Economics
The Open-Access, Open-Assessment E-Journal

Vol. 9, 2015-43 | December 01, 2015 | http://dx.doi.org/10.5018/economics-ejournal.ja.2015-43

FTA Effects on Agricultural Trade with Matching Approaches

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Abstract
While the trade effect of free trade agreements (FTAs) is a global issue, little research has examined the economic effects of trade liberalization on agricultural products with robust empirical methods. In this study, propensity score matching for controlling selection bias is used to examine and analyze the effect of FTAs on the trade of South Korea's agricultural products. To enhance the robustness of the estimated results, differences between the FTA treatment effects in 2010 and 2012 are analyzed. The results reveal that the effect of FTAs on agricultural trade varies slightly, depending on the matching approach used; however, the signs of all estimated average treatment effects on the treated (ATT) values are positive. Analysis of the difference between selection bias controlled through matching and uncontrolled selection bias shows that the value of the average treatment effect (ATE) with uncontrolled bias is greater than the ATT estimate calculated through matching. This implies that controlled versus uncontrolled selection bias can result in different ATE and ATT estimates, and that previous studies on FTA trade effects have overestimated the effect, because selection bias was not fully addressed.

JEL C54 F15 Q17
Keywords Free trade agreement; agricultural trade; selection bias; propensity score matching

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Citation GaSeul Lee and Song Soo Lim (2015). FTA Effects on Agricultural Trade with Matching Approaches. *Economics: The Open-Access, Open-Assessment E-Journal*, 9 (2015-43): 1—26. http://dx.doi.org/10.5018/economics-ejournal.ja.2015-43

Received April 1, 2015 **Published as Economics Discussion Paper** April 9, 2015
Revised November 16, 2015 **Accepted** November 25, 2015 **Published** December 1, 2015

1 Introduction

Since the Uruguay Round in 1994, multilateral free trade negotiations have been led by the World Trade Organization (WTO). However, as the WTO talks have progressed slowly, free trade agreements (FTAs) that lower tariffs and nontariff barriers for goods, services, investments, intellectual properties, and government procurement between signatories are proliferating globally and helping to facilitate mutual trade. According to the WTO Regional Trade Agreements Information System (RTA-IS, rtais.wto.org), 268 FTAs are in force worldwide.

Since the conclusion of an FTA with Chile in April 2004 to "catch up" with global trends, South Korea has ratified nine additional FTAs, with Singapore, the European Free Trade Association (EFTA), the Association of Southeast Asian Nations (ASEAN), India, the European Union (EU), Peru, the United States, Turkey, and Australia. The country also completed five FTAs with Colombia, Canada, China, New Zealand, and Vietnam.[1]

A rapid expansion of FTAs is partly explained by pursuing strategies associated with export led growth models (Palley 2012). Especially, FTA-driven trade creation is regarded as a powerful engine of economic growth for Asian economies, including South Korea (Frankel et al. 1996; Kawai and Wignaraja 2014). However, active pursuit of the so-called mega-FTAs and multiple trade deals en masse by South Korea have created a sense of anxiety in which political leaders and farm organizations are constantly fearful of a surge in imports that may lead to the collapse of whole farm sectors. Relying on foreign sources for more than 70% of its domestic food needs, and struggling with relatively higher production costs, the country has stuck to the negotiation rule of "exclusion from concession or partial opening up" for major agricultural products in every trade liberalization talks.

The "opening up" of the South Korean agricultural markets through the channels of FTAs was not until 2011 when each of the EU and the United States became members of the economic blocs. As Kwon et al. (2005) and Kwock et al. (2010) implied, the country began to import a large amount of agricultural products, which resulted in greater trade deficits.

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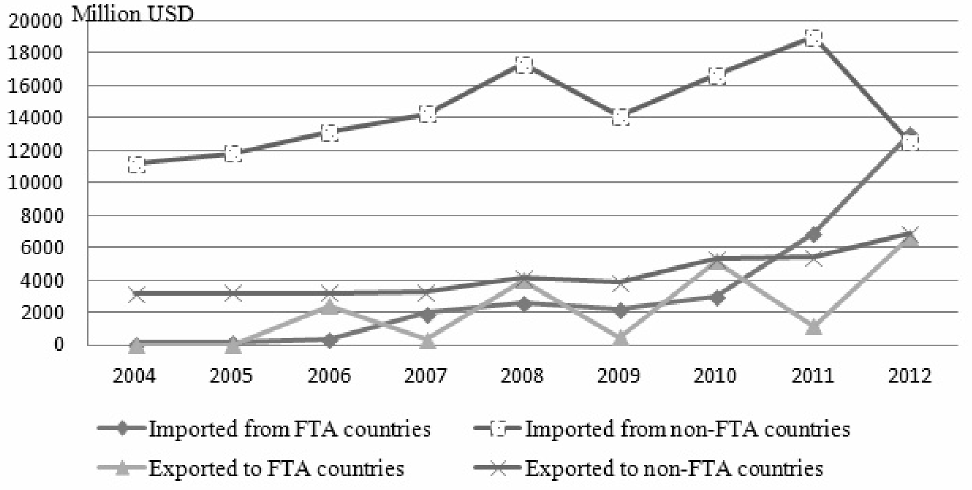
[1] An up-to-data status of South Korea's FTAs is posted at the governmental portal website (fta.go.kr).

Figure 1: Agricultural Trade with FTA and Non-FTA Countries



Source: Global Trade Atlas

Figure 1 illustrates the volumes of agricultural products exported from and imported into South Korea with FTA and non-FTA member countries between 2004 and 2012. A significant increase in imports from the FTA partners explains the large drop in imports from the non-FTA countries in the 2011–12 periods.

Following the WTO's classification, this paper defines agricultural products as goods bearing harmonized system (HS) codes of 01–24 at the two digit level. Agricultural imports and exports alike increased with both FTA and non-FTA partners. Agricultural imports from FTA blocs are found to be rapidly increasing, and in 2012 exceeded the amount from non-FTA countries. Agricultural exports have also increased with FTA members, to gradually offset the trade gap with non-FTA economies. This sheds light on a significant trade effect of successive FTAs.

Table 1 illustrates agricultural trade within FTAs. It shows the volumes of trade with those countries each year from the year in which the respective FTA took effect. As of 2014, 15 FTAs had either been signed or taken effect of which South Korea is a party, but only the FTAs that had been effective for at least two years are treated as full-launch FTAs.

Table 1: Agricultural Trade with Effective-FTA Countries

Unit: Million USD

Country (Year in effect)	Trade	Year in effect	After first year	After second year	After third year	After fourth year	After fifth year	After sixth year	After seventh year	After eighth year
Chile	Import	126	183	233	299	280	308	329	459	484
(2004)	Export	1.2	1.0	0.8	2.4	3.5	3.3	4.5	7.5	5.2
Singapore	Import	37	42	47	52	83	102	94		
(2006)	Export	26	30	40	47	89	85	95		
EFTA	Import	74	103	93	108	144	209	187		
(2006)	Export	5.2	3.6	5.7	5.2	7.0	7.2	14		
ASEAN	Import	1539	2226	1789	2113	3189	3345			
(2007)	Export	314	399	454	607	853	983			
India	Import	346	417	641						
(2010)	Export	12	13	11						

Source: Global Trade Atlas

In comparison to 2004 South Korea's exports to Chile increased 4.3-fold in 2012, the eighth year of the FTA. Imports from Chile have also increased 3.8-fold over the same period. With Singapore, exports and imports have increased 3.6- and 2.5-fold, respectively, in the sixth year of the FTA, in comparison to the year in effect. Exports to and imports from the EFTA have increased 2.7- and 2.5-fold, respectively. In the fifth year of FTA implementation with the ASEAN exports and imports have increased 3.1- and 2.2-fold, respectively. Exports to India have slightly decreased, but imports have increased 1.7-fold.

However, the bilateral trade performance under each FTA framework may not be considered as trade effects on the grounds that multiple FTAs are inextricably interwoven one another and simultaneously effective. Besides, a variety of factors, including exchange rate fluctuations, tariffs, non-tariff measures, and natural disasters can affect trade to a large extent. This means that it may not be appropriate to attribute the trade effect solely to FTAs, given the potential for selection bias. Therefore, selection bias should be controlled to identify the pure effect of FTAs on the trade of South Korea's agricultural products.

To this end, this study uses propensity score matching (PSM) to mitigate selection bias while focusing on a country's observable heterogeneity. PSM is an approach used to address selection bias by applying two strong conditions as restrictions in estimating propensity scores (Blundell and Costa-Dias 2009). Because agricultural trade data, not probabilistic data, are used to classify FTA and non-FTA countries, selection bias can occur. Therefore, PSM is used in this study to analyze the trade effect of FTAs, and to suggest implications. To ensure robust estimation results, data from 2010 and 2012 are compared and explained.

This study is organized as follows. Section 2 describes previous studies that investigated the effects of FTAs with respect to South Korea. Section 3 explains both the characteristics of PSM and the methodology, and it defines the variables used in this study. Section 4 applies PSM and identifies the characteristics of each set of matching-approach results; it also explains the trade effect by comparing differences between 2010 and 2012. Section 5 offers conclusions and implications.

2 Literature Review

While prior studies analyze the feasibility of an FTA prior to negotiations, post-FTA studies explore the economic effects associated with trade policy reforms, including tariff cuts or elimination. Both prior and post-FTA studies focus on the impact of FTAs on trade volume following the reduction or elimination of tariffs in the domestic market.

Widely adopted analytical methods include those that make use of the computable general equilibrium (CGE) model, the partial equilibrium model, and the gravity model. The CGE model quantitatively measures the effect of bilateral FTAs, through the use of virtual simulation; it generates easily understood macro-indexes. However, the CGE model is not ideal for analyzing segmented markets, and its results are considered unreliable due to the unrealistic assumptions therein. The partial equilibrium model often considers agricultural products produced in South Korea and imported as homogeneous goods, to define the difference between domestic demand and supply as an import-demand index. It estimates changes in import demand after price changes have occurred among imported goods, to measure the impact on its own country through the use of estimates. However, it is not ideal either, because domestic and imported agricultural products are considered homogenous goods, and quality differences are hence ignored. The criticism has arisen that using this method contributes to an overestimation of price drops or reduced production. The gravity model adds geographical factors—including economic scale and distance, *inter alia*—to analyze both the factors that determine trade volume between bloc economies and the welfare effect of FTAs. Going beyond analogy with Newton's Law of Gravitation, the recent literature provides a theoretical and economic foundation for gravity modeling (Anderson and van Wincoop 2003; Anderson 2011).

Table 2 lists the studies that have examined the welfare effects of FTAs that have occurred with respect to South Korea's agricultural trade.

Most prior studies have estimated the expected effects of FTAs, in advance of their implementation. On the other hand, the number of post-FTA studies—which analyze the effect of FTAs on an economy, following their implementation—is relatively small. All of these studies focus on bilateral free trade while explaining some of specific agricultural products like beef, red pepper, and fruit.

To verify empirically the effects of FTAs on agricultural trade, it is essential to select and use a method that addresses causes and effects among variables. A key component of this process is to isolate the FTA effect on agricultural trade, because various extraneous demand-and-supply fluctuation factors make it difficult to

Table 2: A Selective List of FTA Studies

Partner countries	Empirical studies			Non-empirical studies
	Computable general equilibrium	Partial equilibrium	Gravity model	
Chile		Eor et al. (1999) Moon and Hong (2004) Kim and Choi (2007) Moon et al. (2012)		Park (2013)
Singapore		Choi and Choi (2004)		
EFTA		Eor et al. (2004)		
ASEAN		Kim (2004)		
India		Lee and Kim (2008)		
EU			Kwock et al. (2010)	
United States	Kim (2001) Lee et al. (2005) Kim (2008) Ahn et al. (2009)	Kwon et al. (2005) Kim (2006) Kim and Jang (2008) Moon et al. (2013)		Cooper and Manyin (2011)

Source: Authors' compilation.

quantify the net effect of an FTA. In the presence of selection bias, estimating a linear regression model is likely to yield biased and inconsistent estimates of parameters.

Selection bias or biased allocation to interventions arises because the selection of countries for analysis is not representative of the population. The lack of the random allocation or experimental designs leads to the problem of selection bias.

This selection problem can be remedied by various methods, including instrumental variable estimation, Heckman's two-stage estimation, the fixed-effects model, and the matching approach (Damondar and Dawn 2008). However, even these methods pose challenges. For instance, it is difficult to pinpoint ideal instrumental variables within an instrumental variable estimation. The fixed-effects model does require lagged variables as an independent variable. In Heckman's two-stage estimation, a huge challenge is to properly specify the selection equation and the outcome equation (Lee et al. 2008; Kim 2010). This paper adopts a matching approach on the grounds that it can produce net outcomes by comparing trade of non-FTA countries that are similar to FTA partners in all relevant characteristics with that of FTA partners. There are only a few studies that applied the matching methods to trade analysis.

Focusing on the distance factor, Baier and Bergstrand (2009) controlled selection bias through the so-called Mahalanobis matching, and estimated the FTA effects by the gravity model. That study finds a stable long-term effect of FTAs and a significant trade creating effect. Chang and Lee (2011) use the pair matching and nonparametric methods and find a significant GATT/WTO membership effect on trade within the FTA framework.

Iacus et al. (2012) introduces coarsened exact matching (CEM), an effective approach to reducing imbalance between a treatment group and a comparison group. This method, however, leads to sample loss in the process of coarsening each section of the treatment group and the comparison group. Therefore, CEM is an approach ideal for a case involving a large sample.

The above matching methods are robust to potential selection bias, but their applications are limited by the reliance on the relatively large sample sizes. In fact, the small number of FTA countries with South Korea makes it difficult to identify similar characteristics among the comparison group and thus causes a selection problem (Dehejia and Wahba 2002). An alternative is to use the PSM method. PSM makes use of bootstrapping, which allows the treatment group and the comparison group to have as many similar or identical propensities as possible (Rosenbaum and Rubin 1983).

Hayakawa (2012) adopts a PSM approach through 1:1 nearest-neighbor matching and suggests that FTAs do not have a great impact on unemployment. Nayga et al. (2011) address the effect of school lunch programs on obesity among elementary school children. This study controls selection bias by opting for the nearest-neighbor, kernel, and radius-matching approaches. In particular, the radius-matching method is carried out by widening the scope of radius by 0.5 units on the basis of the treatment group, to compare changes in the effect of treatment. Kim and Kim (2011) incorporate data matching to analyze wage gaps among temporary workers. They identify differences in the wage effect before and after data matching, and robustly explain the effect of wage gaps by controlling by the ratio of the treatment group to the comparison group.

Up to now, there are only a few studies that employ matching techniques in assessing agricultural trade effects of FTAs. In this regard, the current study ensures a meaningful contribution to the literature.

3 Empirical Methods and Data

3.1 Selection Bias

The trade effect of FTAs or the treatment effect must be based on the net difference observed in trade between FTA partners or the treatment group and non-FTA countries or the control group, given that all other things are held constant. A challenge is to satisfy the latter condition. That is, it is not possible to include a country into both FTA and non-FTA frameworks at the same time, and then compare its respective trade performance. As an alternative, PSM can serve to find a new comparison group that has characteristics similar to the treatment group. The PSM method addresses the problem of selection bias.

The control of selection bias is essential for welfare analysis. A country's welfare effect as brought about by FTAs is defined as the difference between the results borne by an FTA with any other country, and the result seen in a non-FTA country at the same point in time as the treatment country (Heckman et al. 1997). Following Guo and Fraser (2010), Equation (1) defines the treatment effect for country i, denoted as α_i as a difference between the two measured outcome variables, Y_{1i} within an FTA and Y_{0i} outside of the FTA. The outcome variable, Y_i corresponds to FTA treatment, D_i=1 and non-FTA, D_i=0. This equation implies which of the two outcomes would be considered to be due to the FTA, D_i and (1–D_i).

(1) $\alpha_i = Y_{1i} - Y_{0i},\ Y_i = D_i Y_{1i} + (1 - D_i) Y_{0i}$

(2) $ATE = E(\alpha) = E(Y_i\,|D = 1) - E(Y_0|D = 0)$

Equation (2) indicates the mean outcome of treatment, which is called the average treatment effect (*ATE*). It denotes the difference between the average trade outcome with all FTA partners and the average trade outcome with all non-FTA countries. If the comparison of the two average outcomes lead to ATE>0, one may conclude that the FTA promotes trade. However, the accurate trade effect due to an FTA must center on the counterfactual outcome, that is, $E(Y_0|D$=1). This counterfactual term refers to what would have happened if FTA partners had not joined the FTA. Because this term is not observable, one uses $E(Y_0|D$=0) as a perfect proxy. Since FTA participation is not experimental or randomly assigned treatment, the problem of selection bias can appear, that is, $E(Y_0|D=0) \neq E(Y_0|D=1)$.

Equation (3) shows the average treatment effect on the treated (*ATT*), which measures the trade effect on FTA partners. Adding and subtracting the counterfactual term, $E(Y_0|D$=1):

$$
\begin{aligned}
(3)\quad ATT &= E(Y_1|D = 1) - E(Y_0|D = 1) \\
&= E(Y_1|D = 1) - E(Y_0|D = 0) + E(Y_0|D = 0) - E(Y_0|D = 1) \\
&= ATE - S,
\end{aligned}
$$

where S is selection bias, defined as $E(Y_0|D = 1) - E(Y_0|D = 0)$. This equation suggests that if selection bias is completely controlled, or it is equal to 0, the FTA effect can be estimated with only observables. In other words, *ATT* can be estimated by the mean difference between the observed trade outcomes for FTA partners and non-FTA countries.

3.2 Propensity Score Matching (PSM)

PMS addresses the problem of selection bias. This method ensures that estimates for the FTA effect are based on differences of trade performance between comparable countries. PSM begins with the estimation of a conditional probability of FTA participation. The binary level of FTA participation is regressed with characteristics variables that are deemed to affect trade. Then pair matching between observed values of treated and comparison groups is made based on the nearest propensity score. More specifically, the estimation process of the PSM modeling comprises the following two steps.

The first step is to estimate a propensity score, in order to create a comparison group that is similar to the treatment group. Estimation of the propensity score is carried out repeatedly, until the distribution of observable characteristics of the treatment and comparison groups is balanced. Estimation is implemented through discriminant analysis or logit analysis, for which the dependent variable is the existence of an FTA with South Korea and the independent variables are various characteristics that can affect the dependent variable. These methods make probability estimates for treatment-group assignment, while observed variables are already given. While the multivariate normal distribution of variables is assumed in discriminant analysis, logit analysis is less constrained and can reduce selection bias even further than that seen with discriminant analysis (Rubin 1979). Therefore, logit analysis is used in this study, for ease of analysis.

$$(4)\quad P(X) = Pr(Y = 1|X) = E(Y|X)$$

In Equation (4), X is each feature vector of FTA partners and non-FTA countries, and $P(X)$ is the probability of having an FTA under the condition of such features. The key PSM assumptions are described below.

$$(5)\quad (Y_0, Y_1) \perp D|X$$
$$(6)\quad 0 < Pr(D = 1|X) < 1$$

Equation (5) denotes the conditional independent assumption (CIA). Given the observed feature of covariates (X), controlling for these covariates makes the FTA participation of a country (D) independent of the potential trade outcomes $(Y_{0,} Y_1)$.

This means that any feature not observed after controlling for all differences that influence the effect of an FTA does not impact on outcome. This ensures the FTA assignment is very much like a random selection.

Equation (6) refers to the common support assumption. In this equation, $Pr(X)$ is a continuous variable between 0 and 1, implying that the probability distributions of FTA partners and non-FTA countries overlap within the same range (Rosenbaum and Rubin 1983). This equation simply indicates that the proportion of FTA partners and non-FTA countries is greater than 0 for any value of X.

The second step is to find a non-FTA country group with propensity scores similar to those of FTA partner group. By doing that, the observable characteristics of the two groups will have the same distribution. A matching algorithm must be chosen for using the estimated propensity scores to match the two groups. For example, there is stratification matching, kernel matching, and nearest-neighbor matching (Heckman et al. 1997).

Stratification matching partitions the common support of the propensity score into subgroups (strata), and calculates the impact within each strata by computing the mean difference of outcomes between FTA partner and non-FTA country groups. Imbens (2004) notes that the use of five strata eliminates most bias in the case of a normality condition. Kernel matching uses a kernel function to assign weights that are inversely proportional to the distance between the propensity scores of FTA partner and non-FTA country groups. Nearest-neighbor matching matches an FTA partner with the non-FTA country which has the nearest propensity score. Once each FTA partner is matched with a set of non-FTA countries, the mean difference of the two groups can be computed.

In a nutshell, PSM estimators differ in the way the neighborhood for each FTA partner is defined, the common support is addressed, and the weights are assigned to the neighbors, depending on the matching algorithms. This means there is no absolutely superior matching approach, such that one may need to compare the results estimated from different matching methods (Becker and Ichino 2002; Caliendo and Kopeining 2008; Kim 2010).

3.3 Data

Table 3 shows a list of variables and data sources.

Table 3: Data Sources

Variable	Unit	Source
FTAs	Dummy	WTO
Trade value	USD	Global Trade Atlas
GDP per capita	USD	WDI
Total population	Person	WDI
Distance weighed	Km	CEPII
Trade balance	USD	Global Trade Atlas

Note: WDI: World Bank Development Indicators; CEPII: Centre d'Études Prospectives et d'Informations Internationales.

With PSM, ATT estimation must be based on the use of variables that satisfy the assumptions of conditional independence and common support (Baier and Bergstrand 2009). These variables include the volume of agricultural trade between the two countries, GDP per capita, population, distance, and balance of trade.

Agricultural products are defined as products covered under Chapters 1–24 of the Harmonized System Code (HS). The volume of agricultural trade and the balance of trade are obtained from the *Global Trade Atlas*. GDP per capita and population data are sourced from World Bank Development Indicators (WDI). Physical distance between countries is based on the indicators provided by the Centre d'Études Prospectives et d'Informations Internationales (CEPII).

The datasets are cross sectional on the basis of 2010 and 2012. Table 4 reports summary statistics of the data.[2]

South Korea imports agricultural products from 204 countries, and it exports to 195 countries by 2012. The number of FTA partners accounted for 7% in the total number of trading countries in 2010. However, the proportion increased to 22% in 2012 because the EU and the United States had formed FTAs with South Korea.

[2] The summary statistics of 2010 data are provided in the Appendix.

Table 4: Summary Statistics of Data

	Variable	Obs.	Mean	Std. Err.	Min	Max
Import	FTAs	204	0.215686	0.412309	0	1
	Trade value	204	1.25E+08	5.37E+08	0	5.87E+09
	GDP per capita	184	14479.47	20444.74	251.0145	103858.9
	Total population	204	3.57E+07	1.34E+08	9860	1.35E+09
	GDP per capita of South Korea	204	24453.97	0	24453.97	24453.97
	Total population of South Korea	204	5.00E+07	0	5.00E+07	5.00E+07
	Distance weighed	204	9484.03	3744.478	354.549	19563.9
	Trade balance	204	–4.60E+08	5.28E+09	–7.52E+10	1.89E+09
Export	FTAs	195	0.2205128	0.41566	0	1
	Trade value	195	3.54E+07	1.90E+08	0	2.30E+09
	GDP per capita	179	14467.2	20483.53	266.589	103858.9
	Total population	195	3.55E+07	1.35E+08	9860	1.35E+09
	Distance weighed	195	9541.234	3734.13	951.737	19563.9
	Trade balance	193	–4.86E+08	5.43E+09	–7.52E+10	1.89E+09

4 Estimation Results and Discussion

4.1 The Propensity Score

The estimated parameters of the logit model are used to calculate propensity scores, and to investigate the satisfaction of both the CIA and the common support assumption. Table 5 provides the results of logit analysis for importing and exporting countries of South Korea’s agricultural products.[3] The analysis identifies factors that have had an impact on FTA participation.

The parameter estimates for both importing and exporting countries are similar to each other, and illustrate that a country is more likely to participate in an FTA

[3] The logit estimation results with 2010 data are similar to the results for 2012 data; they are provided in the Appendix.

Table 5: Logit Estimation Results: 2012

Explanatory variable	Dependent variable	
	Import	Export
GDP per capita of importers/exporters	0.0000375*** (0.00000917)	0.0000388*** (9.46E-06)
Total population	0.000000000837** (1.13E-09)	0.00000000105** (1.17E-09)
Distance weighed	–0.0001457* (0.0000605)	–0.0001434* (0.000061)
Trade balance	0.00000000000723* (5.79E-11)	0.00000000000953* (6.13E-11)
Constant	–0.6095753 (0.5960046)	–0.6133886 (0.6052889)
Log-likelihood value	–82.490227	–80.840728
Prob > X^2	0.0000	0.0000
Pseudo R^2	0.1654	0.1711

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively

with South Korea if its GDP is greater, its population is larger, it is located geographically near to South Korea, and has a comparatively larger trade balance. In particular, relatively large estimates for GDPs suggest that supply and demand factors of trading countries are relevant to FTA participation.

Table 6 shows the derived common support. In 2010, common support lies between 0.002 and 0.362 for imports and between 0.002 and 0.366 for exports. In 2012, those ranges are 0.061–0.923 and 0.064–0.932, respectively.

The comparison group with a propensity score similar to that of the treatment group is subdivided into several blocks in terms of percentiles, to determine the satisfaction of the CIA. Each of importing and exporting country groups is subdivided into four blocks in 2010, and five blocks in 2012. This grouping allows one to check the difference in average propensity scores between the two groups.

Table 6: Common Support

Year	Sample	No. of countries		Common support	
		Before	After	Minimum	Maximum
2010	Import	15	14	0.002	0.362
	Export	15	14	0.002	0.366
2012	Import	44	42	0.061	0.923
	Export	43	42	0.064	0.932

Since no difference is found between FTA partners and non-FTA countries, the CIA is deemed to be ensured (Kim et al. 2013).[4]

4.2 Multiple Matching

In nearest-neighbor matching, a simplest form, 1:1 matching is used. Stratification matching takes in the same number of blocks as classified during the CIA confirmation. Kernel matching[5] uses the Epanechnikov kernel function, and each bandwidth is set at 0.05 for analysis. Confidence intervals of the FTA effect are estimated through bootstrapping. Resampling through bootstrapping is repeated 1,000 times. This is applied to all matching analyses. It is possible to identify reductions in selection bias by comparing the estimates before and after each matching for which bootstrapping was carried out. Table 7 demonstrates changes in selection bias for each matching method.

Matching can lead to effective or ineffective estimations, depending on how much heterogeneity is controlled between the variables of the two comparison groups, that is, the degree to which bias reduction contributes to measurements of the effect solely of FTAs. The estimation results reveal that each group is balanced

[4] The Stata 13 statistical program calculates the conditional independence. If this assumption is violated, matching is not implemented by Stata 13.

[5] In kernel matching, matching is implemented with a plurality of treatment groups per comparison group sample. In this case, greater weight is given to a treatment group sample for which the propensity score is nearer to that of the comparison group. The Gaussian kernel, Epanechnikov kernel, or Unimodal kernel is used, depending on the assumption that the weight follows a certain distribution function. The Epanechnikov kernel is used in this study to analyze matching.

Table 7: Bias Reductions after Matching

Year	Sample	Matching method	Bias reduction (%, after matching)
2010	Import	Stratification matching	–31.7(%)
		Kernel matching	–29.6(%)
		Nearest-neighbor matching	–38.9(%)
	Export	Stratification matching	–32.5(%)
		Kernel matching	–30.3(%)
		Nearest-neighbor matching	–40.1(%)
2012	Import	Stratification matching	–31.3(%)
		Kernel matching	–28.9(%)
		Nearest-neighbor matching	–39.6(%)
	Export	Stratification matching	–33.7(%)
		Kernel matching	–31.6(%)
		Nearest-neighbor matching	–41.1(%)

with respect to the average of each variable after matching, compared to that prior to matching. Each matching approach reduced bias to varying extents, depending on the matching type. Nearest-neighbor matching reduced bias the most, followed by stratification matching and kernel matching. Therefore, it is concluded that nearest-neighbor matching is the best approach for controlling heterogeneity between the treatment and comparison groups.

Table 8 shows the estimated ATT values in 2010. The treatment group consists of 14 FTA partners while the control group includes 9 countries at a minimum and a maximum of 165 countries, depending on the matching methods. Nearest-neighbor matching holds the smallest number of non-FTA countries within its control group. The ATT estimates imply that FTAs contributed to an increase inagricultural imports by South Korea, ranging from $113 million to $198 million. Similarly, the country's gain in exports is estimated between $40.0 million and $40.4 million. Larger gains in imports than exports account for the fact that the country is a net importer of agricultural products.

Table 8: Agricultural Trade Effects of FTAs in 2010

Matching method		Treatment group (No. of FTA partners)	Control group (No. of non-FTA countries)	ATT (Mill. USD)
Import	Stratification matching	14	165	198** (7.67e+07)
	Kernel matching	14	165	176** (5.35e+07)
	Nearest-neighbor matching	14	11	113*** (1.86e+08)
Export	Stratification matching	14	158	40.3* (2.02e+07)
	Kernel matching	14	158	40.4* (2.10e+07)
	Nearest-neighbor matching	14	9	40.0** (1.70e+07)

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are in parentheses.

Table 9 provides ATT estimates for 2012. The number of FTA partners in the treatment group is increased to 42, because South Korea completed new FTAs with the EU and Peru in 2011 and the United States in 2012. This makes up a total of 44 FTA partners but two countries out of the total were eliminated in the process of calculating the common support. The common support estimation also explains why the nearest-neighbor matching method has the smallest number of countries within the control group. An obvious advantage of working with a small size of the control group is that the heterogeneity with the treatment group is controlled best, and is therefore most effective in addressing selection bias and calculating relatively robust estimation results. It is worth noting that the number of non-FTA countries within the control group is subsequently reduced.

The estimation results demonstrate that an increase in import due to FTAs ranges from $156 million and $206 million in 2012. Export gains are recorded between $47.7 million to $67.4 million in the same year. Among the matching methods, stratification matching yields the largest import effect of FTAs while

Table 9: Agricultural Trade Effects of FTAs in 2012

Matching method		Treatment group (No. of FTA partners)	Control group (No. of non-FTA countries)	ATT (Mill. USD)
Import	Stratification matching	42	137	206** (1.50e+08)
	Kernel matching	42	137	185** (1.44e+08)
	Nearest-neighbor matching	42	23	156*** (1.14e+08)
Export	Stratification matching	42	132	57.2** (4.05e+07)
	Kernel matching	42	132	67.4* (5.31e+07)
	Nearest-neighbor matching	42	20	47.7** (5.93e+07)

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are in parentheses.

kernel matching was the largest in the case of export. The nearest-neighbor matching approach generates the lowest impact in both import and export.

A comparison between 2010 and 2012 estimates provides several implications. First, the trade creation effect of FTAs is accumulating. As the coverage of FTAs increased over the period, the subsequent trade gains have also expanded. Second, the trade creation effect is bi-dimensional. FTAs have boosted both South Korea's imports and exports at the same time. As previously mentioned, asymmetric increases in imports account for a trade deficit in the agricultural sector. Third, it is not apparent if the net trade gains over the two periods are of a credible magnitude. One may argue that a maximum increase of import by $43 million (under nearest-neighbor matching) and a maximum increase of export by $27 million (under kernel matching) are not sufficiently large enough given the fact that the two largest economies in the world, that is, the EU and the United States joined the FTAs with South Korea. Finally, different trade impacts are recorded by matching methods. Stratification matching produced the largest import impacts, followed by kernel matching. On the contrary, the largest export effect is identified by kernel matching.

Finally, Table 10 presents ATE and ATT values estimated through matching. As seen in Equation (3), the gap between ATE and ATT represents selection bias. Any difference between ATE and ATT underlines the presence of selection bias, and thus it is probable that the trade effect calculated on the basis of ATE is overestimated. For example, ATE for 2012 import, $273 million is greater than each ATT estimated by the three matching methods. This sheds light on the proposition that the effect of FTAs on import could be overstated by a range of $67 million (33%) to $117 million (75%). As for 2012 exports, the corresponding overestimates are from $49 million (72%) to 68 million (143%). Similar results were found with 2010 data. Interestingly, the degree of overestimation of exports appears to be much larger than observed for imports.

In summary, South Korea's FTAs are found to contribute to the creation of agricultural trade in both 2010 and 2012. A relatively large extent of selection bias is also identified by matching. This suggests that the impact of FTAs based on ATE is overstated. The estimated ATT, albeit being smaller than ATE, confirms the net trade effect of FTAs and supports the premise that FTAs are creating trade.

Table 10: Comparisons of ATE and ATT

Unit: Million USD

Sample		Import		Export	
		2010	2012	2010	2012
ATE		230	273	153	116
ATT	Stratification matching	198	206	40.3	57.2
	Kernel matching	176	185	40.4	67.4
	Nearest-neighbor matching	113	156	40.0	47.7

5 Conclusion

This study used PSM to control for selection bias, to investigate the effect of FTAs on South Korea's agricultural trade. The treatment effects of FTAs are properly identified and robustly estimated with regard to 2010 and 2012 data. The difference between ATE and ATT estimates are shown to validate the claim that the net trade effects of FTAs have tended to be overstated. In 2010, the overestimates of imports and exports are between $32 million and $117 million, and between $112.6 million and $113 million, respectively. The latter implies that an increase in exports due to FTAs could have been exaggerated by a factor of almost three. The corresponding overestimates in 2012 are between $67 million and $117 million for imports, and between $49 million and $68 million for exports.

According to ATT estimates, FTAs led to the creation of imports of up to $198 million in 2010 and $206 million in 2012, depending on the matching algorithm used. The export impacts, although smaller, are up to $40.4 million in 2010 and $67.4 million in 2012. Despite the magnitudes of impacts varying across the matching methods, they are regarded as enhancing the robustness of the estimated results, namely that FTAs contribute to the creation of agricultural trade in South Korea.

These findings have important consequences for trade analysis. As one of the commonly adopted tools for dealing with biases linked with observable data, PSM is shown to have been methodologically effective in addressing the thorny question of selection bias when evaluating the impact of FTAs. Thus, implementation of the PMS methodology is likely to remedy for overestimation of trade impacts associated with policy intervention arising from selection bias.

Future research should more rigorously evaluate if the CIA and the common support assumption are fully satisfied. It will be otherwise impossible to construct an appropriate counterfactual to measure the trade impacts. Adopting the difference-in-differences (DID) estimator could be effective to correct for any bias associated with the presence of pretreatment information. Finally, panel data or more inclusive data will merit further analysis.

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Appendix 1: Descriptive Statistics of Dependent Variable: 2010[6]

	Variance	Obs.	Mean	Standard error	Minimum	Maximum
Imports	FTAs	204	0.078431	0.269511	0	1
	Trade value	204	9.63E+07	4.64E+08	0	5.33E+09
	GDP per capita	184	13801.99	20764.8	219.5298	145229.8
	Total population	204	3.49E+07	1.32E+08	9827	1.34E+09
	GDP per capita of South Korea	204	22151.21	0	22151.21	22151.21
	Total population of South Korea	204	4.94E+07	0	4.94E+07	4.94E+07
	Distance weighed	204	9484.03	3744.478	354.549	19563.9
	Trade balance	204	–6.94E+08	8.91E+09	–1.27E+10	1.30E+09
Exports	FTAs	195	0.076923	0.267155	0	1
	Trade value	195	2.72E+07	1.49E+08	0	1.85E+09
	GDP per capita	179	13069.49	18448.66	326.6043	102678.8
	Total population	195	3.47E+07	1.33E+08	9827	1.34E+09
	Distance weighed	195	9541.234	3734.13	951.737	19563.9
	Trade balance	193	–7.33E+08	9.16E+09	–1.27E+10	1.30E+09

6 South Korea imports agricultural products from 204 countries and exports to 195 countries.

Appendix 2: Logit Analysis with Matching: 2010

	Import	Export
GDP per capita of importers/exporters	0.0000142* (0.0000107)	0.0000184** (0.0000123)
Total population	1.05E-09* (1.27E-09)	1.13 e-09* (1.30e-90)
Distance weighed	–0.0003338*** (0.000104)	–0.0003273*** 0.000105
Trade balance	8.38E-12* (1.48E-10)	1.15e-11* (1.73e-10)
Constant	–0.2244228 (0.7861946)	–0.299569 (0.8181058)
Log-likelihood value	–40.519918	–39.781692
Prob > X^2	0.0010	0.0008
Pseudo R^2	0.1855	0.1927

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.