility of domestic workers. The causal effect is even more apparent in the case of FDI seeking market access to Asian emerging countries. We find few causal effects of other types of FDI, such as FDI in pursuit of labor cost savings or market access to developed countries. Our study provides the first empirical evidence that MNEs' outward FDI activities may unequally threaten the employment stability of domestic workers through firms' investment purposes and workers' tasks.

Chapter 3 (joint work with Dr. ByeongHwa Choi) studies the impact of China's surge in the global economy on the intensive and extensive margins of firm-level innovative technologies. We derive novel predictions: greater market access after China's WTO accession results in (i) a significant increase in the patent quantity and quality of highly productive firms and (ii) a substantial expansion of technologies to new fields, mostly for highly productive firms. We confirm our predictions empirically using the U.S Patent and Trademark Office patent data matched with Taiwanese firm-level data for the 1998-2014 period.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

TRADE EFFECTS OF THE TRADE CONFLICT: EVIDENCE FROM THE JAPAN-KOREA TRADE DISPUTE

1.1 Introduction

International trade can never be independent of politics, international relations, or history. International conflicts caused by political or historical controversies can create animosity among people in one country against those in another country. Such animosity may harm bilateral trade, and sometimes, these negative effects can last for quite long periods.[1] While economists have long been interested in studying the economic consequences of political tensions between countries, as political challenges to free trade (e.g. the recent China-US trade war) have intensified, trade economists are paying more research attention to this issue.

Starting in July 2019, history-based issues between Japan and Korea began to increase political tensions between the two countries and ultimately caused a trade dispute. This trade dispute encompassed several official and unofficial developments that hindered bilateral trade: the Japanese government's imposition of formal export control against Korea, the Korean government's retaliatory policies, and Korean consumers' boycott of Japanese products. However, it is not obvious whether this trade dispute actually lowered bilateral trade volumes. **Was the trade dispute a real threat to trade or just bluster? If the trade dispute hurt bilateral trade volumes, how great were the negative effects?** Determining the answers to such questions is essential to understanding the relationship between politics and trade. This research topic is even more interesting in the current new-cold-war era of the contraction of free trade in the global economy.

We formally address this research question by applying novel empirical tools from the policy

[1] Che et al. (2015), for example, found that Chinese regions that suffered more casualties during the Sino-Japanese War of 1937-1945 attracted less cross-border investment from Japan-based multinational enterprises and imported fewer products from Japan, even several decades after the Sino-Japanese War.

evaluation literature. As a main empirical framework, we employed the synthetic control method (SCM) developed by Abadie et al. (2010, 2015), a modern data-driven microeconometric approach. The most difficult challenge in assessing the effects of trade disputes is how to construct reliable counterfactuals, - that is, the outcomes that would have emerged in the absence of the trade dispute. The SCM addresses this challenge by constructing a reliable counterfactual from a mixture of control group units. The SCM provides a set of optimal weights to create a combination of control units that is as close as possible to the treated unit in terms of pretreatment characteristics.[2]

We first evaluate the effects of the trade dispute on overall Japanese trade with Korea. The trade dispute directly and indirectly decreased the overall volume of Japanese exports to Korea in the short term. Our SCM estimates indicate that the bilateral trade dispute lowered exports from Japan to Korea by 8.37%-10.64% in the six months after the dispute, which is not a negligible effect. We find a similar decrease in Japanese imports from Korea which is 7.36%, but the effect on Japanese imports from Korea is smaller and less clear than in the case of Japanese exports to Korea. We observe that the negative effect of Japanese exports to Korea was much greater in the last three months than in the first three months after the trade dispute. We also studied product heterogeneity. In regard to product heterogeneity, we find that the trade dispute weakly lowered Japanese exports of both consumption goods and production goods. Within groups of products mainly used for production input, Japanese exports of differentiated products fell by 14.78% which is greater than 10.16% for homogeneous products. This can be understood as a supply-side effect to Korean manufacturing industries.

We then isolate the set of products targeted by the consumer boycott to formally estimate its effects. By separating boycott targeted items which are posted on the boycott websites, we can more precisely disentangle the demand side effect from the trade dispute which are driven by changes in Korean consumers' preferences of Japanese products. The effect of the boycott on Japanese exports to Korea was heterogeneous across the targeted items. There were sizeable drops in Japanese exports

[2] According to Athey and Imbens (2017) "the synthetic control approach developed by Abadie et al. (2010, 2015) and Abadie and Gardeazabal (2003) is arguably the most important innovation in the policy evaluation literature in the last 15 years."

to Korea of boycotted foods and vehicles, but we find little evidence of such declines among other targeted items, including apparel, electrical appliances, and sports and miscellaneous household items. We provide several potential mechanisms which may explain our findings from boycotted items, even though they are not testable due to the lack of proper data. Finally, we implement a difference-in-differences (DD) model to conduct an alternative analysis. The results from the DD model are overall greater than the results from the SCM analysis but they are consistent with those of the SCM model. Our findings highlight that the Japan-Korea trade dispute hurts the volume of bilateral trade at least in the short term, with adverse effects on Japanese exports more apparent than those on Japanese imports. The negative effects are even stronger for a group of the items targeted by the Korean consumer boycott.

The remainder of the paper proceeds as follows. Section 1.2 reviews the literature. Section 1.3 explains the historical background of the Japan-Korea trade dispute and the subsequent Korean consumer boycott of Japanese products. Section 1.4 explains the synthetic control method, our major empirical strategy for identifying the causal treatment effects. Section 1.5 describes our research dataset. Section 1.6 discusses our findings, with section 1.6.1 discussing our results from the SCM analysis. This section includes the results of our analysis of product-wide heterogeneity and robustness checks. Section 1.6.2 describes our findings from the SCM analysis of the Korean consumer boycott. Section 1.6.3 provides the results of the DD model, our alternative empirical specification. Section 1.7 discusses avenues for future research and concludes.

1.2 Literature Review

Our research belongs to the emerging literature on the relationship between international political relationships and international trade. We will briefly introduce a few recent noteworthy papers in this paragraph.[3] Michaels and Zhi (2010) used the period of deterioration in the bilateral relationship between the US and France in 2002-2003 to investigate how public attitudes toward a certain

[3] See Table A.1 for the list of extensive international conflict episodes and corresponding papers that are relevant to our work.

country can affect trade.[4] Michaels and Zhi (2010) documented that unfavorable public opinion toward France in the US lowered bilateral trade and adversely affected business transactions between the two countries. Analyzing the same episode, Pandya and Venkatesan (2016) showed how US consumers' antipathy toward France was revealed in their grocery shopping. US consumers reduced their purchases of French-sounding brands when the degree of US-France tension was high, even when those brands were not French. The research of Fuchs and Klann (2013) focused on China's diplomatic tensions with other countries that have invited the 14th Dalai Lama, the political and spiritual leader of the Tibetan community, for official visits. The Chinese government has warned that extensions of invitations to the 14th Dalai Lama may be met with retaliatory policies against the host country. According to Fuchs and Klann (2013), countries that have invited the 14th Dalai Lama for official visits at the highest political level have experienced a short-term decline in exports to China. The authors' findings confirmed that China restricts its imports to punish countries that extend official invitations to Dalai Lama. Finally, Heilmann (2016) empirically studied the adverse effects of several cases of politically induced consumer boycotts on international trade. Heilmann (2016) examined cross-country international conflicts including the Muhammad cartoon controversy in Denmark and the China-Japan territorial conflict over the Senkaku/Diaoyu Islands.[5] Our study is similar to Heilmann (2016) in that we also use the synthetic control method to quantify the adverse trade effects of the trade dispute. However, we attempt to push the analysis one step further by quantifying heterogeneous treatment effects by product attributes. We try to disentangle the demand-side effect from the Korean consumer boycott and the supply-side effect from the restrictive export policy imposed by the Japanese government.

In the broader context, our work can also be connected with academic papers on the recent

[4] This deterioration occurred because France opposed the US's efforts to obtain a UN Security Council mandate to invade Iraq.

[5] A few other works on the China-Japan territorial conflict episode took different approaches to the topic. Luo and Zhou (2019) decomposed the effect of the Chinese boycott into a cancellation effect (a decline in consumption from consumers' forgoing consumption) and a transfer effect (switching of consumption from Japanese to non-Japanese brands). Tanaka et al. (2019) found that Japanese firms exporting to China lowered their employment in temporary tasks in response to territorial conflict.

China-US trade war. For the last few years, we have seen several political challenges that endanger the global free-trade regime. The China-US trade war, the greatest of these challenges, has attracted considerable research attention from trade economists. A few recent studies have attempted to understand the consequences of the trade war, and they have generally reported undesirable consequences for the US economy. Most studies have examined the price effects of the trade war, finding that the rise in US import tariffs has had little impact on the ex-tariff export price, which is evidence of the complete pass-through of tariffs to US domestic prices. This complete pass-through of US import tariffs means that US consumers and retailers bear most of the cost of tariffs. (Amiti et al. (2019, 2020), Cavallo et al. (2019), Fajgelbaum et al. (2019), and Flaaen et al. (2020)) The retaliatory tariffs imposed by other countries against the US, however, have had different consequences from those of the US import tariffs. These retaliatory tariffs have lowered the US export price, which is evidence that US exporters have suffered substantial welfare costs from retaliatory tariffs (Cavallo et al. (2019)). Beyond price effects, the rise in retaliatory tariffs has lowered US consumption (Waugh (2020)) and manufacturing employment (Flaaen and Pierce (2020)).[6] The effects have not only been felt in the US economy; similar negative effects from the trade war habe also been observed among the Chinese firms (Benguria et al. (2020)). Along with the China-US trade war, another major trade conflict episode of the late 2010s was the Japan-Korea trade dispute, which endangered the free trade regime in East Asia. The Japan-Korea trade dispute, however, was somewhat different from the China-US trade war in the sense that both Japan and Korea used export restrictions rather than import tariffs to elicit a detrimental effect on the target economy. To the best of our knowledge, this paper is the first academic work to empirically study the trade impacts of the Japan-Korea trade dispute. Complementing recent academic papers on the China-US trade war, our work will shed light on the consequences of political challenges to free trade that have arisen over the past decade.

[6] There is even evidence that the Republican party, the ruling party that has led the China-US trade war, has lost votes in regions that have experienced economic losses from retaliatory tariffs (Blanchard et al. (2019)).

1.3 Background

The background of the 2019 Japan-Korea trade dispute and the subsequent Korean consumer boycott of Japanese products involves the historical diplomatic conflicts that have affected the two countries since 1945, when the Japanese occupation of Korea ended. Japan and Korea normalized their diplomatic ties in 1965; however, they have failed to completely resolve several controversial issues dating back to the era when colonized Korea was under Japanese rule, e.g, reparations for the harms suffered by comfort women and forced laborers during the Pacific War, that is, in the Asia-Pacific theater of World War II. Bilateral relations between Korea and Japan have steadily worsened since late 2018, after the Supreme Court of Korea ordered a few major Japanese companies to compensate Korean laborers who were illegally forced into slave labor for war industries in the 1940s. The Korean Supreme Court's decision provoked a backlash from the Japanese government, as it has claimed that the issue of reparations for the Japanese empire's occupation of Korea was completely settled in 1965 when Japan and Korea agreed to normalize their bilateral relationship. The Korean Supreme Court's ruling on forced labor has been thought to be a major cause of the Japanese government's imposition of export restrictions against Korea in July 2019, even though the Japanese government did not officially publicize the motivations behind its new restrictive export policy against Korea.

On July 1st, 2019, the Japanese government announced that it would tighten restrictions on Korea-bound exports of a few chemicals, including fluorinated polyimide, photoresist, and etching gas.[7] All these chemicals are essential to the semiconductor and display industries, which are the main manufacturing industries in Korea. The new restrictive export policy was potentially fatal to Korean chip manufacturers, as Japan is the largest supplier of these chemicals to Korea. The restricted chemicals are defined at the highly disaggregated ten-digit Harmonized System (HS) product-code level, which prevents us from assessing the direct effects of the Japanese government's export retaliation at the detailed level. At the six-digit level, the corresponding HS codes are 392099 (fluorinated polyimide), 370790 (photoresist), and 281111 (etching gas). We observe a huge decline

[7] https://www.meti.go.jp/english/press/2019/0701_001.html

over the intervention period in Japanese exports to Korea for the HS 281111 product code, under which etching gas is categorized. We observe relatively weaker declines in Japanese exports to Korea for the HS 392099 and 370790 product codes.

As a follow-up step, in August 2019, Japan excluded Korea from its ‘white list’ countries for exports of strategic products.[8] These new export policies imposed by the Japanese government induced the Korean government to adopt defensive policies against Japan, e.g. the refusal to renew the General Security of Military Information Agreement (GSoMIA) and the retaliatory removal of Japan from Korea’s own white list. The Japanese government’s new export restrictions and the Korean government’s ensuing retaliations resulted in a trade dispute and restrained bilateral cooperation.[9]

Beyond inciting these formal responses by the Korean government, the export restrictions imposed by Japan infuriated Korean consumers, spurring a consumer boycott of Japanese products and services in Korea. The boycott spread explosively on social networking services (SNSs) among angered Koreans, who posted images to encourage joining the boycott on their SNS platforms (see Figure 1.1 for images of the “No Visit, No Purchase" consumer boycott flyer and protesters at the stores of Japanese fashion brands). In addition to the image of the consumer boycott, a list of Japanese brands that Korean consumers should avoid was circulated. The consumer boycott was led primarily by private consumers, but a number of local governments or public-sponsored stores also actively joined in by refusing to sell Japanese products. The boycott broadly aimed two goals: to reduce trips to Japan (“No Visit") and to reduce the consumption of Japanese products (“No Purchase"). Figure 1.2 clearly shows evidence of an effect of the “No Visit" campaign. The number of Korean tourists visiting Japan dropped sharply from August 2019, one month after the beginning of the consumer boycott in Korea. No similar declining trends appear for other

[8]The Japanese government has controlled exports of strategic products to foreign countries. Strategic products include not only weapons but also broader items that can be potentially converted to munitions. When Japanese firms export strategic products to countries on the white list, however, exporters can choose the option of a simplified review process to receive export permits.

[9]See Table 1.1 for the timeline of events.

destination countries.[10] The dramatic decline in the number of Korean tourists to Japan suggests that the economic effects of the trade dispute and the consumer boycott may be salient in other sectors as well.

1.4 Methodology

We use the SCM developed by Abadie and Gardeazabal (2003) and Abadie et al. (2010, 2015) as our main empirical approach.[11] The SCM was developed to estimate the treatment effects when a single unit is exposed to the treatment event. The most difficult challenge in estimating such treatment effects is how to recover or predict the counterfactual outcome, i.e., the outcome of the treated unit in the absence of exposure to the treatment event. The SCM addresses this problem by combining units in the control group[12] and predicting the counterfactual of the treated unit. The combination is assembled from the control group using the set of weights that achieves the best preintervention fit with the treated unit. Compared to other methods traditionally used in the policy evaluation literature, such as DD, the SCM has more advantages. As SCM predicts the counterfactual from the weighted combination of the control group which achieves the best goodness-of-fit preintervention period, it is less restrictive than the DD model which relies on the simple unweighted average. This also makes the SCM model less suffer from non-parallel trend problem than the DD model. In addition, by plotting the trends of the treated unit and the constructed synthetic unit, a researcher can evaluate the usefulness of the constructed synthetic unit. Therefore, the SCM is more flexible and powerful than DD, and the SCM estimates should be understood as more reliable when the model is viable. Since the seminal paper of Abadie et al. (2010), synthetic control methods have been extensively used in social science studies to identify the effects of a

[10] For Figure 1.2, we include trends in overseas tourism by destination countries for which (1) the numbers of Korean tourists are available at the monthly level and (2) the numbers are meaningful. The monthly numbers of Korean tourists visiting a few countries (e.g., China and France) are not available due to a lack of data.

[11] See Abadie (2020) for a recent review of the synthetic control method.

[12] The control group is also called the donor pool in the SCM literature. We will use the terms interchangeably.

treatment event on the treated unit.[13] We will briefly describe the SCM framework in the context of our analysis of the treatment effects of the Japan-Korea trade dispute and the Korean consumer boycott.

Suppose that we have $j \in \{1, 2, ..., J + 1\}$ countries, where $j = 1$ is the treated country (Korea in our study) and $j \in \{2, ..., J + 1\}$ are J other countries that compose the potential control group. Following the literature on statistical matching, we will call $j \in \{2, ..., J + 1\}$ the donor pool countries. There are $t \in \{1, ..., T\}$ periods; let the intervention event (the Japan-Korea trade dispute and the Korean consumer boycott in our research) occur at $T_0 + 1$, where $0 < T_0 + 1 < T$. Therefore, $\{1, ..., T_0\}$ is the preintervention period before the event, and $\{T_0 + 1, ..., T\}$ is the postintervention period. Let y_{jt} be the outcome variable for country j at time t: the volume of Japanese trade (exports or imports) with a partner country j at time t in our research. y^I_{jt} is the outcome variable of country j at time t if country j was exposed to the intervention. while y^N_{jt} is the outcome variable for country j at time t if country j was not affected by the intervention. Therefore, $y_{jt} = y^I_{jt}$ holds for $j = 1$ and $t \in \{T_0 + 1, ..., T\}$, and $y_{jt} = y^N_{jt}$ for other cases.

The treatment effect for country 1 at time t (α_{1t}), that is, the postintervention effect of the event on treated country 1's outcome variables (y_{1t}), can simply be written as follows.

$$\alpha_{1t} = y^I_{1t} - y^N_{1t} \qquad \text{for } t \in \{T_0 + 1, ..., T\} \tag{1.1}$$

The treatment effect (α_{1t}) consists of two parts: the outcome variable for treated country 1 if it was treated at t (y^I_{1t}) and the outcome variable for treated country 1 if it was not treated at t (y^N_{1t}). The well-known challenges of estimating treatment effects arise from the fact that y^N_{1t} is not observed; y^N_{1t} is counterfactual outcome for the treated country $j = 1$ in the postintervention period $t \in \{T_0+1, ..., T\}$. Synthetic control methods provide us with an intuitive data-driven way to predict y^N_{1t} based on the predictors of donor pool countries not interrupted by the intervention.

Let Z_0 and Z_1 be $k \times J$ and $k \times 1$ matrices of preintervention characteristics for donor pool countries and the treated country, respectively. Z may include outcome variables of countries in

[13] For studies using synthetic control methods in the international trade literature, see Billmeier and Nannicini (2013), Chung et al. (2016), Heilmann (2016) and Cho et al. (2019).

the preintervention period. The difference in the characteristic vectors between the real treated country and an arbitrary combination of donor pool countries is given by $Z_1 - Z_0 W$, where $W = (w_2, ..., w_{J+1})'$ is a $J \times 1$ vector of weights with $0 \leq w_j \leq 1$ (the non-negativity condition) and $w_2 + ... + w_{J+1} = 1$ (the sum-to-one condition).[14] $W^* = (w_2^*, ..., w_{J+1}^*)'$ is a $J \times 1$ vector of optimal weights that minimizes the distance between the preintervention characteristics of the treated country and the synthetic control country, $\|Z_1 - Z_0 W\| \equiv \sqrt{(Z_1 - Z_0 W)' V (Z_1 - Z_0 W)}$, where V is a $k \times k$ symmetric and positive semidefinite matrix.[15]

$$W^*(V) = \underset{W}{\operatorname{argmin}} \|Z_1 - Z_0 W\| \tag{1.2}$$

Abadie et al. (2010) shows that if the number of preintervention periods ($t \in \{0, ..., T_0\}$) is large enough relative to the postintervention period ($t \in \{T_0 + 1, ..., T\}$), the treatment effects on the treated country can be estimated as follows.

$$\hat{\alpha}_{1t} = y_{1t} - \sum_{j=2}^{J+1} w_j^* y_{jt} \qquad \text{for } t \in \{T_0 + 1, ..., T\}. \tag{1.3}$$

The SCM approach compares the real outcome variable of the treated country and the weighted combination of outcome variables in donor pool countries, where weights are set to achieve the best fit between the preintervention characteristics of the treated country and those of the combination of donor pool countries. The reliability of estimates is determined by the quality of preintervention fit. We report the preintervention root mean-squared prediction error (RMSPE) between real Korea and synthetic Korea to assess preintervention goodness of fit.[16]

Unlike in classical regression-based methods, in the SCM framework, the standard errors commonly used for statistical inference are not available. For statistical inference, following studies

[14] We will call the combination of donor pool countries the synthetic control country.

[15] Among $k \times k$ symmetric and positive semidefinite matrices, Abadie et al. (2010)'s SCM algorithm finds V such that the mean-squared prediction error of the outcome variable is minimized for the preintervention period.

[16] The RMSPE is defined as $\{\frac{1}{T_0} \sum_{t=1}^{T_0} (y_{1t} - \sum_{j=2}^{J+1} w_j^* y_{jt})^2\}^{\frac{1}{2}}$, the average of the squared errors between the treated unit's outcome and the synthetic counterpart's outcome in the preintervention period. Most previous works using the SCM have evaluated preintervention goodness of fit by means of either the RMSPE or the eyeball test.

conducted since Abadie et al. (2010), we implement so-called 'placebo tests' to infer the significance of our SCM estimates. The basic idea behind placebo tests is to implement the SCM analysis repeatedly for all units in the donor pool[17] as if they were exposed to the treatment event. Placebo test results can be reported in an informal 'eyeball test' by drawing the trends in the treatment effect for each placebo unit (which is $\hat{y}^I_{jt} - \hat{y}^N_{jt}$) and checking the distribution of their SCM estimates. If the treated unit was uniquely affected by the treatment event, the postintervention SCM estimates for the treated unit should lie away from other placebo countries' SCM estimates within the distribution of placebo outcomes. In contrast, if the treated unit was not affected by the treatment event, the treated unit's postintervention estimate will not be distinguishable from those of the placebo countries' estimates and should lie within the same range. In our research context, we will run placebo tests by iteratively performing SCM analysis. If the trade dispute and the consumer boycott exclusively affected Japanese trade with Korea but less affected Japanese trade with other countries, the placebo tests should reveal nonsignificant treatment effects for the placebo countries, and the postintervention SCM estimates for Korea should lie at the edge of the placebo countries' distribution. In a more formal way, placebo test results can be also reported by drawing the distribution of the RMSPE ratios between the postintervention and the preintervention periods. The method relies on the intuition that if the treatment uniquely affected the treated unit, the post/pre RMSPE ratio of the treated unit should be largely different from the RMSPE ratios of the placebo units. [18]

Before we move on to the next data section, we discuss a potential confounding issue. In the SCM framework, donor pool units should be unaffected by the treatment event to estimate the causal treatment effect. In our research context, Japanese trade diversion with donor pool countries may bias the estimate of the causal treatment effect upward in absolute values. If the trade dispute

[17] We call the units in the donor pool placebo units if we are discussing them in the context of a placebo test.

[18] For the eyeball test, following the previous papers using the SCM technique, we dropped donor pool countries with preintervention RMSPE greater than five times of Korea to exclude ill-fitted countries. The second RMSPE ratio test is relatively free from this cutoff selection issue as it normalized the ratio by preintervention RMSPE of each country.

caused Japanese firms divert their exports or substitute their imports with other 3rd countries in the donor pool, the 2nd term on the right-hand side of equation (1.3) will rise, which leads to upward bias. If this is the case, our SCM estimates should be understood in different ways. First, our SCM estimates are the overall trade deterioration from the trade dispute, which is the sum of the direct causal treatment effect and the indirect effect from the trade diversion. Second, our SCM estimates themselves become the upper bounds of the causal treatment effects, as the direction of the bias is always upward. Third, we can calculate the lower bound of the causal treatment effect by imposing the strongest assumptions on trade diversion. To calculate the lower bound, we assume that the Japanese products that cannot be sold in Korea because of the trade dispute are completely shipped to and sold in a 3rd country (i.e., perfect export diversion to a single market). If the 3rd country contributes to creating synthetic Korea by ω percent, the causal treatment effect becomes the $(\frac{1}{1+\omega})$ times the estimated treatment effect, as ω times the causal treatment effect was diverted to the 3rd country. Hence, the lower bound of the treatment effect is $(\frac{1}{1+\omega^o})$ times the estimated treatment effect if the trade diversion was completely made to a country with the largest weight ω^o. The same assumption can be applied to the case of Japanese import substitution from a 3rd country. Even after we accept the possibility of the trade diversion from the trade dispute, our SCM estimates can still be used to limit the range of the causal treatment effects in a conservative way.

In addition to defining bounds of the causal treatment effect, we employ a simple but intuitive regression model to test whether the evidence of sizeable trade diversions from the trade dispute is observed. For each donor pool country c, we run the following simple linear regression model.

$$\log(y_{ct}) = \beta_c \cdot \text{PostDispute}_t + \gamma_{1c} \cdot \text{Year}_t + \gamma_{2c} \cdot \text{Month}_t + \epsilon_{ct} \tag{1.4}$$

where y_{ct} is the Japanese exports or imports with donor pool country c and PostDispute_t is the indicator of the post-dispute periods. t and Month_t represent yearly fixed effects and monthly fixed effects, respectively. The regression model uses the time variation between before and after trade dispute periods. If the Japan-Korea trade dispute caused extraordinary trade diversion for Japanese trade, β_c should be at least positive after we control yearly fixed effects and monthly fixed effects. From the model (1.4), we can test whether there exists strong evidence of Japanese trade diversion beyond the yearly fixed effects and monthly fixed effects, even though the model does not completely rule out the possibility of trade diversion.[19]

1.5 Data

We use product-level international trade data at monthly frequency from UN Comtrade. The UN Comtrade dataset provides information on bilateral exports and imports at a disaggregated six-digit HS product-code level. The SCM is known to perform better with longer preintervention periods. We employ data covering the six years (72 months), from 2014 to 2019, which provides information for a sufficiently long period before the Japan-Korea trade dispute. Datasets for six months of the postintervention period are currently available, so we will estimate the treatment effects for three different divisions of the post-intervention period: the first three months from July 2019 to September 2019; the last three months from October 2019 to December 2019; and the full six months from July 2019 to December 2019.

Regarding the selection of donor pool units, Abadie et al. (2010) recommended that researchers choose unit preintervention attributes similar to those of the treated unit to improve the quality of preintervention fit. We restrict the composition of the donor pool used for the construction of synthetic Korea to countries that have preintervention attributes similar to Korea's. For the donor pool, we select ten countries such that (1) a share of Japanese exports to the country that is greater than 1% and (2) a GDP per capita that is greater than 30% of that of Korea. There are eleven countries in our donor pool: the US, Canada, China, Hong Kong, Singapore, Thailand, Germany, the UK, France, Australia, and Mexico. Together, our donor pool countries account for major shares of bilateral trade in Japanese products: 62.1% of Japanese exports and 54.8% of Japanese imports.[20] Most countries in our donor pool are major advanced countries with attributes similar to those of Korea. Table 1.2 reports the optimal weights used to construct the synthetic control Korea. The

[19] The results of simple regression model and lower bounds will be provided in the appendix, from Table A.4 to Table A.8.

[20] We include China and Thailand because of their importance for Japanese trade, although they do not meet our country selection criteria for GDP per capita.

preintervention RMSPEs are also included in the table.

We now briefly discuss our choice of predictors: preintervention country-level attributes for the construction of synthetic Korea. We first employ widely used gravity variables that play crucial roles as predictors of bilateral trade. Population and GDP per capita are used, as they have been generally accepted as good proxy measures of export market size.[21] We add the years of education variable as a proxy measure of skilled labor in production. We collect the population and GDP per capita variables from the IMF database and the average years of education variable from the Barro and Lee educational attainment dataset.[22] In addition to gravity variables, we use a set of preintervention outcome variables to improve the goodness-of-fit between real Korea and synthetic Korea in the preintervention period. In choosing preintervention outcome variables as predictors, Kaul et al. (2018) pointed out that using all preintervention outcome variables as separate predictors would achieve the perfect preintervention fit but it would render all other predictors powerless. We therefore choose not to use all preintervention outcome variables as separate predictors to keep the major gravity variables as relevant predictors. Even after excluding the use of all preintervention outcome variables, there exist countless ways of using preintervention outcome variables as predictors. Between numerous combinations of preintervention outcome variables, we perform the cross-validation tests proposed by Dube and Zipperer (2016) and pick the yearly averaged outcome variables as additional predictors.[23] All predictors are averaged over the preintervention period

[21] Geographic distance between a country and Japan is another important gravity variable that can be employed as a predictor. However, the geographic distance between Japan and Korea is the shortest among all nations analyzed, so the geographic distance from Japan is not a proper predictor for use in SCM analysis if we retain the nonnegativity assumption. We confirm that including geographic distance from Japan as a predictor does not change our main arguments but worsens the preintervention fits. We also note that the geographic distance measure will be added later in the DD specification.

[22] We use average years of education as evaluated in 2010.

[23] Regarding the model selection problem, Dube and Zipperer (2016) proposed the cross-validation test which compares averaged RMSPEs in the postintervention period between models and chooses the model that provides the smallest value. We confirmed that using yearly averaged preintervention outcome variables provides smaller averaged postintervention RMSPEs than other sets of predictors, such as (1) using the averaged preintervention outcome variable, (2) using the last preintervention outcome variable, (3) using the odd years of preintervention outcome variables,

to make them time constant. We check the balancedness of predictors by comparing the averages of predictors between real Korea and synthetic Korea in Table A.2 and Table A.3. From these balancedness checks, we confirm that synthetic Korea closely resembles real Korea with respect to the predictors.

1.6 Results

1.6.1 Overall Effects

1.6.1.1 Main Specification

We begin our baseline synthetic control analysis by estimating the treatment effects on the outcome variables of interest: total Japanese exports to Korea and total Japanese imports from Korea. The results from our baseline synthetic control analysis can be understood as the treatment effects of all events induced by the Japan-Korea trade dispute: the Japanese government's export restrictions, the Korean government's retaliations, the boycott by angry Korean consumers, and the localization of products imported from Japan. Figures 1.3 and 1.4 depict our main results for total Japanese export and import trade with Korea. Figures 1.3a and 1.4a show the trends of the outcome variables for real Korea (solid line) and synthetic Korea (dotted line), respectively. The right two panels of Figures 1.3 and 1.4 report the placebo test results in different ways. Figures 1.3b and 1.4b draw the trends in treatment effects for all the placebo countries; each line stands for the treatment effects (which is $y^I_{jt} - y^N_{jt}$) on country j, with the solid black line corresponding to Korea and the gray lines to the placebo countries. Figures 1.3c and 1.4c describe the distribution of the postintervention/preintervention RMSPE ratio.

Figure 1.3a shows a substantial gap in the values of the postintervention outcome variables (total Japanese exports to Korea) for real Korea and synthetic Korea, and the gap diverges as time goes on after the trade dispute. In the counterfactual case of synthetic Korea, total Japanese exports to Korea should have trended upward in late 2019, but in real Korea, the trade dispute dragged down

and (4) using the even years of pre-intervention outcome variables. For the cross-validation test results, see Table A.9 in the appendix.

the actual trends. Our estimates from the baseline SCM model suggest that total Japanese exports to Korea decreased by -5.03% in the first three months and -16.03% in the second three months after the trade dispute, resulting in -10.64% overall in the six months after the trade dispute relative to the predicted export values. Figure 1.4a shows a similar but weaker result for total Japanese imports from Korea: the value of total imports was smaller than the predicted value by -12.85% in the first three months and -1.62% in the second three months after the trade dispute, resulting in -7.36% overall in the six months after the trade dispute. The adverse effects on Japanese exports grew after the trade dispute, but the effects on Japanese imports vanished as time passed, which suggests that the negative effects of the trade dispute on Japanese exports might have been initially small but may have been amplified later through several potential mechanisms: the Korean government's retaliatory actions, the Korean consumer boycott, Korean corporations' import substitution, or Japanese corporations' export diversion to third countries. The results highlight that the scale of the adverse effects of the Japan-Korea trade dispute on Japanese trade with Korea may not be negligible. The trade dispute was not a simple bluster but a real threat to bilateral product trade between Japan and Korea. We summarize the estimated treatment effects for the three-month and six-month periods in Table 1.3.

The right two panels of Figures 1.3 and 1.4 describe the results of iteratively performing the SCM analysis on all placebo countries. For Japanese exports in Figure 1.3b, the solid black line representing the treatment effect on Korea lies below most of those of the placebo units during the postintervention period, which implies that the treatment effect on Japanese exports to Korea was significant and that the decline in Japanese exports to Korea in the postintervention period was driven exclusively by the bilateral trade dispute, not by worldwide common shocks. For Japanese imports in Figure 1.4b, in contrast, the solid black line passes through a cluster of other gray lines that represent the outcomes of placebo countries. From Figures 1.3c and 1.4c which describe the postintervention/preintervention RMSPE ratio distributions, we observe findings consistent with those in Figures 1.3b and 1.4b. For the case of Japanese exports in Figure 1.3c, the postintervention/preintervention RMSPE ratio of Korea is the highest among all 12 countries in the sample, which implies that the trade dispute had systematic effects on Japanese exports to Korea. In addition, we observe that the RMSPE ratio of Korea is distinguishable from those of eleven other countries. In contrast, for Japanese imports in Figure 1.4c, there are three countries with postintervention/preintervention RMSPE ratios greater than that of Korea. From the placebo test results in Figures 1.3b, 1.3c, 1.4b, and 1.4c, we can infer that the treatment effect on Japanese imports from Korea was not only smaller but also less apparent than the effect on Japanese exports to Korea. The small effect for Japanese imports from Korea may be because the Korean government's retaliatory export restrictions were not strong, as the Korean government has relied more on noneconomic tools for retaliation than on economic retaliation.

We close the current subsection by discussing the magnitude of our baseline estimates. Comparing our results with other trade conflict cases would help us gain a better understanding of the size of the shocks from the Japan-Korea trade dispute. From our baseline SCM analysis, we find that Japanese exports to Korea had decreased by 10.6% six months post-conflict. Our finding is slightly greater than the estimate of Heilmann (2016) on the 2012 Japan-China territorial conflict and the Chinese consumer boycott of Japanese products: a 9.1% decline in Japanese exports to China within six months of the conflict. In regard to the China-US trade war, Amiti et al. (2019) found that a 1% increase in US import tariffs was associated with a 1.4% to 6.3% decrease in US import values.[24] Fajgelbaum et al. (2019) also found results similar to those of Amiti et al. (2019), which makes the estimates of the latter even more convincing. If we borrow the estimates from Amiti et al. (2019), our result corresponds to the impact of the 1.7%-7.6% tariff rate increase on US imports during the China-US trade war, although we should be cautious in comparing different trade conflict cases. The comparison with the China-US trade war tells us that the detrimental consequences of the Japan-Korea trade dispute were quite large. The strong effect within a short period may arise from the fact that Japan aimed to harm Korean manufacturing in a speedy manner

[24]The two different numbers of 1.4% and 6.3% in Amiti et al. (2019) depend upon whether products with zero import values/quantities are included. In regard to our case, we found little evidence that the trade dispute changed the number of products (i.e. the extensive margin of products) traded between Japan and Korea.

by restraining its exports. We can also infer that the Korean consumer boycott strengthened the negative effect of the trade dispute.

1.6.1.2 Heterogeneity across products

We found that the Japan-Korea trade dispute significantly lowered Japanese exports to Korea. We will close section 1.6.1.1 by discussing product-wide heterogeneity in the treatment effect on Japanese exports to Korea.

We first examine whether the trade dispute heterogeneously lowered the volume of Japanese exports to Korea based on product use. If the goal of Japanese export restrictions was to threaten the supply chain of production inputs for Korean manufacturing, the negative effect would be more substantial for products that serve as either capital goods or intermediate production inputs than for final consumption goods. In contrast, the Korean consumer boycott of Japanese products likely affected goods which are mainly used for consumption more than intermediate or capital goods. To test these hypotheses on product heterogeneity, we match HS-product level information to Broad Economic Categories (BEC), which classify products by their final use.[25] We group products as either consumption goods or production inputs (intermediate goods plus capital goods) and conduct an SCM analysis for each group.[26]

From Figures 1.5 and 1.6, which describe the results, we observe that both products used for consumption and products used for production input experienced decreases in exports, but the magnitudes of the treatment effects are smaller than what we have observed from the total exports. Production inputs experienced a decrease in exports to Korea by 6.07% for six month and products used for consumption experienced a decrease in exports to Korea by 8.81%. Placebo tests imply those estimates are not only smaller but also less significant than the estimate of overall exports. The analysis for consumption goods also implies that the decline in Japanese exports csan be relatively

[25] See Table A.12 for a description of Broad Economic Categories (BEC).

[26] Within the production inputs group, we also conduct an SCM analysis for capital goods and intermediate goods, separately. We observe clear negative effects on both groups, but the preintervention fit is better for intermediate goods than for capital goods.

greater for a first few months after the trade dispute, but Japanese exports of consumption goods rebounded at the very end of 2019. This suggests that the decrease in Japanese exports induced by the Korean consumer boycott can be more salient during a first few months of the post-dispute period.

The second dimension of our analysis of heterogeneous effects is the degree of product differentiation (or substitutability) in Korea. We study whether the trade dispute heterogeneously decreased Japanese product exports to Korea based on the level of product differentiation. Korean manufacturers largely rely on imports from Japan to source their machinery and intermediate inputs for production. Most products that Korean manufacturers import from Japan for production are differentiated products, which require advanced technologies and are less substitutable. If the purpose of the Japanese government's export restrictions was to damage Korean manufacturing industries, Japan should have targeted its export restrictions toward differentiated products because Korea would be less able to escape from the Japanese export restriction for differentiated products than for homogeneous products. The decline in Japanese exports caused by the trade dispute, in that case, would be greater for differentiated products (which are less substitutable) than for homogeneous products (which are more substitutable). To group products by their degree of differentiation, we use the product-level estimates of import demand elasticities in Korea from Soderbery (2018) as a measure of product differentiation.[27] Soderbery (2018) structurally estimated country-product level trade elasticities within the standard quantitative trade model, and these estimates have several advantages over other available estimates such as those of Broda and Weinstein (2006).[28] Under the quantitative trade model with constant elasticity of substitution (CES) preference on the part of the importer country's representative consumer, differentiated products should have smaller elasticities of import demand than homogeneous products, as differentiated products are less substitutable than

[27]The trade elasticity estimates are available from the author's website (Link). See Soderbery (2018) for more details.

[28]Trade economists have widely used the elasticity estimates of Broda and Weinstein (2006) when they need estimates of import demand elasticities. Compared to Broda and Weinstein (2006), Soderbery (2018) used more recent trade data, employed a novel estimation methodology, and provided estimates of trade elasticities defined at a more disaggregated product level.

homogeneous products. We first restrict the range of products to production input (either intermediate inputs or capital goods in BEC classification). Within products for production input, we group them either as differentiated products or homogeneous products. We define differentiated products as the group of products whose import demand elasticities are lower than average. The other group of products is defined as homogeneous products.

Figures 1.7 and 1.8 depict our results for differentiated products and homogeneous products, respectively. Within the range of products for production, we find that the size of the decline in Japanese exports is more salient for differentiated production input (14.78% for the six months) than for homogeneous production input (10.16% for the six months). This highlights the possibility that the adverse effect of the trade dispute was greater for differentiated products than for homogeneous products, as the differentiated products that are used heavily by Korean manufacturers became the major battlefield of the bilateral trade dispute. Japan exports products for production input more than products for consumptions. Within groups of products used for production input, Japan exports differentiated products more than homogeneous products. Therefore, we can infer that our finding of Japanese total export decline in 1.6.1.1 should be largely explained by products which are mainly used for production input and more differentiated.[29]

1.6.1.3 Robustness Tests

We implement three more SCM analyses on Japanese total exports and imports as robustness tests. We first check if our main arguments are sensitive to the selection of the donor pool countries.

[29]We also tried the SCM analysis for the group of strategic products which are under the Japanese export control. The Japanese government may control exports of strategic products for its national security. The Japanese government's white list removal of Korea in August 2019 requires Japanese exporters to take more complicated review process when they export group of strategic products. As the Japanese government uses its own product classification schedule, we use the correspondence table provided by the Korean Security Agency of Trade and Industry to identify the strategic items as best as we can. Our SCM analysis of strategic items reveals similar results with the results from the products for production input which are more differentiated, but the magnitude was slightly weaker and the preintervention fit was worse than the case of differentiated production input. See https://japan.kosti.or.kr for the correspondence table.

Eleven countries are selected as our donor pool in the baseline analysis. Those countries are economically leading countries, so they are expected to play a significant role in creating synthetic Korea. However, there is a potential concern that our results can be sensitive to the selection of donor pool countries. To address this concern, we expand the donor pool to include other OECD member countries, including those that do not meet our selection criteria, and perform the SCM analysis again.[30] Figures A.1 and A.2 describe our results based on the expanded donor pool. We confirm that the newly added donor pool countries contribute little to creating synthetic Korea and the results remain almost unchanged. We can be confident that the original eleven donor pool countries are adequate to create a reliable counterfactual Korea. The other robustness test concerns the pre-treatment effects before the beginning of the trade dispute. As discussed in section 1.3, the Korean Supreme Court's judgement on the issue of forced labor during the Pacific War is believed to have been a major trigger of the Japan-Korea trade dispute. The judgement was made on October 31st 2018, raising the question of whether bilateral trade between Japan and Korea had been worsening since the Korean Supreme Court's decision, i.e., whether the anticipation effects exist. To empirically answer this question, we implement SCM analysis as if the trade dispute had started earlier in November 2018.[31] From Figure A.3, we observe that the actual trade and the synthetic counterparts do not diverge between November 2018 and June 2019, the period between the Korean Supreme court's judgement and the Japanese government's imposition of the new export restriction. This makes us more confident that our baseline findings are driven by the trade dispute events but not by other event before the trade dispute. We also perform our main SCM analysis again with data from either longer periods or shorter periods to check if our results are sensitive to the use of different preintervention periods. We observe that using data for preintervention periods of different lengths does not alter our main results. Figure A.4 shows the results with the shortened pre-intervention periods from 2016 to 2019, which shows that the main results are still valid.

[30] The newly added countries are as follows: Austria, Chile, Czechia, Denmark, Estonia, Finland, Greece, Hungary, Ireland, Iceland, Israel, Italy, Lithuania, Luxembourg, Latvia, Netherlands, Norway, New Zealand, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, and Turkey.

[31] This is the same as 'in-time placebo' test which was performed in Abadie et al. (2015).

We close this section by discussing the potential confounding problems from trade diversion which we discussed in section 1.4. As we suggested in section 1.4, we first run a simple regression model (1.4) for each of Japan's major trading partners and report the results in Table A.4. From the regression analysis, we found little evidence of trade diversion between Japan and other major partner countries across different export and import measures, which alleviates the concerns from the sizeable trade diversion. Although we found little evidence of trade diversion, it is safe to understand our estimates either as the combination of the treatment effect and the indirect effect from the trade diversion or the upper bounds of the causal treatment effects. To restrict the range of the treatment effects, we calculate the lower bounds of treatment effects after assuming complete trade diversion to the 3rd country that contributes the most to creating synthetic Korea. Tables A.6 and A.7 report the results. For the case of Japanese total exports, for example, the lower bound of the treatment effect is 8.37%. The number is calculated based on the assumption of complete export diversion to Singapore, which accounts for 27.2% of the construction of synthetic Korea.[32]

1.6.2 Consumer Boycott Effects

We now examine the effects of the consumer boycott of Japanese products as part of the Japan-Korea trade dispute. Our main findings in section 1.6.1 can be understood as the overall consequences of the Japan-Korea trade dispute. To isolate the treatment effects from those of the consumer boycott, we restrict the range of products to those boycotted during the second half of 2019. We first collect the names of boycotted Japanese brands from two websites that publicly advertised the boycott, and then we identify their major products. See Table A.13 for the list of boycotted Japanese brands.[33] We then categorize the boycotted products by their attributes. We construct five groups of products: three groups of nondurable products (apparel, foods, and miscellaneous household items) and two groups of durable products (appliance and vehicles). We

[32] $\frac{1}{1+0.272} \times 10.64\% = 8.37\%$

[33] According to anecdotal evidence from the media, some groups of Japanese brands were more heavily boycotted than others because of the brand's political stance, e.g., sponsoring Japanese far-right organizations.

finally define the boycotted products at the four-digit HS code level. For example, the Japanese alcohol brand *Asahi*'s major product is beer, so we include the four-digit HS code for beer (2203) in our list of targeted products. The websites for the consumer boycott list the targeted Japanese brands along with their major products as tags, so we use the tag information to precisely identify the boycotted items. Our list covers an extensive set of products boycotted by Korean consumers.

We implement a synthetic control analysis for each group of boycotted products. The images from Figure 1.9 to Figure 1.13 visualize our SCM results for each product, and Table 1.5 includes the sizes of the treatment effects for the groups of boycotted products. We observe several interesting findings on the effects of the consumer boycott. First, the impact of the consumer boycott on Japanese exports to Korea is heterogeneous across products. We find strong negative effects on boycotted foods and vehicles and weak negative effects on appliances but found little evidence of negative effects on sports items and apparel. There was a weak temporary decline in apparel exports after the boycott: however, Figure 1.9 suggests that we cannot clearly isolate the boycott effect from the trend of synthetic Korea. There are strong seasonal fluctuations in apparel exports, and the boycott effects are not distinguishable from the seasonal trend.

Our findings for apparel are somewhat surprising and puzzling, as major Japanese fashion brands were strongly targeted in the Korean consumer boycott, according to media reports. However, we can list a few potential mechanisms that may explain these findings: (1) The first possibility is that the boycott effect itself was smaller than we expected. The consumer boycott of Japanese fashion brands seemed quite strong according to the media, which reported several boycott protests held in front of Japanese-brand apparel shops. Instead of visiting stores, however, Korean consumers may still have purchased products from Japanese fashion brands through other modes of shopping such as online platforms. If Korean consumers kept purchasing Japanese apparel online, the real impact of the boycott might be smaller than observed in media reports. (2) The second possibility is that boycotted brands may account for only small shares of overall Japanese-made apparel. (3) The last possible mechanism is outsourcing. Japanese fashion brands source substantial amounts of their apparel from manufacturers in Asian developing countries. If the Japanese fashion brands boycotted by Korean consumers import their products from third countries, Japanese apparel exports to Korea may not have been harmed by the Korean consumer boycott. Most Japanese fashion brands that were boycotted in Korea sell low-end casual clothes, and they largely source their items from manufacturers in developing countries. In contrast, Japanese fashion brands selling high-end clothes were less affected by the consumer boycott. Japanese fashion brands source their low-end apparel from developing countries because the brands require cheap labor in production. On the other hand, Japanese fashion brands source their high-end apparel from domestic manufacturers, as advanced technologies, intricate designs, and quality textiles are more important for those items. When we consider the sourcing strategy of Japanese fashion brands and the quality of the apparel, the outsourcing hypothesis appears more plausible.

Unlike in the case of apparel, we find a sharp decline in Japanese exports of boycott-targeted foods, which suggests that the Korean boycott of Japanese grocery brands seriously harmed their sales in Korea. Among durable goods, we observe a noticeable negative effect of the boycott on targeted Japanese vehicles but a weaker transient negative effect on Japanese appliances. Our SCM analysis suggests a 66% decline in Japanese exports of boycotted foods and a 37% decline in Japanese exports of boycotted vehicles for six months after the boycott. It is natural to ask why we observe these significant negative effects of the Korean consumer boycott on targeted foods and vehicles.[34] We can propose several potential mechanisms driving our findings, although we cannot formally test them. The brand awareness effect of Japanese products is the first candidate. A few Japanese food and vehicle brands are very well known in Korea, and Korean consumers have accepted those brands as symbols of either Japanese products or of Japan itself. If Korean consumers strongly avoided purchasing those brands of products, the adverse effects of the boycott could be magnified.[35] In addition to the brand awareness effect, Korean consumers' concerns about the safety of Japanese foods may be another powerful potential explanation of our findings on foods.

[34] Within boycotted foods, we confirmed the sharp decrease in Japanese exports from both alcohol and non-alcohol items.

[35] During the Japan-China territorial dispute in 2012, infuriated Chinese consumers destroyed and burned Japanese-brand vehicles, which are thought to be symbols of Japanese products.

Since the *Fukushima Daiichi* nuclear disaster in 2011, Korean consumers have been skeptical about the safety of Japanese foods and have doubted whether Japanese foods are free of radioactive contamination. Such suspicion on the part of Korean consumers would likely have strengthened the effects of the boycott on Japanese foods.

We evaluated the significance of the treatment effects for the boycotted products by running placebo tests. As expected, from the right panels of Figure 1.9 to Figure 1.13, which describe the placebo test results, we can confirm the significant negative treatment effects for boycotted foods and vehicles but insignificant effects on other boycott-targeted products. Little evidence of other worldwide events that may have influenced Japanese exports of boycotted foods and vehicles is observable in the placebo test results; the decrease in Japanese exports of boycotted foods and vehicles can be explained mostly by the boycott event. We evaluate the potential possibility of export diversion from the regression analysis and report our results in Table A.5. The regression analysis reveals weak evidence of export diversion to China for boycotted vehicles; however, little evidence of export diversion was found from other boycotted product cases. As China contributes zero to synthetic Korea for the boycotted vehicle case, the potential export diversion of Japanese vehicles to China does not bias our treatment effect estimates. In Table A.8, we provide the lower bounds of the treatment effects for each boycotted product case based on the complete export diversion scenario.

1.6.3 Alternative DD Specification

We now implement a DD analysis and compare the DD results with the SCM results. Our parsimonious DD model is expressed as follows.

$$\log y_{ct} = \beta_0 \cdot \text{Treated}_c + \beta_1 \cdot \text{Post}_t + \beta_2 \cdot (\text{Treated}_c \times \text{Post}_t) + X_{ct}\Gamma + \epsilon_{ct} \tag{1.5}$$

where the outcome variable y_{ct} can be either the exports or imports of Japan with trade partner c at time t. $\text{Treated}_c = 1$ if partner country c is Korea, and $\text{Treated}_c = 0$ for the partner countries in the control group. As the control group of our DD model, we use the same countries as those in the donor pool selected in section 1.6 for the synthetic control analysis. $\text{Post}_t = 1$ if $t \geq$ July 2019, that is, the postintervention period after the trade dispute. The estimate for the interaction term $\hat{\beta}_2$ will be the parameter of interest, which will capture the treatment effect of the trade dispute on Japanese bilateral trade with Korea. We control for country-level attributes(X_{ct}) such as GDP per capita, population, geographic distance from Japan, and years of education to estimate our parameters more precisely. In addition to country-level attributes, we include country-specific trends as additional regressors to allow every country to follow different trends. As a final specification, we include country fixed effects(κ_c) and time trends(η_t), which control for all unobservable fixed attributes and worldwide common trends.[36] We also carry out the same DD analysis of the consumer boycott effects. For the dependent variables in the DD models on the consumer boycott, we use the export volume from Japan to Korea by group of boycotted products, which are defined at the HS four-digit level.

The DD model has been widely used in policy evaluation studies to estimate treatment effects due to its simplicity. There exist a few required conditions to be satisfied to make DD estimates valid. The most critical condition is the parallel trend assumption between the treated group and the control group in the pretreatment periods. If the trends of outcome variables between the treated and unweighted averages of the control group are not parallel in the pretreatment periods, the validity of the DD estimate is threatened. In addition, if the DD model fails to control any important predictors of bilateral trade, the model may also suffer from omitted variable bias. The SCM approach can be free from concerning issues related to the DD model, as the SCM relies on data-driven predictions of counterfactual outcomes, which is the weighted average of control group units, while the DD model relies on the unweighted average of control group units, which is more restrictive. By comparing the magnitude and significance of estimates from two different models, we can evaluate which model provides more reliable estimates.

Table 1.6, Table 1.7, and Table 1.8 report our results from the DD model. First, our findings from the DD model are highly consistent with the SCM results discussed in section 1.6. According

[36] This type of DD specification is the so-called generalized DD model. See Pierce and Schott (2016) for an example of international trade work using the generalized DD model.

to columns (1) to (4) in Table 1.6, the trade dispute lowered total Japanese exports to Korea from 10.7% to 11.8% for six months after the trade dispute. The DD estimates of 10.7% to 11.8% are comparable with the 10.6% from the SCM model, although the DD estimates are slightly greater than the SCM estimate. Between columns (2) and (3) in Table 1.6, we observe that including country-specific trends changes the size of DD estimates by 1.1%, which raises the possibility that the parallel trend condition is not fully satisfied in the case of Japanese exports. Hence, the small gap between the SCM estimates and the DD estimates may be attributable to the parallel trend assumption that the DD model is more difficult to satisfy than the SCM model. The DD estimates for Japanese exports are strongly significant, which allows us to argue with more confidence that there were negative effects of the trade dispute on Japanese exports. On the other hand, from columns (5) to (8) in Table 1.6, our DD estimates indicate that the trade dispute decreased Japanese imports from Korea by 5.0% to 7.3%, which is also comparable with the 7.3% from the SCM model. The estimates for Japanese imports are not statistically significant which is consistent with the placebo test results for Japanese imports from Korea in the SCM analysis. Our findings from the DD model raise a red flag that the negative impact from the trade dispute may be less apparent for Japanese imports from Korea than for Japanese exports to Korea. Tables 1.7 and 1.8 report DD model results for consumer-boycotted products. In the DD model, the effects on boycotted foods and vehicles are large and strongly significant, but those on other products are not, which is consistent with our arguments from SCM analysis. However, the magnitudes of DD estimates for boycotted foods and vehicles are greater than the corresponding SCM estimates. This again raises the concerns that the DD model may not be free from either omitted variable bias or nonparallel pretreatment trends between treated and control groups, or both.

1.7 Conclusion

This paper studies the effects of the recent Japan-Korea trade dispute and the Korean consumer boycott of Japanese products during the second half of 2019. We employ the SCM developed by Abadie et al. (2010, 2015) to address our research topic. Our SCM results highlight sizeable decreases in bilateral trade volumes between Japan and Korea, with the effects more apparent for Japanese exports to Korea than Japanese imports from Korea. We confirm that the effects on Japanese exports can be stronger for differentiated production input items which are mainly targeted by the Japanese government to threaten the supply chain of the Korean manufacturing sector. We next evaluate the treatment effects of the demand shock induced by the trade dispute by isolating our products of interest. The impacts of the consumer boycott varied across boycotted items, with the negative impact being especially noticeable for targeted foods and vehicles. We also provide the bounds of the treatment effects in a conservative way by assuming the extreme trade diversion scenarios, even though our simple regression analysis shows little evidence of trade diversion. We carry out different types of DD analyses as alternative models. The results from the DD models are generally consistent with the SCM results and strengthen our arguments.

This paper contributes to the trade literature by providing new empirical evidence describing how political tensions between countries can distort bilateral trade. Our research can be further extended in various ways. One possible extension is to study the effects of the trade dispute over a longer period. Although the Japan-Korea trade dispute was a relatively short-term situation in late 2019, the negative effects of the trade dispute may last over longer periods through different mechanisms. We could not address the long-run effect, as the trade dispute was quite recent, and data are currently available for only the first six months after the dispute. Another meaningful extension would be to study the impacts on other aspects of the economy beyond bilateral trade. The negative shock from bilateral trade shrinkage can be transmitted to the economy through different mechanisms, such as rises in either consumer or producer prices. Such price effects could have detrimental impacts on consumers' welfare through decreases in consumption. In addition, the trade dispute may also affect investments and employments of firms, which ultimately change firm-level performances such as output, productivity, markups, and profits.[37] We expect that such

[37]The rise in trade policy uncertainty from the trade dispute can be a potential mechanism. Several previous studies such as Handley and Limão (2015, 2017), Coelli (2018), Liu and Ma (2020) have studied how reduction in trade policy uncertainty from trade liberalization episodes may boost bilateral trade and enhance firm-level investments and R&D activities.

extensions can be meaningful and will help us gain a deeper understanding of the consequences of this trade dispute from a different angle. We shall extend our research in the future.

Table 1.1: Timeline of the major Japan-Korea trade dispute events

Time	Events
Oct-18	The Korean Supreme Court's decision on the reparation of wartime forced labor issue
Jul-19	The Japanese government restricted exports of a certain chemical products to Korea
Jul-19	Korean consumers' boycott of Japanese products started
Aug-19	The Japanese government removed Korea from its white list country
Aug-19	The Korean government announced that it will not extend GSOMIA
Sep-19	The Korean government removed Japan from its white list country

Table 1.2: Weights for Synthetic Control & Root Mean Squared Prediction Error(RMSPE)

	Exports	Imports
Australia	0.082	0.425
Canada	0.005	0.167
China	0.249	0.096
Germany	0.074	0.13
France	0	0.106
Britain	0	0
Hong Kong	0.103	0.016
Mexico	0	0
Singapore	0.272	0
Thailand	0	0
United States	0.215	0.059
RMSPE	0.054	0.060

Table 1.3: Estimated Treatment Effects: Japanese Bilateral Trade with Korea

	Exports	Imports
First 3-months	-5.04%	-12.85%
Last 3-months	-16.03%	-1.62%
6-months	-10.64%	-7.36%

Estimated treatment effects are calculated as the percentage gap of trade volumes between actual Korea and synthetic Korea. We evaluate them by three months and six months of the post-intervention periods after Japan-Korea trade dispute.

Table 1.4: Estimated Treatment Effects by Product Group: Japanese Exports to Korea

	Consumption	Production	Homogeneous	Differentiated	Export Control
First 3-months	-7.34%	0.35%	-6.96%	-6.93%	-6.05%
Last 3-months	-10.32%	-12.20%	-13.55%	-22.12%	-17.83%
6-months	-8.81%	-6.07%	-10.16%	-14.78%	-12.09%

Estimated treatment effects are calculated as the percentage gap of trade volumes between actual Korea and synthetic Korea. We evaluate them by three months and six months of the post-intervention periods after Japan-Korea trade dispute.

Table 1.5: Estimated Treatment Effects: Boycotted Items

	Non Durables			Durables	
	Apparel	Foods	Sports & Misc.	Appliances	Vehicles
First 3-months	0.592%	-50.870%	-6.935%	-0.209%	-15.974%
Last 3-months	-0.136%	-79.214%	-4.278%	-12.222%	-60.763%
6-months	0.255%	-66.036%	-5.651%	-6.490%	-37.302%

Estimated treatment effects are calculated as the percentage gap of trade volumes between actual Korea and synthetic Korea. We evaluate them by three months and six months of the post-intervention periods after Japan-Korea trade dispute.

Table 1.6: Difference-in-Differences: Japanese trade with Korea

VARIABLES	(1) Exports	(2) Exports	(3) Exports	(4) Exports	(5) Imports	(6) Imports	(7) Imports	(8) Imports
$\text{Treated}_c \times \text{Post}_t$	-0.118***	-0.107***	-0.117***	-0.118***	-0.0503	-0.0731	-0.0729	-0.0503
	(0.0196)	(0.0201)	(0.0164)	(0.0205)	(0.0341)	(0.0538)	(0.0495)	(0.0355)
Treated_c	0.785**	-2.035***	-1.974***		0.614	0.684	0.682	
	(0.302)	(0.541)	(0.425)		(0.389)	(1.316)	(1.312)	
Post_t	0.00624	0.0395	-0.0656		0.0502	-0.120	-0.119	
	(0.0196)	(0.0783)	(0.0609)		(0.0341)	(0.124)	(0.123)	
Country Controls (X_{ct})	N	Y	Y	N	N	Y	Y	N
Country-Specific Time Trends	N	N	Y	N	N	N	Y	N
Country Fixed Effects (κ_c)	N	N	N	Y	N	N	N	Y
Year-Monthly Trends (η_t)	N	N	N	Y	N	N	N	Y
Observations	864	864	864	864	864	864	864	864
R-squared	0.051	0.700	0.814	0.992	0.019	0.651	0.651	0.978

The dependent variable ‘Exports’ is the Japanese total exports to country c, and ‘Imports’ is the Japanese total imports from country c. All dependent variables are logged. Column (1) and (5) are results from simple DD model without control variables, where Column (2) and (6) include country level control variables. Column (3) and (7) include country-specific time trends as additional regressors to verify common trend assumption. Column (4) and (8) are results from the Generalised DD model with country fixed effects (κ_c) and year-monthly trends (η_t). Standard errors, clustered by country, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 1.7: Difference-in-Differences: Consumer Boycotted Products

VARIABLES	(1) Apparel	(2) Apparel	(3) Foods	(4) Foods	(5) Sports & Misc.	(6) Sports & Misc.	(7) Appliances	(8) Appliances	(9) Vehicles	(10) Vehicles
$\text{Treated}_c \times \text{Post}_t$	-0.196*	-0.208*	-1.129***	-1.138***	-0.0378	-0.0517	-0.145	-0.158	-0.489***	-0.486***
	(0.0915)	(0.0910)	(0.1021)	(0.0810)	(0.0856)	(0.0785)	(0.0863)	(0.0892)	(0.0602)	(0.0596)
Treated_c	-3.448**	-3.374*	-3.012***	-2.957***	-2.427**	-2.347**	-3.429***	-3.353***	-1.481*	-1.493*
	(1.554)	(1.555)	(0.641)	(0.542)	(0.869)	(0.866)	(0.619)	(0.488)	(0.728)	(0.727)
Post_t	0.318*	0.197	0.264**	0.168	0.140	0.000430	-0.109	-0.242*	-0.0548	-0.0334
	(0.169)	(0.190)	(0.0893)	(0.101)	(0.103)	(0.0834)	(0.135)	(0.127)	(0.117)	(0.112)
Country Controls (X_{ct})	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-Specific Time Trends	N	Y	N	Y	N	Y	N	Y	N	Y
Observations	831	831	864	864	864	864	864	864	864	864
R-squared	0.579	0.628	0.731	0.774	0.715	0.800	0.633	0.764	0.794	0.796

The dependent variables are Japanese exports to country c grouped by boycotted products, which are all logged. All specifications include country level control variables. Even numbered columns additionally include country-specific time trends as additional regressors to verify common trend assumption. Standard errors, clustered by country, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 1.8: Generalized Difference-in-Differences: Consumer Boycotted Products

VARIABLES	(1) Apparel	(2) Foods	(3) Sports & Misc.	(4) Appliances	(5) Vehicles
$\text{Treated}_c \times \text{Post}_t$	-0.213*	-1.125***	-0.0236	-0.153	-0.475***
	(0.1054)	(0.0807)	(0.0902)	(0.0935)	(0.0661)
Country Fixed Effects (κ_c)	Y	Y	Y	Y	Y
Year-Monthly Trends (η_t)	Y	Y	Y	Y	Y
Observations	831	864	864	864	864
R-squared	0.934	0.972	0.956	0.973	0.963

The dependent variables are Japanese exports to country c grouped by boycotted products, which are all logged. All specifications include country fixed effects (κ_c) and year-monthly trends (η_t). Standard errors, clustered by country, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

(a) 'No Visit, No Purchase'

(b) Consumer boycott of the Japanese fashion brand

Figure 1.1: Korean consumers' boycott of Japan

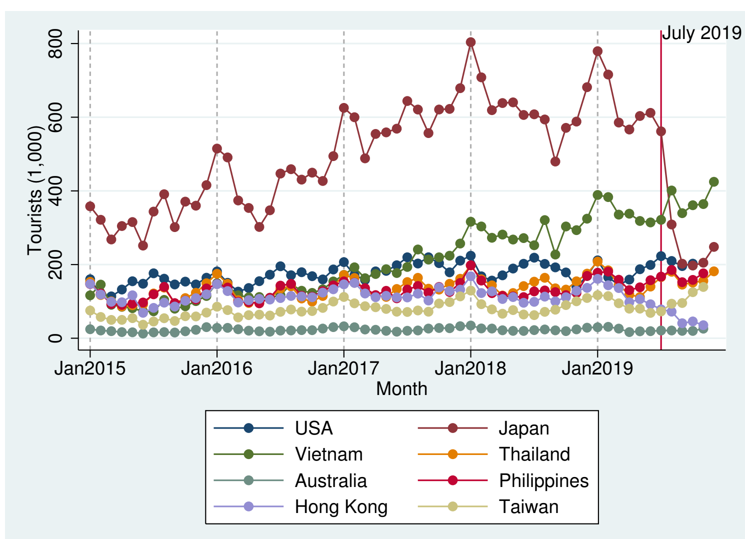
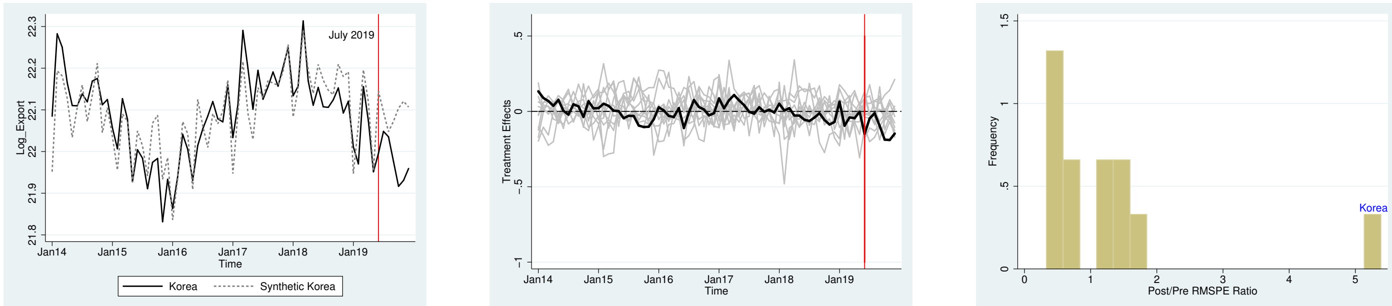


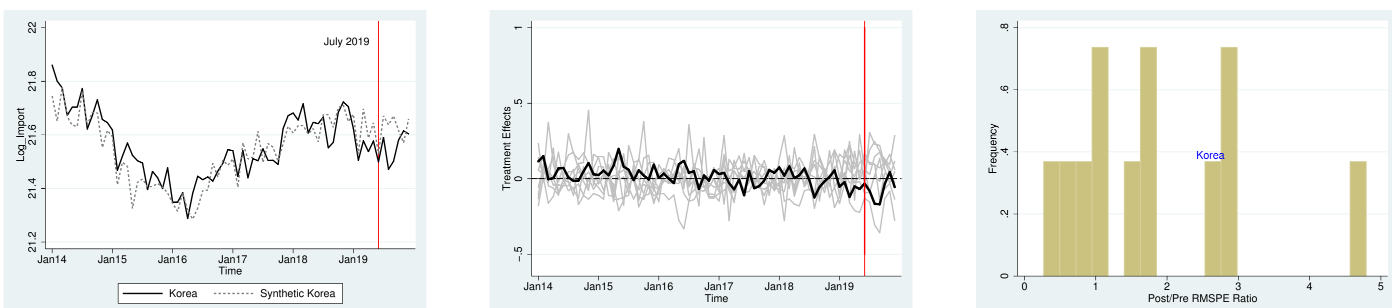
Figure 1.2: Number of Korean overseas tourists by destination country

(Figure 1.2) Source: Korea Tourism Organization



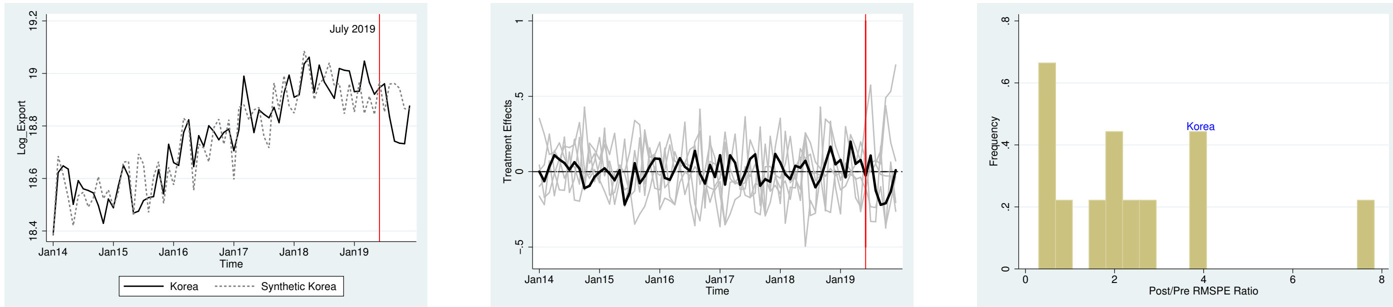
(a) Real Korea vs. Synthetic Korea (b) Placebo Test (c) Post-Pre RMSPE Ratio

Figure 1.3: Synthetic Control Analysis on Japanese Total Exports to Korea



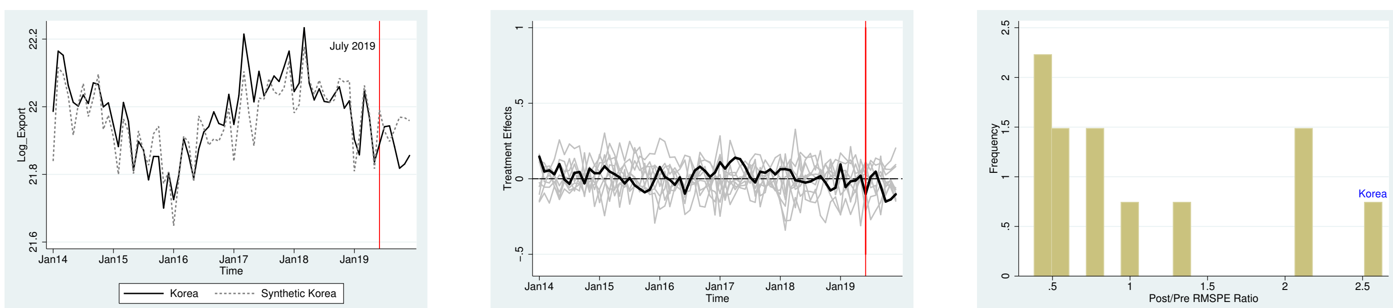
(a) Real Korea vs. Synthetic Korea (b) Placebo Test (c) Post-Pre RMSPE Ratio

Figure 1.4: Synthetic Control Analysis on Japanese Total Imports from Korea



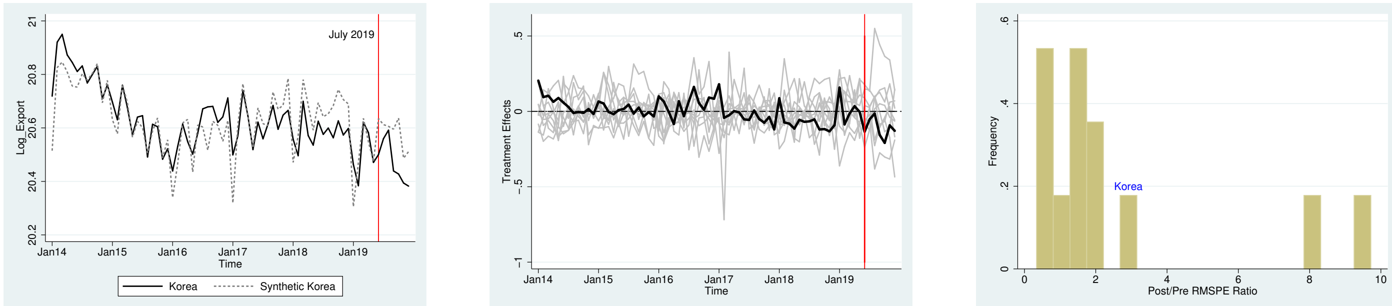
(a) Real Korea vs. Synthetic Korea (b) Placebo Test (c) Post-Pre RMSPE Ratio

Figure 1.5: Synthetic Control Analysis on Japanese Exports to Korea, Consumption goods



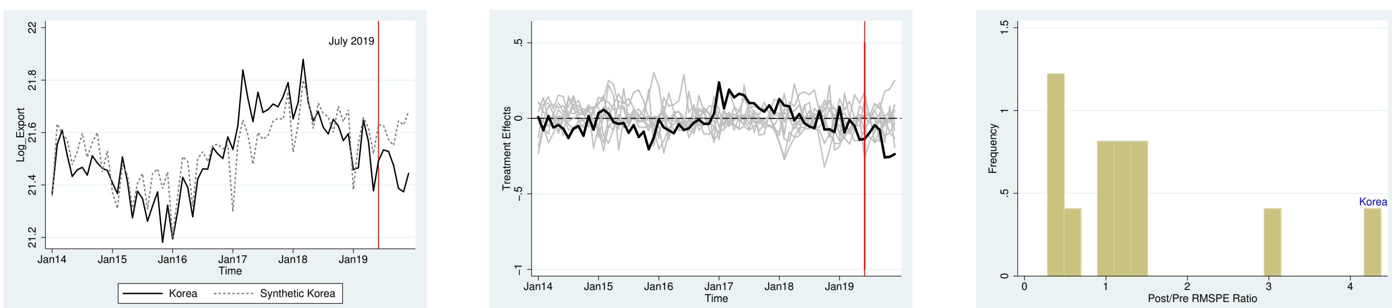
(a) Real Korea vs. Synthetic Korea (b) Placebo Test (c) Post-Pre RMSPE Ratio

Figure 1.6: Synthetic Control Analysis on Japanese Exports to Korea, Production Input



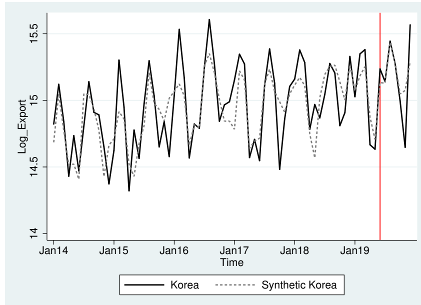
(a) Real Korea vs. Synthetic Korea (b) Placebo Test (c) Post-Pre RMSPE Ratio

Figure 1.7: Synthetic Control Analysis on Japanese Exports to Korea, Homogeneous Products

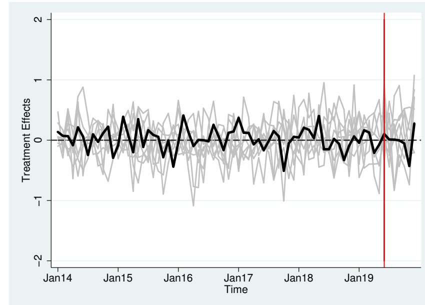


(a) Real Korea vs. Synthetic Korea (b) Placebo Test (c) Post-Pre RMSPE Ratio

Figure 1.8: Synthetic Control Analysis on Japanese Exports to Korea, Differentiated Products

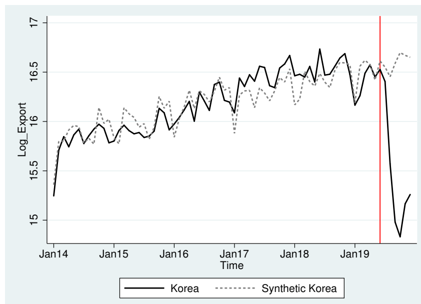


(a) Real Korea vs. Synthetic Korea

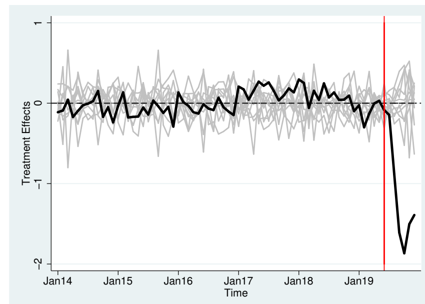


(b) Placebo Test

Figure 1.9: Synthetic Control Analysis on Boycott Target Products: Apparel

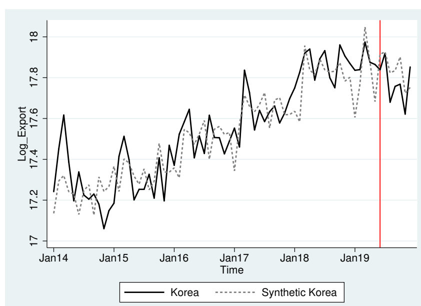


(a) Real Korea vs. Synthetic Korea

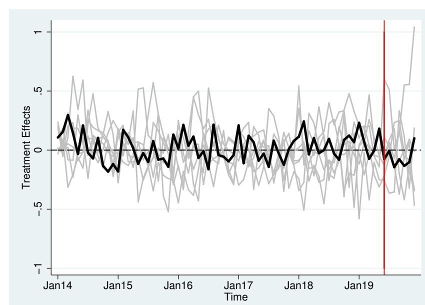


(b) Placebo Test

Figure 1.10: Synthetic Control Analysis on Boycott Target Products: Foods

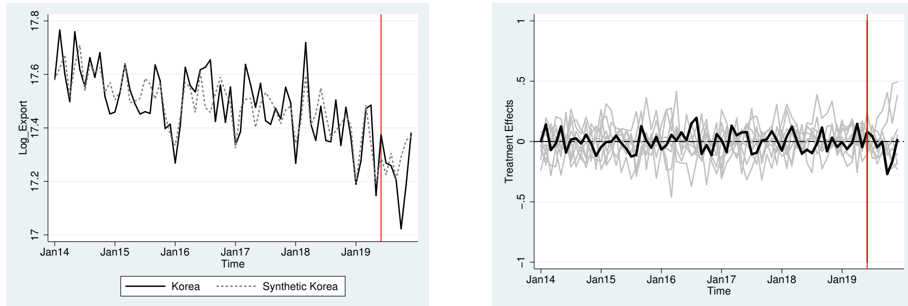


(a) Real Korea vs. Synthetic Korea



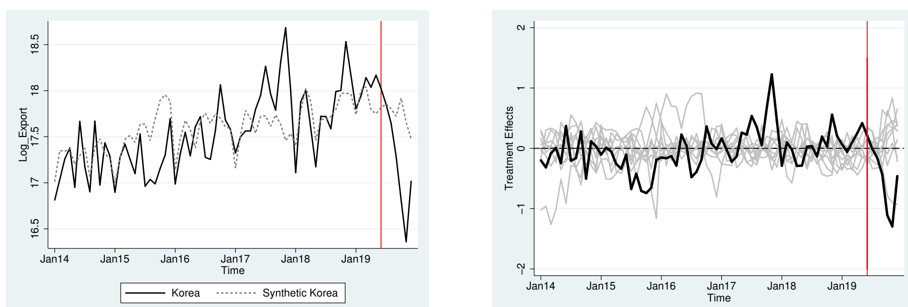
(b) Placebo Test

Figure 1.11: Synthetic Control Analysis on Boycott Target Products: Sports & Misc. Household Items



(a) Real Korea vs. Synthetic Korea (b) Placebo Test

Figure 1.12: Synthetic Control Analysis on Boycott Target Products: Appliances



(a) Real Korea vs. Synthetic Korea (b) Placebo Test

Figure 1.13: Synthetic Control Analysis on Boycott Target Products: Vehicles

CHAPTER 2

GLOBAL INVESTMENTS BY MULTINATIONAL ENTERPRISES AND EMPLOYMENT VOLATILITY: EVIDENCE FROM KOREA

2.1 Introduction

Do multinational enterprises' (MNEs') cross-border investment behaviors make the employment of workers in the firm's home country more volatile? MNEs' outward investment has been frequently cited in the media as a major source of weakening employment stability for workers in the home country. This question has been actively debated because of its policy-relevant importance in the labor market. Several issues, such as a lack of appropriate data, however, have limited trade economists from reaching a concrete consensus.

This paper studies the impact of Korean MNEs' investments abroad on workers' employment volatility in the firms' home country of Korea. From a unique dataset of firm-level data matched with disaggregated industry-level outward foreign direct investment (FDI) data, we addressed the role of outward FDI on the employment volatility of domestic workers, which is a proxy measure for job stability. From the literature, we move one step forward by studying the differential impact of outward FDI motivations on workers in different tasks. We disentangle firm-level FDI motivations by "seeking market access" and "seeking cost saving", and also disentangle workers' tasks by "production tasks (blue-collar)" and "management tasks (white-collar)". As empirical tools, we implemented two different approaches. We first employed a linear fixed effects model as our baseline tool to see the long-run relationship between outward FDI and the employment volatility of domestic workers. We next employed the difference-in-differences (DD) model combined with matching to address potential endogeneity issues in the baseline fixed effects model. From the DD model, we determined short-run causal effects of outward FDI on employment volatility.

This paper contributes to the literature in three ways. First, from unique datasets that enable us to identify motivations of outward FDIs, we study how the different types of firm-level outward

FDIs disproportionately affect workers' employment volatility in the home country. In addition, we also study the heterogeneous impacts of workers' employment volatility by assigned tasks. The role of FDI motivations and the impact on employees' tasks are previously unstudied areas in the literature, and our paper will provide new empirical evidence. Lastly, to the best of our knowledge, this paper is the first academic work to empirically study the relationship between MNEs' outward FDI and employment volatility in Korea, an economically developed country in East Asia.

The relationship between MNEs' cross-border investments and employment volatility of workers in the home country is theoretically ambiguous. The first possible mechanism is the transmission of shocks between countries.[1] If a supply or demand shock from the host country arises and the shock was transmitted to the home country, the employment volatility of home workers at MNEs can become greater if MNEs adjust their employment. In contrast, in the case of the shock at the home country, MNEs which enter multiple countries may more easily spread out the shock, which leads to lower employment volatility than non-MNEs. The substitution and complementarity of workers between countries, skills, and tasks can be another factor. Within an MNE, if workers at the foreign affiliate replace workers at the home country, the bargaining power of home workers will decrease and the labor demand of home workers will become more elastic, ultimately raise the employment volatility of home workers.[2] It is more likely to imagine such substitution between production workers in the host country and the home country when an MNE from the developed country reallocates its production facilities from home country to an emerging country with cheap labor. However, there is another possibility that the employment of homeworkers becomes more stable if workers at the foreign affiliate and the workers at the home country are complementary. If the MNE fragment the production process and allocate labor-intensive tasks to an emerging country, for example, unskilled workers in the emerging country and skilled workers in the home country may complement each other. Similar logic can be applied between different tasks: production workers in the emerging country and management workers in the home country. In addition, the motivations of

[1] Vannoorenberghe (2012), Vannoorenberghe et al. (2016)

[2] Senses (2010) Rodrik (1997)

investments and attributes of host countries can make the problem more complicated. As mentioned, cross-border investments to an emerging country can be more connected to substitution between production workers in the home country and the host country. The effect can be greater if an MNE enters the emerging country seeking cost-saving purposes than other reasons. On the other hands, in theory, FDI in developed countries for market access purposes can be connected to the rise of the employment volatility of management workers in the home country if the investment leads firms to hire more local management workers for their local business activities in host countries and replace management workers in the home country. In short, the relationship between MNEs' cross-border investments and employment volatility is theoretically not determined and becomes an empirical research agenda.

Our paper builds on and augments several strands of literature in international trade. Most closely, our work connects with a small but growing body of research on firms' global business activities (exports/imports, offshoring, and FDI) and employment volatility. Bergin et al. (2009) examined the topic by comparing the volatility of Mexican firms in "maquiladoras", Mexican sectors that take intermediate input from foreign firms and process them into final goods with corresponding US industries. In Bergin et al. (2009), the employment volatility of Mexicam firms in maquiladoras was much greater than that of the corresponding US industries; their main findings were largely driven by extensive margins (i.e., exit and entry) of maquiladoras. Kurz and Senses (2016) is the most similar paper to ours. Using US export transaction data and firm-level data, Kurz and Senses (2016) explored the association between firm-level exporting behaviors and the volatility of employment growth. Relative to non-trading firms, firms that both export and import and firms that only export (without importing) show a lower level of employment volatility, whereas firms that only import (without exporting) show a higher level of employment volatility. They also found that several features of a firm's trading behaviors, such as the duration of trade, the number and types of products traded, and the characteristics of partner countries, largely explain the variation in employment volatility across firms. Using French data, Bas et al. (2019) examined the impact of a firm's export activity on employment volatility across skilled and unskilled workers. In their paper, exporting firms adjust relatively more unskilled employment than skilled employment in terms of employment volatility. Their findings indicate that a higher level of exports from globalization will induce the divergence of job stability levels between skilled and unskilled workers. Kiyota et al. (2020) examined the linkage between FDI and the intra-firm trade of Japanese firms and employment volatility. For Japanese firms, employment volatility rises as the share of intrafirm exports increases in manufacturing industries, whereas volatility declines as the share of intrafirm imports increases in wholesale industries.

More broadly, our research can be related to the literature on how MNEs' global activity shapes the labor market in the home country. Several papers in the literature have tried to determine the impact of MNEs' global business activities on the labor market in the home country. Here, we list and summarize a few recent papers that could be relevant to ours: Hummels et al. (2014) and Görg and Görlich (2015). Hummels et al. (2014) found unequal wage effects of offshoring across workers' different skill levels in the Danish labor market. In Hummels et al. (2014), offshoring raised the wages of skilled workers but lowered the wages of unskilled workers. Moreover, the wage effects of offshoring were also associated with workers' tasks, even conditional on skill levels. Workers with routine tasks should bear more wage losses from offshoring than workers with tasks requiring scientific knowledge sets. Görg and Görlich (2015) focused on the differential effects of offshoring by workers' skills and contract types. In Görg and Görlich (2015), who used German data, offshoring was associated with an increase in unemployment risks for unskilled workers, and the effects were even greater for temporary workers than for permanent workers. Offshoring was also associated with a decrease in unemployment risks for skilled workers. Regarding the impact of offshoring on domestic workers' wages and job stability, both Hummels et al. (2014) and Görg and Görlich (2015) found positive effects of offshoring for workers who are skilled, do non-routine tasks and are permanently employed. However, offshoring will likely have adverse effects on the wages and job stability of workers who are unskilled, do routine tasks, and are temporarily employed.

More specifically, regarding academic papers on Korea, our research is connected to several academic works on the relationship between Korean MNEs' global business activities and the

Korean labor market. Debaere et al. (2010) studied the differential impacts of outward foreign direct investment (FDI) on home employment growth by destination country. They found that investments in less-developed countries lower employment growth in the short run but found few consistent patterns of investments in more-developed countries. Lee and Lee (2015) investigated the impact of offshoring on the wages of manufacturing workers in Korea, who are grouped by types of their employment contracts: permanent workers and temporary workers. From Korean individual panel data matched with offshoring data, offshoring raised wages in general, but temporary workers enjoy fewer benefits from offshoring than permanent workers.

The previously cited works suggest two aspects that are connected to our research. First, each FDI motivation may play different roles in the labor market. Second, the effects of offshoring may also vary by worker type. All these findings motivate our research. Although existing studies have significantly contributed to the literature, topics that deserve further study remain. To the best of our knowledge, no study in the literature has addressed how the effects of foreign investment on employment volatility vary by investment purpose. Additionally, little is understood about the disproportionate consequences of MNEs' global investments on the employment volatility of domestic workers in different tasks. From unique data in Korea, our work will fill this gap in the literature.

2.2 Data

In this section, we discuss the main datasets that are used in our empirical analysis: Korean firm-level data and industry-level outward investment data. We also describe how we linked two different datasets and calculated firm-level foreign investment amounts by motivation.

2.2.1 Korean Firm-Level Data

For firm-level information on business activities, we employed the 2006-2017 waves of the Survey of Business Activities ("기업활동조사" in Korean. hereafter "SBA data"). SBA data are a detailed Korean firm-level dataset annually surveyed by Statistics Korea, the official statistics department of the Korean government. SBA data have a panel structure, so each firm has its own unique ID, and we can trace each firm across years. SBA data cover all Korean business entities with more than 50 regular workers and 300 million Korean won (approximately 300 thousand US dollars) of capital stock. The data have several advantages that facilitated our research. First, SBA data are administrative annual survey data; all firms that meet certain standards are legally required to report their information on business activities. Therefore, the panel data are highly balanced with a low sample attrition rate.[3] Second, to improve the quality of the data, Statistics Korea merges the surveyed information with information from other official administrative datasets. SBA data suffer from fewer measurement error issues than other widely used firm-level datasets that fully rely on the surveyed information. Third, SBA data include firm-level employment information at a highly disaggregated level. In addition to the total number of employees for each firm, for example, the data include the number of regular workers for different types of tasks, e.g., manager, production, service, sales, transportation, and research. Therefore, the data provide the opportunity to study the heterogeneous effects of a firm's global investment activity on the employment stability of workers in different tasks. Last and most importantly, the data include the information of parent firms and domestic/foreign affiliate firms.[4] The affiliate-level information includes the affiliate's location and 2-digit industry, the ownership share of its parent firm, and the invested amount. We can therefore measure vertical investment linkages between Korean parent firms and their foreign affiliates.[5] Table 3.6 gives the descriptive statistics of the major variables from our main SBA dataset.

[3]See table 2.1 for the number of yearly observations.

[4]SBA includes the affiliate-level information for affiliates such that Korean parent firms own more than 20% of the affiliate's ownership.

[5]We restricted our sample to firms with more than 3 years of consecutive observations to guarantee sufficient data periods for the employment volatility calculations. For nonmanufacturing sectors, we used the service and sales industries and excluded the construction industry. See table B5 for industry classification.

2.2.2 Korean Industry-Level Outward FDI Data

Previous studies in the FDI literature have found it difficult to measure the purpose of outward investments by firm. Due to the lack of suitable data, most previous works (e.g., Debaere et al. (2010)) have used the information of investment destination countries to determine the purpose of FDI. They have generally defined the investment in emerging countries as cost saving FDI (or vertical FDI) and the investment in developed countries as market access FDI (or horizontal FDI). As the market size of major emerging countries such as China and India has been rapidly rising, MNEs from developed countries have invested in emerging countries not only for cost saving purposes but also for market access. The traditional approach of using destination country information risks over-evaluating cost saving FDI and under-evaluating market access FDI in developing countries.

SBA data provide a great deal of information on Korean firms' business activities. However, the data do not include information on a firm's foreign investment purposes. To determine a firm's motivations for outward foreign investment more accurately, we used disaggregated industry-level outward FDI data ("해외직접투자통계" in Korean. hereafter "KEXIM-OFDI data") collected by the Korean Export-Import (KEXIM) Bank. If a firm wires money to its foreign affiliates for investment, KEXIM collects the information on investments from the investor. After that, KEXIM aggregates the information at the industry level and publicizes the information. The collected information is highly detailed, including the investor's location, industry, and size; the country of the affiliate; and, most importantly, the purpose of the investment.[6] The original KEXIM-OFDI data grouped the outward FDI motivations into eight categories, but the original definitions are less clear and do not allow us separate different FDI motivations in a meaningful way. We reclassified the FDI motivations into five groups.[7]

Instead of the classical destination-based approach, we implement a more direct approach to identify the firm-level size of outward FDI by different motivations. Our approach requires two steps: matching SBA data and KEXIM-OFDI data as a 1st step and computing the firm-

[6]KEXIM data provide location information at the province and metropolitan levels and industry information at the six-digit level.

[7]See table 2.3 for our definitions of FDI motivations.

level share of outward FDI by different motivations as a 2nd step. We need a key identifier at the disaggregated level to merge the SBA data and KEXIM-OFDI data. As a key identifier for linking two datasets, we made the 1×5 vector of [Year, Location, Industry, Size, Destination] for every firm's foreign investment information in SBA data and the industry-level information in the KEXIM-OFDI data. For example, if a small-sized food manufacturer in Seoul invested in China in 2006, the identifier vector of the firm's investment information is [2006, Seoul, Manufacture of food products, Small and medium sized, China]. We match SBA data and KEXIM-OFDI data by linking identical vectors in both datasets. After merging two datasets, we calculated the firm-level outward investment amounts for different purposes. For the calculation, from KEXIM-OFDI data that provide industry-level information, we first computed the industry-level share of investment purposes for every vector. We finally summed the investment amount by investment purposes at the firm level using previously calculated shares as weights. For illustration purposes, we provide a simple example of our datawork in B.0.1.

Compared to other previously used methods to recover FDI motivations, such as the destination-based approach, our approach has the benefit of providing more accurate information about outward FDI purposes at the firm level. For example, suppose that there is a firm that invested in Vietnam for cost saving purposes and Indonesia for market access purposes. The destination-based approach cannot distinguish investment motivations between Vietnam and Indonesia, as they are both emerging countries. However, our approach can separate different motivations between countries. Moreover, even within the same destination country and industry, MNEs with unequal attributes may invest in the destination country for different purposes. For example, while a mega-scale automobile company builds its production facilities in China for market access purposes, small firms supplying vehicle parts to the final producer may move their production facilities to China to save production costs. Our approach can also address this issue, as we determine FDI motivations through firm-level attributes such as location, size, and industry. Lastly, MNEs can also use FDI for multiple purposes; this type of FDI is called "complex FDI". By using the destination country and industry-level share of investment purposes from the disaggregated industry-level data, our approach provides reasonable estimates of firm-level outward FDI amounts for multiple purposes. Our approach can measure Korean MNEs' global investment activities by motivation at the firm level, albeit with a few limitations.

2.3 Employment Volatility

In this section, we discuss the measure of employment volatility, which is our main variable of interest. We employed the "residual approach", the widely used method in literature such as Kurz and Senses (2016) and other subsequent papers, to compute firm-level employment volatility. For the measure for the residual approach, we first estimate the following simple linear fixed effect model and obtain residual $\hat{e}$.

$$\log(E_{ist}) - \log(E_{ist-1}) = \alpha + \kappa_i + \eta_{st} + e_{ist} \tag{2.1}$$

where E_{ist} is the employment level of firm i in industry s in year t. "Employment" means the number of regular workers, which are workers with employment contracts longer than one year. To capture the heterogeneous effects on workers in different tasks, we also used the number of workers with production tasks and workers with management tasks.[8] κ_i is the firm-level fixed effect, and η_{st} is the industry-specific time trend. Our residual $\hat{e}$ from equation (2.1) captures the deviation in firm $i's$ employment growth from the predicted employment growth. We define employment volatility as the standard error of the residual.

$$\hat{\sigma}_{is} = \sqrt{\frac{1}{\omega - 1}\sum_{t=1}^{\omega}\hat{e}_{ist}^2} \tag{2.2}$$

where ω is the window of observation lengths.

Figure 2.1 describes the distributions of our employment volatility measures constructed by the residual approach. In the manufacturing sector, we can observe that the employment volatility of Korean MNEs is higher overall than the employment volatility of Korean domestic firms. However,

[8] "Management tasks" are defined as tasks related to headquarters operations, including human resources, management, accounting, and research and development. For workers with "production tasks", we aggregated the number of employees who work on the production line at the headquarters and at domestic affiliates.

from the non-manufacturing sector, we find little difference of the employment volatility between Korean MNEs and domestic firms. Figure 2.2 and Figure 2.3 show the distributions of employment volatility for workers in different tasks, including production tasks and management tasks.[9] For the two different tasks of production and management, the employment volatility of MNEs is higher than that of domestic firms. All these observations bring us back to the importance of the sectoral heterogeneity of the impact of outward FDI on workers' job stability by task.

2.4 Empirical Analysis

We now introduce our reduced-form empirical models in Section 2.4. We employ two different models to study the role of MNEs' outward FDI on employment volatility. The first model is a cross-sectional linear fixed effects model that captures the relationship between long-term employment volatility and FDI by sector and investment motivation. The second model is a DD model with matching that estimates the short-run causal treatment effects of being an MNE on employment volatility. The results from our two models will provide different perspectives for understanding how MNEs' foreign investment activities impact the employment volatility of workers in the home country.

2.4.1 Fixed Effects Model

In this section, we describe our baseline cross-sectional linear fixed effects model and estimated results. To empirically test the linkage between employment volatility and a firm's outward FDI, we begin our empirical analysis by estimating the following simple cross-sectional regression model.

$$\log \hat{\sigma}_{isp} = \alpha + \beta_1 \text{Korean\_MNE}_{isp} + \beta_2 \bar{X}_{isp} + \zeta_1 D_{sp} + \epsilon_{isp} \tag{2.3}$$

Our key variable of interest is Korean_MNE_{isp}, a dummy variable that takes a value of one if firm i is located in province (or metropolitan area) p, belongs to industry s and invested in affiliates abroad

[9] For the nonmanufacturing sector, we do not illustrate the distribution of employment volatility for workers with production tasks because of small observations.

with more than 20% of ownership.[10] We include several firm control variables, $\bar{X}_{is}$, to control for firm-level characteristics that affect the firm's employment decisions. The variables are averaged across the range of observations. To alleviate potential endogeneity issues such as omitted variable problems, we also control for industry-region fixed effects (D_{sp}). We expect these effects to capture industry-level unobserved time-invariant attributes that may vary by region.

We also advance beyond our baseline model and study the role of different outward FDI motivations on employment volatility. To capture the purposes of outward investment by firm, we create firm-level discrete variables: “cost saving FDI" and “market access FDI". To construct the “cost saving FDI" variable, we assign a value of one if the share of foreign investment from cost saving FDI motivations is greater than 20% of the firm's overall foreign investment amount. We construct the "market access FDI" variable in the same way. We estimate the following modified baseline model with interaction terms to determine the differential effects of labor cost saving motivations and market access motivations on employment volatility.

$$\begin{aligned}\log \hat{\sigma}_{isp} &= \alpha + \beta_1 \text{Korean\_MNE}_{isp} + \beta_2 (\text{Korean\_MNE}_{isp} \times \text{FDI types}_{isp}) \\ &\quad + \beta_3 \bar{X}_{isp} + \zeta_1 D_{sp} + \epsilon_{isp} \qquad (2.4)\end{aligned}$$

where FDI $\text{types}_{isp} \in \{\text{Cost Saving}_{isp}, \text{Market Access}_{isp}\}$. All standard errors are clustered at the industry-region level.

Table 2.4, Table 2.5, and Table 2.6 report the results from our baseline linear fixed effects model. Table 2.4 includes the results for all firms, where Table 2.5 and Table 2.6 include the results for all firms in manufacturing industries and nonmanufacturing industries, respectively. For each table, employment volatility measures were constructed from the number of total workers (columns (1)-(3)), the number of workers with production tasks (columns (4)-(6)), and the number of workers with management tasks (columns (7)-(9)).

Our results highlight several notable observations from Korean firms. First, overall, the outward FDI of Korean firms is positively associated with the volatility of their employment in the long

[10]To maintain the consistency of the industry classifications, firms that switched sectors are not used in our analysis.

run. Relative to non-MNEs, being an MNE with foreign affiliates raises employment volatility overall and the finding is mainly driven by firms in the manufacturing sector. This is similar to the results presented in Kiyota et al. (2020) which used the Japanese firm-level data. Additionally, being an MNE is more strongly associated with the rise in the employment volatility of workers with production tasks than workers with management tasks. The size of the coefficient for workers with production tasks (0.061) is more than three times greater than the coefficient for workers with management tasks (0.018). Different FDI motivations play important roles in explaining the growth of employment volatility according to workers' tasks. In general, both the labor cost saving motivation and market access motivation are positively associated with the employment volatility of workers across different tasks except in one case: the labor cost saving motivation is not positively associated with the employment volatility of workers in management tasks. In the sample of manufacturing industries, we obtain similar results: we can confirm strong positive effects of both cost saving and market access motivations, and the effects are greater for workers in production tasks than for workers in management tasks. In nonmanufacturing industries, however, we find smaller effects, and the patterns are less clear.

We find unequal impacts of labor cost saving FDI on workers in production tasks and management tasks in Table 2.5, which could be interesting. To explain our findings regarding labor cost saving FDI, we can rely on the substitution and complementary effects of cheap foreign workers with different types of domestic workers. As previously studied in Rodrik (1997), shifting parts of the production process to emerging countries with low labor costs would substitute cheap foreign workers for domestic workers in the production line. These substitution effects are likely to increase the elasticity of labor demand for home production workers and lower their bargaining power, which all threaten employment stability. On the other hand, consistent with previous studies such as Hummels et al. (2014) and Görg and Görlich (2015), shifting the production process to emerging countries can increase the relative demand for workers in non-routine management tasks by strengthening headquarters roles such as HR management and R&D. If this is the case, the job stability of workers in management tasks can be improved. Our findings are consistent with those potential mechanisms and suggest that labor cost saving FDI may play different roles in shaping the job stability of domestic workers by task.

2.4.1.1 Robustness Tests

We also performed several robustness tests to check our main findings in section 2.4.1 are reliable. Following five cases of robustness tests were done and the results are available in Table 2.7, Table 2.8, and Table 2.9. We confirmed that robustness tests results are highly consistent with main results in section 2.4.1. (1) We tried the alternative employment volatility measure, the standard deviation of firm employment growth[11], to tackle the concern that our main findings may be sensitive to the use of different employment volatility measure. (2) Firms' entry and exit can be an issue, so we use the balanced sample with full observations. (3) Someone may concern that data with shorter length of periods may earn different result. we split periods by 6 years windows, 2006-2011 and 2012-2017 and estimate the employment volatility by samples, merge two datasets, and run regression with period fixed effects. (4) We only included the number of regular workers in our baseline analysis. In calculating the number of workers, we added the number of temporary workers.[12] (5) Instead of 20% rule in defining the firm's FDI motivations, we used the firm's outward investment share by purposes.

2.4.2 DD with Matching

In section 2.4.1, we find several interesting empirical findings regarding outward FDI and employment volatility. As firms do not randomly make their decisions regarding outward FDI, there may be concern that our findings in section 2.4.1 are biased due to endogeneity issues such as simultaneity. More precisely, there could be unobservables that affect firms' FDI decisions and employment adjustment and may not be fully controlled by fixed effects. The results in section

[11] $\hat{\sigma}_i^o = \sqrt{\frac{1}{\omega-1}\sum_{\tau=0}^{\omega}(\gamma_{it+\tau} - \bar{\gamma}_{it})^2}$

[12] SBA data collects the number of temporary workers by firm, but the dataset does not include the information of assigned tasks for temporary workers.

2.4.1 should be understood as conditional correlations between employment volatility and Korean MNEs' outward FDI by motivation. To address potential endogeneity issues and obtain estimates of treatment effects from Korean MNEs' outward FDI, we use a DD method with matching.

We now delve into our identification strategy in more detail. Let T_{it} be the indicator for the treatment: a firm i newly becoming an MNE at t by gaining its first foreign affiliates. $T_{it} = 1$ if the treatment event of i occurs at t. Let $\hat{\sigma}_i(j)$ be the employment volatility of firm i; the status of treatment is $j \in \{0, 1\}$, where 0 means non-treated and 1 means treated. The causal effect of the average treatment effects on the treated (ATT), which is our variable of interest, can be written as follows.

$$\tau_{\text{ATT}} = E[\Delta\hat{\sigma}_{it}(1) - \Delta\hat{\sigma}_{it}(0) | T_{it} = 1] \tag{2.5}$$

where $\Delta\hat{\sigma}_{it}(1) = \hat{\sigma}_{it}^{\text{after}}(1) - \hat{\sigma}_{it}^{\text{before}}(1)$ and $\Delta\hat{\sigma}_{it}(0) = \hat{\sigma}_{it}^{\text{after}}(0) - \hat{\sigma}_{it}^{\text{before}}(0)$, the difference of employment volatility between before-treatment periods and after-treatment periods.

The major challenge in estimating ATT above (equation (2.5)) is that we cannot observe $\Delta\hat{\sigma}_{it}(0)|T_{it} = 1$, the change in employment volatility if a firm i is not treated at t conditional on treatment, $T_{it} = 1$. $\Delta\hat{\sigma}_{it}(0)|T_{it} = 1$ is an outcome of the counterfactual situation, so there is a missing data issue. The propensity score matching (PSM) method developed by Rosenbaum and Rubin (1983) can be applied here to address the missing data problem in a fine manner. The PSM approach has been widely employed in empirical social science research, including academic works studying MNE activities and several labor market variables such as Debaere et al. (2010), Monarch et al. (2017), Eppinger (2019), and Choi and Greaney (2020). The basic idea of the PSM approach is to find and impute $\Delta\hat{\sigma}_{it}(0)$ from a suitable control group, that is, a group of non-treated firms that are comparable to the treated firms in terms of observed covariates.

Our estimation procedure consists of three steps.

Step 1. Estimate the probability of being treated, i.e., of becoming an MNE at t, by running the probit model of $T_{it} = f(X_{it-1})$ + Fixed Effects + ϵ_{it}. X_{it-1} are lagged predictors to calculate the probability of being treated, $p_{it}(X_{it-1})$.

Step 2. Match each treated firm to firms in the potential control group carefully from the predicted probability of being treated, $p(X_{it-1})$, in step 1. We define the potential control group as a set of firms that are (i) never treated, solely domestic firms during all observed periods and (ii) for which employment volatility measures for the before-ω years and after-ω years are all available. For each treated observation, we restrict the potential control group as firms within the same year-industry, and we do not allow matching across years and industries.[13,14] Matched firms that belong to the potential control group are purely domestic firms, but they should be the most similar to treated firms in terms of ex ante observables. We will call these matched firms the "control group".

Step 3. Construct the DD estimator by running the following model.

$$\hat{\sigma}_{it}^{k} = \alpha + \beta_1 k + \beta_2 T_{it} + \beta_3 (k \cdot T_{it}) + \epsilon_{it} \tag{2.6}$$

where $k = 1$ if the dependent variable is the employment volatility measure of firm i for ω periods after t, and $k = 0$ otherwise. This is the specification of the DD model, and the estimate of β_3 will capture the causal effect of the treatment, as shown in equation (2.5).

As predictors of being treated at step one, we choose six covariates of outward FDI determinants: sales revenue, labor cost, labor-capital ratio, profit, a dummy variable for exporters, and a dummy variable for conglomerates. All predictors are lagged, and we also add industry fixed effects and year trends.[15] Table 2.11 is the result of probit model predictions at step one. After the first step in the prediction, we match two firms in the potential control group with a single treated firm. For matching, we employ radius matching with a caliper of 0.001 to find suitable firms for the control

[13] We confirm that allowing matching between industries (not between years) does not alter our main arguments.

[14] We may allow matching firms between different years by interpreting our panel dataset as a pooled cross-sectional dataset. This approach requires strict exogeneity, which is quite a strong assumption. See Wooldridge (2001, 2012) for details.

[15] Some industries have too few firms within the same province, which makes it harder to implement proper matching if we control for industry-region fixed effects. Instead of applying industry-region fixed effects, we use industry fixed effects and time effects to obtain a higher degree of freedom in matching. Standard errors are clustered at the industry level.

group. For the employment volatility calculation of firm i's before and after periods, we use data for the four-year window ($\omega = 4$). All firms in the treated group and the control group should be between 2010 and 2014, as they must have employment volatility data for both before and after periods.[16] There are 554 treated firms in the 2010-2014 waves of SBA data, and 270 firms are matched.

The key component of our inference is the second step: how to match firms between the treated group and the potential control group as much as possible. For the causal interpretation of our estimates, two well-known conditions of "unconfoundedness (or ignorability)" and "common support" should be satisfied at the second step of matching.

- (Unconfoundedness / Ignorability) $\Delta\hat{\sigma}_{it}(1), \Delta\hat{\sigma}_{it}(0) \perp T_{it} | p(X_{it-1})$
- (Common Support) $0 < p_{it}(X_{it-1}) < 1$ for all i

The first unconfoundedness assumption implies the independence of outcome variables with respect to the treatment effect, conditioning on covariates. Without ideal external variables, unconfoundedness is not a directly testable condition. Instead, to ensure that our matching successfully accounts for differences between firms in terms of observable covariates, we implement the so-called balancedness test. We compare the mean of covariates between the treated group and the control group and confirm that there is little evidence of significant mean differences between groups. For the second common support assumption, we drop observations of treated firms if their propensity scores are out of the common support.

Table 2.12 shows the results of our balancedness test, with mean comparisons between treated firms and non-treated firms before and after matching. Columns (1) to (3), which show the results of the mean comparisons between the treated and non-treated groups before matching, clearly reveal that two groups are very different with respect to observables ex ante. Treated firms that begin investing abroad are more likely to be exporters, members of a conglomerate, have greater sales,

[16] For example, firm i's "before" employment volatility measure at $t = 2010$ is found using i's employment data for 2006-2009, where its "after" employment volatility is found using data for 2010-2014. See Figure 2.4 for a graphical example.

be more profitable, and pay more labor costs than non-treated firms but are less labor intensive. All t-statistics of the mean differences reject the null hypothesis of identical means between groups at the 1% significance level. Nevertheless, propensity score matching for the treated firms reveals more similarity between the two groups in terms of ex ante observables. From Columns (4)-(8), we observe that the means of ex ante observables between the treated and control groups became more similar, with smaller values of the t-statistics testing for mean differences. In general, the standardized bias is close to or smaller than 5%, and the variance ratio is close to one. While the inferences are informal, we can be confident that our matching procedure appears to build a reliable control group from table 2.12.

Before we move to our results from our DD model (2.6), we emphasize that our results from the two different models (the cross-sectional linear fixed effects model and DD model with matching) should be interpreted carefully. Here, we note that there are two important differences between our models. First, the first model captures correlation between a firm's multinational status and employment volatility conditional on covariates, whereas the second model captures the causal effect of the treatment event, that is, the transition from a domestic firm to a multinational enterprise. Second, the window lengths of the employment volatility measures are different. For the first linear fixed effect model, the maximum length of employment volatility will be twelve years, as we used the full sample. In the second DD model, on the other hand, the window length for employment volatility measures is fixed at four years, as we used four-year observations before and after the treatment event. Employment volatility in the first model measures the job stability of workers over a longer period than the measure in the second model. We should therefore interpret the results from the two different models from a different angle. The results of our first model can be thought to show the long-run relationship between long-run employment volatility and a firm's multinational status. The results from the second model, on the other hand, illustrate the causal treatment effects on the short-term employment volatility when a firm newly becomes an MNE by gaining its first foreign affiliates.

Table 2.13 show our estimates of the DD model of employment volatility by workers' tasks.[17] For the treatment of T, Panel A of Table 2.13 reports estimates from all treated firms in 2010-2014. In Panel A, we find overall weak positive treatment effects on employment volatility, and the size and significance of the effects are smaller in nonmanufacturing industries than in manufacturing industries. To delve into the different roles of labor cost saving FDI and market access FDI, we narrow down our treated sample to firms that became MNEs due to labor cost saving motivations and market access motivations in 2010-2014. For labor cost saving FDI and market access FDI, we report our estimates in Panel B and Panel C of Table 2.13, respectively. In Panel B of Table 2.13, which reports the results for labor cost saving FDI, we find little evidence that FDI has raised the employment volatility of domestic workers across different tasks. This finding is somewhat puzzling because the shift in production facilities towards emerging countries for cost savings has been cited in the media as a major threat to domestic workers' employment stability. The division of tasks and the overlap of skills or tasks between foreign workers and domestic may be able to explain our findings. If Korean MNEs that initiate FDI for labor cost savings moved all their routine tasks abroad, there could be little overlap in skills or tasks between foreign workers (who are unskilled and specialize in routine tasks) and domestic workers (who are skilled and specialize in complex tasks). If this is the case, FDI for labor cost savings may not threaten the employment of domestic workers in Korea.[18] In Panel C of Table 2.13, on the other hand, we find positive effects of market access FDI. The table suggests that the firm's transition from non-MNE to MNE for market access purposes will weaken the employment stability of workers in the short run at the 10% significance level. In section 2.4.1, we observe a long-run positive relationship between outward FDI and the employment volatility of production line workers, and the relationship holds for both labor cost saving FDI and market access FDI. In the short run, however, the results for only market access FDI can be confirmed as a causal treatment effect in section 2.4.2.

[17]For all DD specifications in our paper, we bootstrap our model by repeatedly running regressions 200 times and report the bootstrapped estimates of coefficients and standard errors. We do not report the estimates if the number of observations is too small, as the results will likely suffer from small sample bias.

[18]We cannot test this mechanism due to a lack of proper variables.

Destination Countries: Developed Countries vs. Emerging Countries In Table 2.13, we find that market access FDI plays an important role in explaining the rise in short-term employment volatility in Korean MNEs. Different country-level attributes may disproportionately affect the employment stability of domestic workers, as we discussed in Section 2.1. We now dig into a more detailed analysis by groups of destination countries. The trends in Korean MNEs' outward FDI in the 2000s show a clear notable pattern: a gradual increase in market access FDI in Asian emerging countries.[19] Before the 2000s, the major reason for FDI in emerging Asian countries was to take advantage of low relative labor costs. Since the early 2000s, however, the rapid growth of Asian emerging economies has altered Korean MNEs' motivations for investments in Asian emerging countries from labor cost savings to market access. Market access FDI in Asian emerging economies has been explained major parts of Korean MNEs' outward FDI since the early 2000s.[20] The surge of Asian economies and the subsequent market expansion have provided strong incentives for Korean corporations to shift their production facilities from Korea to Asian economies. This reallocation of production facilities between Korea and Asian emerging countries may substitute Korean workers on domestic production lines with local workers in Asian countries. Therefore, it is worthwhile to determine whether different groups of destination countries exhibit different roles of market access FDI in employment volatility.[21] Panel A and Panel B of Table 2.14 include our results for market access FDI in Asian emerging countries and developed countries, respectively. From Panel A of Table 2.14, we observe that market access FDI in Asian emerging countries strongly increases the employment volatility of domestic workers in production tasks. From Panel B of Table 2.14, which reports the results for market access FDI in developed countries, however, we find little evidence that FDI increases the employment volatility of domestic workers across

[19] See Table B6 for the list of developed countries and Asian emerging countries.

[20] See Figure 2.5 for the trends in outward FDI in 2006-2017.

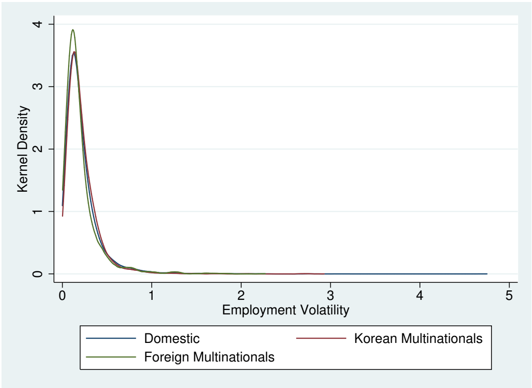
[21] If domestic workers with production tasks were relatively unskilled, market access FDI in Asian countries would be more likely threaten their job stability than market access FDI in developed countries, as the relative costs of unskilled workers are lower in emerging countries. SBA data do not provide skill-level (or education-level) data for workers, which prevents us from testing this hypothesis.

different tasks. This finding suggests that even given the same purpose of market access FDI, the effects on employment volatility can vary by the attributes of destination countries.

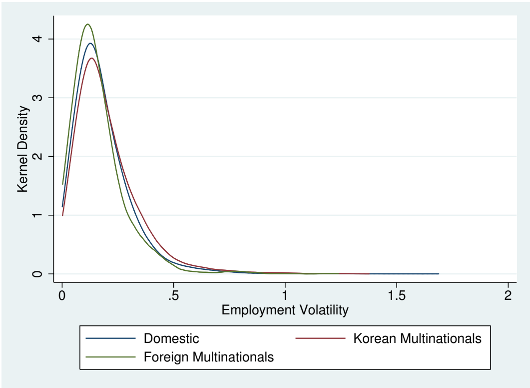
2.5 Conclusion

The outward FDI of MNEs has been widely acknowledged as a major cause of weakening employment stability among domestic workers. Few academic papers, however, have studied which types of FDI matter and which types of workers are more or less affected by MNEs' FDI. This paper studies the role of MNEs' outward FDI on the employment volatility of domestic workers. Our paper contributes to the literature by focusing on two different dimensions: motivations for FDI and workers' tasks. We match firm-level data with industry-level FDI data to identify the firm-level motivations of outward FDI at the most disaggregated level. Our cross-sectional fixed effects model reveals that the outward FDI of MNEs is highly associated with the increase in domestic workers' employment volatility. In regard to the motivations for outward FDI, both the cost-saving motivation and the market access motivation were associated with the increase in employment volatility, and the degree of this association was strongest for production workers in the manufacturing sector. We also utilize a DD model to estimate the causal treatment effects of FDI on employment volatility. Prior to the implementation of the DD analysis, we used a matching method to have a reliable control group and to address the confounding issues from the non-randomness of MNEs' FDI decisions. Our DD estimators confirm that outward FDI for market access purposes increases the employment volatility of domestic workers. The effect of market-access-seeking FDI in Asian emerging countries on production workers had the strongest effect, but we find no such adverse effect of market access FDI in developed countries. We find little evidence that FDI to save labor cost raises the employment volatility of domestic workers, which is inconsistent with the commonly accepted understanding and needs further research.

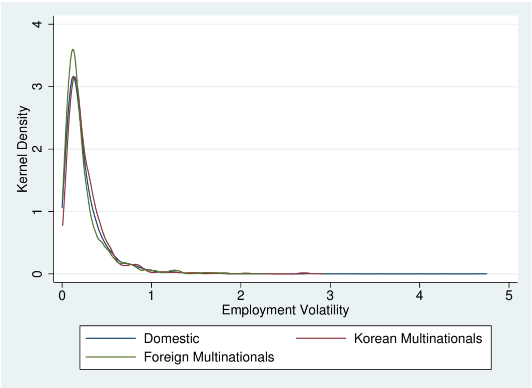
2.5.1 Figures



(a) All



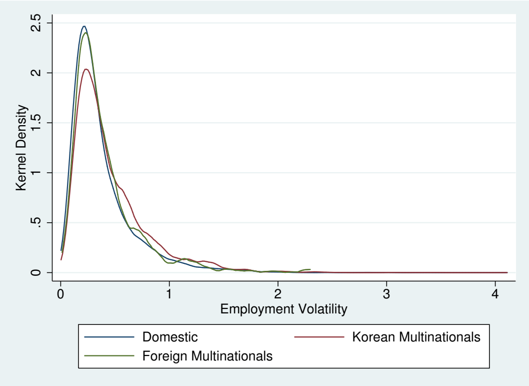
(b) Manufacturing



(c) Non Manufacturing

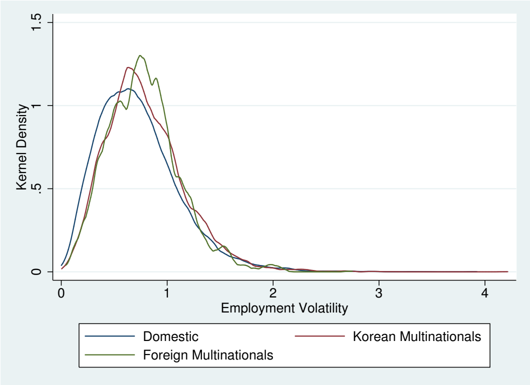
Figure 2.1: Distributions of Employment Volatility

(Figure 2.1) Source: Survey of Business Activities, 2006-2017

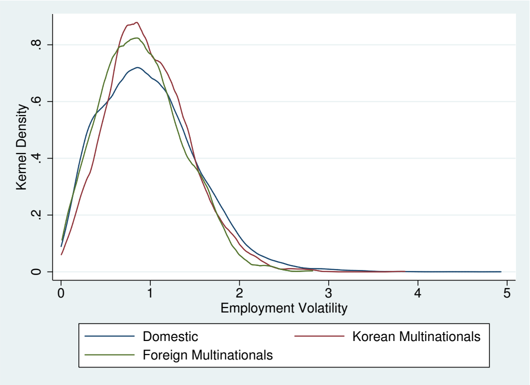


(a) Manufacturing

Figure 2.2: Distribution of Employment Volatility, Production Tasks



(a) Manufacturing



(b) Non Manufacturing

Figure 2.3: Distributions of Employment Volatility, Management Tasks

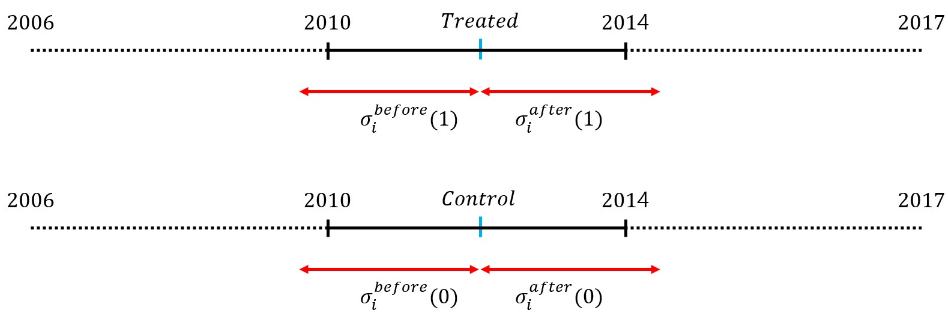


Figure 2.4: Employment Volatility, Before and After Treatment

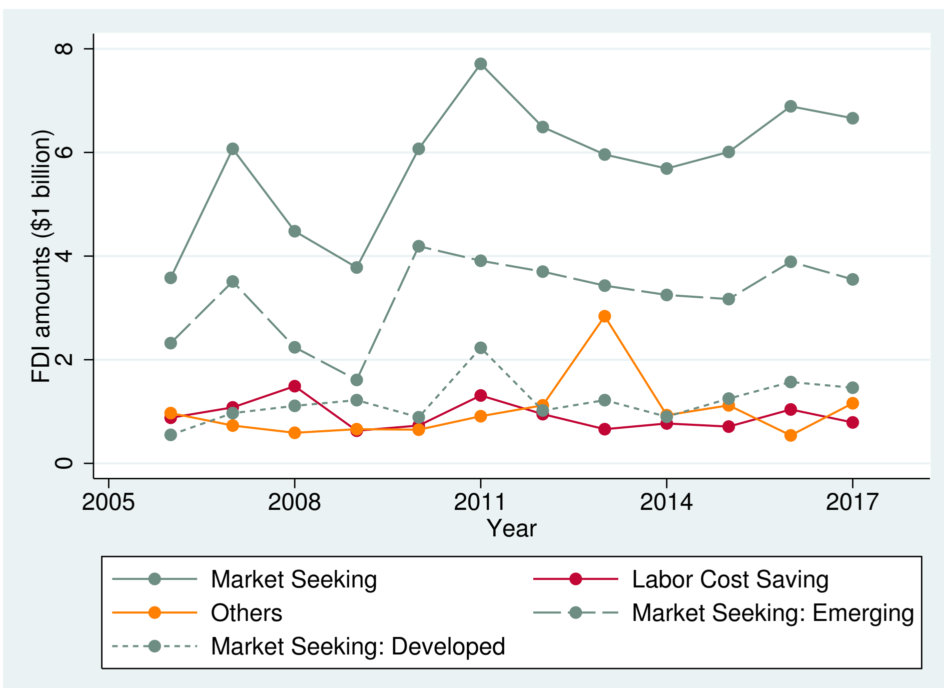


Figure 2.5: Trends of outward FDIs in Manufacturing Sector, by motivations

(Figure 2.5) Source: KEXIM-OFDI data, 2006-2017

2.5.2 Tables

Table 2.1: Number of Observations, by Sectors

Year	Manufacturing	Service	Sales	Total
2006	4,591	2,247	580	7,418
2007	4,768	2,423	612	7,803
2008	5,287	2,857	668	8,812
2009	5,069	2,980	688	8,737
2010	4,920	3,031	903	8,854
2011	5,253	3,348	971	9,572
2012	5,571	3,346	1,010	9,927
2013	5,573	3,513	1,079	10,165
2014	5,483	3,593	1,184	10,260
2015	5,403	3,731	1,223	10,357
2016	5,169	3,499	1,163	9,831
2017	5,029	3,363	1,117	9,509
Total	62,116	37,931	11,198	111,245

Source: Survey of Business Activities, 2006-2017

Table 2.2: Summary Statistics

	(1) All		(2) Korean Multinationals		(3) Domestic Firms	
	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev
Workers	321.30	1,640.17	661.51	3,274.73	224.70	605.73
Capital Stock	12.59	81.51	28.26	143.59	8.13	50.86
Sales	179.37	1,792.01	560.54	3,751.66	71.14	271.61
Assets	176.63	1,876.03	567.86	3,933.48	65.54	264.29
Liabilities	83.68	649.83	257.72	1,341.36	34.26	142.37
Profits	9.67	217.77	32.34	458.93	3.23	29.97
Conglomerate	0.04	0.20	0.08	0.27	0.03	0.18
Exporter	0.44	0.50	0.77	0.42	0.35	0.48
Importer	0.38	0.48	0.62	0.48	0.31	0.46
Observations	111,245		24,602		86,643	
Number of Firms	13,154		2,111		11,043	

Korean multinationals represent firms which own affiliates abroad, while domestic firms are not. The unit for Capital Stock, Sales, Assets, Liabilities, and Profits is 1 million Korean won (approximately 0.9 thousand US dollars). Conglomerate = 1 if a firm is a member of any conglomerate. Exporter and Importer are 1 if a firm do exporting and importing, respectively. Source: Survey of Business Activities, 2006-2017.

Table 2.3: Group of FDI purposes

Original FDI Purposes	Redefined FDI Purposes
Others	Unknown
Not Available	Unknown
Low Labor Cost	Cost Saving FDI
Export Promotion	Market Access FDI
Enter the Local Market	Market Access FDI
Overcome Trade Barriers	Market Access FDI
Enter a Third Country	Export-Platform FDI
Resource Development	Resource Development
Securing of Raw Materials	Resource Development
Introducing Advanced Technologies	Advanced Technologies

The first column represents the original definitions of FDI purposes in KEXIM OFDI data. The second column reports our edited definitions.

Table 2.4: Baseline: Outward FDI and Employment Volatility, All

	All Employment			Production Tasks Employment			Management Tasks Employment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Korean MNE	0.0189***	0.0142**	-1.90e-05	0.0607***	0.0495***	0.0256*	0.0184*	0.0246*	-0.0129
	(0.00528)	(0.00552)	(0.00843)	(0.0131)	(0.0126)	(0.0147)	(0.0110)	(0.0127)	(0.0146)
Korean MNE ×Cost-Saving		0.0193***			0.0359***			-0.0255*	
		(0.00745)			(0.0136)			(0.0146)	
Korean MNE ×Market-Access			0.0245***			0.0470***			0.0405***
			(0.00866)			(0.0126)			(0.0140)
Both	-0.0262***	-0.0265***	-0.0289***	0.0264	0.0245	0.0200	0.0228	0.0231	0.0184
	(0.00639)	(0.00637)	(0.00637)	(0.0188)	(0.0191)	(0.0190)	(0.0146)	(0.0146)	(0.0150)
Export Only	-0.00936	-0.00938	-0.0100	0.0313	0.0299	0.0295	0.0408	0.0408	0.0397
	(0.00993)	(0.00994)	(0.00970)	(0.0285)	(0.0287)	(0.0285)	(0.0259)	(0.0258)	(0.0256)
Import Only	-0.0118	-0.0117	-0.0121	0.00122	0.000665	0.000745	-0.0247	-0.0248	-0.0252
	(0.0118)	(0.0118)	(0.0118)	(0.0269)	(0.0270)	(0.0270)	(0.0218)	(0.0218)	(0.0218)
Workers	-0.181	-0.174	-0.207	-1.703***	-1.699***	-1.765***	2.030***	2.021***	1.987***
	(0.283)	(0.284)	(0.281)	(0.519)	(0.518)	(0.532)	(0.713)	(0.714)	(0.716)
Capital Stock	0.00116	0.00127	0.00139	-0.00631	-0.00567	-0.00602	0.000553	0.000414	0.000932
	(0.00599)	(0.00597)	(0.00597)	(0.00583)	(0.00580)	(0.00583)	(0.00457)	(0.00456)	(0.00456)
Sales	-0.00339	-0.00331	-0.00325	0.00634**	0.00642**	0.00670**	-0.000546	-0.000643	-0.000317
	(0.00219)	(0.00220)	(0.00227)	(0.00299)	(0.00299)	(0.00323)	(0.00652)	(0.00654)	(0.00670)
Profit	-0.0464	-0.0477	-0.0430	-0.0444	-0.0467	-0.0397	-0.0188	-0.0170	-0.0133
	(0.0386)	(0.0384)	(0.0386)	(0.0799)	(0.0790)	(0.0788)	(0.0826)	(0.0828)	(0.0830)
Equity	0.000937	0.000955	0.000889	0.00132	0.00135	0.00126	-0.00208	-0.00210	-0.00216
	(0.000691)	(0.000691)	(0.000698)	(0.00134)	(0.00132)	(0.00131)	(0.00135)	(0.00135)	(0.00136)
Industry-Region FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	13,134	13,134	13,134	7,100	7,100	7,100	13,134	13,134	13,134
R-squared	0.108	0.109	0.109	0.150	0.151	0.152	0.111	0.111	0.111

The dependent variable is the employment volatility constructed by residual approach. Column (1)-(3) include the results for employment volatility of all workers within a firm. Column (4)-(6) include the results for employment volatility of workers with production tasks. Column (7)-(9) include the results for employment volatility of workers with management tasks. All firm level variables are averaged over the window of observations. Standard errors are clustered at the industry-region level. *** p<0.01, ** p<0.05, * p<0.1

Table 2.5: Baseline: Outward FDI and Employment Volatility, Manufacturing

	All Employment			Production Tasks Employment			Management Tasks Employment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Korean MNE	0.0218***	0.0160***	0.00983*	0.0611***	0.0502***	0.0260*	0.0293**	0.0402***	-0.00311
	(0.00491)	(0.00484)	(0.00577)	(0.0133)	(0.0128)	(0.0149)	(0.0115)	(0.0137)	(0.0159)
Korean MNE ×Cost-Saving		0.0179**			0.0342**			-0.0342*	
		(0.00738)			(0.0135)			(0.0210)	
Korean MNE ×Market-Access			0.0160***			0.0471***			0.0435***
			(0.00581)			(0.0125)			(0.0162)
Both	-0.0152**	-0.0162**	-0.0174**	0.0219	0.0199	0.0155	0.0161	0.0181	0.0102
	(0.00762)	(0.00761)	(0.00771)	(0.0195)	(0.0197)	(0.0196)	(0.0200)	(0.0200)	(0.0206)
Export Only	0.00423	0.00339	0.00372	0.0164	0.0149	0.0148	-0.00222	-0.000620	-0.00362
	(0.0121)	(0.0121)	(0.0121)	(0.0286)	(0.0288)	(0.0286)	(0.0318)	(0.0316)	(0.0319)
Import Only	-0.00431	-0.00466	-0.00450	0.000145	-0.000473	-0.000343	-0.0268	-0.0261	-0.0273
	(0.0111)	(0.0111)	(0.0111)	(0.0279)	(0.0279)	(0.0280)	(0.0304)	(0.0304)	(0.0304)
Workers	-0.145	-0.143	-0.169	-1.847***	-1.842***	-1.917***	1.047	1.043	0.982
	(0.159)	(0.159)	(0.161)	(0.588)	(0.586)	(0.602)	(0.887)	(0.884)	(0.876)
Capital Stock	-0.00369**	-0.00337*	-0.00359**	-0.00623	-0.00563	-0.00593	0.00616	0.00556	0.00644
	(0.00180)	(0.00183)	(0.00182)	(0.00631)	(0.00628)	(0.00632)	(0.00813)	(0.00820)	(0.00809)
Sales	-0.00129	-0.00127	-0.00113	0.00817***	0.00820***	0.00864***	-0.00175	-0.00178	-0.00132
	(0.00105)	(0.00106)	(0.00111)	(0.00308)	(0.00308)	(0.00324)	(0.00720)	(0.00718)	(0.00734)
Profit	-0.00477	-0.00588	-0.00335	-0.0546	-0.0567	-0.0505	-0.0722	-0.0701	-0.0684
	(0.0258)	(0.0260)	(0.0259)	(0.0802)	(0.0794)	(0.0791)	(0.0893)	(0.0897)	(0.0884)
Equity	0.000157	0.000178	0.000136	0.00137	0.00141	0.00131	-0.000292	-0.000332	-0.000347
	(0.000472)	(0.000478)	(0.000478)	(0.00135)	(0.00134)	(0.00133)	(0.00116)	(0.00116)	(0.00115)
Industry-Region FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	6,935	6,935	6,935	6,859	6,859	6,859	6,935	6,935	6,935
R-squared	0.066	0.068	0.067	0.131	0.132	0.132	0.059	0.060	0.060

The dependent variable is the employment volatility constructed by residual approach. Column (1)-(3) include the results for employment volatility of all workers within a firm. Column (4)-(6) include the results for employment volatility of workers with production tasks. Column (7)-(9) include the results for employment volatility of workers with management tasks. All firm level variables are averaged over the window of observations. Standard errors are clustered at the industry-region level. *** p<0.01, ** p<0.05, * p<0.1

Table 2.6: Baseline: Outward FDI and Employment Volatility, Non-Manufacturing

	All Employment			Production Tasks Employment			Management Tasks Employment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Korean MNE	0.0119	0.0120	-0.0269	0.0160	0.0247	-0.0206	-0.0139	-0.0135	-0.0458
	(0.0159)	(0.0156)	(0.0270)	(0.0556)	(0.0539)	(0.0902)	(0.0237)	(0.0235)	(0.0299)
Korean MNE ×Cost-Saving		-0.00236			1.234***			-0.0123	
		(0.0475)			(0.0146)			(0.114)	
Korean MNE ×Market-Access			0.0462*			0.0447			0.0380
			(0.0245)			(0.116)			(0.0281)
Both	-0.0321***	-0.0321***	-0.0355***	0.0541	0.0454	0.0480	0.0184	0.0184	0.0155
	(0.00980)	(0.00980)	(0.00994)	(0.0699)	(0.0715)	(0.0659)	(0.0191)	(0.0191)	(0.0196)
Export Only	-0.0143	-0.0143	-0.0155	0.486**	0.481**	0.483**	0.0675**	0.0675**	0.0665**
	(0.0145)	(0.0145)	(0.0137)	(0.203)	(0.204)	(0.207)	(0.0328)	(0.0328)	(0.0325)
Import Only	-0.0135	-0.0135	-0.0142	-0.0129	-0.0127	-0.0125	-0.0282	-0.0282	-0.0288
	(0.0184)	(0.0183)	(0.0184)	(0.0962)	(0.0966)	(0.0966)	(0.0295)	(0.0294)	(0.0294)
Workers	0.0934	0.0935	0.0720	-0.987	-0.950	-0.988	2.835***	2.835***	2.817***
	(0.464)	(0.464)	(0.457)	(1.420)	(1.450)	(1.424)	(0.938)	(0.936)	(0.945)
Capital Stock	0.00366	0.00367	0.00438	0.128**	0.130**	0.136**	0.00172	0.00173	0.00230
	(0.0105)	(0.0105)	(0.0104)	(0.0598)	(0.0613)	(0.0546)	(0.00518)	(0.00517)	(0.00513)
Sales	-0.00926	-0.00926	-0.00930	-0.0461	-0.0468	-0.0447	0.00923	0.00921	0.00920
	(0.00693)	(0.00698)	(0.00687)	(0.0276)	(0.0287)	(0.0298)	(0.00931)	(0.00927)	(0.00951)
Profit	-0.291***	-0.291***	-0.285**	0.606	0.591	0.768	0.208	0.207	0.213
	(0.110)	(0.109)	(0.110)	(1.402)	(1.385)	(1.642)	(0.195)	(0.195)	(0.195)
Equity	0.00304	0.00304	0.00289	0.00481	0.00579	0.00105	-0.00609***	-0.00609***	-0.00621***
	(0.00185)	(0.00185)	(0.00193)	(0.0258)	(0.0260)	(0.0308)	(0.00233)	(0.00234)	(0.00236)
Industry-Region FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	6,199	6,199	6,199	241	241	241	6,199	6,199	6,199
R-squared	0.092	0.092	0.093	0.219	0.240	0.219	0.096	0.096	0.096

The dependent variable is the employment volatility constructed by residual approach. Column (1)-(3) include the results for employment volatility of all workers within a firm. Column (4)-(6) include the results for employment volatility of workers with production tasks. Column (7)-(9) include the results for employment volatility of workers with management tasks. All firm level variables are averaged over the window of observations. Standard errors are clustered at the industry-region level. *** p<0.01, ** p<0.05, * p<0.1

Table 2.7: Robustness: Outward FDI and Employment Volatility, All

	All Employment			Production Tasks Employment			Management Tasks Employment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	(Panel A) Alternative Employment Volatility Measure								
Korean MNE	0.0186***	0.0142***	-0.00179	0.0493***	0.0399***	0.0111	0.0225**	0.0266**	-0.0178
	(0.00476)	(0.00492)	(0.00759)	(0.0113)	(0.0114)	(0.0133)	(0.0102)	(0.0118)	(0.0136)
Korean MNE × Cost-Saving		0.0184***			0.0307**			-0.0167	
		(0.00688)			(0.0120)			(0.0136)	
Korean MNE × Market-Access			0.0264***			0.0509***			0.0521***
			(0.00782)			(0.0117)			(0.0124)
Observations	13,134	13,134	13,134	7,300	7,300	7,300	13,134	13,134	13,134
R-squared	0.103	0.104	0.104	0.123	0.124	0.125	0.117	0.117	0.117
	(Panel B) Balanced Sample								
Korean MNE	0.0103*	0.00758	-0.00717	0.0408***	0.0378**	0.00480	0.0326**	0.0368**	0.0136
	(0.00540)	(0.00609)	(0.00906)	(0.0150)	(0.0153)	(0.0176)	(0.0136)	(0.0150)	(0.0193)
Korean MNE × Cost-Saving		0.0124			0.0111			-0.0187	
		(0.00761)			(0.0178)			(0.0164)	
Korean MNE × Market-Access			0.0231**			0.0492***			0.0252
			(0.00954)			(0.0188)			(0.0173)
Observations	4,993	4,993	4,993	3,207	3,207	3,207	4,993	4,993	4,993
R-squared	0.159	0.159	0.160	0.224	0.225	0.227	0.221	0.221	0.221
	(Panel C) Six-years window								
Korean MNE	0.0153***	0.0122***	0.00249	0.0551***	0.0479***	0.0241	0.0219*	0.0257**	-0.00506
	(0.00414)	(0.00428)	(0.00677)	(0.0124)	(0.0129)	(0.0153)	(0.0115)	(0.0127)	(0.0124)
Korean MNE × Cost-Saving		0.0132*			0.0244			-0.0165	
		(0.00752)			(0.0158)			(0.0148)	
Korean MNE × Market-Access			0.0168**			0.0420***			0.0353***
			(0.00660)			(0.0133)			(0.0136)
Observations	20,347	20,347	20,347	11,399	11,399	11,399	20,347	20,347	20,347
R-squared	0.087	0.087	0.088	0.134	0.134	0.135	0.090	0.090	0.090
	(Panel D) Investment Shares								
Korean MNE	0.0189***	0.0148***	0.00591	0.0607***	0.0464***	0.0390**	0.0184*	0.0219*	-0.00842
	(0.00528)	(0.00553)	(0.00816)	(0.0131)	(0.0135)	(0.0159)	(0.0110)	(0.0128)	(0.0139)
Korean MNE × (% of Cost-Saving)		0.0357**			0.101***			-0.0304	
		(0.0168)			(0.0385)			(0.0392)	
Korean MNE × (% of Market-Access)			0.0216**			0.0384**			0.0445***
			(0.0101)			(0.0154)			(0.0164)
Observations	13,134	13,134	13,134	7,100	7,100	7,100	13,134	13,134	13,134
R-squared	0.108	0.108	0.109	0.150	0.151	0.151	0.111	0.111	0.111
	(Panel E) Temporary Workers Included								
Korean MNE	0.0184***	0.0150**	-0.00218						
	(0.00614)	(0.00623)	(0.00965)						
Korean MNE × Cost-Saving		0.0140							
		(0.00929)							
Korean MNE × Market-Access			0.0267***						
			(0.00990)						
Observations	13,134	13,134	13,134						
R-squared	0.137	0.137	0.138						

The dependent variable is the employment volatility constructed by the residual approach, except Panel A which used the alternative volatility measure. Column (1)-(3) include the results for employment volatility of all workers within a firm. Column (4)-(6) include the results for employment volatility of workers with production tasks. Column (7)-(9) include the results for employment volatility of workers with management tasks. All firm level variables are averaged over the window of observations. All specifications include firm-level control variables and industry-region fixed effects. Panel C additionally includes period fixed effects. Standard errors are clustered at the industry-region level. *** p<0.01, ** p<0.05, * p<0.1

Table 2.8: Robustness: Outward FDI and Employment Volatility, Manufacturing

	All Employment			Production Tasks Employment			Management Tasks Employment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				(Panel A) Alternative Employment Volatility Measure					
Korean MNE	0.0215***	0.0162***	0.00750	0.0526***	0.0435***	0.0142	0.0339***	0.0422***	-0.00346
	(0.00457)	(0.00444)	(0.00506)	(0.0114)	(0.0114)	(0.0133)	(0.0103)	(0.0126)	(0.0148)
Korean MNE ×Cost-Saving		0.0167**			0.0285**			-0.0261*	
		(0.00684)			(0.0119)			(0.0141)	
Korean MNE ×Market-Access			0.0188***			0.0516***			0.0501***
			(0.00524)			(0.0118)			(0.0145)
Observations	6,935	6,935	6,935	6,904	6,904	6,904	6,935	6,935	6,935
R-squared	0.065	0.067	0.067	0.113	0.114	0.116	0.061	0.061	0.063
				(Panel B) Balanced Sample					
Korean MNE	0.0160***	0.0139**	0.00646	0.0417***	0.0400**	0.00498	0.0372***	0.0441***	0.0219
	(0.00526)	(0.00602)	(0.00708)	(0.0152)	(0.0154)	(0.0180)	(0.0138)	(0.0154)	(0.0194)
Korean MNE ×Cost-Saving		0.00771			0.00647			-0.0250	
		(0.00712)			(0.0174)			(0.0165)	
Korean MNE ×Market-Access			0.0131*			0.0503**			0.0209
			(0.00685)			(0.0194)			(0.0185)
Observations	3,104	3,104	3,104	3,103	3,103	3,103	3,104	3,104	3,104
R-squared	0.099	0.100	0.101	0.204	0.204	0.207	0.108	0.109	0.108
				(Panel C) Six-years window					
Korean MNE	0.0153***	0.0122***	0.00249	0.0551***	0.0479***	0.0241	0.0219*	0.0257**	-0.00506
	(0.00414)	(0.00428)	(0.00677)	(0.0124)	(0.0129)	(0.0153)	(0.0115)	(0.0127)	(0.0124)
Korean MNE ×Cost-Saving		0.0132*			0.0244			-0.0165	
		(0.00752)			(0.0158)			(0.0148)	
Korean MNE ×Market-Access			0.0168**			0.0420***			0.0353***
			(0.00660)			(0.0133)			(0.0136)
Observations	20,347	20,347	20,347	11,399	11,399	11,399	20,347	20,347	20,347
R-squared	0.087	0.087	0.088	0.134	0.134	0.135	0.090	0.090	0.090
				(Panel D) Investment Shares					
Korean MNE	0.0218***	0.0174***	0.0136**	0.0611***	0.0471***	0.0379**	0.0293**	0.0387***	0.00117
	(0.00491)	(0.00476)	(0.00605)	(0.0133)	(0.0138)	(0.0162)	(0.0115)	(0.0137)	(0.0146)
Korean MNE × (% of Cost-Saving)		0.0303*			0.0969**			-0.0652*	
		(0.0165)			(0.0385)			(0.0374)	
Korean MNE × (% of Market-Access)			0.0146**			0.0412***			0.0502**
			(0.00688)			(0.0155)			(0.0194)
Observations	6,935	6,935	6,935	6,859	6,859	6,859	6,935	6,935	6,935
R-squared	0.066	0.067	0.067	0.131	0.132	0.132	0.059	0.060	0.060
				(Panel E) Temporary Workers Included					
Korean MNE	0.0190***	0.0145**	0.00859						
	(0.00633)	(0.00595)	(0.00680)						
Korean MNE ×Cost-Saving		0.0143							
		(0.00920)							
Korean MNE ×Market-Access			0.0140**						
			(0.00597)						
Observations	6,935	6,935	6,935						
R-squared	0.064	0.065	0.065						

The dependent variable is the employment volatility constructed by the residual approach, except Panel A which used the alternative volatility measure. Column (1)-(3) include the results for employment volatility of all workers within a firm. Column (4)-(6) include the results for employment volatility of workers with production tasks. Column (7)-(9) include the results for employment volatility of workers with management tasks. All firm level variables are averaged over the window of observations. All specifications include firm-level control variables and industry-region fixed effects. Panel C additionally includes period fixed effects. Standard errors are clustered at the industry-region level. *** p<0.01, ** p<0.05, * p<0.1

Table 2.9: Robustness: Outward FDI and Employment Volatility, Non-Manufacturing

	All Employment			Production Tasks Employment			Management Tasks Employment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	(Panel A) Alternative Employment Volatility Measure								
Korean MNE	0.0114	0.0112	-0.0274	-0.0227	-0.0250	-0.0777	-0.0124	-0.0125	-0.0640**
	(0.0138)	(0.0136)	(0.0243)	(0.0480)	(0.0484)	(0.0732)	(0.0220)	(0.0217)	(0.0258)
Korean MNE ×Cost-Saving		0.00540			0.236			0.00363	
		(0.0430)			(0.268)			(0.0908)	
Korean MNE ×Market-Access			0.0462**			0.0650			0.0614***
			(0.0223)			(0.0687)			(0.0233)
Observations	6,199	6,199	6,199	396	396	396	6,199	6,199	6,199
R-squared	0.089	0.089	0.091	0.227	0.229	0.229	0.111	0.111	0.111
	(Panel B) Balanced Sample								
Korean MNE	-0.0105	-0.0116	-0.0562*	-0.0590	-0.0371	-0.0874	0.00431	0.00367	-0.0233
	(0.0153)	(0.0162)	(0.0311)	(0.0654)	(0.0641)	(0.0686)	(0.0346)	(0.0349)	(0.0516)
Korean MNE ×Cost-Saving		0.0449			1.255***			0.0275	
		(0.102)			(0.0230)			(0.115)	
Korean MNE ×Market-Access			0.0547*			0.0384			0.0330
			(0.0317)			(0.0345)			(0.0409)
Observations	1,889	1,889	1,889	104	104	104	1,889	1,889	1,889
R-squared	0.165	0.165	0.168	0.246	0.302	0.246	0.174	0.174	0.175
	(Panel C) Six-years window								
Korean MNE	0.0102	0.0104	-0.00915	-0.0493	-0.0480	-0.0941	-0.0152	-0.0139	-0.0386
	(0.0122)	(0.0124)	(0.0230)	(0.0826)	(0.0823)	(0.160)	(0.0258)	(0.0253)	(0.0268)
Korean MNE ×Cost-Saving		-0.00664			0.570			-0.0473	
		(0.0438)			(0.379)			(0.0755)	
Korean MNE ×Market-Access			0.0232			0.0553			0.0280
			(0.0192)			(0.141)			(0.0281)
Observations	9,120	9,120	9,120	314	314	314	9,120	9,120	9,120
R-squared	0.078	0.078	0.078	0.269	0.279	0.270	0.073	0.073	0.073
	(Panel D) Investment Shares								
Korean MNE	0.0119	0.0110	-0.0164	0.0160	-0.0189	0.0533	-0.0139	-0.0189	-0.0439
	(0.0159)	(0.0157)	(0.0264)	(0.0557)	(0.0570)	(0.0752)	(0.0237)	(0.0242)	(0.0304)
Korean MNE × (% of Cost-Saving)		0.0274			1.463***			0.160	
		(0.0760)			(0.323)			(0.277)	
Korean MNE × (% of Market-Access)			0.0398			-0.0577			0.0422
			(0.0272)			(0.0895)			(0.0315)
Observations	6,199	6,199	6,199	241	241	241	6,199	6,199	6,199
R-squared	0.092	0.092	0.092	0.219	0.230	0.220	0.096	0.096	0.096
	(Panel E) Temporary Workers Included								
Korean MNE	0.0158	0.0165	-0.0317						
	(0.0156)	(0.0155)	(0.0294)						
Korean MNE ×Cost-Saving		-0.0190							
		(0.0457)							
Korean MNE ×Market-Access			0.0566**						
			(0.0278)						
Observations	6,199	6,199	6,199						
R-squared	0.122	0.122	0.123						

The dependent variable is the employment volatility constructed by the residual approach, except Panel A which used the alternative volatility measure. Column (1)-(3) include the results for employment volatility of all workers within a firm. Column (4)-(6) include the results for employment volatility of workers with production tasks. Column (7)-(9) include the results for employment volatility of workers with management tasks. All firm level variables are averaged over the window of observations. All specifications include firm-level control variables and industry-region fixed effects. Panel C additionally includes period fixed effects. Standard errors are clustered at the industry-region level. *** p<0.01, ** p<0.05, * p<0.1

Table 2.10: Robustness: Outward FDI and Employment Volatility - Mechanisms

	All Employment			Production Tasks Employment			Management Tasks Employment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(Panel A) All Industries									
Korean MNE	0.0151**	0.0111*	-0.000204	0.0431***	0.0357**	0.0170	-0.0120	-0.00457	-0.0314**
	(0.00647)	(0.00653)	(0.00952)	(0.0144)	(0.0138)	(0.0147)	(0.0123)	(0.0135)	(0.0155)
Korean MNE × Cost-Saving		0.0200***			0.0291**			-0.0370**	
		(0.00738)			(0.0137)			(0.0144)	
Korean MNE × Market-Access			0.0228**			0.0431***			0.0289*
			(0.00912)			(0.0140)			(0.0152)
Both Export & Import	-0.0225***	-0.0223***	-0.0239***	0.0188	0.0179	0.0157	0.00503	0.00476	0.00327
	(0.00694)	(0.00692)	(0.00692)	(0.0215)	(0.0216)	(0.0217)	(0.0171)	(0.0171)	(0.0173)
Export Only	-0.00355	-0.00360	-0.00381	0.0236	0.0225	0.0226	0.0315	0.0316	0.0312
	(0.0100)	(0.0100)	(0.00989)	(0.0295)	(0.0298)	(0.0296)	(0.0254)	(0.0254)	(0.0253)
Import Only	-0.0103	-0.0103	-0.0106	-0.00190	-0.00221	-0.00196	-0.0350	-0.0351	-0.0354
	(0.0113)	(0.0113)	(0.0114)	(0.0291)	(0.0291)	(0.0292)	(0.0242)	(0.0242)	(0.0242)
Export Intensity	0.000432	9.16e-06	-0.000625	-0.0132	-0.0131	-0.0150	-0.0531*	-0.0523*	-0.0544*
	(0.0125)	(0.0126)	(0.0126)	(0.0319)	(0.0319)	(0.0317)	(0.0302)	(0.0303)	(0.0305)
Import Intensity	-0.00882	-0.00854	-0.00746	-0.0371	-0.0363	-0.0351	-0.0151	-0.0156	-0.0134
	(0.0118)	(0.0119)	(0.0119)	(0.0273)	(0.0274)	(0.0273)	(0.0281)	(0.0280)	(0.0282)
Both Intra-firm Export & Import	0.00374	0.00172	-0.00112	0.0320*	0.0290*	0.0204	0.0843***	0.0880***	0.0781***
	(0.00724)	(0.00717)	(0.00650)	(0.0164)	(0.0169)	(0.0177)	(0.0138)	(0.0136)	(0.0145)
Intra-firm Export Only	0.00128	0.000493	-0.00414	0.0363*	0.0346*	0.0243	0.0465***	0.0480***	0.0397**
	(0.00737)	(0.00737)	(0.00699)	(0.0204)	(0.0205)	(0.0217)	(0.0158)	(0.0158)	(0.0164)
Intra-firm Import Only	-0.00352	-0.00472	-0.00717	0.00406	0.00220	-0.00598	0.0678***	0.0701***	0.0632**
	(0.0157)	(0.0157)	(0.0152)	(0.0269)	(0.0273)	(0.0271)	(0.0253)	(0.0253)	(0.0257)
Intra-firm Export Intensity	0.0585	0.0568	0.0635*	-0.0548	-0.0550	-0.0455	-0.0360	-0.0328	-0.0296
	(0.0360)	(0.0366)	(0.0364)	(0.0797)	(0.0785)	(0.0800)	(0.1000)	(0.101)	(0.100)
Intra-firm Import Intensity	-0.0510	-0.0510	-0.0440	0.210***	0.205***	0.226***	-0.138**	-0.138**	-0.129**
	(0.0367)	(0.0363)	(0.0361)	(0.0706)	(0.0708)	(0.0716)	(0.0553)	(0.0557)	(0.0547)
Observations	12,102	12,102	12,102	7,068	7,068	7,068	12,102	12,102	12,102
R-squared	0.117	0.118	0.118	0.153	0.153	0.154	0.121	0.121	0.121
(Panel B) Manufacturing Industries									
Korean MNE	0.0195***	0.0150***	0.00962*	0.0437***	0.0363**	0.0179	-0.00186	0.00907	-0.0183
	(0.00559)	(0.00563)	(0.00581)	(0.0147)	(0.0141)	(0.0147)	(0.0137)	(0.0152)	(0.0166)
Korean MNE × Cost-Saving		0.0170**			0.0280**			-0.0418***	
		(0.00736)			(0.0136)			(0.0153)	
Korean MNE × Market-Access			0.0163**			0.0428***			0.0273
			(0.00654)			(0.0140)			(0.0173)
Both Export & Import	-0.0135*	-0.0141*	-0.0147*	0.0137	0.0128	0.0107	0.00865	0.0101	0.00670
	(0.00796)	(0.00793)	(0.00798)	(0.0221)	(0.0222)	(0.0223)	(0.0217)	(0.0217)	(0.0220)
Export Only	0.00606	0.00526	0.00573	0.00952	0.00825	0.00853	0.00408	0.00606	0.00352
	(0.0123)	(0.0123)	(0.0123)	(0.0298)	(0.0301)	(0.0299)	(0.0317)	(0.0315)	(0.0317)
Import Only	-0.00433	-0.00459	-0.00441	-0.00385	-0.00422	-0.00396	-0.0291	-0.0285	-0.0293
	(0.0113)	(0.0113)	(0.0113)	(0.0300)	(0.0301)	(0.0301)	(0.0318)	(0.0318)	(0.0318)
Export Intensity	-0.0183	-0.0183	-0.0190*	-0.00835	-0.00827	-0.0102	-0.0516	-0.0517	-0.0528
	(0.0112)	(0.0114)	(0.0113)	(0.0319)	(0.0319)	(0.0317)	(0.0352)	(0.0353)	(0.0355)
Import Intensity	-0.00827	-0.00772	-0.00748	-0.0347	-0.0339	-0.0326	-0.000755	-0.00211	0.000572
	(0.0122)	(0.0122)	(0.0122)	(0.0275)	(0.0277)	(0.0275)	(0.0365)	(0.0365)	(0.0367)
Both Intra-firm Export & Import	0.00356	0.00181	-0.000815	0.0331**	0.0302*	0.0215	0.0811***	0.0853***	0.0737***
	(0.00519)	(0.00513)	(0.00558)	(0.0167)	(0.0172)	(0.0183)	(0.0151)	(0.0149)	(0.0158)
Intra-firm Export Only	0.00527	0.00428	0.000738	0.0272	0.0255	0.0152	0.0431**	0.0456**	0.0355*
	(0.00669)	(0.00669)	(0.00747)	(0.0191)	(0.0193)	(0.0206)	(0.0196)	(0.0197)	(0.0200)
Intra-firm Import Only	-0.00198	-0.00337	-0.00574	0.00915	0.00709	-0.000783	0.0299	0.0333	0.0236
	(0.0143)	(0.0142)	(0.0144)	(0.0283)	(0.0286)	(0.0285)	(0.0340)	(0.0340)	(0.0344)
Intra-firm Export Intensity	0.0391	0.0390	0.0426	-0.0799	-0.0797	-0.0704	-0.0978	-0.0977	-0.0918
	(0.0326)	(0.0332)	(0.0329)	(0.0826)	(0.0815)	(0.0831)	(0.111)	(0.112)	(0.111)
Intra-firm Import Intensity	0.0250	0.0216	0.0312	0.199**	0.193**	0.215***	-0.136*	-0.127	-0.125
	(0.0273)	(0.0275)	(0.0274)	(0.0767)	(0.0769)	(0.0776)	(0.0822)	(0.0829)	(0.0820)
Observations	6,906	6,906	6,906	6,832	6,832	6,832	6,906	6,906	6,906
R-squared	0.069	0.070	0.070	0.134	0.134	0.135	0.062	0.063	0.063
(Panel C) Non-Manufacturing Industries									
Korean MNE	0.00313	0.00335	-0.0324	-0.0189	-0.00516	-0.0470	-0.0344	-0.0324	-0.0679**
	(0.0166)	(0.0163)	(0.0314)	(0.0944)	(0.0964)	(0.154)	(0.0242)	(0.0242)	(0.0343)
Korean MNE × Cost-Saving		-0.00689			0.940***			-0.0611	
		(0.0533)			(0.207)			(0.0702)	
Korean MNE × Market-Access			0.0440			0.0405			0.0415
			(0.0283)			(0.129)			(0.0314)
Both Export & Import	-0.0294**	-0.0293**	-0.0317**	0.0616	0.0666	0.0599	0.000934	0.00104	-0.00131
	(0.0127)	(0.0127)	(0.0129)	(0.0988)	(0.0990)	(0.102)	(0.0253)	(0.0253)	(0.0256)
Export Only	-0.0132	-0.0133	-0.0138	0.534***	0.529***	0.533***	0.0615*	0.0614*	0.0610*
	(0.0163)	(0.0163)	(0.0159)	(0.194)	(0.193)	(0.195)	(0.0355)	(0.0355)	(0.0352)
Import Only	-0.0129	-0.0129	-0.0138	0.00527	0.0108	0.00700	-0.0408	-0.0408	-0.0417
	(0.0178)	(0.0178)	(0.0178)	(0.112)	(0.114)	(0.111)	(0.0344)	(0.0344)	(0.0344)
Export Intensity	0.0934*	0.0936*	0.0928*	-0.600**	-0.554*	-0.595**	-0.131*	-0.129*	-0.131*
	(0.0544)	(0.0555)	(0.0546)	(0.294)	(0.296)	(0.292)	(0.0719)	(0.0719)	(0.0719)
Import Intensity	-0.00748	-0.00755	-0.00482	-0.126	-0.145	-0.129	-0.0255	-0.0261	-0.0230
	(0.0215)	(0.0217)	(0.0219)	(0.180)	(0.180)	(0.178)	(0.0433)	(0.0432)	(0.0436)
Both Intra-firm Export & Import	-0.00252	-0.00250	-0.00703	-0.0567	-0.0642	-0.0671	0.0697*	0.0699*	0.0654
	(0.0228)	(0.0228)	(0.0205)	(0.121)	(0.124)	(0.105)	(0.0395)	(0.0391)	(0.0406)
Intra-firm Export Only	-0.00835	-0.00840	-0.0157	0.389*	0.328	0.378*	0.0419	0.0415	0.0350
	(0.0185)	(0.0186)	(0.0157)	(0.213)	(0.214)	(0.213)	(0.0264)	(0.0266)	(0.0275)
Intra-firm Import Only	0.000830	0.000836	-0.00202	-0.0736	-0.0745	-0.0829	0.102**	0.102**	0.0993**
	(0.0316)	(0.0316)	(0.0303)	(0.102)	(0.103)	(0.0934)	(0.0402)	(0.0400)	(0.0405)
Intra-firm Export Intensity	0.0907	0.0902	0.102	2.814**	2.764**	2.808**	0.473	0.469	0.483
	(0.0932)	(0.0937)	(0.0944)	(1.131)	(1.140)	(1.117)	(0.358)	(0.355)	(0.357)
Intra-firm Import Intensity	-0.0912*	-0.0913*	-0.0854*	0.427**	0.472**	0.443**	-0.147*	-0.147*	-0.141*
	(0.0537)	(0.0535)	(0.0512)	(0.205)	(0.225)	(0.185)	(0.0789)	(0.0785)	(0.0779)
Observations	5,196	5,196	5,196	236	236	236	5,196	5,196	5,196
R-squared	0.107	0.107	0.108	0.281	0.293	0.282	0.112	0.112	0.112

The dependent variable is the employment volatility constructed by the residual approach. Column (1)-(3) include the results for employment volatility of all workers within a firm. Column (4)-(6) include the results for employment volatility of workers with production tasks. Column (7)-(9) include the results for employment volatility of workers with management tasks. All firm level variables are averaged over the window of observations. All specifications include firm-level control variables and industry-region fixed effects.*** p<0.01, ** p<0.05, * p<0.1

Table 2.11: Probit Estimation of PSM

VARIABLES	(1) Treatment
Exporter	0.314***
	(0.0448)
Sales	0.102***
	(0.0322)
Labor Cost	0.0124
	(0.0391)
Profit	0.0827***
	(0.0257)
Labor Capital Ratio	-0.0602**
	(0.0240)
Conglomerate	0.0294
	(0.0982)
Constant	58.00**
	(28.77)
Industry Fixed Effects	Y
Year Trends	Y
Pseudo R-squares	0.06
Observations	17,732

The dependent variable is an indicator of Treatment. All covariates are lagged variables and their values are log-transformed. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.12: Balancedness: Before Matching & After Matching

	Before Matching			After Matching				
	Treated	Untreated	t-stat	Treated	Control	t-stat	% Bias	Variance Ratio
Exporter	0.59	0.327	13.02***	0.503	0.542	-0.91	-7.6	
Sales	4.16	3.437	14.16***	3.805	3.716	1.08	9.4	1.05
Labor Cost	2.252	1.954	8.58***	2.013	1.999	0.71	5.1	1.09
Ordinary Profit	1.56	0.911	13.37***	1.226	1.192	0.72	5.0	0.92
Labor Capital Ratio	0.716	1.144	-7.564***	0.804	0.839	-0.44	-3.7	0.87
Conglomarate	0.061	0.036	3.11***	0.029	0.026	0.23	2	
Observations	554	18735		270	638			

Table 2.13: Difference-in-Differences

	All Employment			Production Tasks Employment			Management Tasks Employment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sectors	All	Manufacturing	Non-Manufacturing	All	Manufacturing	Non-Manufacturing	All	Manufacturing	Non-Manufacturing
				(Panel A) All FDI					
DD Estimates(β_3)	0.0292**	0.0302**	0.0234	0.0192	0.0162		0.0446	-0.00631	0.168
	(0.0133)	(0.0151)	(0.0401)	(0.0370)	(0.0362)		(0.0495)	(0.0658)	(0.137)
Observations	1,816	1,432	384	1,278	1,257		1,816	1,432	384
R-squared	0.007	0.006	0.014	0.021	0.023		0.004	0.001	0.016
				(Panel B) Cost Saving FDI					
DD Estimates(β_3)	0.0271	0.0291	0.000499	0.0488	0.0522		0.109	0.0336	
	(0.0231)	(0.0260)	(0.0867)	(0.0573)	(0.0607)		(0.127)	(0.159)	
Observations	430	410	20	363	361		430	410	
R-squared	0.006	0.007	0.206	0.016	0.017		0.004	0.001	
				(Panel C) Market Access FDI					
DD Estimates(β_3)	0.0233*	0.0221*	0.0209	0.0369	0.0317		0.0220	-0.00852	0.0469
	(0.0132)	(0.0130)	(0.0420)	(0.0305)	(0.0281)		(0.0692)	(0.0811)	(0.218)
Observations	1,406	1,128	278	980	961		1,406	1,128	278
R-squared	0.006	0.004	0.026	0.017	0.019		0.003	0.000	0.019

The dependent variable is the employment volatility constructed by residual approach. Column (1)-(3) include the results for employment volatility of all workers within a firm. Column (4)-(6) include the results for employment volatility of workers with production tasks. Column (7)-(9) include the results for employment volatility of workers with management tasks. Standard errors are clustered at the industry level and they are bootstrapped based on 200 replications. *** p<0.01, ** p<0.05, * p<0.1

Table 2.14: Difference-in-Differences : Market Access by destination countries

	All Employment			Production Tasks Employment			Management Tasks Employment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sectors	All	Manufacturing	Non-Manufacturing	All	Manufacturing	Non-Manufacturing	All	Manufacturing	Non-Manufacturing
(Panel A) Market Access to Asian emerging countries									
DD Estimates(β_3)	0.0374	0.0274	0.0967	0.0798**	0.0838**		0.0478	-0.0283	0.441
	(0.0234)	(0.0249)	(0.068)	(0.0393)	(0.0369)		(0.107)	(0.113)	(0.303)
Observations	902	798	104	694	687		902	798	104
R-squared	0.008	0.004	0.073	0.015	0.016		0.008	0.005	0.097
(Panel B) Market Access to Developed countries									
DD Estimates(β_3)	-0.00505	0.00211	-0.0207	-0.0279	-0.0585		-0.0865	-0.0637	-0.211
	(0.0268)	(0.0386)	(0.0358)	(0.0833)	(0.0912)		(0.105)	(0.111)	(0.230)
Observations	560	394	166	314	303		560	394	166
R-squared	0.006	0.004	0.013	0.041	0.054		0.002	0.001	0.006

The dependent variable is the employment volatility constructed by residual approach. Column (1)-(3) include the results for employment volatility of all workers within a firm. Column (4)-(6) include the results for employment volatility of workers with production tasks. Column (7)-(9) include the results for employment volatility of workers with management tasks. Standard errors are clustered at the industry level and they are bootstrapped based on 200 replications. *** p<0.01, ** p<0.05, * p<0.1

CHAPTER 3

TRADE AND MARGINS OF INNOVATIVE TECHNOLOGIES: EVIDENCE FROM PATENT-FIRM MATCHED DATA

[1]

3.1 Introduction

How market expansion and subsequent tougher competition affect firms' innovative activities is a longstanding research question in several fields of economics.[2] International trade has not been an exception. Since the pioneering work of Autor et al. (2013), the recent rise of China in the global economy has motivated trade economists to further study the impact of the China shock on many sides of the economy, including technology innovations. In the literature on trade and innovations, most previous works have paid attention to the changes in technology scale measured by the number of patents. This can be understood as adjustments of "intensive margins of technologies", raising or reducing firms' amounts of innovative technologies. However, when firms make decisions regarding R&D activities, they should decide not only the amounts of their research efforts but also the areas of technologies. The latter, technology scope adjustment, can be understood as "extensive margins of technologies". From market expansion and tougher competition following trade liberalization, some firms may shrink their technology diversity and dedicate most of their R&D efforts to initially strong fields, while others expand their technology frontiers to their new or less frequently used

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[2]Regarding market expansion and innovations, Acemoglu and Linn (2004), for example, found that the rise of the potential market size from demographic changes in the U.S. heavily encouraged corporations in pharmaceutical industries to produce new nongeneric drugs and molecular entities through innovation. Aghion et al. (2005) is the classic work on market competition and innovation.

fields. Despite its importance, the extensive margin of technologies has attracted little research attention.

The extensive margin of innovative technologies can play key roles in shaping economic performance through at least three mechanisms. First, making new products requires technologies in new fields. If market expansions induce firms to expand their range of product portfolios, it will also cause firms to expand their technology fields. Figure 3.1 describes the distribution of technology diversity and U.S. import product diversity by country-year observations.[3] At the country-year level, Figure 3.1 shows a positive relationship between the diversity of innovative technologies and the diversity of products that are exported to the U.S., which supports the first mechanism. Second, more diverse technologies can be used to enhance the quality of products. Access to technologies in new areas can raise the quality of products that the firm produces. To see the relationship between the quality of products that are internationally traded and the diversity of innovative technologies, we estimated a simple reduced-form equation between the unit price of imported products in the U.S. and the technology diversity of each country at the country-year level. Table 3.1 shows that the country-year level diversity of technologies is positively associated with the unit price of products that the country exports to the U.S. controlling for several high-dimensional unit, product, product-unit, year, and country fixed effects. We added the number of patents as an additional control variable to implement a 'horse-race' regression between technology diversity and technology quantity, and technology diversity still explains many U.S. import price variations even after controlling for patent numbers. This highlights the importance of technology diversity in product quality. Last, more diverse technologies can induce firms to produce products in a more efficient way, which lowers overall production costs. All this suggestive evidence motivates our research to disentangle the margins of innovative technologies.

The goal of this paper is to study the impact of China's surge in the global economy in the early

[3]We used U.S. HS-level import product data provided by Peter Schott's U.S. trade database (https://sompks4.github.io/sub_data.html) to construct country-year level U.S. import product diversity. For the country-year level technology diversity measure, we used the USPTO granted patent data.

2000s on both intensive and extensive margins of firm-level innovative technologies. To achieve this goal, we focus mainly on the case of Taiwan, a major trade partner of China. From its unique experience in terms of exports, Taiwan provides us with a suitable case for our research. The share of Taiwanese manufacturing exports to China has enormously increased since the early 2000s. Figure 3.2 describes the trends of Taiwanese manufacturing exports to China and the world. Since China's WTO entry in December 2001, the share of Taiwanese manufacturing sectoral exports to China has risen remarkably from 3-5% in the late 1990s to 20%-25% in the late 2010s.

A set of stylized facts on Taiwanese firms' patenting behaviors in the U.S. motivate our research. From data on patents granted by the U.S. Patent and Trademark Office (USPTO), we observe that Taiwanese firms' patenting behaviors since the early 2000s have been remarkably distinguishable from those of other major countries. Table 3.2 and Figure 3.3 show the patent quantity growth in the early 2000s. Regarding the growth of patent amounts, Taiwan and Korea, two major East Asian countries that are strongly export-oriented, have a much higher growth rate of patent amounts than other competing major countries. Tables 3.3 and 3.4 show another stylized fact of Taiwanese firms' patenting behavior on technology distribution. We observe sizable changes in technology distribution from Taiwanese originated patents after China's WTO entry. On the one hand, the share for the top technology class (H01: mostly semiconductor-related technology) has declined from 49% to 29%. On the other hand, the shares for a few other technology classes, such as G06 (computing 8.9% $\rightarrow$ 13%) and G02 (Optics 2.4% $\rightarrow$ 6.5%), have risen. During the post-WTO period, the technology distribution of patents of Taiwanese origin became more flattened and less concentrated on a few top technologies. These two stylized facts of the USPTO patents filed by Taiwanese firms motivate our research questions.

The paper consists of two major parts: a theoretical model and empirical analysis. Our theoretical model combines several elements. Consumers have preferences for the quantity and quality of products, which are presented as a quadratic functional form of utility. Firms are heterogeneous in productivity, and they should use product-specific technologies to produce products. The quality of products manufactured by a firm is determined by the firm's overall range of technologies, which reflect the technology spillover channel between products. In this context, our model provides a few predictions. Highly productive firms are more likely to expand their technologies to new fields, as they can earn higher profits from more products, while less productive firms are not. As far as there exists a group of highly productive firms that expand their technology frontiers, there must be another group of less productive firms that shrink their technology scopes. Using detailed USPTO patent data and Taiwanese firm-level trade and balance sheet data, we build not only the quantity and quality of innovative technologies but also the scopes and distributions of technologies within a firm and empirically confirm our theoretical predictions.

This paper is closely related to the growing literature on trade and innovations, most of which has used patent data to measure firms' innovative outcomes. Recent papers by Bloom et al. (2016), Autor et al. (2019), and Aghion et al. (2018) are the most influential papers in the literature.[4] Bloom et al. (2016) and Autor et al. (2019) studied the impact of stronger import competition due to the surge of China on firm-level innovations. However, their main results were mixed, and the question remains open. Bloom et al. (2016) focused on the European quota reduction event of clothing and textile industries after China's WTO entry. By utilizing European firm-level data matched with patent data from the European Patent Office, they found that a higher level of import competition from quota removal had led surviving firms within the industry to increase their R&D activities, encouraging patent filing and the adoption of new IT technologies. On the same research question, however, Autor et al. (2019) found the opposite results of Bloom et al. (2016). Autor et al. (2019) found that a stronger import shock from China discouraged innovative activities and patenting behaviors among U.S. firms. Hence, Bloom et al. (2016) and Autor et al. (2019) sparked an ongoing debate, which inspired more future work to be done. Aghion et al. (2018) is the most well-known work on the causal effect of export demand shock. Using product-level export information for French firms, Aghion et al. (2018) constructed a firm-level export demand shock and found its positive impact on firms' innovation, especially since the effect is larger for initially more productive firms. In addition to the aforementioned three papers, there are a few more recent papers that are worth

[4]For a very recent literature review, see Shu and Steinwender (2019).

mentioning here. Regarding import competition shocks, for example, Bombardini et al. (2018) studied the Chinese case by utilizing greater import competition from China's WTO accession. In Bombardini et al. (2018), tougher import competition from import tariff cuts stimulates Chinese firms to conduct more innovation, but the impact is meaningful only for initially productive firms. Regarding export demand shock, Coelli et al. (2020) utilized sizable tariff cuts from the worldwide trade liberalization during the 1990s (Uruguay rounds and subsequent start of the WTO regime), and Coelli (2018) used the Chinese firms' removal of trade policy uncertainty from U.S. conferral of Permanent Normal Trade Relations (PNTR) in late 2001.[5] Our research belongs to the broad literature on trade and innovation, but our work contributes to the literature by examining the case of a new country and the new margin of innovation that no other papers have studied.[6]

Our study can also be better understood through the lens of another research line in international trade, the role of multi-product firms, even though we do not focus on products. A significant portion of international trade is led by a small number of firms producing multiple products.[7] Hence, several recent studies have addressed the issue of how firms adjust their scales and scopes of exporting products in response to a trade shock. Seminal theory works in the literature have employed different types of models, such as monopolistic competition with constant elasticity of substitution (CES) preferences (Bernard et al. (2010, 2011)), monopolistic competition with quadratic preferences (Mayer et al. (2014)), and oligopoly models with quadratic preferences (Eckel and Neary (2010)). Despite different modeling techniques, these works have proposed similar results about changes in product scope: trade liberalization induces exporters to drop their less efficient products, as those products will no longer become profitable to serve. Nevertheless, the driving mechanisms

[5]Until the U.S. granted PNTR status to China in late 2001, China's status of Normal Trade Relations (NTR) import tariff rates was renewed from the House of U.S. Congress every year, which increased uncertainties from a sudden rise in future import rates. Regarding the effect of removing such sudden uncertainties of tariff spikes, Pierce and Schott (2016, 2018) studied the effect on U.S. manufacturing employment and U.S. firms' investment. Coelli (2018) could be understood as a part of this new research strand.

[6]For more relevant recent empirical works on trade and innovation, see Gong and Xu (2017), Hombert and Matray (2018), Lim et al. (2018), Liu and Ma (2016), and Zhang (2018).

[7]See Bernard et al. (2007) and Bernard et al. (2010).

of product-range shrinkage are different between models. In the monopolistic competition with CES preferences-based model (Bernard et al. (2011)), all firms should drop their least profitable products as prices should decrease from the competition, but markups are fixed, which is similar to the selection idea of Melitz (2003). Unlike this model, in Mayer et al. (2014), markups are variable, and all firms have products with different competencies. Tougher competition from trade liberalization lowers the markups of all products and induces firms to skew their sales toward the core product. Eckel and Neary (2010) shared a similar idea of a variable markup channel with Mayer et al. (2014). However, they found another insightful result from the strategic behaviors of oligopolists. In addition to stronger industry-wide competition resulting from trade liberalization, an increase in a firm's total output may hurt the output of each product within the firm, which is called the 'cannibalization effect'.[8] Only a few theory papers have addressed conditions for the product scope expansion of heterogeneous firms, and Qiu and Zhou (2013) is one of them.

Notwithstanding similar results from several theoretical works, empirical evidence is mixed. Several previous studies have found that export product scope expansion occurs due to trade liberalization for a group of firms (Baldwin and Gu, 2009; Berthou and Fontagné, 2013; Eckel et al., 2015; Arkolakis et al., 2016; Lopresti, 2016; Macedoni, 2019). Baldwin and Gu (2009) find that tariff reduction mandated by the Canada-U.S. Free Trade Agreement has a significantly negative effect on firms' product scope, but the decline is smaller for large exporting firms. They also find that there is an ambiguous impact on the product scope of existing exporters. Berthou and Fontagné (2013) find that the most productive French firms expand their export product range to the Eurozone, while less productive firms export a smaller product scope. Eckel et al. (2015) show that firms in differentiated-good sectors invest to improve quality-based competence.

Technology is a key part of production, and innovative technologies should play key roles in product diversification and/or quality improvement. We build a simple theory model in the spirit

[8]The channel of 'cannibalization' between products has been widely modeled in previous studies that have frameworks similar to ours (e.g. Eckel and Neary, 2010; Eckel et al., 2015; Flach and Irlacher, 2018). However, it is not reasonable to model cannibalization between technologies, as different sets of technologies should play different roles as an input of production. Here, we do not introduce the mechanism of 'cannibalization between technologies' in our model.

of Qiu and Zhou (2013) and address conditions for the product scope expansion of heterogeneous firms. Our research contributes to the literature by studying the scope adjustments of innovative technologies, which has not been studied previously.

The remainder of the article is organized as follows. Section 3.2 develops our theoretical framework. Section 3.3 describes the data we use for empirical analysis. Section 3.4 presents our empirical strategy and results. Section 3.5 concludes.

3.2 Simple Theory Model

This section introduces an international trade model of heterogeneous firms with multiple products. The model is based primarily on the framework of Qiu and Zhou (2013) but is differentiated from the benchmark model by introducing a product quality upgrading channel through technology adoption. In our model, the production of each product requires different technologies, so each product has its corresponding technology as an input. The quality of each firm's product is determined by the firm's overall range of technology: a wider technology scope implies a higher quality of all within-firm products. This feature reflects the knowledge spillover linkage between products within a firm. Although one technology is directly used as a production input for a single product, tacit-knowledge, know-how, and skills from technology development can be applied to other products for quality improvement.[9]

The model herein can be understood in the international trade literature of heterogeneous firms with quadratic preference and linear demand systems (see Melitz and Ottaviano (2008) and Antoniades (2015) for the single product case; Eckel and Neary (2010), Mayer et al. (2014), and Qiu and Zhou (2013) for the multiproduct case). Unlike the widely used Melitz-type model with CES preference (see Bernard et al. (2011) for the multiproduct case), a linear demand system has the advantage of allowing markups to vary by firm.

[9] Regarding modeling technology spillover between products in the international trade literature, see Flach and Irlacher (2018), for example.

3.2.1 Environment

3.2.1.1 Preference

For the demand side, there are L identical consumers in the economy. There exists a numeraire and continuum of differentiated products for consumption, and the representative consumer cares for both the quantity and quality of differentiated products for her preference. Following Antoniades (2015), the consumer's quadratic utility function can be expressed as follows:

$$U = q_0^c + \alpha \int (q_i^c + z_i) di - \frac{1}{2}\beta\{\int (q_i^c - z_i) di\}^2 - \frac{1}{2}\gamma \int (q_i^c - z_i)^2 di \tag{3.1}$$

where q_0^c and q_i^c are the quantity of individual c's consumption of the numeraire and product i, respectively, and z_i is the quality of product i. Therefore, the utility function captures the consumer's preference for both the quantity and quality of product i. All preference parameters α, β, and γ are nonnegative. α and β capture the degree of substitution between each variety and the numeraire. γ is the parameter of product differentiation.[10] p_i is the market price of product i, and we define $P \equiv \int p_i di$. Additionally, the number of all products is defined as $M \equiv \int di$. The representative consumer's utility maximization problem can be written as $\max_{q_i^c} U$ s.t. $q_0^c + \int p_i q_i^c di = I^c$, where I^c is the consumer's total income.

By aggregating the first-order condition of the representative consumer's utility maximization problem, we can derive the following simple linear demand formula for product i [11]

$$p_i = A + \gamma z_i - \frac{\gamma}{L} q_i \tag{3.2}$$

where $q_i \equiv L q_i^c$ is the economy-wide consumption of product i. $A \equiv \frac{\alpha\gamma + \beta P}{\beta M + \gamma}$ is the industry-wide demand shifter, which an individual consumer accepts as given. Note that a consumer is willing to pay a higher price for a high-quality good.

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[10] If $\gamma = 0$, all products are homogeneous, and the consumer cares only about his aggregate consumption.

[11] See C.0.1 for the detailed steps for deriving demand equation (3.2).

3.2.1.2 Production

Labor is the only factor of production that is provided by L consumers. Prior to market entrance, every firm should pay the fixed entrance cost f. After the entrance, a firm should draw its productivity x from the distribution $G(x) \in [0, \infty]$. A smaller x means higher productivity with a lower unit cost of production. Therefore, $x = 0$ is the most productive firm in the market.

After drawing its productivity, a firm can produce the range of products, $v \in [0, \infty)$. Following several previous studies on multiple products (Eckel and Neary (2010), Mayer et al. (2014), Qiu and Zhou (2013)), we call $v = 0$ the "core product," the product that a firm can most efficiently produce. For the unit cost of making product v for a firm with productivity x, $c(x, v)$, we set the following reasonable assumptions. The unit cost rises as a firm becomes less productive or produces a product that is far from its core product, $v = 0$.

$$\frac{\partial c(x,v)}{\partial x} > 0 \ , \ \ \frac{\partial c(x,v)}{\partial v} > 0 \ , \ \ c(x,0) = x$$

For the production of a product v, a firm should adopt a product-specific technology corresponding to v, and adoption requires fixed costs, $h(v)$. We assume $h'(v) > 0$, so a firm should pay increasing technology adoption costs as it produces products that are far from its core product, $v = 0$.

Hence, the profit from producing product v (gross of its technology adoption costs) for a firm with productivity x can be expressed as

$$\pi(x,v) = \underbrace{\{p(x,v) - c(x,v)\}}_{\text{mark-up}} q(x,v) = \{(A + \gamma z(x,v) - \frac{\gamma}{L} q(x,v)) - c(x,v)\} q(x,v) \tag{3.3}$$

and the profit maximization of a firm with productivity x would be

$$\begin{aligned} \max_{q,\omega} \Pi(x) &= \int_0^\omega \pi(x,v)dv - \int_0^\omega h(v)dv \\ &= \int_0^\omega [\{(A + \gamma z(x,v) - \frac{\gamma}{L} q(x,v)) - c(x,v)\} q(x,v)]dv - \int_0^\omega h(v)dv. \end{aligned} \tag{3.4}$$

For a given product v, the optimal price, quantity, markup, and profit (gross technology adoption cost) of a firm with productivity x can be summarized as follows:

$$q^*(x,v) = \frac{L}{2\gamma}(A + \gamma z(x,v) - c(x,v)) \tag{3.5a}$$

$$p^*(x,v) = \frac{1}{2}(A + \gamma z(x,v) + c(x,v)) \tag{3.5b}$$

$$p^*(x,v) - c(x,v) = \frac{1}{2}(A + \gamma z(x,v) - c(x,v)) \tag{3.5c}$$

$$\pi^*(x,v) = \frac{L}{4\gamma}(A + \gamma z(x,v) - c(x,v))^2. \tag{3.5d}$$

From the profit maximization problem (3.4), a firm with productivity x makes its optimal decisions for two variables: the optimal product scope $v^*(x)$ and the quantity of production for each product, $q^*(x,v)$. Once a firm with productivity x decides its optimal product (and technology) scope $v^*(x)$, the quality of products is $z(v^*(x))$, which is a function of its technology frontier, $v^*(x)$. The slope of the quality function is positive ($\frac{\partial z(\cdot)}{\partial v^*} > 0$), so the overall quality of a firm's products should rise as it produces more products with diverse technologies.

At the product frontier of a firm with productivity x, $v^*(x)$, the firm should earn positive profit from $v^*(x)$, which exactly covers technology adoption costs for its production, $h(v^*(x))$. Therefore, the following condition should hold at $v^*(x)$. This is the zero profit condition (ZPC) within a firm with productivity x, and Figure C.1 graphically describes this condition.

$$\frac{L\{A + \gamma z(v^*(x)) - c(x, v^*(x))\}^2}{4\gamma} = h(v^*(x)) \tag{3.6}$$

Our first proposition deals with the comparative statics of productivity and the optimal technology scope. By totally differentiating (3.6) with respect to x, we can derive the following proposition.[12]

Proposition 1 (Productivity and technology scope)

Under the condition $\gamma \frac{\partial z(x,v^*(x))}{\partial v^*} < \frac{\partial c(x,v^*)}{\partial v}$ is being satisfied, then

1. $\frac{\partial v^*(x)}{\partial x} < 0$

[12] For proofs of all propositions in the paper, see C.0.2.

2. $\frac{dc(x,v^*(x))}{dx} = \frac{\partial c(x,v^*(x))}{\partial x} + \frac{\partial c(x,v^*(x))}{\partial v}\frac{\partial v^*(x)}{\partial x} > 0$

As far as the marginal benefit from technology expansion through quality upgrading is not sufficient to cover a fraction of the unit cost increase, Proposition 1.1 implies that more productive firms will produce more comprehensive ranges of products with more diverse technologies, while less productive firms will work in the opposite direction. The assumption of Proposition 1, $\gamma\frac{\partial z(x,v^*(x))}{\partial v^*} < \frac{\partial c(x,v^*)}{\partial v}$, implies a downward-sloping profit function in v. Hereafter, we accept the assumption as given.[13]

Proposition 1.2 suggests that more productive firms (with lower x) should produce the marginal product ($v^*(x)$) more efficiently than less productive firms (with higher x). This result comes from the condition of increasing technology adoption costs, $h(\cdot)' > 0$. As $h(\cdot)$ is increasing in v, more productive firms with a broader scope of products can afford higher technology adoption costs at the frontier.

3.2.1.3 Equilibrium

Here, we discuss the least productive firm in the market. From Proposition 1.1, the least productive firm with productivity x_n should produce only its core product with no positive net profit (i.e., $v^*(x_n) = 0$). Accordingly, for the firm with productivity x_n, the following zero profit condition should hold.[14]

$$\frac{L\{A + \gamma z(0) - c(x_n, 0)\}^2}{4\gamma} = h(0) \tag{3.7}$$

Additionally, from Proposition 1.2 and our assumptions on the unit cost function, $c(x, v) < c(x, v^*(x)) < c(x_n, v^*(x_n)) = x_n$ holds for all $x < x_n$ and $v < v^*(x)$ for a given x. That is, x_n is not only the lowest productivity but also the highest unit cost of production in the market.

After each firm makes its optimal decision on the production quantity and scope, the aggregate profit of a firm is written as follows:

[13] Without the assumption, our comparative statics results of Proposition 1 become ambiguous.

[14] As $c(x_n, 0) = x_n$, $x_n = A + \gamma z(0) - \sqrt{\frac{4\gamma h(0)}{L}}$

$$\Pi(x) \equiv \int_0^{v^*(x)} \pi(x, v)dv - \int_0^{v^*(x)} h(v)dv. \tag{3.8}$$

Anticipating industry-wide demand shifter A, the expected profit of a firm before market entrance is

$$\Pi^e(A) \equiv \int_0^{x_n} \Pi(x)dG(x) \tag{3.9}$$

As mentioned in the previous section, any arbitrary firm can freely enter the market after paying the fixed entry cost, f. Firms will keep entering the market until their expected profit upon the entrance becomes equal to the entrance cost, which establishes the following free entry condition (FE).[15]

$$\Pi^e(A) = f \tag{3.10}$$

3.2.2 Trade Liberalization

We now discuss the role of trade liberalization in our model. Our model assumes L identical consumers, which can be viewed as L countries with a population of unity. Following previous studies, we define trade liberalization as an increase in L, which can be understood as access to more globally integrated markets. The second proposition below describes the impact of trade liberalization on the industry-wide demand curve and the entry/exit decision of the least productive firm.

Proposition 2

1. $\frac{dA}{dL} < 0$
2. $\forall x \leq x_n$, $\exists \tilde{c}(x)$ *such that* $c(x, v) < \tilde{c}(x) \rightleftharpoons \frac{\partial \pi^*(x,v)}{\partial L} > 0$
3. Trade liberalization $(dL > 0) \rightarrow \frac{\partial \tilde{c}(x)}{\partial x} < 0$

15 $\frac{d\Pi(x)}{dx} < 0$, $\frac{d\Pi(x)}{dA} > 0$, $\frac{d\Pi^e(A)}{dA} > 0$, $\frac{d\Pi^e(A)}{dL} > 0$

4. *If* $\tilde{c}(x_n) < x_n \rightarrow \frac{dx_n}{dL} < 0$

Trade liberalization will raise the expected profit of firms, which induces more firms to enter the market. To meet the free entry condition (3.10), the industry-wide demand shifter A should decrease, which also lowers each firm's markup (Proposition 2.1). Each firm has its own cutoff level of the unit cost. From trade liberalization, a firm can earn more profits from products with costs below the cutoff but earn fewer profits from products with costs above the cutoff (Proposition 2.2). As we add the quality of products to the model, which is endogenously determined by a firm's choice, the cost cutoff varies with firm productivity, which is different from Qiu and Zhou (2013). Trade liberalization will raise the cost cutoff for firms with high productivity, which allows additional positive profits from more products (Proposition 2.3). As long as the least productive firm's cost cutoff is smaller than the firm's unit cost ($c(x_n, v^*(x_n)) = x_n$), the least productive firm with productivity x_n should exit the market due to trade liberalization, and the remaining marginal firm's unit cost becomes lower (Proposition 2.4)

Proposition 2 indicates that every firm has its range of products from which it can earn higher profits. For the rest of the products, firms should bear a decrease in profits. More productive firms have a broader set of products providing higher profits. Then, how do firms adjust their product and technology scope following trade liberalization? The next proposition addresses this question.

Proposition 3

1. $c(x, v^*(x)) \lesseqgtr \tilde{c}(x) \rightleftharpoons \frac{dv^*(x)}{dL} \gtreqless 0$

2. If $c(0, v^*(0)) < \tilde{c}(0)$, then $\exists \bar{x} \in (0, x_n]$ such that $c(x, v^*(x)) > \tilde{c}(x)$ for $x > \bar{x}$.

Proposition 3 provides our main results for a firm's technology and product scope adjustments. Trade liberalization will make the firm expand its technology scope if the unit cost of its least productive product ($c(x, v^*(x))$) is smaller than its cost cutoff $\tilde{c}(x)$. For firms with a greater unit cost of the least productive product than the cost cutoff, trade liberalization should induce them to shrink their scope of technologies (Proposition 3.1). Additionally, if the most productive firm expands the scope, then there must exist a group of firms (which are less productive) shrinking their scope of technologies. It is impossible for all firms to expand the scope simultaneously (Proposition 3.2). Figure C.2 illustrates the range of firms that expand and shrink their technology scopes.

To summarize, our model yields predictions on trade-induced adjustments of technology scope. Following trade liberalization, more productive firms will have more sets of products from which they earn higher profits. If trade liberalization raises the profits of all products within a firm (including the marginal product), the firm would surely expand its product scope by adopting new technologies. As far as the most productive firm expands the technology frontier, there must be other firms with low productivity that shrink the technology frontier. Our model predicts that trade liberalization and subsequent market expansion have heterogeneous effects on the technology scope depending on the initial productivity of firms.

3.3 Data

Armed with testable predictions from the theory model, we now move on to the empirical analysis. We employed three different sets of data: U.S. patent bibliography data, Taiwanese firm-level data, and bilateral trade data. This section briefly describes our dataset.

3.3.1 U.S. Patent Data

To measure firm-level innovation, we used bibliography data on patents granted by the USPTO, which cover all U.S. published patents. Patent bibliography data have fruitful detailed information about patents, which can be used as a proxy for the patent filing firms' R&D outcomes. Therefore, patent data have been extensively used in empirical studies on innovation.

Using U.S. patent data has a few additional advantages over using Taiwanese patent data. First, U.S. patent bibliography data have citation information, which can be used as a measure of patent quality. Moreover, for Taiwanese firms, patenting in the U.S. requires more cost and efforts than patenting only in Taiwan. Thus, U.S. patents will be a better measure of valuable innovation than

Taiwanese patents, as U.S. patents should be high-end enough to cover additional costs. Finally, patenting in the U.S. is a cross-border activity for Taiwanese firms. Hence, Taiwanese firms' U.S. patents will contain more export-oriented intellectual property (to be lawfully protected in the U.S., another major trade partner of Taiwan) than only domestically filed patents.

For the period between 2002 and 2014, we used raw data from the USPTO bulk data service[16]. The raw dataset is a set of stacked .xml files, so we cannot directly use the data for our research without data handling. We used Python3 to load, cut, and scrap relevant information from the raw data.[17] For data between 1998 and 2001, we used the NBER patent database constructed by Hall et al. (2001).[18] We built several variables for technology innovation margins from the patent data.

3.3.2 Other Data

The firm-level data are retrieved from the database of the Taiwan Economic Journal (TEJ). The TEJ dataset covers Taiwanese firms that are listed on the Taiwan Stock Exchange. Our firm-level dataset includes an overview and detailed financial information from balance sheet data. For product- and industry-level trade variables, we used the UN Comtrade database, which provides product information of bilateral trade between countries at the HS 6-digit level at most.

3.3.3 Data Construction

Our empirical analysis requires extensive data cleaning to match the different datasets. The hardest part is how to match assignee names in USPTO patent data to firm names in firm-level data with few errors. There are several issues that make matching firm names between datasets difficult. First, there are different styles in the use of postfix and punctuation: e.g., "Co. Ltd", "Company Limited", and "Incorporated". Second, typos and abbreviations can also cause serious problems in linking data. Third, renamed firms may be underrepresented compared with nonrenamed firms

[16] https://bulkdata.uspto.gov/

[17] More specifically, the 'beautifulsoup' package was used to scrap relevant information from the raw data.

[18] https://sites.google.com/site/patentdataproject/Home/downloads

unless their old names are matched with their current names. Here, we describe our data matching process. To minimize the first expression style issue, we dropped all unnecessary postfix and punctuation marks and standardized firm names from patent- and firm-level data. Next, to handle the issue of typos and abbreviations, we borrowed cleaned assignee names from PatentsView[19], a research purpose ready-made data supported by the USPTO. Disambiguation algorithms used in PatentsView data are based on machine-learning techniques, and they provide powerful tools for identifying correct names of patent assignees. However, the algorithm is, of course, not perfect, and we still observed evidence of incorrect disambiguation for a nonnegligible number of firms. The power of disambiguation becomes weaker for small firms, as their number of observations is too small to guarantee successful cleaning. Therefore, when a standardized name from the first step and a disambiguated name from PatentsView data are not the same, we manually check the case and finalize the name of the firm.[20] For renamed firms, we additionally tracked the history of name changes and matched old names to the current names.[21]

Between 1995 and 2018, Taiwanese applicants filed 156,935 patents with the USPTO, 146,835 of which had assignee information in their bibliography records. We dropped 17,047 patents filed by non-corporate assignees (e.g., colleges, research institutes, governments, and hospitals). Among the 129,788 patents filed by Taiwanese corporations, we successfully matched 108,156 patents (83%) to firm information in TEJ data. Hence, the data used in this study represent the majority of patents filed by Taiwanese corporations.[22] We grouped firms by exporter status and patent filer status and report descriptive statistics of a few major variables in Table 3.6. We can confirm from Table 3.6 that firms that both export and file patents hire more employees, earn higher sales, spend more on R&D activities and are less financially constrained than other firms. Among exporters, patent-filing firms are more export oriented than non-patent-filing firms.

[19] http://www.patentsview.org/download/

[20] See Table 3.5 for a representative example of the firm name cleaning process. See table 3.7 for the number of patents and assignees by matching procedures.

[21] TEJ data include supplemental information on naming history up to last three old names.

[22] In the TEJ dataset, while the number of firms varies by year, the maximum number of annual observations is 2,750. We successfully matched 1,127 firms to the U.S. patent data.

3.3.4 Variable Descriptions

We built several variables from our patent data to measure the diverse features of a firm's technology innovation. We measured the intensive margins of firm-level innovative technologies. The raw number of patent counts is the first crude measure of intensive margins. Although there have been several arguments against using the patent count as an output indicator of innovation, the patent count is still a good indicator of inventive output. It has been pointed out in the literature on patent use that the value of patents may not be the same across patents. Some patents may be more valuable than others. To address this issue, following the standard method of previous empirical studies, we built a citation-based measure of weighted patent counts as a proxy for patent value. Our citation-based measure is the number of citations quoted by future patents within fixed periods.[23] Additionally, we employed the number of self-citations within fixed periods as a measure of technology accumulation within a firm.[24] For citation variables, we count the number of forward citations for two years after the patent is granted.

We also measured the extensive margins of innovative technologies. First, we built a dummy variable that takes a value of 1 if a firm filed at least one patent that belongs to a new technology field in which they had never filed a patent. Second, we used the number of technology fields that a firm applied for its patents. We counted both the number of technology fields based on each year and the cumulative number of technology fields from previous years. Third, we used two statistical variables to measure a firm's technology distribution. Let s_{ikt} denote the share of patent technology class k[25] for a firm i at year t.[26] The first variable is the Herfindahl index, which is defined as

[23] Although the usefulness of forward citations as a measure of patent value has been questioned and criticized, recent works of Kogan et al. (2017) and Moser et al. (2018) still confirmed the usefulness of citation-based measures.

[24] On the relationship between patent value and self-citation measure, see Hall et al. (2005).

[25] Technology class (k) corresponds to the 3-digit-level CPC classification system of patents in our paper.

[26] The time notation t corresponds to the year of patent application by a firm i. Firms in foreign countries have two options for applying for patents in the U.S.: a direct application and an international application. In the first option, the firm submits an application to the USPTO directly. When pursuing an international application, the firm files a domestic application first and then starts the USPTO application through the patent office in the host country. For the second option of the

$\sum_k s_{ikt}^2$. The index will decrease as the firm owns technologies in more diverse fields. The second variable is the entropy index, which is defined as $\sum_k s_{ikt} \log(s_{ikt})$. Entropy is the measure of distribution skewness and decreases as the technology distribution becomes less skewed toward the tail. Relative to the Herfindahl index, which measures mere technology diversity, entropy is more closely associated with access to new or less frequently used technology fields, which lowers the skewness of the technology distribution.

To summarize, our dependent variables are (1) the raw number of patents, (2) the number of citations within a limited term, (3) the number of self-citations within a limited term, (4) R&D expenditure, (5) an indicator for filing patents in new technology fields, (6) the number of technology fields in which a firm filed a patent, (7) the Herfindahl index and (8) the entropy index. Table 3.8 summarizes the proxies for technology innovation.

We also need an export exposure variable at the firm level. We used the industry-wide export share of China relative to the world, weighted by a firm's initial share of exports in total sales, i.e., $\text{Export\_Exposure}_{ist0} \equiv (\frac{\text{Export}}{\text{Sales}})_{ist0} \times (\frac{\text{Export}^{TWE \to CHN}}{\text{Export}^{TWE \to WLD}})_{st0}$. By multiplying $(\frac{\text{Export}}{\text{Sales}})_{ist0}$, our research takes into account the importance of exports for each firm in the base period.

3.4 Empirical Evidence

3.4.1 Generalized Difference-in-Differences Model

Our empirical study examines the effect of trade liberalization on the margins of firm-level innovative activities proxied by patent outcomes. To empirically test our theoretical predictions, we exploited the difference-in-differences framework and employed China's WTO accession in 2001 as a natural experiment. China's WTO accession unequally affects Taiwanese firms' technology innovations. We can predict that firms that are initially more exposed to exports and more produc-

international application, an applicant can claim the date of domestic application as the priority date of the patent in the U.S., and this date is called the foreign priority date. If a foreign priority date is available, it cannot exceed the date of the U.S. application. The foreign priority date should be closer to the timing of the firm's innovative activity for the patent than the date of the USPTO application. We use the year of the foreign priority date as t if available. Otherwise, the year of the U.S. application is t.

tive are heavily affected by WTO accession. The generalized difference-in-differences (hereafter generalized DD) model with firm and industry-time fixed effects will capture such heterogeneous effects of WTO accession, depending on the level of export exposure. Our generalized DD models are similar to empirical specifications in Pierce and Schott (2016). The models are as follows:

Generalized DD Model 1

$$
\begin{aligned}
Y_{ist} &= \beta \cdot \left(\text{PostWTO}_t \times \text{Export\_Exposure}_{ist0}\right) \\
&\quad + (\text{PostWTO}_t \times \bar{X}_{ist0}) \cdot \Gamma_0 + X_{ist-1} \cdot \Gamma_1 + \kappa_i + \eta_{st} + \epsilon_{ist} \qquad (3.11)
\end{aligned}
$$

Generalized DD Model 2

$$
\begin{aligned}
Y_{ist} &= \beta \cdot \left(\text{PostWTO}_t \times \text{Export\_Exposure}_{ist0} \times \text{Productivity}_{ist0}\right) \\
&\quad + (\text{PostWTO}_t \times \bar{X}_{ist0}) \cdot \Gamma_0 + X_{ist-1} \cdot \Gamma_1 + \kappa_i + \eta_{st} + \epsilon_{ist} \qquad (3.12)
\end{aligned}
$$

where PostWTO_t is a dummy variable indicating the post-WTO accession period, which takes a value of 1 for $t > 2001$. Firm-fixed effects (κ_i) absorb all observed and unobserved firm-level attributes that do not vary by year. Compared to the standard DD model, the generalized DD model with firm-fixed effects allows intercepts to vary by firm, which is less restrictive.[27] We also included industry-level time trends (η_{st}) to control all cyclical fluctuations by industry. To raise the precision of our estimates, we included pretreatment firm-level attributes ($\bar{X}_{ist0}$) and one-year-lagged firm-level attributes (X_{ist-1}), which capture firm-level performance measures at different periods. We included labor cost expenditures and fixed assets as proxies of firm-level labor input and capital input, respectively. Standard errors are clustered by firm to allow autocorrelations across years within a firm. The parameter of interest, β, captures treatment effects from the WTO accession by different levels of export exposure and productivity, which are evaluated during the pre-WTO periods.

[27] For empirical international trade studies using the generalized DD model, see Pierce and Schott (2016) and Lu and Yu (2015), for example.

Genalized DD (Model 1) Results Here

Table 3.9 for intensive margins

Table 3.10 for extensive margins

Genalized DD (Model 2) Results Here

Table 3.11 for intensive margins

Table 3.12 for extensive margins

3.4.2 Instrumental Variables

In Section 3.4.1, we employed a generalized DD framework using Chinese WTO accession as an exogenous trade liberalization event. The generalized DD framework relies on the assumption that the effects of trade liberalization (WTO accession) on Taiwanese firms' technology innovation decisions vary by each firm's export exposure and productivity level evaluated during the pre-WTO period (t_0). As an alternative empirical specification, we employed a lagged variable regression with instrumental variables. We estimated the linear regression model with lagged variables using ordinary least squares (OLS) and instrumental variables (IV) approaches.

Linear Panel Fixed Effects Model with Lagged Variables

$$\begin{aligned} Y_{ist} &= \beta_1 \cdot \text{Export\_Exposure}_{ist-1} + \beta_2 \cdot (\text{Export\_Exposure}_{ist-1} \times \text{Productivity}_{ist0}) \\ &\quad + X_{ist-1} \cdot \Gamma_1 + \eta_{st} + \epsilon_{ist} \end{aligned} \tag{3.13}$$

There could be a concern that our firm-level export shock variable might be endogenous to the firm's technology innovation decision. We used an instrumental variables (IV) approach to tackle the endogeneity issue. The valid IV for the export exposure measure should satisfy two conditions of relevancy and exogeneity. The IV should be strongly relevant to the firm-level export exposure variable, and they should affect Taiwanese firms' patenting decisions only through the channel of exporting to China. We use the following two IV: Chinese import demand and Chinese import tariff rates against Taiwan. [28]

3.4.2.1 Chinese Import Demand

We first used industry-level Chinese imports from major trade partners of China as an instrument for the export exposure variable. Changes in market demand in China will strongly affect its imports from foreign countries, so our IV should be positively correlated with Taiwanese exports to China. In addition, if Chinese imports from foreign countries are driven mainly by the variation in domestic market demand rather than supply shock from foreign countries, then our IV would be affected little by Taiwanese firms' exporting behaviors.

Following the spirit of previous studies such as Autor et al. (2013) and Autor et al. (2019), we used the ratio of Chinese imports from its major partners to Chinese imports from the world (except Taiwan) as our instrumental variable for the industry-level Taiwanese export measures. We chose three developed countries that account for a large share of Chinese imports, that is, the U.S., Japan and Korea.[29] Our instrumental variable can be written as follows:

$$\text{Chinese\_Import\_IV}_{ist} = \left(\frac{\text{Export}}{\text{Sales}}\right)_{ist0} \times \left(\frac{\text{Import}^{CHN\leftarrow\{DEV\}}}{\text{Import}^{CHN\leftarrow\{WLD\setminus TWN\}}}\right)_{st} \tag{3.14}$$

where $\{DEV\} = \{USA, JPN, KOR\}$. We use $\text{Chinese\_Import\_IV}_{ist}$ as an instrumental variable for our key explanatory variable, $\text{Export\_Exposure}_{ist} = \left(\frac{\text{Export}}{\text{Sales}}\right)_{ist0} \times \left(\frac{\text{Export}^{TWE\rightarrow CHN}}{\text{Export}^{TWE\rightarrow WLD}}\right)_{st}$.

3.4.2.2 Chinese Import Tariff Rates

The second instrumental variable for Taiwanese firms' export exposure is the gap of Chinese industry-level import tariff rates against Taiwan between pre-WTO periods ($t0$) and each year of post-WTO periods ($t1$). China's accession to the WTO in 2001 significantly lowered its import

[28] For convenience of interpretation, we multiplied the firm-specific Chinese export exposure measure by 100.

[29] Our IV results are robust to including imports from other European developed countries such as Britain, Germany and France. Results are available upon request.

tariff rates against Taiwanese products, which boosted its imports from Taiwan. As the change in tariff rates was driven mainly by the rules of WTO regimes applied to all member countries, tariff reduction could be understood as an exogenous trade liberalization shock to Taiwanese firms. We used the HS six-digit product-level (p) tariff rate information from The UNCTAD Trade Analysis Information System (TRAINS) to construct industry-level tariff rates.[30] [31] As we rely on firm-level data that group firms by the four-digit industry level (s), the six-digit product-level tariff data should be transformed into the four-digit industry level. Our four-digit industry-level measure of tariff rate changes can be written as follows:

$$\Delta\tau_{s,t1} = \sum_{p\in s} \omega_{p,s}(\tau_{p,t1} - \tau_{p,t0}) \tag{3.15}$$

where $\omega_{p,s}$ is the weight for aggregating product-level tariff rates to industry-level tariff rates. The weight $\omega_{p,s}$ is product p's share of Taiwanese exports to China within industry s in pre-WTO periods, i.e., $\omega_{p,s} = (\frac{Export^{TWE\rightarrow CHN}_{p,t0}}{\sum_{p\in s} Export^{TWE\rightarrow CHN}_{p,t0}})$. For the data of pre-WTO periods $t0$, we used the data for the period 1996–2001. As we used the share of exports in pre-WTO periods as the weight $\omega_{p,s}$, which is fixed, the variation of the industry-level tariff rates is driven solely by the change in product-level tariff rates. Figure 3.4 depicts the evolution of industry-level Chinese import tariff rates ($\tau_{s,t}$) against Taiwan from 1996 to 2014. As well documented in Brandt et al. (2017), we observe a few distinct patterns from the trend of tariff rates. First, tariff reduction has proceeded gradually, with a sharp tariff cut in 2002 from 14.5% to 10.0% in terms of median tariff rates. Second, there has been significant variation in tariff rates across industries. Third, the between-industry variation in tariff rates has been consistently diminishing. For example, the gap in tariff rates between the 90th percentile and 10th percentile was 37.5% (=43.5%-6.0%) in 1996, but it became 14.6% (=15.0%-0.4%) in 2014.

[30] https://unctad.org/en/Pages/DITC/Trade-Analysis/Non-Tariff-Measures/NTMs-trains.aspx

[31] Tariff information of 2012 and 2013 is not available in the TRAINS system. We recovered the missing tariff rates for 2012 and 2013 by interpolating the import tariff rates of 2011 and 2014, when they were both available.

Recall the linear panel fixed effects model with lagged variables in equation (3.13). The coefficient of interest is β_2.

Linear Panel Fixed Effects Model with Lagged Variables - OLS

Table 3.13 for intensive margins

Table 3.14 for extensive margins

Linear Panel Fixed Effects Model with Lagged Variables - IV

Table 3.15 for intensive margins

Table 3.16 for extensive margins

3.4.3 Use of Alternative Innovation Data: Taiwan Patent Office Data

Patents are the outcomes of firm-internal selection processes. Domestic applicants tend to file more patents in their home country than foreign applicants. Only a proportion of the total domestic patents are filed abroad. Extending protection to foreign countries increases the costs of patenting. The applicants will only accept these additional costs on the condition that expected revenues outweigh patenting costs. Thus, domestic patents may cover a broader range of technological activities than USPTO patents.

Further, firms that patent in the U.S. are more export-oriented than firms that seek protection for their inventions solely in the domestic market. Using domestic patent data can address the problem of selection bias.

We check the robustness by examining the Taiwan Intellectual Property Office patents applied by firms during the 1998-2014 period. We match assignee names to the list of TEJ firms.[32] The number of patents applied during this time period is 2052. For estimation purposes, a few firms with incomplete data for all relevant variables were eliminated. After the elimination procedure, the total number of firms remaining for the empirical analysis is 221, and the number of patents is 1271. Data on patent citations were not used because of their low quality.

[32] There are 63-254 firms matched, depending on the year.

We estimated the generalized DD model (equation (3.12)).

Table 3.17 for intensive margins

Table 3.18 for extensive margins

Our results are robust to alternative patent data. Greater export demand has a more positive influence on both the intensive and extensive margins of technology innovations for initially more productive firms than less productive ones. The result for the (log) number of new technologies is not available because the number of observations is too small.

3.4.4 Use of Alternative Trade Data: Taiwan Customs Trade Data

To generate more exogenous export demand shock measures than industry-level export variables (Aghion et al. (2018)), we used detailed transaction-level export data from the Customs Administration, Ministry of Finance, Taiwan for the 2006-2016 period.[33] All export transactions going through Taiwanese customs are included. The value of this dataset is mainly in the rich information it contains; most relevantly, it records the annual value and quantity of export transactions by firm for product-country destination pairs. A product is assigned a six-digit category in the 2002 Harmonized System (HS). Since the customs data lack information on firms' production activities such as employment and capital structure, we linked the customs transaction data to firms' balance sheet information filed by the Taxation Administration by matching the unique identification code of the firm. After matching the firm data with customs data, 3079-3508 firms are matched, depending on the year. After matching the firm data with customs data and patent data, 242-287 firms are matched, depending on the year.

We defined export demand as follows:

$$\text{Export\_Demand}_{it} = \sum_{j,p} \frac{X_{ijpt_0}}{X_{ijt_0}} \log(M_{jpt}) \tag{3.16}$$

[33] The selection of the sample period depends on data availability.

where X_{ijpt_0} denotes firm i's export of product p to destination country j in the initial year (i.e., 2006 or 2007) and M_{jpt} denotes country j's import from the world other than Taiwan of product p in year t. After taking the log, we weight the demand shocks by the export share of Taiwan during the initial year.[34]

We estimated the linear panel fixed effects model using customs data.

Table 3.19 for intensive margins

Table 3.20 for extensive margins

Our results are robust to alternative trade data. Greater export demand has a more positive influence on both the intensive and extensive margins of technology innovations for initially more productive firms than less productive ones. In columns with interaction, the marginal effect of export demand itself is not statistically significant. Initial productivity has a significantly positive effect on the intensive and extensive margins of technology innovations.

3.5 Conclusion

In this paper, we ask the following questions: what is the impact of market expansion on Taiwanese firms' innovation decisions? Which firms are affected the most?

Our theoretical and quantitative analysis obtains several key results. Theoretically, we show that following trade liberalization and subsequent market expansion, more productive firms expand their technology scopes, while less productive firms shrink their technology scopes. Quantitatively, we first show that market expansion has positive impacts on both the intensive and extensive margins of a firm's technology innovation. Second, we find that the impacts are more pronounced for initially more productive firms.

Motivated by micro-level evidence, our study provides a useful framework for future research. An intriguing question is the impact of foreign direct investment on firms' innovation decisions in

[34] An alternative measure of demand shock is $\text{Export\_Demand}_{it} = \log\left(\sum_{j,p} \frac{X_{ijpt_0}}{X_{ijt_0}} M_{jpt}\right)$. This measure gives similar results.

the receiving country.

3.5.1 Figures and Tables

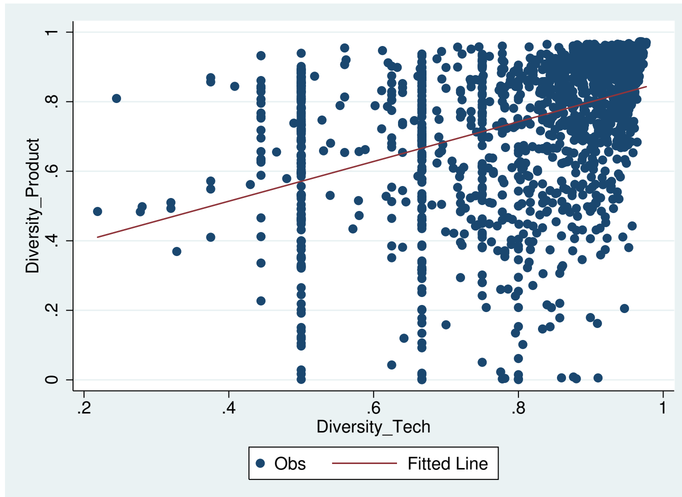


Figure 3.1: Technology Diversity and U.S. Import product diversity

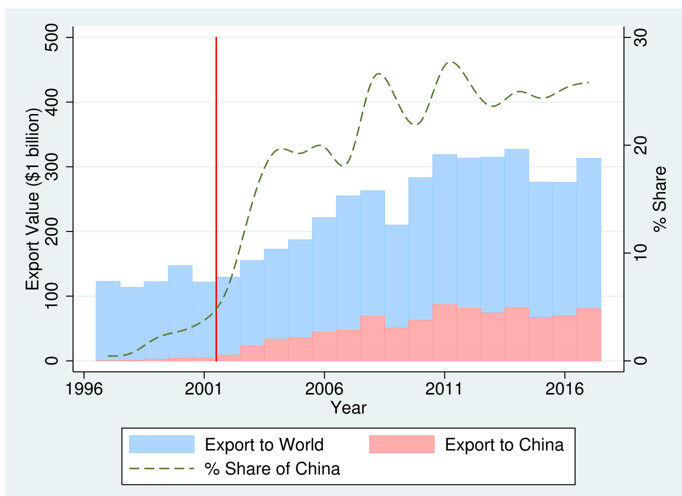


Figure 3.2: Export trends of Taiwan manufacturing industries, 1997-2017

(Figure 3.2) Source: UN Comtrade

(Figure 3.3) Source: USPTO granted patents, published between 1995-2018. For calculation of patent growth rate by each country, we used pre-WTO periods (1995-2001) as our base years. So the percentage rate of application year t means the number of applications at year t divided by the country's overall number of applications in pre-WTO periods. (i.e. For country c at year t,

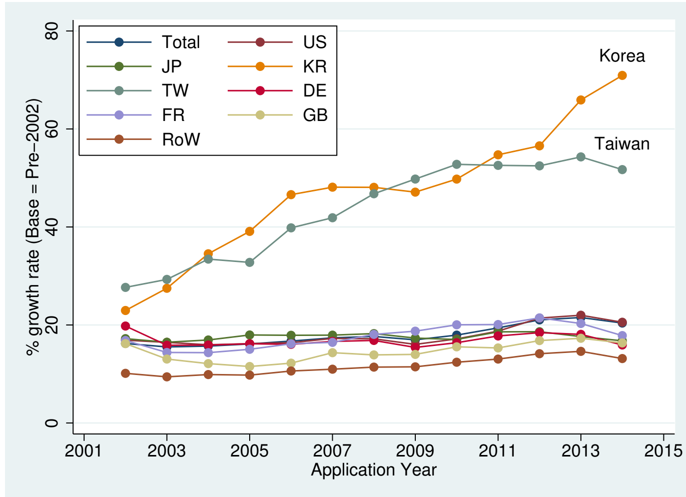


Figure 3.3: Growth of Patents by country, 2002-2014

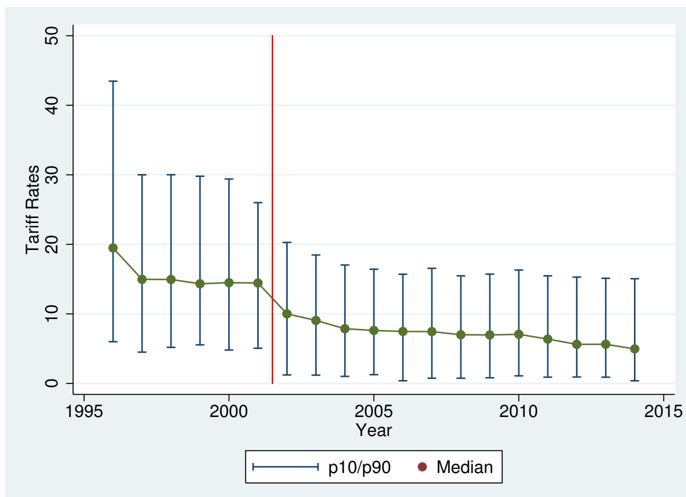


Figure 3.4: Evolution of Chinese Import Tariff Rates against Taiwan, 1996-2014

Growth Rate$_{ct}$ = $\frac{\text{\# of Applications}_{ct}}{\sum_{t=1995}^{2001} \text{\# of Applications}_{ct}}$)

(Figure 3.4) Source: The UNCTAD Trade Analysis Information System (TRAINS). Industry-level import tariff rates are calculated by authors.

Table 3.1: Quality Ladder Hypothesis: Reduced Form Country-Year Evidence

VARIABLES	(1) Price	(2) Price	(3) Price	(4) Price	(5) Price	(6) Price
Technologies Diversity	0.367***	0.367***	0.0405***	0.386***	0.385***	0.0196
	(0.0214)	(0.0214)	(0.0139)	(0.0177)	(0.0176)	(0.0144)
Number of Patents				-0.00219	-0.00210	0.0174***
				(0.00194)	(0.00192)	(0.00428)
Unit (u) Fixed Effects	Yes	No	No	Yes	No	No
Product (p) Fixed Effects	Yes	No	No	Yes	No	No
Product × Unit (up) Fixed Effects	No	Yes	Yes	No	Yes	Yes
Country(c) Fixed Effects	No	No	Yes	No	No	Yes
Year(t) Trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,153,744	1,153,743	1,153,742	1,153,744	1,153,743	1,153,742
R-squared	0.691	0.696	0.731	0.691	0.696	0.731

Dependent variables are log transformed unit prices of US import products in manufacturing industries. The unit price of import products is defined as the import value divided by the import quantity at the HS 6-digit import product level, i.e. $\text{US Import Price}_{pucst} = \left(\frac{\text{US Import Value}}{\text{US Import Quantity}}\right)_{pucst}$. Standard errors, clustered by products, are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 3.2: Number of USPTO granted patents by country, applied between 1995-2014

App_Year	Total	USA	Japan	Korea	Taiwan	China	Germany	Great Britain	France	RoW
1995	148,596	69,877	30,272	2,078	1,031	45	7,605	2,459	3,404	31,825
1996	148,343	66,244	32,190	3,513	1,547	45	7,745	2,323	3,171	31,565
1997	173,784	78,997	37,587	3,825	1,945	64	9,001	2,566	3,669	36,130
1998	171,706	78,685	34,936	3,917	3,012	98	9,348	2,671	3,740	35,299
1999	181,173	84,487	36,243	3,573	3,979	91	11,165	2,808	4,338	34,489
2000	187,836	91,959	41,897	4,054	3,279	181	12,308	2,928	4,827	26,403
2001	196,858	95,555	47,129	4,825	4,220	297	14,112	3,303	4,861	22,556
2002	196,043	95,626	44,794	5,920	5,261	420	14,104	3,087	4,717	22,114
2003	187,554	93,117	42,890	7,089	5,571	505	11,309	2,487	4,031	20,555
2004	189,615	90,302	44,082	8,904	6,358	729	11,340	2,309	4,020	21,571
2005	194,911	91,589	46,755	10,082	6,232	991	11,526	2,197	4,212	21,327
2006	202,056	92,733	46,580	12,015	7,572	1,718	11,440	2,327	4,527	23,144
2007	209,959	97,642	46,656	12,409	7,964	2,120	11,867	2,734	4,609	23,958
2008	213,366	97,169	47,466	12,401	8,894	2,826	12,008	2,648	5,065	24,889
2009	205,023	90,756	45,100	12,148	9,464	3,637	10,993	2,668	5,248	25,009
2010	216,675	97,080	44,358	12,833	10,036	5,051	11,680	2,962	5,613	27,062
2011	234,437	106,037	48,405	14,112	9,996	6,211	12,663	2,919	5,628	28,466
2012	254,236	121,124	48,474	14,584	9,977	6,871	13,139	3,205	6,008	30,854
2013	260,079	124,428	45,891	16,998	10,325	8,652	12,896	3,295	5,688	31,906
2014	246,392	116,318	43,650	18,291	9,831	10,148	11,348	3,113	4,996	28,697

Source: USPTO granted patents, published between 1995-2018.

(Table 3.2) We do not report the numbers for the recent years after 2014, as they are not free from the censoring issue caused by patent review process. For international applications, it takes three years of review process on average from the application to the final publication.

Table 3.3: Technology distribution of Patents, Before 2002, Taiwan

Rank	CPC Class	Definition	Count	Share (%)
1	H01	BASIC ELECTRIC ELEMENTS	8,090	48.76
2	G06	COMPUTING; CALCULATING; COUNTING	1,469	8.85
3	H04	ELECTRIC COMMUNICATION TECHNIQUE	997	6.01
4	G11	INFORMATION STORAGE	791	4.77
5	H05	ELECTRIC TECHNIQUES NOT OTHERWISE PROVIDED FOR	601	3.62
6	G03	PHOTOGRAPHY; CINEMATOGRAPHY; ELECTROGRAPHY; HOLOGRAPHY	501	3.02
7	G02	OPTICS	393	2.37
8	G01	MEASURING ; TESTING	373	2.25
9	H03	BASIC ELECTRONIC CIRCUITRY	365	2.2
10	H02	GENERATION; CONVERSION OR DISTRIBUTION OF ELECTRIC POWER	288	1.74
11	G09	EDUCATION; CRYPTOGRAPHY; DISPLAY; ADVERTISING; SEALS	230	1.39
12	C23	COATING METALLIC MATERIAL; CHEMICAL SURFACE TREATMENT; DIFFUSION TREATMENT OF METALLIC MATERIAL	197	1.19
13	Y02	TECHNOLOGIES OR APPLICATIONS FOR MITIGATION OR ADAPTATION AGAINST CLIMATE CHANGE	187	1.13
14	B24	GRINDING; POLISHING	175	1.05
15	F16	ENGINEERING ELEMENTS AND UNITS; GENERAL MEASURES FOR PRODUCING AND MAINTAINING EFFECTIVE FUNCTIONING OF MACHINES OR INSTALLATIONS; THERMAL INSULATION IN GENERAL	159	0.96

Table 3.4: Technology distribution of Patents, After 2002, Taiwan

Rank	CPC Class	Definition	Count	Share (%)
1	H01	BASIC ELECTRIC ELEMENTS	35,736	29
2	G06	COMPUTING; CALCULATING; COUNTING	15,948	12.94
3	H04	ELECTRIC COMMUNICATION TECHNIQUE	10,948	8.88
4	G02	OPTICS	8,045	6.53
5	H05	ELECTRIC TECHNIQUES NOT OTHERWISE PROVIDED FOR	6,602	5.36
6	G11	INFORMATION STORAGE	5,878	4.77
7	H03	BASIC ELECTRONIC CIRCUITRY	4,573	3.71
8	H02	GENERATION; CONVERSION OR DISTRIBUTION OF ELECTRIC POWER	3,998	3.24
9	G01	MEASURING ; TESTING	3,670	2.98
10	G09	EDUCATION; CRYPTOGRAPHY; DISPLAY; ADVERTISING; SEALS	3,641	2.95
11	Y02	TECHNOLOGIES OR APPLICATIONS FOR MITIGATION OR ADAPTATION AGAINST CLIMATE CHANGE	3,164	2.57
12	G03	PHOTOGRAPHY; CINEMATOGRAPHY; ELECTROGRAPHY; HOLOGRAPHY	3,024	2.45
13	F16	ENGINEERING ELEMENTS AND UNITS; GENERAL MEASURES FOR PRODUCING AND MAINTAINING EFFECTIVE FUNCTIONING OF MACHINES OR INSTALLATIONS; THERMAL INSULATION IN GENERAL	1,507	1.22
14	F21	LIGHTING	1,439	1.17
15	G05	CONTROLLING; REGULATING	1,098	0.89

Source: USPTO granted patents (matched with TEJ data), published between 1995-2018

Table 3.5: Example of cleaning assignee names (The case of “Hon Hai Precision")

assignee_name (raw)	assignee_name (cleaned)	assignee_name (patentsview)	assignee_name (final)
A Hon Hai Precision Ind. Co., Ltd.	A HON HAI PRECISION	HON HAI PRECISION	HON HAI PRECISION
Hoa Hai Precision Ind. Co., Ltd.	HOA HAI PRECISION	HOA HAI PRECISION	HON HAI PRECISION
Hon Hahi Precision Ind. Co., Ltd.	HON HAHI PRECISION	HON HAI PRECISION	HON HAI PRECISION
Hon Hai Aprecision Ind. Co., Ltd.	HON HAI APRECISION	HON HAI PRECISION	HON HAI PRECISION
HON HAI PECISION INDUSTRY CO., LTD.	HON HAI PECISION	HON HAI PRECISION	HON HAI PRECISION
Hon Hai Preciasion Industry Co., Ltd.	HON HAI PRECIASION	HON HAI PRECISION	HON HAI PRECISION
Hon Hai Precisiion Inc. Co., Ltd.	HON HAI PRECISIION	HON HAI PRECISION	HON HAI PRECISION
Hon Hai Precision Idnustry Co., Ltd.	HON HAI PRECISION IDNUSTRY	HON HAI PRECISION	HON HAI PRECISION
Hon Hai Precision In. Co., Ltd.	HON HAI PRECISION IN	HON HAI PRECISION	HON HAI PRECISION
Hon Hai Precoision Ind. Co., Ltd.	HON HAI PRECOISION	HON HAI PRECISION	HON HAI PRECISION
Hon Hai Prescision Ind. Co., Ltd.	HON HAI PRESCISION	HON HAI PRECISION	HON HAI PRECISION
Hon Hai Precidion Ind. Co., LTD	HON HAI PRECIDION	HON HAI PRECIDION	HON HAI PRECISION
Hon Hai Predcision Ind. Co., Ltd.	HON HAI PREDCISION	HON HAI PREDCISION	HON HAI PRECISION
Hon Haiprecision Ind. Co., Ltd.	HON HAIPRECISION	HONHAI PRECISION	HON HAI PRECISION
HON HAU PRECISION INDUSTRY CO., LTD.	HON HAU PRECISION	HON HAO PRECISION	HON HAI PRECISION
Ion Hai Precision Ind. Co. Ltd.	ION HAI PRECISION	ION HAI PRECISION	HON HAI PRECISION
Jon Hai Precision Ind. Co., Ltd.	JON HAI PRECISION	JON HAI PRECISION	HON HAI PRECISION
Hon Hai Precsion Industry Co., Ltd.	HON HAI PRECSION	HON HAI PRECSION	HON HAI PRECISION
Hon Hai Precsision Industry Co., Ltd.	HON HAI PRECSISION	HON HAI PRECSION	HON HAI PRECISION
Hon Hai Preicision Industry Co., Ltd.	HON HAI PREICISION	HON HAI PRECSION	HON HAI PRECISION

The table includes 20 cases of different expressions for “Hon Hai Precision". Column 1: original name of assignee from the raw data. Column 2: capitalized and standardized (leave letters only, and drop unnecessary postfix) name of assignee. Column 3: disambiguated assignee names from Patentsview data, which used machine-learning based algorithms. Column 4: final assignee names for analysis.

Table 3.6: Summary Statistics

	(1) Innovator	(2) Exporter-Non Innovator	(3) Non Exporter-Non Innovator
Age	19.60	23.08	23.46
	(11.6)	(13.7)	(13.6)
Employee	2,704.61	1,259.67	922.44
	(19,673.7)	(11,223.1)	(4,356.2)
Capital	176,427.20	83,803.31	96,334.14
	(894,263)	(375,494.4)	(623,589.4)
Sales	369,731.40	164,479.70	131,722.90
	(2,458,730)	(884,873.8)	(508,328.2)
R&D Expenditures	11,294.47	1,318.87	146.09
	(56,596.8)	(6,419.4)	(678.1)
Debt-Equity Ratio	38.93	57.70	154.53
	(1,219.7)	(1,433.6)	(3,457.8)
Export_Share	0.63	0.43	-
	(0.32)	(0.36)	-
Patents	6.5	-	-
	(53.5)	-	-
Observations	13,052-13,819	12,110-13,440	2,363-2,782
Firms	1,075	1,159	279

'Innovator' is defined as a firm which files at least a single patent to USPTO. 'Exporter' is defined as a firm which reports positive exports. 'Capital' is the value of total fixed assets, and 'Sales' is the total revenue of domestic sales and exports. 'Export_Share' is the ratio of the value of Exports to the value of total sales. The unit of Capital, Sales, and R&D expenditures is US dollar, and the value of all variables are realized. Source: Taiwan Economic Journal (TEJ) data, 1997-2014.

Table 3.7: Number of Patents by matching process

	Raw Data	Patents with Assignee Information	Patents filed by Corporations	Matched with TEJ data
Number of Patents	156,935	146,835	129,788	108,156
Number of Assignees		7,925	7,058	1,127

Table 3.8: Description of Patent Variables

Margins	Variables	Description
Intensive	Num_Patents	Raw Number of Patents
	Num_Cited	Number of Citations within 3 years
	Num_SelfCited	Number of Self Citations within 3 years
	R&D Expenditures	R&D Expenditures
Extensive	Num_Tech (Current)	Number of Technology classes, measured at the current year
	Num_Tech (Cumul)	Number of Technology classes, measured by cumulative years
	Num_NewTech	Number of New technology classes
	D_NewTech	1 if a firm filed technologies in a new field(s).
	Helfindahl (Current)	Herfindahl index for technology diversity, measured at the current year
	Helfindahl (Cumul)	Herfindahl index for technology diversity, measured by cumulative years
	Entropy (Current)	Entropy index for technology skewedness, measured at the current year
	Entropy (Cumul)	Entropy index for technology skewedness, measured by cumulative years

Table 3.9: Generalized DD Model 1 - Intensive Technology Margins

VARIABLES	(1) Num_Patents	(2) Num_Cited	(3) Num_SelfCited	(4) R&D Expenditure
$\text{Post2002}_t \times \text{Export\_Exposure}_{ist0}$	0.355**	0.399*	0.258*	-0.0216
	(0.171)	(0.204)	(0.136)	(0.199)
Fixed Effects	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}
Firm Controls	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}
Pre-periods Firm Controls	$\text{Post2002}_t \times \bar{X}_{ist0}$	$\text{Post2002}_t \times \bar{X}_{ist0}$	$\text{Post2002}_t \times \bar{X}_{ist0}$	$\text{Post2002}_t \times \bar{X}_{ist0}$
Observations	2,019	2,019	2,019	1,999
R-squared	0.841	0.781	0.776	0.965

All dependent variables are log transformed. Num_Patents is the firm-level number of granted patents applied at year t. Num_Cited is the firm-level number of cited patents. Num_SelfCited is the firm-level number of self-citations. Firm-level export shock is constructed as $\text{Export\_Exposure}_{ist0} = (\frac{\text{Export}}{\text{Sales}})_{ist0} \times (\frac{\text{Export}^{\text{TWN}\rightarrow\text{CHN}}}{\text{Export}^{\text{TWN}\rightarrow\text{WLD}}})_{st0}$. All specifications include individual firm-level fixed effects(κ_i) and industry-year trends(η_{st}). Robust standard errors, clustered by firms, are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 3.10: Generalized DD Model 1 - Extensive Technology Margins

VARIABLES	(1) Num_Tech(Current)	(2) Num_Tech(Cumul)	(3) Num_NewTech	(4) D_NewTech	(5) Herfindahl(Current)	(6) Herfindahl(Cumul)	(7) Entropy(Current)	(8) Entropy(Cumul)
$Post2002_t \times Export\_Exposure_{ist0}$	0.219**	0.0896	0.115	0.0328	-0.0386*	-0.0128	-0.219**	-0.101
	(0.0971)	(0.0550)	(0.0976)	(0.0784)	(0.239)	(0.0218)	(0.103)	(0.0792)
Fixed Effects	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}
Firm Controls	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}
Pre-periods Firm Controls	$Post2002_t \times \bar{X}_{ist0}$	$Post2002_t \times \bar{X}_{ist0}$	$Post2002_t \times \bar{X}_{ist0}$	$Post2002_t \times \bar{X}_{ist0}$	$Post2002_t \times \bar{X}_{ist0}$	$Post2002_t \times \bar{X}_{ist0}$	$Post2002_t \times \bar{X}_{ist0}$	$Post2002_t \times \bar{X}_{ist0}$
Observations	2,019	2,019	2,019	2,019	2,019	2,019	2,019	2,019
R-squared	0.793	0.953	0.390	0.343	0.618	0.917	0.698	0.928

All dependent variables are log transformed. Num_Tech(Current) is the firm-level number of technology class at year t. Num_Tech(Cumul) is the firm-level cumulative number of technology class. Num_NewTech is the number of technology class that the firm firstly filed at t. D_NewTech is one if a firm filed new technology class at t. Firm-level export shock is constructed as $Export\_Exposure_{ist0} = (\frac{Export}{Sales})_{ist0} \times (\frac{Export^{TWE \rightarrow CHN}}{Export^{TWE \rightarrow WLD}})_{st0}$. All specifications include individual firm-level fixed effects(κ_i) and industry-year trends(η_{st}). Robust standard errors, clustered by firms, are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 3.11: Generalized DD Model 2 - Intensive Technology Margins

VARIABLES	(1) Num_Patents	(2) Num_Cited	(3) Num_SelfCited	(4) R&D Expenditure
$Post2002_t \times Export\_Exposure_{ist0} \times Productivity_{ist0}$	0.0624**	0.0657**	0.0427**	-0.00962
	(0.0267)	(0.0325)	(0.0212)	(0.0289)
Fixed Effects	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}
Firm Controls	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}
Pre-periods Firm Controls	$Post2002_t \times \bar{X}_{ist0}$	$Post2002_t \times \bar{X}_{ist0}$	$Post2002_t \times \bar{X}_{ist0}$	$Post2002_t \times \bar{X}_{ist0}$
Observations	1,765	1,765	1,765	1,745
R-squared	0.848	0.789	0.792	0.966

All dependent variables are log transformed. Num_Patents is the firm-level number of granted patents applied at year t. Num_Cited is the firm-level number of cited patents. Num_SelfCited is the firm-level number of self-citations. Firm-level export shock is constructed as $Export\_Exposure_{ist0} = (\frac{Export}{Sales})_{ist0} \times (\frac{Export^{TWN \to CHN}}{Export^{TWN \to WLD}})_{st0}$. All specifications include individual firm-level fixed effects(κ_i) and industry-year trends(η_{st}). Robust standard errors, clustered by firms, are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 3.12: Generalized DD Model 2 - Extensive Technology Margins

VARIABLES	(1) Num_Tech(Current)	(2) Num_Tech(Cumul)	(3) Num_NewTech	(4) D_NewTech	(5) Herfindahl(Current)	(6) Herfindahl(Cumul)	(7) Entropy(Current)	(8) Entropy(Cumul)
$Post2002_t \times Export\_Exposure_{ist0} \times Productivity_{ist0}$	0.0356**	0.0131	0.0221*	0.0101	-0.00598	-0.00167	-0.0352**	-0.0155
	(0.0147)	(0.00836)	(0.0139)	(0.0130)	(0.00409)	(0.00334)	(0.0155)	(0.0119)
Fixed Effects	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}
Firm Controls	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}
Pre-periods Firm Controls	$Post2002_t \times \bar{X}_{ist0}$	$Post2002_t \times \bar{X}_{ist0}$	$Post2002_t \times \bar{X}_{ist0}$	$Post2002_t \times \bar{X}_{ist0}$	$Post2002_t \times \bar{X}_{ist0}$	$Post2002_t \times \bar{X}_{ist0}$	$Post2002_t \times \bar{X}_{ist0}$	$Post2002_t \times \bar{X}_{ist0}$
Observations	1,765	1,765	1,765	1,765	1,765	1,765	1,765	1,765
R-squared	0.797	0.953	0.382	0.338	0.624	0.916	0.701	0.926

All dependent variables are log transformed. Num_Tech(Current) is the firm-level number of technology class at year t. Num_Tech(Cumul) is the firm-level cumulative number of technology class. Num_NewTech is the number of technology class that the firm firstly filed at t. D_NewTech is one if a firm filed new technology class at t. Firm-level export shock is constructed as $Export\_Exposure_{ist0} = (\frac{Export}{Sales})_{ist0} \times (\frac{Export^{TWE \to CHN}}{Export^{TWE \to WLD}})_{st0}$. All specifications include individual firm-level fixed effects(κ_i) and industry-year trends(η_{st}). Robust standard errors, clustered by firms, are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 3.13: Linear Panel Fixed Effects model with Lagged Variables, OLS - Intensive Technology Margins

VARIABLES	(1) Num_Patents	(2) Num_Cited	(3) Num_SelfCited	(4) R&D Expenditure
$\text{Export\_Exposure}_{ist-1} \times \text{Productivity}_{ist0}$	0.0111	0.00807	0.00392	0.0106*
	(0.00682)	(0.00861)	(0.00789)	(0.00565)
$\text{Export\_Exposure}_{ist-1}$	-0.0610	-0.0381	-0.00721	-0.0596
	(0.0436)	(0.0522)	(0.0468)	(0.0386)
Fixed Effects	η_{st}	η_{st}	η_{st}	η_{st}
Firm Controls	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}
Observations	1,508	1,508	1,508	1,489
R-squared	0.553	0.467	0.353	0.824

All dependent variables are logged. Num_Patents is the firm-level number of granted patents applied at year t. Num_Cited is the firm-level number of cited patents (within three years) applied at year t. Num_SelfCited is the firm-level number of self-cited patents (within three years) applied at year t. Firm-level export shock is constructed as $\text{Export\_Exposure}_{ist-1} = 100 \times (\frac{\text{Export}}{\text{Sales}})_{ist0} \times (\frac{\text{Export}^{\text{TWN}\rightarrow\text{CHN}}}{\text{Export}^{\text{TWN}\rightarrow\text{WLD}}})_{st-1}$. All specifications include industry-year trends(η_{st}) and lagged firm-level control variables ($\bar{X}_{ist-1}$). Robust standard errors, clustered by firms, are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 3.14: Linear Panel Fixed Effects model with Lagged Variables, OLS - Extensive Technology Margins

VARIABLES	(1) Num_Tech(Current)	(2) Num_Tech(Cumul)	(3) Num_NewTech	(4) D_NewTech	(5) Herfindahl(Current)	(6) Herfindahl(Cumul)	(7) Entropy(Current)	(8) Entropy(Cumul)
Export_Exposure$_{ist-1}$ × Productivity$_{ist0}$	0.00605**	0.00651**	0.000934	-6.14e-05	-0.00156**	-0.00155**	-0.00630**	-0.00635**
	(0.00292)	(0.00311)	(0.00148)	(0.00118)	(0.000628)	(0.000638)	(0.00246)	(0.00273)
Export_Exposure$_{ist-1}$	-0.0270	-0.0286	-0.00290	0.00131	0.00781*	0.00642	0.0311*	0.0267
	(0.0191)	(0.0214)	(0.0102)	(0.00854)	(0.00451)	(0.00434)	(0.0169)	(0.0190)
Fixed Effects	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}
Firm Controls	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}
Observations	1,508	1,508	1,508	1,508	1,508	1,508	1,508	1,508
R-squared	0.554	0.640	0.211	0.201	0.349	0.403	0.450	0.492

All dependent variables are logged. Num_Tech(Current) is the firm-level number of technology class at year t. Num_Tech(Cumul) is the firm-level cumulative number of technology class. Num_NewTech is the number of technology class that the firm firstly filed at t. D_NewTech is one if a firm filed new technology class at t. Firm-level export shock is constructed as $\text{Export\_Exposure}_{ist-1} = 100 \times (\frac{\text{Export}}{\text{Sales}})_{ist0} \times (\frac{\text{Export}^{\text{TWN}\rightarrow\text{CHN}}}{\text{Export}^{\text{TWN}\rightarrow\text{WLD}}})_{st-1}$. All specifications include industry-year trends(η_{st}) and lagged firm-level control variables ($\bar{X}_{ist-1}$). Robust standard errors, clustered by firms, are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 3.15: Linear Panel Fixed Effects model with Lagged Variables, IV approach- Intensive Technology Margins

VARIABLES	(1) Num_Patents	(2) Num_Cited	(3) Num_SelfCited	(4) R&D Expenditure
$\text{Export\_Exposure}_{ist-1} \times \text{Productivity}_{ist0}$	0.0124*	0.0156	0.0111	0.0179***
	(0.00722)	(0.0100)	(0.0111)	(0.00610)
$\text{Export\_Exposure}_{ist-1}$	-0.0707	-0.0863	-0.0537	-0.105**
	(0.0462)	(0.0621)	(0.0668)	(0.0409)
Fixed Effects	η_{st}	η_{st}	η_{st}	η_{st}
Firm Controls	$\bar{X}_{ist-1}$	$\bar{X}_{ist-1}$	$\bar{X}_{ist-1}$	$\bar{X}_{ist-1}$
Kleibergen-Paap Wald F statistic			90.64	
Hansen OverId test (p-value)	0.61	0.84	0.85	0.26
Observations	1,508	1,508	1,508	1,489
R-squared	0.489	0.380	0.286	0.769

All dependent variables are logged. Num_Patents is the firm-level number of granted patents applied at year t. Num_Cited is the firm-level number of cited patents (within three years) applied at year t. Num_SelfCited is the firm-level number of self-cited patents (within three years) applied at year t. Firm-level export shock is constructed as $\text{Export\_Exposure}_{ist-1} = 100 \times (\frac{\text{Export}}{\text{Sales}})_{ist0} \times (\frac{\text{Export}^{\text{TWN}\rightarrow\text{CHN}}}{\text{Export}^{\text{TWN}\rightarrow\text{WLD}}})_{st-1}$. All specifications include industry-year trends(η_{st}) and lagged firm-level control variables ($\bar{X}_{ist-1}$). Robust standard errors, clustered by firms, are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 3.16: Linear Panel Fixed Effects model with Lagged Variables, IV approach - Extensive Technology Margins

VARIABLES	(1) Num_Tech(Current)	(2) Num_Tech(Cumul)	(3) Num_NewTech	(4) D_NewTech	(5) Herfindahl(Current)	(6) Herfindahl(Cumul)	(7) Entropy(Current)	(8) Entropy(Cumul)
$\text{Export\_Exposure}_{ist-1} \times \text{Productivity}_{ist0}$	0.00900**	0.0112***	0.00413*	0.00163	-0.00250***	-0.00260***	-0.00963***	-0.0110***
	(0.00361)	(0.00340)	(0.00242)	(0.00148)	(0.000787)	(0.000858)	(0.00306)	(0.00336)
$\text{Export\_Exposure}_{ist-1}$	-0.0443*	-0.0568**	-0.0188	-0.00675	0.0135**	0.0123**	0.0523**	0.0543**
	(0.0230)	(0.0232)	(0.0155)	(0.0103)	(0.00545)	(0.00559)	(0.0202)	(0.0227)
Fixed Effects	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}
Firm Controls	$\bar{X}_{ist-1}$	$\bar{X}_{ist-1}$	$\bar{X}_{ist-1}$	$\bar{X}_{ist-1}$	$\bar{X}_{ist-1}$	$\bar{X}_{ist-1}$	$\bar{X}_{ist-1}$	$\bar{X}_{ist-1}$
Kleibergen-Paap Wald F statistic					90.6			
Hansen OverId test (p-value)	0.78	0.77	0.81	0.67	0.37	0.38	0.46	0.70
Observations	1,508	1,508	1,508	1,508	1,508	1,508	1,508	1,508
R-squared	0.333	0.516	0.021	0.012	0.141	0.112	0.218	0.207

All dependent variables are logged. Num_Tech(Current) is the firm-level number of technology class at year t. Num_Tech(Cumul) is the firm-level cumulative number of technology class. Num_NewTech is the number of technology class that the firm firstly filed at t. D_NewTech is one if a firm filed new technology class at t. Firm-level export shock is constructed as $\text{Export\_Exposure}_{ist-1} = 100 \times (\frac{\text{Export}}{\text{Sales}})_{ist0} \times (\frac{\text{Export}^{\text{TWN}\rightarrow\text{CHN}}}{\text{Export}^{\text{TWN}\rightarrow\text{WLD}}})_{st-1}$. All specifications include industry-year trends(η_{st}) and lagged firm-level control variables ($\bar{X}_{ist-1}$). Robust standard errors, clustered by firms, are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 3.17: Robustness: Taiwan Patent Office Data - Intensive Technology Margins

Variables	(1) Num_Patents
$\text{Post2002}_t \times \text{Export\_Exposure}_{ist0} \times \text{Productivity}_{ist0}$	0.063*
	(0.036)
Fixed Effects	κ_i, η_{st}
Firm Controls	X_{ist-1}
Pre-periods Firm Controls	$\text{Post2002}_t \times \bar{X}_{ist0}$
Observations	1034
R-squared	0.834

Notes: Robust standard errors, clustered by firm, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.18: Robustness: Taiwan Patent Office Data - Extensive Technology Margins

Variables	(1) Num_Tech (Current)	(2) Num_Tech (Cumul)	(3) D_NewTech	(4) Herfindahl (Current)	(5) Herfindahl (Cumul)	(6) Entropy (Current)	(7) Entropy (Cumul)
$\text{Post2002}_t \times \text{Export\_Exposure}_{ist0} \times \text{Productivity}_{ist0}$	0.061***	0.038***	-0.005	-0.026	0.003	-8.853**	-6.732*
	(0.020)	(0.011)	(0.006)	(0.037)	(0.038)	(3.728)	(3.560)
Fixed Effects	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}	κ_i, η_{st}
Firm Controls	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}
Pre-periods Firm Controls	$\text{Post2002}_t \times \bar{X}_{ist0}$	$\text{Post2002}_t \times \bar{X}_{ist0}$	$\text{Post2002}_t \times \bar{X}_{ist0}$	$\text{Post2002}_t \times \bar{X}_{ist0}$	$\text{Post2002}_t \times \bar{X}_{ist0}$	$\text{Post2002}_t \times \bar{X}_{ist0}$	$\text{Post2002}_t \times \bar{X}_{ist0}$
Observations	1034	1034	1034	1034	1653	1034	1653
R-squared	0.806	0.939	0.333	0.792	0.834	0.835	0.802

Notes: Robust standard errors, clustered by firm, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.19: Robustness: Taiwan Customs Trade Data - Intensive Technology Margins

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Num_Patents		Num_Cited		Num_SelfCited		R&D Expenditure	
Export Demand$_{it}$	0.003	-0.333***	0.021	-0.281**	0.019	-0.169**	-0.031	-0.632***
	(0.029)	(0.122)	(0.030)	(0.110)	(0.022)	(0.072)	(0.031)	(0.143)
Export Demand$_{it}$		0.023***		0.021**		0.012**		0.042***
× Productivity$_{it0}$		(0.009)		(0.008)		(0.005)		(0.010)
Fixed Effects	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}
Firm Controls	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}
Observations	1,819	1,694	1,819	1,694	1,819	1,694	1,762	1,643
R-squared	0.356	0.403	0.248	0.273	0.196	0.222	0.502	0.560

Notes: Robust standard errors, clustered by firm, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.20: Robustness: Taiwan Customs Trade Data - Extensive Technology Margins

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Num_Tech (Current)		Num_Tech (Cumul)		Num_NewTech		D_NewTech	
Export Demand$_{it}$	0.004	-0.168***	-0.013	-0.200**	0.001	-0.020	-0.000	-0.029
	(0.016)	(0.061)	(0.017)	(0.078)	(0.010)	(0.037)	(0.007)	(0.026)
Export Demand$_{it}$		0.012***		0.013**		0.001		0.002
× Productivity$_{it0}$		(0.004)		(0.005)		(0.003)		(0.002)
Fixed Effects	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}
Firm Controls	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}
Observations	1,809	1,684	1,809	1,684	1,616	1,498	1,616	1,498
R-squared	0.276	0.321	0.418	0.448	0.131	0.143	0.115	0.125
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Herfindahl (Current)		Herfindahl (Cumul)		Entropy (Current)		Entropy (Cumul)	
Export Demand$_{it}$	-0.000	0.054**	-0.001	0.033*	-0.003	0.147**	0.002	0.122**
	(0.005)	(0.023)	(0.005)	(0.018)	(0.014)	(0.057)	(0.013)	(0.055)
Export Demand$_{it}$		-0.004**		-0.002**		-0.010***		-0.008**
× Productivity$_{it0}$		(0.002)		(0.001)		(0.004)		(0.004)
Fixed Effects	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}	η_{st}
Firm Controls	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}	X_{ist-1}
Observations	1,809	1,684	1,819	1,694	1,809	1,684	1,819	1,694
R-squared	0.151	0.173	0.169	0.182	0.199	0.228	0.258	0.277

Notes: Robust standard errors, clustered by firm, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

APPENDICES

APPENDIX A

FIRST APPENDIX

Table A.1: Literature Review

Episodes	Periods	Papers
US-France conflict over the Iraq war	2002-2003	Michaels and Zhi (2010) Davis and Meunier (2011) Pandya and Venkatesan (2016) Heilmann (2016)
China-Japan rift over the Japanese prime minister's Yasukuni Shrine visits	Early 2000s	Davis and Meunier (2011)
China-Japan rift over the Japanese histoy textbook controversies	2005	Fisman et al. (2014)
Muhammad cartoon crisis in Denmark	2006	Heilmann (2016)
Conflicts between China and other nations over the invitation of the 14th Dalai Lama	-	Fuchs and Klann (2013)
Export sanctions against Iranian nuclear weapons program	2008	Haidar (2017)
China-Norway rift from the 2010 Nobel Peace Prize	2010	Kolstad (2020)
China-Japan territorial conflict on Senkaku/Diaoyudao islands	2012	Heilmann (2016) Fisman et al. (2014) Luo and Zhou (2019) Tanaka et al. (2019)
Russia-Western countries conflict after Crimean crisis	2014	Crozet and Hinz (2020) Bluszcz and Valente (2019) Makarin and Korovkin (2019)
China-Korea conflict over the deployment of U.S. THAAD system	2017	Kim and Lee (2019)

Table A.2: Balancedness of Predictors - Exports

	Korea	Synthetic Korea
Exports (Average 2014)	22.16	22.11
Exports (Average 2015)	21.99	22.01
Exports (Average 2016)	22.03	22.04
Exports (Average 2017)	22.17	22.13
Exports (Average 2018)	22.15	22.17
GDP per capita	10.31	10.43
Population	10.84	11.22
Education	12.05	11.00

Table A.3: Balancedness of Predictors - Imports

	Korea	Synthetic Korea
Imports (Average 2014)	21.72	21.67
Imports (Average 2015)	21.49	21.44
Imports (Average 2016)	21.42	21.40
Imports (Average 2017)	21.53	21.54
Imports (Average 2018)	21.66	21.65
GDP per capita	10.31	10.65
Population	10.84	10.93
Education	12.05	11.43

Table A.4: Trade Diversion

	Total Exports					
	(1) CHN	(2) USA	(3) DEU	(4) SGP	(5) HKG	(6) AUS
$PostDispute_t$	-0.0438	-0.0619	-0.0213	-0.139**	-0.0117	-0.165**
	(0.0554)	(0.0381)	(0.0502)	(0.0595)	(0.0496)	(0.0648)
R-squared	0.337	0.185	0.161	0.078	0.276	0.167

	Total Imports					
	(1) CHN	(2) USA	(3) DEU	(4) SGP	(5) HKG	(6) AUS
$PostDispute_t$	0.0283	-0.0167	-0.0195	-0.151**	-0.333	0.112
	(0.0539)	(0.0402)	(0.0516)	(0.0593)	(0.276)	(0.0942)
R-squared	0.062	0.255	0.108	0.134	0.022	0.039

	Exports - Consumption goods					
	(1) CHN	(2) USA	(3) DEU	(4) SGP	(5) HKG	(6) AUS
$PostDispute_t$	-0.0328	-0.0103	0.0273	-0.0147	-0.249**	-0.315
	(0.0703)	(0.0507)	(0.0677)	(0.0617)	(0.110)	(0.241)
R-squared	0.861	0.574	0.139	0.783	0.426	0.113

	Exports - Production goods					
	(1) CHN	(2) USA	(3) DEU	(4) SGP	(5) HKG	(6) AUS
$PostDispute_t$	-0.0580	-0.0717*	-0.0200	-0.129**	0.0435	-0.135**
	(0.0582)	(0.0388)	(0.0518)	(0.0631)	(0.0504)	(0.0663)
R-squared	0.283	0.203	0.185	0.161	0.504	0.197

	Exports - Production goods (Homogeneous)					
	CHN	USA	DEU	SGP	HKG	AUS
$PostDispute_t$	-0.116*	-0.0375	-0.0352	-0.0676	0.0183	-0.319***
	(0.0608)	(0.0509)	(0.0762)	(0.0623)	(0.0706)	(0.0762)
R-squared	0.227	0.112	0.473	0.241	0.532	0.277

	Exports - Production goods (Differentiated)					
	(1) CHN	(2) USA	(3) DEU	(4) SGP	(5) HKG	(6) AUS
$PostDispute_t$	-0.0505	-0.0937**	-0.0155	-0.0714	0.0218	-0.0881
	(0.0596)	(0.0397)	(0.0494)	(0.0546)	(0.0463)	(0.0623)
R-squared	0.349	0.254	0.056	0.061	0.347	0.050

All specifications include dummy variables for yearly and monthly fixed effects. Observations are 72 for all specifications.

Table A.5: Trade Diversion - Consumer Boycott

	Boycotted apparel					
	(1) CHN	(2) USA	(3) DEU	(4) SGP	(5) HKG	(6) AUS
$PostDispute_t$	0.217	-0.0803	0.0477	-0.0889	0.0761	-0.380*
	(0.151)	(0.181)	(0.465)	(0.192)	(0.108)	(0.221)
R-squared	0.418	0.260	0.070	0.358	0.119	0.366
	Boycotted foods					
	(1) CHN	(2) USA	(3) DEU	(4) SGP	(5) HKG	(6) AUS
$PostDispute_t$	-0.125	-0.0651	-0.0162	-0.146**	-0.211***	-0.0896
	(0.112)	(0.0531)	(0.133)	(0.0663)	(0.0734)	(0.0604)
R-squared	0.874	0.486	0.356	0.697	0.527	0.652
	Boycotted misc. household items					
	(1) CHN	(2) USA	(3) DEU	(4) SGP	(5) HKG	(6) AUS
$PostDispute_t$	-0.170*	-0.0703	0.131	0.116	-0.313***	-0.00477
	(0.0951)	(0.0602)	(0.0973)	(0.0953)	(0.0997)	(0.0938)
R-squared	0.846	0.282	0.179	0.835	0.753	0.436
	Boycotted appliances					
	(1) CHN	(2) USA	(3) DEU	(4) SGP	(5) HKG	(6) AUS
$PostDispute_t$	-0.0462	0.0672*	-0.224***	-0.101	-0.0795	-0.124**
	(0.0578)	(0.0381)	(0.0492)	(0.0787)	(0.0638)	(0.0591)
R-squared	0.114	0.359	0.287	0.558	0.644	0.555
	Boycotted vehicles					
	(1) CHN	(2) USA	(3) DEU	(4) SGP	(5) HKG	(6) AUS
$PostDispute_t$	0.196*	-0.209***	0.0514	-0.792***	-0.271**	-0.121
	(0.111)	(0.0569)	(0.111)	(0.197)	(0.126)	(0.0764)
R-squared	0.390	0.369	0.210	0.414	0.174	0.055

All specifications include dummy variables for yearly and monthly fixed effects. Observations are 72 for all specifications.

Table A.6: Lower Bounds of Treatment Effects: Bilateral Trade with Korea

	Exports	Imports
Weight(ω)	0.27	0.43
Lower Bound	-8.37%	-5.16%

Table A.7: Lower Bounds of Treatment Effects: Japanese Exports to Korea, Product Heterogeneity

	Consumption	Production	Homogeneous	Differentiated
Weight(ω)	0.38	0.44	0.48	0.55
Lower Bound	-6.40%	-4.22%	-6.89%	-9.54%

Table A.8: Lower Bounds of Treatment Effects: Boycotted Items

	Apparel	Foods	Sports & Misc.	Appliances	Vehicles
Weight(ω)	0.68	0.33	0.51	0.21	0.423
Lower Bound	0.15%	-49.69%	-3.74%	-5.35%	-26.21%

Lower bound of the treatment effect is defined as the $\frac{1}{(1+\omega)}$ times the corresponding estimated treatment effects in SCM models, where the ω is the value of the highest weight in constructing synthetic Korea. The lower bounds are calculated based on the complete trade diversion assumption.

Table A.9: Cross validation tests

	(1)	(2)	(3)	(4)	(5)
Exports					
Preintervention	0.009	0.013	0.012	0.011	0.011
Postintervention	0.008	0.016	0.012	0.012	0.012
Imports					
Preintervention	0.224	0.236	0.232	0.232	0.229
Postintervention	0.299	0.316	0.305	0.305	0.302
Predictors					
Yearly outcomes	Y				
Last year outcomes		Y			
Averaged outcomes			Y		
Odd-years outcomes				Y	
Even-years outcomes					Y
Other controls	Y	Y	Y	Y	Y

Each column provides the average of RMSPEs in the preintervention periods and the postintervention periods. Model (1) uses yearly outcome variables, model (2) uses outcome variables in the last year, model (3) uses average outcome variables, model (4) uses outcome variables in odd years, model (5) uses outcome variables in even years as predictors. All models include major gravity variables as predictors. The treated unit's RMSPEs were not used in calculating the averages.

Table A.10: Heterogeneity - Top 15 items, Japanese Exports to Korea

HS Codes (4-digit)	Description
8486	Machines and Apparatus for Semiconductor Devices
8542	Electronic Integrated Circuits and Microassemblies
3920	Plastic Plates, Sheets, Film, Foil and Strip
7208	Iron or Non-alloy Steel; Flat-rolled Products
2902	Cyclic Hydrocarbons
2710	Petroleum Oils, Oils from Bituminous Minerals, Not Crude
7204	Ferrous Waste and Scrap
9001	Optical Fibres and Optical Fibre Bundles
2707	Oils and Other Products of the Distillation of High Temperature Coal Tar
3824	Prepared Binders for Foundry Moulds or Cores
8708	Motor Vehicles; Parts and Accessories
7207	Iron or Non-alloy steel; Semi-finished Products
8479	Machinery and Mechanical Appliances; Having Individual Functions
8703	Motor Cars and Other Motor Vehicles; Principally Designed for the Transport of Persons
3818	Chemical Elements doped for use in Electronics, in the form of Discs or Wafers

Table A.11: Heterogeneity - Bottom 15 items, Japanese Exports to Korea

HS Codes (4-digit)	Description
5303	Jute and Other Textile Bast Fibres
5704	Carpets and other Textile Floor Coverings; of Felt
5904	Linoleum, whether or not cut to shape
6501	Hat-forms, Hat Bodies and Hoods of Felt
5908	Textile Wicks, Woven, Plaited or Knitted; for lamps, stoves, lighters, or candles
5201	Cotton; Not Carded or Combed
5113	Woven Fabrics of Coarse Animal Hair
2616	Precious Metal Ores and Concentrates
1208	Flours and Meals of Oil Seeds or Oleaginous Fruits
4301	Raw Furskins
905	Vanilla
1501	Lard
1601	Sausages and Similar Products of Meat
6603	Trimmings, Parts and Accessories of Articles of no. 6601 or 6602
3704	Photographic Plates, Film, Paper, Paperboard and Textiles

Table A.12: Heterogeneity - Broad Economic Categories (BEC) Classifications

Group	BEC Codes	BEC Description	# of Corresponding HS codes
Consumption Goods	112	Food and beverages, primary, mainly for household consumption	234
	122	Food and beverages, processed, mainly for household consumption	359
	321	Fuels and lubricants, processed (motor spirit)	3
	522	Transport equipment, non-industrial	19
	61	Consumer goods not elsewhere specified, durable	139
	62	Consumer goods not elsewhere specified, semi-durable	374
	63	Consumer goods not elsewhere specified, non-durable	225
Intermediate Goods	111	Food and beverages, primary, mainly for industry	80
	121	Food and beverages, processed, mainly for industry	87
	21	Industrial supplies not elsewhere specified, primary	316
	22	Industrial supplies not elsewhere specified, processed	2401
	31	Fuels and lubricants, primary	10
	322	Fuels and lubricants, processed (other than motor spirit)	16
	42	Parts and accessories of capital goods (except transport equipment)	264
	53	Parts and accessories of transport equipment	104
Capital Goods	41	Capital goods (except transport equipment)	630
	521	Transport equipment, industrial	49

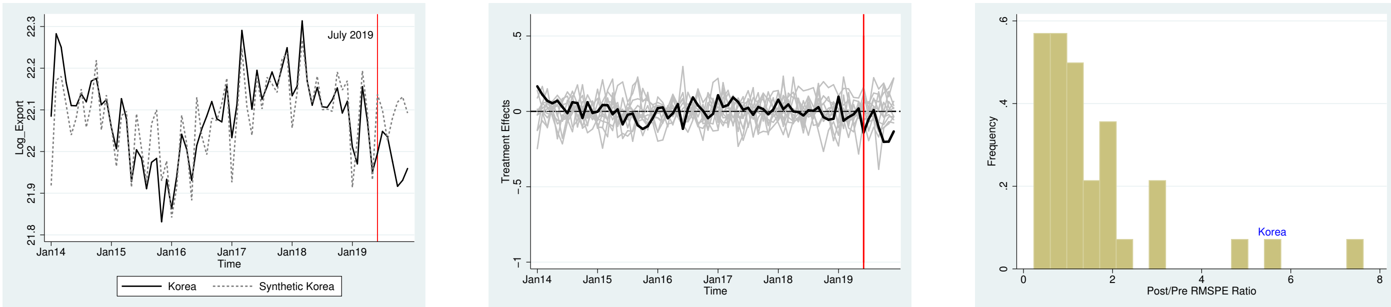
Source: UN Trade Statistics (Link)

Table A.13: Korean Consumer Boycott of Japanese Products: Target Brands, Items, and Corresponding HS Product Codes

Target Brands	Target Items	Group	HS (4digit)	HS (2digit)
Uniqlo, MUJI, Descente, ABC Mart, Daks	Casual Clothes (Male and Female)	Apparel	6101-6108, 6201-6208	61, 62
	Other Casual Clothes and Sportsware		6109, 6110, 6112, 6211	61, 62
Asics, Mizuno	Sports Shoes and Sneakers		6404	64
Kikkoman, S&B (Golden Curry)	Spice (Soy Sauce, Curry)	Foods	2103	21
Morinaga, Pocky, Calbee, Dojima Roll, Royce	Chocolate, Caramel		1702	17
	Sugar Candies		1704	17
	Cookies and Bakery		1905	19
Asahi, Kirin, Sapporo, Santori	Beer		2203	22
All Sake Brands	Fermented Liquor		2206	22
UCC Coffee	Roasted Coffee		901	9
DHC	Cosmetic and Makeup	Sports & Misc. Household Items	3304	33
Uni-ball, Pilot, Zebra, Pentel, Tombow	Pens and Pencils		9608, 9609	96 96
Goo.n, Merries	Baby Diaper		9619	96
Daiwa, Gamakatsu, Shimano, Megabass,	Fishing Rod		9505	95
Honma, Xxio, Cleveland, Mitsubishi, Mizuno	Golf Club		9506	95
Mizuno, Molten, Mikasa, Zett	Sports Items (e.g. Racket, Ball)		9506	95
Sony, Hitachi, Panasonic, Toshiba, Sanyo, JVC, TDK	Televisions	Appliances	8528	85
	Computers (Desktop / Labtop)		8471	84
	Audio Equipment		8519	85
	Video Equipment		8521	85
Jojirushi	Rice Cooker		8516	85
Epson, Fuji Xerox, Brother	Printer and Copier		8443	84
Canon, Nikkon, Olympus	Camera		9006	90
	Optical Lense		9002	90
Casio, Seiko	Watch		9102	91
Toyota, Honda, Nissan, Mitsubishi, Subaru	Passenger Cars	Vehicles	8703	87
Honda, Yamaha, Suzuki	Motorcycle		8711	87

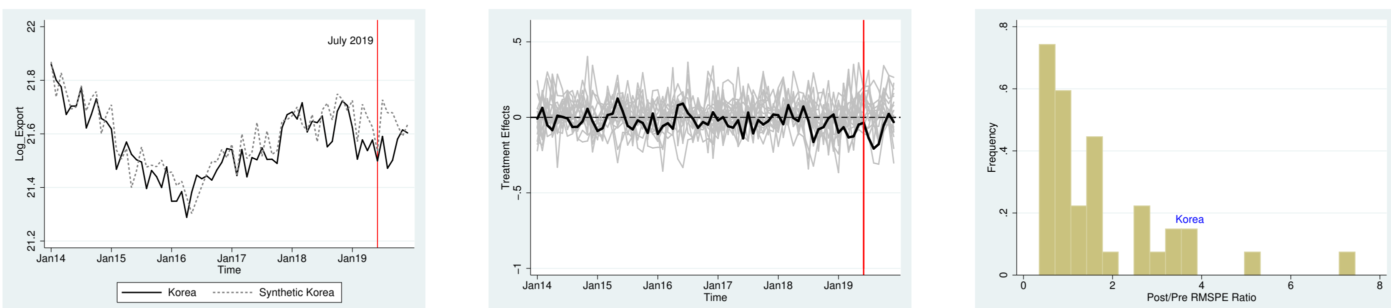
Source: Web-based lists of target Japanese brands for Boycott[1]

[1] https://nonojapan.com/ and http://nojp.info/



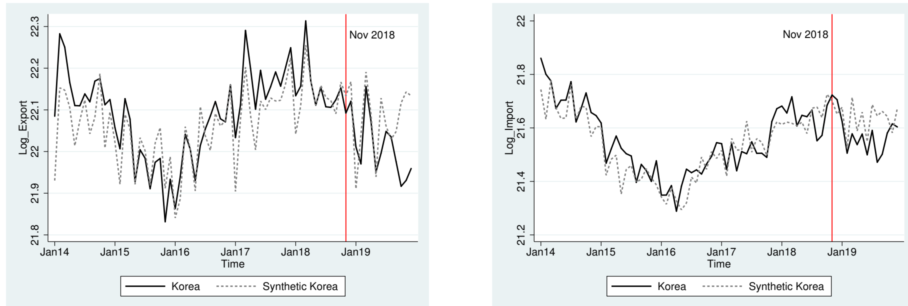
(a) Real Korea vs. Synthetic Korea (b) Placebo Test (c) Post-Pre RMSPE Ratio

Figure A.1: Synthetic Control Analysis on Japanese Total Exports to Korea, Expanded Donor Pool



(a) Real Korea vs. Synthetic Korea (b) Placebo Test (c) Post-Pre RMSPE Ratio

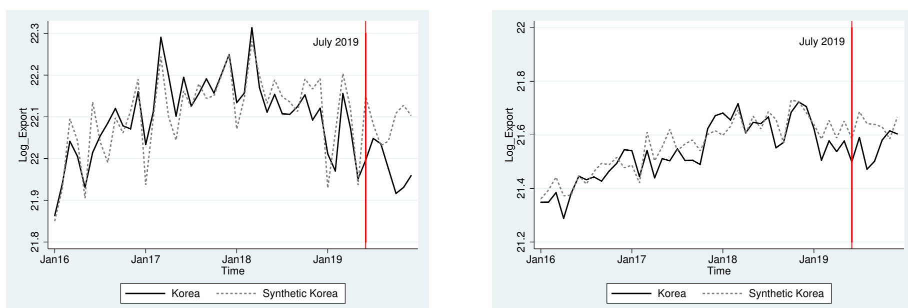
Figure A.2: Synthetic Control Analysis on Japanese Total Imports from Korea, Expanded Donor Pool



(a) Real Korea vs. Synthetic Korea

(b) Real Korea vs. Synthetic Korea

Figure A.3: Synthetic Control Analysis on Japanese Total Exports and Imports, Anticipation Effects



(a) Real Korea vs. Synthetic Korea

(b) Real Korea vs. Synthetic Korea

Figure A.4: Synthetic Control Analysis on Japanese Total Exports and Imports, Shortened Pre-periods

APPENDIX B

SECOND APPENDIX

B.0.1 Example of FDI Motivation Identification

For the reader's convenience, we provide a hypothetical example of matching between firm-level SBA data and industry-level KEXIM-OFDI data in B.0.1. From the firm-level SBA data, suppose we observed that firm 'A', a member of a conglomerate in Seoul producing textile products, made investments in foreign affiliates in 2010 as follows. (See table B1).

Table B1: Example: The firm A's foreign investment in 2010 from SBA data

Year	Location	Size	Industry	Destination	Investment Amounts
2010	Seoul	Conglomarate	Manufacture of Textiles	Taiwan	40
				USA	60
				China	200
				Vietnam	100
				France	100

We can create 5 different 1×5 vectors [Year, Location, Industry, Size, Destination] for each foreign investment, i.e., [2010, Seoul, Manufacture of Textiles, Conglomerate, 'Destination Country'].

Next, we turn to the industry-level KEXIM-OFDI data. Suppose that the industry-level foreign investment information is given as follows for each corresponding vector (See table B2).

Table B2: Example: Industry level FDI information from KEXIM-OFDI data

Year	Location	Size	Industry	Destination	Investment Purpose	Share
2010	Seoul	Conglomarate	Manufacture of Textiles	Taiwan	Market Access	0.2
2010	Seoul	Conglomarate	Manufacture of Textiles	Taiwan	Export Platform	0.7
2010	Seoul	Conglomarate	Manufacture of Textiles	Taiwan	Others	0.1
2010	Seoul	Conglomarate	Manufacture of Textiles	USA	Market Access	0.6
2010	Seoul	Conglomarate	Manufacture of Textiles	USA	Advanced Technology	0.4
2010	Seoul	Conglomarate	Manufacture of Textiles	China	Labor Cost Saving	0.4
2010	Seoul	Conglomarate	Manufacture of Textiles	China	Market Access	0.6
2010	Seoul	Conglomarate	Manufacture of Textiles	Vietnam	Labor Cost Saving	0.8
2010	Seoul	Conglomarate	Manufacture of Textiles	Vietnam	Market Access	0.2
2010	Seoul	Conglomarate	Manufacture of Textiles	France	Others	1

After merging SBA affiliate-level data with KEXIM-OFDI data, from the share information in the KEXIM-OFDI data, we can decompose foreign investments of firm A by the motivation for the investment as follows. (See table B3).

Table B3: Example: Firm A's investment amounts by destinations and purposes

Year	Location	Size	Industry	Destination	Investment Purpose	Investment Amounts
2010	Seoul	Conglomarate	Manufacture of Textiles	Taiwan	Market Access	8=40×0.2
					Export Platform	28=40×0.7
					Others	4=40×0.1
				USA	Market Access	36=60×0.6
					Advanced Technology	24=60×0.4
				China	Labor Cost Saving	80=200×0.4
					Market Access	120=200×0.6
				Vietnam	Labor Cost Saving	80=100×0.8
					Market Access	20=100×0.2
				France	Others	100=100×1

After aggregating all investments by investment motivation, firm A's investment can be finally summarized as follows. (See table B4).

We can say that firm A's primary motivation for foreign investment in 2010 was market access, as it ranked the top among all FDI purposes. However, we also observe that firm A has invested nonnegligible amounts abroad for labor cost savings, even though this was not the primary purpose of the investment. This is because the industry-level shares of labor cost saving FDI to China and Vietnam were quite high in the KEXIM-OFDI data, and firm A has invested mostly in those

Table B4: Example: Firm A's investment amounts by purposes

Year	Location	Size	Industry	Investment Purpose	Investment Amounts
2010	Seoul	Conglomarate	Manufacture of Textiles	Market Access	184
				Labor Cost Saving	160
				Export Platform	28
				Advanced Technology	24
				Others	104

countries.[1]

[1] There is a practical issue in merging SBA data and KEXIM-OFDI data. In reporting the amount of investment, SBA data use the stock amount of investment, whereas KEXIM-OFDI data use the flow of money wired to affiliates. Definitions of investments are not perfectly consistent between data. To address this issue, we match the vector from SBA data to the most recent 3-year observations in the KEXIM-OFDI data. We confirm that changing the number of years when matching datasets does not significantly alter our results.

Table B5: Industry Classification

Code	Sector	Industry description	% Multinationals
10	Manufacturing	Manufacture of Food products	19.68
11	Manufacturing	Manufacture of Beverages	26.13
12	Manufacturing	Manufacture of Tobacco products	
13	Manufacturing	Manufacture of Textiles, except apparel	22.30
14	Manufacturing	Manufacture of Wearing apparel, clothing accessories and fur articles	40.18
15	Manufacturing	Tanning and Dressing of Leather , Manufacture of Luggage and Footwear	42.08
16	Manufacturing	Manufacture of Wood and of products of Wood and Cork, except furniture	26.00
17	Manufacturing	Manufacture of Pulp, Paper and Paper products	15.05
18	Manufacturing	Printing and Reproduction of Recorded media	10.83
19	Manufacturing	Manufacture of Coke, hard-coal and lignite fuel briquettes and Refined Petroleum Products	61.17
20	Manufacturing	Manufacture of Chemicals and chemical products except pharmaceuticals and medicinal chemicals	33.54
21	Manufacturing	Manufacture of Pharmaceuticals, Medicinal Chemicals and Botanical Products	21.52
22	Manufacturing	Manufacture of Rubber and Plastic Products	33.57
23	Manufacturing	Manufacture of Other Non-metallic Mineral Products	19.13
24	Manufacturing	Manufacture of Basic Metal Products	26.71
25	Manufacturing	Manufacture of Fabricated Metal Products, Except Machinery and Furniture	26.65
26	Manufacturing	Manufacture of Electronic Components, Computer, Radio, Television and Communication Equipment and Apparatuses	46.00
27	Manufacturing	Manufacture of Medical, Precision and Optical Instruments, Watches and Clocks	44.95
28	Manufacturing	Manufacture of Electrical Equipment	38.10
29	Manufacturing	Manufacture of Other Machinery and Equipment	32.97
30	Manufacturing	Manufacture of Motor Vehicles, Trailers and Semitrailers	35.78
31	Manufacturing	Manufacture of Other Transport Equipment	20.04
32	Manufacturing	Manufacture of Furniture	37.39
33	Manufacturing	Other manufacturing	34.41
34	Manufacturing	Maintenance and Repair Services of Industrial Machinery and Equipment	
45	Sales	Sale of Motor Vehicles and Parts	3.69
46	Sales	Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	15.13
47	Sales	Retail Trade, Except Motor Vehicles and Motorcycles	11.92
49	Service	Land Transport ; Transport Via Pipelines	2.34
50	Service	Water Transport	33.84
51	Service	Air Transport	28.26
52	Service	Storage and support activities for transportation	15.94
55	Service	Accommodation	8.96
56	Service	Food and beverage service activities	10.17
58	Service	Publishing activities	18.31
59	Service	Motion picture, video and television programme production, sound recording and music publishing activities	18.67
60	Service	Broadcasting	3.70
61	Service	Telecommunications	25.32
62	Service	Computer programming, consultancy and related activities	18.92
63	Service	Information service activities	15.04
68	Service	Real Estate Activities	8.88
69	Service	Renting and leasing; except real estate	28.89
70	Service	Research and Development	13.17
71	Service	Professional Services	17.09
72	Service	Architectural, Engineering and Other Scientific Technical Services	8.89
73	Service	Professional, Scientific and Technical Services, n.e.c.	22.40
74	Service	Business Facilities Management and Landscape Services	1.45
75	Service	Business Support Services	3.92
84	Service	Public administration and defence; compulsory social security	
85	Service	Education	15.11
86	Service	Human health activities	
87	Service	Social Work Activities	
90	Service	Creative, Arts and Recreation Related Services	6.80
91	Service	Sports activities and amusement activities	5.07
94	Service	Membership Organizations	
95	Service	Maintenance and Repair Services	2.57
96	Service	Other Personal Services Activities	6.10

Table B6: Developed Countries & Emerging Countries

Group	Countries
Developed Countries	**(Asia)** Hong Kong, Israel, Japan, Singapore **(America)** Canada, United States **(Europe)** Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Netherlands, Italy, Luxembourg, Norway, Sweden, Switzerland, United Kingdom **(Oceania)** Australia, New Zealand
Emerging Countries	**(Asia)** Cambodia, China, Indonesia, Laos, Malaysia, Philippines, Thailand, Vietnam

APPENDIX C

THIRD APPENDIX

C.0.1 Derivation of Equation (3.2)

The representative consumer's utility maximization can be written as

$$\max_{q_i^c} U \quad \text{subject to} \quad q_0^c + \int p_i q_i^c di = I^c$$

where $U = q_0^c + \alpha \int (q_i^c + z_i)di - \frac{1}{2}\beta\{\int (q_i^c - z_i)di\}^2 - \frac{1}{2}\gamma \int (q_i^c - z_i)^2 di$ and I^c is the consumer's total expenditure. The first-order condition of the utility maximization problem is

$$p_i = \alpha - \gamma(q_i^c - z_i) - \beta \int (q_i^c - z_i)di$$

By aggregating f.o.c with respect to i, we obtain

$$\begin{aligned}
\int p_i di &= \int \{\alpha - \frac{\gamma}{L}(q_i - Lz_i) - \frac{\beta}{L}\int (q_i - Lz_i)di\}di \\
P &= M(\alpha - \frac{\beta}{L}\int (q_i - Lz_i)di) - \frac{\gamma}{L}\int (q_i - Lz_i)di \\
M\alpha - P &= \frac{\beta M + \gamma}{L}\int (q_i - Lz_i)di \\
\int (q_i - Lz_i)di &= \frac{L(M\alpha - P)}{\beta M + \gamma}
\end{aligned}$$

where $P = \int p_i di$, $M = \int di$, and $q_i^c = \frac{1}{L}q_i$. By substituting the equation above into the FOC again, we obtain the final simple demand function formula of equation (3.2).

$$\begin{aligned}
p_i &= \alpha - \frac{\beta}{L}\frac{L(M\alpha - P)}{\beta M + \gamma} + \gamma z_i + \frac{\gamma}{L}q_i \\
&= A + \gamma z_i - \frac{\gamma}{L}q_i
\end{aligned}$$

where $A = \alpha - \frac{\beta(M\alpha - P)}{\beta M + \gamma} = \frac{\alpha\gamma + \beta P}{\beta M + \gamma}$.

C.0.2 Proofs of Propositions

- **Proposition 1**

  From (3.6),

$$\frac{L\{A+\gamma z(v^*(x))-c(x,v^*(x))\}^2}{4\gamma}=h(v^*(x))$$

By totally differentiating the above equation (zero profit condition at the product frontier) with respect to x, we can express $\frac{\partial v^*(x)}{\partial x}$ as follows.

$$\frac{\partial v^*(x)}{\partial x}=\frac{B\cdot\frac{\partial c(x,v^*(x))}{\partial x}}{B\cdot\left\{\gamma\frac{\partial z(v^*(x))}{\partial v^*}-\frac{\partial c(x,v^*(x))}{\partial v}\right\}-\frac{\partial h(v^*(x))}{\partial v}}$$

where $B\equiv\frac{L\{A+\gamma z(v^*(x))-c(x,v^*(x))\}}{2\gamma}>0$.
As $\frac{\partial c(x,v^*(x))}{\partial x}>0$ and $\frac{\partial h(v^*(x))}{\partial v}>0$, $\frac{\partial v^*(x)}{\partial x}<0$ if $\gamma\frac{\partial z(x,v^*(x))}{\partial v^*}<\frac{\partial c(x,v^*(x))}{\partial v}$.
Accordingly, $\frac{dc(x,v^*(x))}{dx}=\frac{\partial c(x,v^*(x))}{\partial x}+\frac{\partial c(x,v^*(x))}{\partial v}\frac{\partial v^*(x)}{\partial x}>0$

- **Proposition 2**

  Proposition 2.1

  By totally differentiating the free entry condition (3.10) with respect to L, we obtain

$$\frac{\partial\Pi^e}{\partial L}+\frac{\partial\Pi^e}{\partial A}\frac{\partial A}{\partial L}=0$$

As $\frac{\partial\Pi^e}{\partial L}>0$ and $\frac{\partial\Pi^e}{\partial A}>0$, $\frac{\partial A}{\partial L}<0$.

Proposition 2.2

By totally differentiating the optimal profit function with respect to L, we obtain the following equation.

$$\begin{aligned}\frac{\partial\pi^*(x,v)}{\partial L}&=\frac{\{A+\gamma z(v^*(x))-c(x,v)\}^2}{4\gamma}+\frac{L\{A+\gamma z(v^*(x))-c(x,v)\}}{2\gamma}\Big(\frac{dA}{dL}+\gamma\frac{dz}{dv^*}\frac{dv^*}{dL}\Big)\\&=\frac{\{A+\gamma z(v^*(x))-c(x,v)\}}{4\gamma}\Big\{A+\gamma z(v^*(x))-c(x,v)+2L\Big(\frac{dA}{dL}+\gamma\frac{dz(v^*(x))}{dv^*}\frac{dv^*(x)}{dL}\Big)\Big\}\end{aligned}$$

Define the firm's unit cost cutoff as $\tilde{c}(x)\equiv A+\gamma z(v^*(x))+2L\big(\frac{dA}{dL}+\gamma\frac{dz(v^*(x))}{dv^*}\frac{dv^*(x)}{dL}\big)$. Then $c(x,v)\lesseqgtr\tilde{c}(x)\rightleftharpoons\frac{d\pi^*(x,v)}{dL}\gtreqless 0$.

Proposition 2.3

For trade liberalization ($dL > 0$),

$$\begin{aligned}\frac{d\tilde{c}(x)}{dx} &= \gamma\frac{dz(v^*(x))}{dv^*}\frac{dv^*(x)}{dx} + 2L\gamma\frac{1}{dx}\frac{dz(v^*(x))}{dv^*}\frac{dv^*(x)}{dL} \\ &= \gamma\frac{dz(v^*(x))}{dv^*}\frac{dv^*(x)}{dx}(1 + 2L\frac{1}{dL}) < 0\end{aligned}$$

Proposition 2.4

By totally differentiating (3.7), the zero profit condition of the least productive firm with respect to L, we obtain

$$\frac{d\pi^*(x_n, 0)}{dL} = \frac{(A + \gamma z(0) - x_n)^2}{4\gamma} + \frac{L(A + \gamma z(0) - x_n)}{2\gamma}\Big(\frac{dA}{dL} - \frac{dx_n}{dL}\Big) = 0$$

Then, by Proposition 2.2,

$$\frac{dx_n}{dL} = \frac{1}{2L}\Big(A + \gamma z(0) - x_n + 2L \cdot \frac{dA}{dL}\Big) = \frac{1}{2L}\big(\tilde{c}(x_n) - x_n\big) < 0$$

as far as $\tilde{c}(x_n) < x_n$.

- **Proposition 3**

Proposition 3.1

From (3.6),

$$\frac{L\{A + \gamma z(v^*(x)) - c(x, v^*(x))\}^2}{4\gamma} = h(v^*(x))$$

By totally differentiating the above equation (zero profit condition at the product frontier) with respect to L, we obtain

$$\begin{aligned}&\frac{\{A + \gamma z(v^*(x)) - c(x, v^*(x))\}^2}{4\gamma} + \frac{L\{A + \gamma z(v^*(x)) - c(x, v^*(x))\}}{2\gamma} \\ &\cdot\Big\{\frac{dA}{dL} + \gamma\frac{dz(v^*(x))}{dv^*(x)}\frac{dv^*(x)}{dL} - \frac{\partial c(x, v^*(x))}{\partial v}\frac{dv^*(x)}{dL}\Big\} = \frac{dh(v^*(x))}{dv}\frac{dv^*(x)}{dL}\end{aligned}$$

$$\begin{aligned}&\frac{\{A + \gamma z(v^*(x)) - c(x, v^*(x))\}}{4\gamma} \\ &\cdot\Big\{(A + \gamma z(v^*(x)) - c(x, v^*(x)) + 2L\Big(\frac{dA}{dL} + \gamma\frac{dz(v^*(x))}{dv^*(x)}\frac{dv^*(x)}{dL} - \frac{\partial c(x, v^*(x))}{\partial v}\frac{dv^*(x)}{dL}\Big)\Big\} \\ &= \frac{dh(v^*(x))}{dv}\frac{dv^*(x)}{dL}\end{aligned}$$

Recall that $\tilde{c}(x) = A + \gamma z(v^*(x)) + 2L\left(\frac{dA}{dL} + \gamma \frac{dz(v^*(x))}{dv^*}\frac{dv^*(x)}{dL}\right)$. Therefore,

$$\frac{\{A + \gamma z(v^*(x)) - c(x, v^*(x))\}}{4\gamma}\{(\tilde{c}(x) - c(x, v^*(x))\} = \frac{dv^*(x)}{dL}\left(\frac{dh(v^*(x))}{dv} + 2L\frac{\partial c(x, v^*(x))}{\partial v}\right)$$

As $A + \gamma z(v^*(x)) - c(x, v^*(x)) > 0$, $\frac{dh}{dv} > 0$, and $\frac{\partial c(x,v^*(x))}{\partial v} > 0$,

$c(x, v^*(x)) \lesseqgtr \tilde{c}(x) \rightleftharpoons \frac{dv^*(x)}{dL} \gtreqless 0$

Proposition 3.2

Suppose that $c(0, v^*(0)) < \tilde{c}(0)$. Then, to meet free entry condition, $\tilde{c}(x_n) < c(x_n, v^*(x_n)) = x_n$. From the continuity of the cost function, there must be $\bar{x} \in (0, x_n)$ such that $c(\bar{x}, v^*(\bar{x})) = \tilde{c}(\bar{x})$. Then, $c(x, v^*(x)) \lesseqgtr \tilde{c}(x)$ for $x \lesseqgtr \bar{x}$ should hold, by Proposition 1.2 ($\frac{dc(x,v^*(x))}{dx} > 0$). Thus, from Proposition 3.1, $\frac{dv^*(x)}{dL} \lesseqgtr 0$ for $x \gtreqless \bar{x}$.

C.1 Discussion of the Structural Estimation

C.1.1 Estimation of Productivity

We describe our strategy for productivity estimation in Appendix C.1.1. We followed the newly developed Kim et al. (2019)(hereafter KLS(2019)), which is an upgraded extension of the widely used Ackerberg et al. (2015)(hereafter ACF(2015))'s two-step control function approach. Our production function is the value-added production function as follows:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it} \tag{C.1}$$

where l_{it} denotes logged labor input, k_{it} denotes logged capital input, ω_{it} is the unobserved productivity shock that follows the 1st-order Markov process,[1] and ϵ_{it} is an iid shock. Our goal is to correctly estimate $\hat{\omega}_{it}$, total factor productivity (TFP), which is not observed by the researcher but potentially affects the firm's labor and capital input decision. Once we estimate output elasticities of labor and capital, $(\hat{\beta}_l, \hat{\beta}_k)$, we obtain the estimate of TFP from $\hat{\omega}_{it} = y_{it} - \hat{\beta}_0 - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it}$. However, ordinary least squares (OLS) estimation will yield bias in $(\hat{\beta}_l, \hat{\beta}_k)$ due to simultaneity between labor capital input and productivity shocks. Control function methods have been widely used to tackle such endogeneity issues from productivity shocks ω_{it}.

The modern literature on production function estimation based on the control function technique starts from the seminal work of Olley and Pakes (1996) (hereafter OP(1996)) and the following work of Levinsohn and Petrin (2003) (hereafter LP(2003)). Early in the literature, OP(1996) proposed investment as a proxy for productivity shock. However, the lumpiness of investments (i.e., zero or missing values of investments) weakens the precision of OP(1996)'s estimates, and LP(2003) suggested intermediate input as an alternative proxy to deal with the lumpiness of investments. Since LP(2003)'s work, intermediate input (m_{it}) has generally been used as a proxy variable for the productivity shock to rule out endogeneity. ACF(2015) also used m_{it} as a proxy. ACF(2015) went one step further by suggesting an alternative two-step control function approach to elegantly deal

[1] $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$, and ξ_{it} is an iid shock.

with the endogeneity issue plus the functional dependence problem that OP(1996) and LP(2003) suffered from. KLS(2019) extended and strengthened ACF(2015).

We define the intermediate input function as follows.

$$m_{it} = f(l_{it}, k_{it}, \omega_{it}) \tag{C.2}$$

where $f(\cdot)$ is assumed to be monotone with respect to ω_{it}. Then, the productivity shock ω_{it} can be expressed by the inverse of $f(\cdot)$.

$$\omega_{it} = f^{-1}(l_{it}, k_{it}, m_{it}) \tag{C.3}$$

Step 1.

We first estimated the following equation using OLS.

$$\begin{aligned} y_{it} &= \beta_0 + \beta_l l_{it} + \beta_k k_{it} + f^{-1}(l_{it}, k_{it}, m_{it}) + \epsilon_{it} \\ &= \phi(l_{it}, k_{it}, m_{it}) + \epsilon_{it} \end{aligned} \tag{C.4}$$

and obtained the estimate of the predicted part, $\hat{\phi}(l_{it}, k_{it}, m_{it})$, which should be used in the next step.

Step 2.

As the productivity shock follows the first-order Markov process, our value-added production function can be written as follows.

$$\begin{aligned} y_{it} &= \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \{g(\omega_{it-1}) + \xi_{it}\} + \epsilon_{it} \\ &= \beta_0 + \beta_l l_{it} + \beta_k k_{it} + g(\phi(l_{it-1}, k_{it-1}, m_{it-1}) - \beta_0 - \beta_l l_{it-1} - \beta_k k_{it-1}) + \xi_{it} + \epsilon_{it} \end{aligned} \tag{C.5}$$

Therefore, the sum of two iid shocks $\xi_{it} + \epsilon_{it}$ is

$$\xi_{it} + \epsilon_{it} = y_{it} - \beta_0 - \beta_l l_{it} - \beta_k k_{it} - g(\phi(l_{it-1}, k_{it-1}, m_{it-1}) - \beta_0 - \beta_l l_{it-1} - \beta_k k_{it-1}) \tag{C.6}$$

We finally used the following moment conditions to estimate the output elasticities of $(\hat{\beta_l}, \hat{\beta_k})$. For the estimation, we used the generalized methods of moments (GMM) approach.

$$E[(\xi_{it} + \epsilon_{it}) \otimes \begin{bmatrix} 1 \\ k_{it} \\ l_{it-1} \end{bmatrix}] = 0 \tag{C.7}$$

As pointed out by KLS(2019), however, ACF(2015) may not be robust to the selection of initial values in the GMM estimation of Step 2 because the objective function of GMM may have multiple local minima. Following the suggestion of KLS(2019)'s sequential approach, we divided grids of initial values for β_l and β_k from 0 to 1 by the length of 0.1. For each point in the grid, we searched estimates of output elasticities $(\hat{\beta_l}, \hat{\beta_k})$ that minimize the objective function. We finally chose the estimates $(\hat{\beta_l}, \hat{\beta_k})$ for which the value of the objective function becomes minimal across all initial points in the grids.

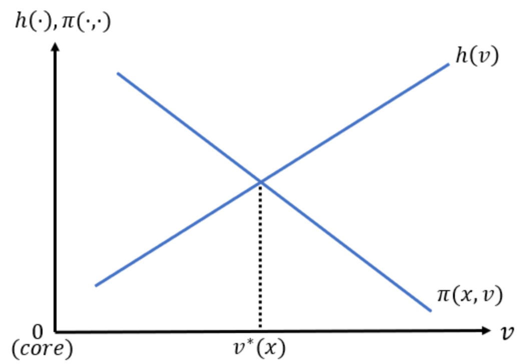


Figure C.1: Optimal product-technology scope, $v^*(x)$

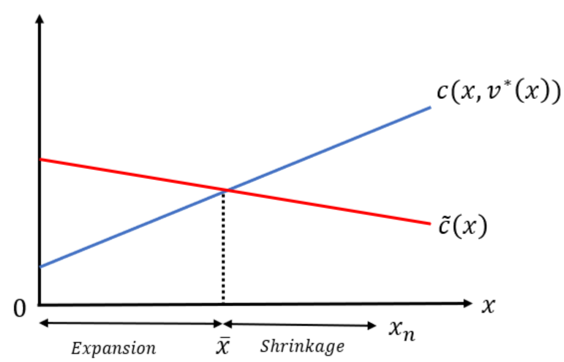


Figure C.2: Firm-level scope adjustment

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