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Naoto Jinji
Xingyuan Zhang
Shoji Haruna

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Research Project Center
Graduate School of Economics
Kyoto University
Yoshida-Honmachi, Sakyo-ku
Kyoto City, 606-8501, Japan

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Do Regional Trade Agreements Enhance International Technology Spillovers?*

JINJI Naoto[†] ZHANG Xingyuan[‡] HARUNA Shoji[§]

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Abstract

We examine whether regional trade agreements (RTAs) enhance international technology spillovers by using a panel of patent application and citation data for 142 countries/regions during 1990–2006 at the United States Patent and Trademark Office. We use patent citation data as a proxy for technology spillovers. A gravity-like model is estimated by the negative binomial model and the fixed effects negative binomial (FXNB) model. We find that technology spillovers between two countries/regions measured by patent citations are greater if they are signatories to the same RTA. This finding is quite robust for different estimation techniques. The estimated results from the FXNB model suggest that there is no significant difference in the effects of free trade agreements and customs unions on technology spillovers. We also find that General Agreement on Tariffs and Trade (GATT) and World Trade Organization (WTO) membership and participation in the Information Technology Agreement of WTO facilitate technology spillovers across signatories.

Keywords: regional trade agreement; technology spillovers; patent citations; economic distance; gravity model.

JEL classification: F15; O33.

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[†] Corresponding author. Faculty of Economics, Kyoto University, Yoshida-honmachi, Sakyo-ku, Kyoto 606-8501, Japan. Phone & fax: +81-75-753-3511. E-mail: jinji #at-mark# econ.kyoto-u.ac.jp.

[‡] Faculty of Economics, Okayama University, 3-1-1 Tsushima-Naka, Kita-Ku, Okayama 700-8530, Japan.

[§] Faculty of Economics, Okayama University, 3-1-1 Tsushima-Naka, Kita-Ku, Okayama 700-8530, Japan.

1 Introduction

A rapid proliferation of regional trade agreements (RTAs) has been observed during the last two decades. Although early studies on the economic effects of RTAs focused on their static effects, such as trade creation and trade diversion (Viner, 1950), relatively recent studies have addressed the dynamic effects of RTAs (e.g., Ben-David, 1993; Bustos, 2011; Ederington and McCalman, 2008; Schiff and Wang, 2003). For example, Bustos (2011) estimates the effects of Mercosur on Argentinean firms' technology adoption and finds that a tariff reduction by Brazil induced statistically significant increases in technology spending and the innovation indexes of Argentinean firms.

RTAs may also enhance technology spillovers across countries (Das and Andriamananjara, 2006). Although RTAs are primarily aimed at expanding trade in goods by reducing tariffs on imports, many recent RTAs pursue a deeper integration (Baldwin, 2011). For example, liberalization of investment and harmonization of intellectual property rights protection policy are included in RTAs. Thus, it is expected that RTAs affect the flow of knowledge across countries.[1] In this paper, we attempt to empirically investigate this issue.

For measuring technology spillovers, one approach pioneered by Jaffe et al. (1993) is to employ patent citation data (e.g., Branstetter, 2006; Hall et al., 2001; Haruna et al., 2010; Jaffe and Trajtenberg, 1999; Jinji et al., 2010, 2011; MacGarvie, 2006; Maurseth and Verspagen, 2002). The advantage of using patent citations as a proxy for technology spillovers is that they are a direct measure of knowledge flows (Hall et al., 2001). In particular, patent applicants at the United States Patent and Trademark Office (USPTO) have a legal duty to list the patents that they cite on the front page of the application document. We follow this approach to measure technology spillovers.

In the literature of technology spillovers based on patent citations, the localization of technology spillovers has been well documented (Jaffe et al., 1993; Maurseth and Verspagen, 2002; Murata et al., 2010; Paci and Usai, 2009). That is, technology spillovers measured by patent citations decrease as geographical distance extends. However, previous studies in the literature have paid little attention to the effects of "economic distance" on the localization of technology spillovers. Economic distance is a measure of proximity (or farness) between two locations in an economic sense, which is affected by not only geographical distance but also other factors such as infrastructure, transportation mode, and public policy. Thus, for a given geographical distance, the economic distance between two countries (or regions) can vary, depending on policy and other technological factors. Keeping this in mind, economic distance may be more important for technology spillovers than simple geographical distance. Since the membership of the same RTA or any other organization to facilitate international trade of goods may affect the economic distance between two countries, it may also matter for the localization of

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[1] Trade in goods itself works as a major channel of technology spillovers. See Acharya and Keller (2009), Coe and Helpman (1995), and Xu and Wang (1999) for empirical evidence and Keller (2004) for a survey of the literature.

technology spillovers.

To our knowledge, only Peri (2005) and Jinji et al. (2013) have investigated the effects of RTAs on technology spillovers. Using a sample of 18 countries with 147 subnational regions in Western Europe and North America for the period of 1975–1996, Peri (2005) estimates a gravity-like model to examine the effects of several resistance factors on patent citations. He finds that regional, national, and linguistic borders have a significantly negative effect on technology spillovers, whereas the effect of "trade blocs" on technology spillovers is insignificant. However, his study is partial from the perspective of the analysis of RTA's effects on technology spillovers, because he includes only EEC/EC/EU and North American Free Trade Agreement (NAFTA) as "trade blocs."[2] Given that NAFTA entered into force on January 1, 1994, and that his sample period ends in 1996, the trade-bloc dummy in his analysis may mainly capture the effects of EEC/EC/EU. On the other hand, our earlier paper (Jinji et al., 2013) employs an empirical framework similar to that in this paper and finds a significantly positive effect of RTAs on technology spillovers for the sample of 103 countries during 1990–1999. However, the analysis in that paper is still limited because only nine RTAs are included.[3] Unlike these previous studies, in this paper, we conduct a more comprehensive analysis of the effects of RTAs on technology spillovers by extending the sample to 142 countries and the coverage of RTAs to 110. All RTAs notified to the World Trade Organization (WTO) that entered into force by the final year of our sample period are included as long as at least two countries in our sample are their signatories. As explained below, we employ panel estimation techniques to estimate the effects of RTAs, which are not used in the previous two papers.

Using patent application and citation data at the USPTO, we construct a panel for 17,120 pairs of the citing and cited countries/regions from the sample of 142 countries/regions for 17 years from 1990 to 2006.[4] The reason why the USPTO's data are used is that the share of non-domestic residents in all applications is much higher at the USPTO than that at other major patent offices such as the European Patent Office (EPO) and the Japanese Patent Office (JPO). Thus, the USPTO's data are the best available data in the world to capture cross-country technology spillovers by patent citations. We derive an empirical model that is quite similar to the standard gravity model in the trade literature and estimate it. Then, following the literature of the gravity model (e.g., Rose, 2004; Bair and Bergstrand, 2007), the effect of RTAs is captured by a dummy variable that indicates membership of the same

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[2] The formal names of EEC/EC/EU are the European Economic Community/the European Community/the European Union.

[3] The nine RTAs are those included in the dataset provided by Andrew K. Rose. See section 2 for more detail. The analysis in that paper is also limited in terms of the empirical strategy because it does not address the technical issues that we discuss in section 3.

[4] Our analysis is also different from those in the previous papers (Peri, 2005; Jinji et al., 2013) in terms of the sample period. Although Peri (2005) covers until 1996, we think that it is important to include the late 1990s and 2000s because the number of RTAs increased rapidly in these periods. Our earlier paper (Jinji et al., 2013) does not cover the 2000s. Note that our sample period ends in 2006 because of the unavailability of reliable patent data after 2006.

RTA among pairs of countries/regions.[5] Since the effect of RTAs may be different according to RTA types, such as free trade agreements (FTAs) and customs unions (CUs), we also estimate the model by including separate dummies for FTAs and CUs. In addition to the effects of RTAs, the role of the General Agreement on Tariffs and Trade (GATT)/WTO in international technology spillovers is investigated. We include dummy variables for GATT/WTO membership and participation in the Information Technology Agreement (ITA) of the WTO.[6]

We estimate the empirical model for technology spillovers using a negative binomial (NB) model, which is a standard technique to estimate regression models with count data as the dependent variable (Cameron and Trivedi, 1998). To account for heterogeneity specific to pairs of citing and cited countries/regions, we also employ fixed effects negative binomial (FXNB) model, which is a standard panel estimation technique for count data.

This paper is the first comprehensive study of the effects of RTAs on international technology spillovers. The main findings of this paper are as follows. First, we find that RTAs have a positive and significant effect on technology spillovers measured by patent citations. This finding is quite robust for different estimation techniques (i.e., NB and FXNB) and is consistent with Jinji et al.'s (2013), but is different from Peri's (2005). The significantly positive effect of RTAs on technology spillovers remains even when the US is excluded from the sample. Although we find that FTAs have a stronger effect on technology spillovers than CUs, the difference becomes insignificant once we employ a panel estimation technique (i.e., FXNB). Second, we find that GATT/WTO and the ITA of WTO also enhance technology spillovers among members and signatories. Although the coefficient of GATT/WTO dummy is significantly negative in the NB estimations, it becomes significantly positive in the FXNB estimations. Overall, we find that the gravity-like model is applicable to the study of technology spillovers.

Our empirical results confirm that RTAs actually enhance technology spillovers across countries. The estimated effect of RTAs is the average effect among all RTAs. Since we include medium- and low-income countries as well as high-income countries in our sample, our results imply that even medium- and low-income countries can on average benefit from technology spillovers by forming RTAs. Thus, countries will have an additional incentive to sign RTAs. Our finding also implies that economic distance *does* matter for technology spillovers.

The remainder of the paper is organized as follows. In Section 2, we describe the data employed in our empirical analysis. In Section 3, we explain the empirical framework. In Section 4, we present our empirical results. Section 5 concludes the paper.

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[5] Head and Mayer (2012) provide a useful survey of recent developments in the literature of the gravity model.

[6] The ITA (the formal name is the "Ministerial Declaration on Trade in Information Technology Products") is a tariff cutting mechanism, aiming at the expansion of world trade in information technology products. It was originally signed by 29 countries/regions at the Singapore Ministerial Conference of the WTO in December 1996.

2 Description of the Data

The data on patent applications and patent citations are taken from the April 2012 edition of the EPO Worldwide Patent Statistical Database (PATSTAT). We extract the patent statistics of the USPTO from the PATSTAT. This dataset includes information on the application date, the country name of the assignee, the main US patent class, and citations made and received for each patent. In our analysis, we use patent application data from 1975 to 2006 and patent citation data from 1990 to 2006.

The sample includes countries and regions that have at least one patent application to the USPTO during the sample period. Our sample covers 142 countries and regions, which are listed in Table A.1. We then construct a panel of 17,120 pairs of the citing and cited countries/regions for 17 years from 1990 to 2006.

The information used to construct control variables in the gravity equation is taken from the web page of Andrew K. Rose.[7] For details of the data, see Rose (2004, 2005). Although the original Rose dataset covers only until 1999, we extend his dataset to 2006. We also expand substantially the coverage of RTAs in the Rose dataset. The original Rose dataset covers only nine RTAs: EEC/EC/EU, US–Israel FTA, NAFTA, CARICOM, PATCRA, ANZCERTA, CACM, Mercosur, and ASEAN.[8] We expand the coverage of RTAs to 110 on the basis of the information taken from the web page of the WTO.[9] All RTAs notified to WTO that entered into force by 2006 and to which at least two countries/regions in our sample are signatories are included in the sample. FTAs, CUs, and economic integration agreements (EIAs) are included, but partial scope agreements (PSAs) are not included. The list of RTAs covered in our sample is shown in Table A.2.[10]

3 Empirical Framework

Our prime interest is in estimating the effects of RTAs on technology spillovers across countries. In this section, we specify a model of knowledge flows between countries and discuss our empirical strategy to estimate the model.

We first measure technology spillovers from country j to country i at time t by extending the

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[7] http://faculty.haas.berkeley.edu/arose/

[8] Besides NAFTA and EEC/EC/EU (already defined above), the formal names of these RTAs are US–Israel FTA: the United States–Israel Free Trade Agreement; CARICOM: the Caribbean Community; PATCRA: the Agreement on Trade and Commercial Relations between Australia and Papua New Guinea; ANZCERTA: Australia New Zealand Closer Economic Agreement; CACM: Central American Common Market; Mercosur: Mercado Común del Sur; and ASEAN: the Association of Southeast Asian Nations.

[9] http://rtais.wto.org/UI/PublicMaintainRTAHome.aspx

[10] Although PATCRA is included in the original Rose dataset, it is excluded from our RTA coverage because only one signatory of PATCRA is included in our sample.

framework proposed by Jaffe et al. (1993), Jaffe and Trajtenberg (1999), and Peri (2005). Let Φ_{ijt} be a measure of technology spillovers from country j to country i at time t in terms of the actual effects on the research output in country i. Then, we assume that Φ_{ijt} depends on both knowledge stock in country j at t, K_{jt}, and the research ability of firms in country i at t, Q_{it}, as follows:

$$\Phi_{ijt} = (Q_{it})^{\alpha_1}(\tilde{\phi}_{ijt}K_{jt})^{\alpha_2}, \tag{1}$$

where $\tilde{\phi}_{ijt} \in [0,1]$ is the degree of accessibility for firms in country i to the knowledge stock in country j at t. Thus, $(\tilde{\phi}_{ijt}K_{jt})$ is the effective unit of country j's knowledge stock from the perspective of firms in country i. Parameters α_1 and α_2 are both positive. For notational simplicity, we relabel $\tilde{\phi}_{ijt}$ as $\phi_{ijt} \equiv (\tilde{\phi}_{ijt})^{\alpha_2}$.

The degree of accessibility for firms in country i to the knowledge stock in country j at t, ϕ_{ijt}, depends on the *economic distance* between i and j, which is affected by not only bilateral geographical distance but also other potential *resistance factors* (Peri, 2005, p. 310). The latter include the use of a common language, the membership of the same RTA, and the membership of GATT/WTO. Note that unlike geographical distance, the economic distance between two countries can vary over time. Let $\boldsymbol{x}_{ijt}$ be a set of bilateral country characteristics. Then, we have

$$\begin{aligned}\phi_{ijt} &= \phi(\boldsymbol{x}_{ijt}) \\ &= (Dist_{ij})^{\beta_1} e^{\beta_2(Lang_{ij})} e^{\gamma_1(RTA_{ijt})} e^{\gamma_2(FTA_{ijt})} e^{\gamma_3(CU_{ijt})} e^{\gamma_4(WTO_{ijt})} e^{\gamma_5(ITA_{ijt})},\end{aligned} \tag{2}$$

where the details of the variables on the right-hand side of the equation are as follows:

- $Dist_{ij}$: The distance between i and j.
- $Lang_{ij}$: A dummy variable that takes the value of unity if i and j have a common language, and zero otherwise.
- RTA_{ijt}: A dummy variable that takes the value of unity if i and j both belong to the same RTA at t, and zero otherwise.
- FTA_{ijt}: A dummy variable that takes the value of unity if i and j both belong to the same FTA at t, and zero otherwise.
- CU_{ijt}: A dummy variable that takes the value of unity if i and j both belong to the same CU at t, and zero otherwise.
- WTO_{ijt}: A dummy variable that takes the value of unity if both i and j are GATT/WTO members at t, and zero otherwise.
- ITA_{ijt}: A dummy variable that takes the value of unity if both i and j are participants of ITA of WTO at t, and zero otherwise.

Since Φ_{ijt}, Q_{it}, and K_{jt} in Eq. (1) are not directly observable, we need to use some proxies for those variables in our analysis. First, we use C_{ijt}, the number of patent citations made by the patents of country i to those of country j at time t, as a proxy for Φ_{ijt}. Following Peri (2005), we assume the following relationship:

$$C_{ijt} = \tilde{\lambda}_{ij} \Phi_{ijt} e^{\epsilon_{ijt}}, \tag{3}$$

where $\tilde{\lambda}_{ij}$ refers to the time–invariant individual effect associated with patent citations between the two countries and $e^{\epsilon_{ijt}}$ is an error term with zero-mean distribution. Second, we use the stocks of patents in countries i and j at t, P_{it} and P_{jt}, as proxies for the research ability of country i, Q_{it}, and the knowledge stock in country j, K_{jt}, respectively. We construct P_{it} (and P_{jt}) from the data on patent applications at the USPTO by using the following perpetual inventory method:

$$P_{it} = A_{it} + (1 - \delta) P_{it-1}, \tag{4}$$

where A_{it} is the number of patent applications made by country i at the USPTO during period t and δ is the depreciation rate. Following convention in the literature, we use $\delta = 0.15$ (Hall et al., 2005). When we construct the patent stock data, we use the number of patent applications in 1975 as the initial value of P_{it}. Since we use patent application data from 1975 and our sample period begins in 1990, the value of P_{it} in 1990 estimated by the perpetual inventory method (Eq. (4)) is influenced little by the initial value of P_{it}. Moreover, in the estimation, we use patent stock variables with one period of lag to account for simultaneity bias. That is, we use $\ln(P_{it-1})$ and $\ln(P_{jt-1})$, the values of the patent stocks at the beginning of the year in our estimation. Substitute Eqs. (1) and (2) and P_{it} and P_{jt} into Eq. (3) to obtain

$$C_{ijt} = \tilde{\lambda}_{ij} (P_{it})^{\alpha_1} (P_{jt})^{\alpha_2} (Dist_{ij})^{\beta_1} e^{\beta_2 (Lang_{ij})} e^{\gamma_1 (RTA_{ijt})} e^{\gamma_2 (FTA_{ijt})} e^{\gamma_3 (CU_{ijt})} e^{\gamma_4 (WTO_{ijt})} e^{\gamma_5 (ITA_{ijt})} e^{\epsilon_{ijt}}. \tag{5}$$

This equation is quite similar to the standard gravity equation that specifies the relationship between the volume of bilateral trade and the market sizes of the two countries with bilateral geographical distance (see, e.g., Anderson and van Wincoop, 2003; Bair and Bergstrand, 2007; Rose, 2004, 2005). The difference from the standard gravity equation is that we have the flow of knowledge (C_{ijt}) on the left-hand side and the stocks of knowledge (P_{it} and P_{jt}) on the right-hand side. Eq. (5) can be rewritten as

$$\begin{aligned} C_{ijt} \quad = \quad & \tilde{\lambda}_{ij} \exp\Big(\alpha_1 \ln(P_{it}) + \alpha_2 \ln(P_{jt}) + \beta_1 \ln(Dist_{ij}) + \beta_2 Lang_{ij} \\ & + \gamma_1 RTA_{ijt} + \gamma_2 FTA_{ijt} + \gamma_3 CU_{ijt} + \gamma_4 WTO_{ijt} + \gamma_5 ITA_{ijt} + \epsilon_{ijt} \Big), \end{aligned} \tag{6}$$

where $\ln(P_{it})$ and $\ln(P_{jt})$ are the logarithm values of patent stocks for countries i and j, respectively, and $\ln(Dist_{ij})$ is the logarithm of the distance between i and j.

Since C_{ijt} is count data, we estimate Eq. (6) by the NB model, which is a standard technique for estimating the model with count variables (Cameron and Trivedi, 1998). In the NB model, the data are assumed to be generated by a Poisson process, but more flexible modeling of the variance is allowed to account for overdispersion. To capture the time-invariant heterogeneity $\tilde{\lambda}_{ij}$ in (6), which is specific to the pairs of the citing and cited countries/regions, we also employ the FXNB model proposed by Hausman et al. (1984), which is a standard panel estimation technique for count data.[11] Moreover, as an alternative model, we employ the random effects negative binomial (RENB) model, which is also proposed by Hausman et al. (1984) and is another standard technique for count data.[12] We then implement the Hausman test to check which of the FXNB and RENB models is the preferred one.

Table A.3 shows the descriptive statistics of the variables and Table A.4 shows the correlations among variables.

In Eq. (6), the expected signs of the coefficients of $\ln(P_{it})$ and $\ln(P_{jt})$ are both positive, because the chance to cite a patent will increase if the citing and cited countries have larger patent stocks. The citing country's patent stock $\ln(P_{it})$ is considered to reflect its absorptive capacity of technology and the cited country's patent stock $\ln(P_{jt})$ represents its potential opportunity of being cited. Moreover, $Lang_{ij}$ is expected to have a positive coefficient, whereas $\ln(Dist_{ij})$ is expected to have a negative coefficient for the same reason as in the usual gravity analysis.[13]

The coefficient of RTA measures the effect of RTAs on technology spillovers under the assumption that all RTAs have the same effect on technology spillovers. The RTAs represented by the dummy variable RTA include 110 RTAs listed in Table A.2. In addition, the coefficients of FTA and CU respectively measure the effects of FTAs and CUs separately, so that we can investigate whether the effects of RTAs differ depending on the type of RTAs. We expect positive signs for all coefficients of RTA, FTA, and CU.

We also estimate the effects of GATT/WTO on technology spillovers. The coefficient of WTO represents the effects of GATT/WTO on technology spillovers if both of the partners are GATT/WTO members. Since GATT/WTO membership is expected to enhance trade between trade partners and hence enhance technology spillovers between them, the expected sign of the coefficient of WTO is also positive. Moreover, the ITA of the WTO is aimed at facilitating trade in information technology

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[11] As shown in Appendix, individual effects of the pair of citing and cited countries/regions are not additive but multiplicative with the parameters for other explanatory variables in the FXNB model. This property distinguishes the estimator of the FXNB model from other fixed effect estimators by allowing us to estimate the coefficients of time–invariant regressors in addition to time–varying regressors (Cameron and Trivedi, 2005). See Appendix for more details on the FXNB model.

[12] The details of the RENB model are also explained in Appendix.

[13] We exclude some of the dummy variables that are commonly used in the gravity model. Such dummy variables represent the adjacency of the partners and the former colonial relationship between the partners. We exclude these variables because they are considered to be irrelevant to technology spillovers.

(IT) products. Since the IT industry is one of the industries in which technology spillovers are most active, we also expect that the coefficient of ITA is positive.

When we estimate Eq. (6), there are two potential problems to be considered: simultaneity bias and selection bias. First, since decisions to participate in RTAs and GATT/WTO as well as in ITA are endogenous for countries, the inclusion of dummies associated with those decisions in explanatory variables may involve simultaneity bias. This issue is particularly important in the analysis of RTAs with the standard gravity equations (see, e.g., Bair and Bergstrand, 2007). However, since our interest is in technology spillovers among countries and the dependent variable in our model is patent citation, we can assume that all decisions on trade agreements are exogenous and that the dummies associated with those decisions are uncorrelated with the error term. Second, we may need to care about selection bias in the estimation of the effects of RTAs. Excluding some RTAs just for convenience will cause our sampling not to be random, resulting in a biased sample. As we explained in the previous section, we include all RTAs notified to WTO that entered into force by the end of our sample period and to which at least two countries/regions in our sample are signatories. This means that we include as many RTAs as possible in our analysis. Therefore, the selection bias should be held to a minimum in our case. Moreover, we try to treat these problems by employing the panel estimation techniques.

In addition, an important issue in the recent literature on the gravity model is how to deal with the so-called "multilateral (price) resistance terms" (Anderson and van Wincoop, 2003), which are functions of price variables in each of the trade partners. Several methods have been proposed. First, Anderson and van Wincoop (2003) and Feenstra (2004, Ch. 5) suggest that estimating the cross-section gravity equation with country-specific fixed effects is a computationally easy method for accounting for this issue. Bair and Bergstrand (2007) argue that in a panel setting time-varying country specific dummies capture the multilateral price terms. Moreover, Bair and Bergstrand (2007) and Bair et al. (2011) argue that a first-differencing model has certain potential advantages over fixed effects panel analysis in estimating the effects of RTAs. Hur and Lee (2012) test the relative performance of the methods proposed by the existing studies as well as other specifications, such as individual country dummies with year dummies and time-varying country dummies with pair fixed effects. Unlike the standard gravity model for bilateral trade flow, however, our model consists of patent applications and citations rather than GDPs and trade volumes. Thus, omitting multilateral price terms is less likely to be a problem in our case. Nevertheless, the issue of multilateral resistance still matters to our analysis for a different reason. Peri (2005) finds that, in addition to geographic characteristics, technological characteristics play an important role in knowledge flow. That is, differences in technological specialization and sophistication across countries/regions have significant effects on technology spillovers. In this paper, we try to capture these effects by utilizing the FXNB model.

Furthermore, our specification in Eq. (6) and estimation by the FXNB model can also address the issue raised by Santos Silva and Tenreyro (2006). They point out the problem of estimating log-linearized models by ordinary least squares (OLS), which has been a well-known practice in the literature of the gravity model. They demonstrate the advantage of estimating the gravity model of bilateral trade flows measured in levels by the Poisson pseudo-maximum likelihood (PPML) estimator. In fact, our empirical strategy, which estimates the FXNB model by the maximum likelihood (ML) technique, is more general than the method proposed by Santos Silva and Tenreyro (2006). This is because the NB model belongs to the family of modified Poisson models and allows overdispersion.

4 Empirical Results

In this section, we report our estimation results. We first report our findings from the NB model and then those from the FXNB model.

The estimation results from the NB model are reported in Table 1. Columns (1) and (2) indicate the estimation results for the whole sample, and columns (3) and (4) indicate the estimation results for the sample that excludes the US. Because the number of patent citations made or received by the US is disproportionately larger than those of other countries, it is worth examining how the results are affected by excluding the US.

As shown in Table 1, all of the control variables have highly significant coefficients with the expected signs in all regressions. The coefficients of the log of the US patent applications made by citing and cited countries/regions ($\ln(P_i)$ and $\ln(P_j)$) are positive and highly significant. This means that pairs of countries/regions holding more patents experience higher technology spillovers. The log of the distance between the trade partners ($\ln(Dist)$) has a negative and highly significant coefficient in all regressions. The common language dummy ($Lang$) has a positive and highly significant coefficient in all regressions. The above results imply that countries sharing a common language exchange technological knowledge more, whereas geographical distance tends to reduce knowledge spillovers. These effects of common language and geographical distance on technology spillovers are similar to those on the volume of trade in the standard gravity model. Our results are consistent with the findings from the previous studies (Jaffe and Trajtenberg, 1999; Peri, 2005).

The estimated results concerning the effects of RTAs are also as expected. The coefficients of RTA, FTA, and CU are all positive and highly significant in all regressions. This result implies that RTAs have a positive effect on technology spillovers. Moreover, the coefficient of FTA is larger than that of CU in both columns (2) and (4), which suggests that FTA has a stronger effect on technology spillovers than does CU.

Our finding regarding the effects of RTAs on technology spillovers is quite different from that of Peri (2005). Recall that Peri finds no significant effect of the RTA dummy (which he calls the "trade-bloc" dummy). One possible reason why the RTA dummy is insignificant in his analysis is that, as pointed out in section 1, his RTA dummy mainly captures the effect of RTA in Europe (EEC/EC/EU), whereas he uses the USPTO data (as does this paper), in which citations are unevenly more frequent for pairs involving the US. Jinji et al. (2013), who also use the USPTO data, find that the significance of the EEC/EC/EU dummy depends on the estimation technique. In particular, the EEC/EC/EU dummy is insignificant in the period of 1990–1999 when the model is estimated by the NB.

The only unexpected result in Table 1 is the estimated coefficient of WTO. It is negative and significant in all regressions. This unexpected result may be due to our estimation technique, namely, the NB model. Since the NB model does not control for the individual effects of pairs of citing and cited countries/regions, our estimates of the effects of WTO may be biased. In contrast, the estimated coefficient of ITA is positive and significant, as expected.

Table 2 reports the estimated results by the FXNB model. As in Table 1, the estimation results for the whole sample are reported in columns (1) and (2), and the results based on the sample excluding the US are reported in columns (3) and (4) in each table.

The estimated results of the FXNB model are improved from those of the NB model. All of the control variables have highly significant coefficients with the expected signs, except for $Lang$. Although the estimated coefficient of $Lang$ is negative and significant in the whole sample (columns (1) and (2)), it is positive and significant in the sample excluding the US (columns (3) and (4)). The unexpected sign of $Lang$ in the whole sample may be due to highly frequent citations between the US and non-English speaking countries/regions, compared to other pairs sharing a common language.

The estimated coefficients of RTA, FTA, and CU are all positive and highly significant in all cases of the FXNB model. Unlike the results from the NB model, however, there is no significant difference in the estimates of FTA and CU. Thus, the stronger effect of FTA on technology spillovers observed in the NB model seems not to be robust.

A substantial improvement from the NB model is found in the estimates of WTO. In Table 2, WTO has a positive and highly significant coefficient in all regressions. This suggests the importance of estimating the model by the panel analysis technique. As shown in Table 1, ITA has a significantly positive effect on technology spillovers, though the significance level is slightly lower in columns (3) and (4) in Table 2. Thus, these results suggest that GATT/WTO membership and participation in ITA of WTO are both effective in increasing the bilateral flow of technological knowledge.

We also estimate the model by the RENB.[14] However, as shown at the bottom of Table 2, the Hausman test rejects the null hypothesis that the RENB is the preferred model in all cases.

As Bair and Bergstrand (2007) argue, it is reasonable to include RTA dummies lagged in one or two periods in the estimation because the economic effects of RTAs are likely to emerge some years after they legally enter into force. The same argument may apply to the effects of GATT/WTO and ITA. At the same time, it is also meaningful to estimate the model with lagged RTA and WTO dummies from the viewpoint of a robustness check. Thus, we implement the FXNB estimations with

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[14] The estimated results of the RENB model are available from the corresponding author upon request.

one- or two-period lagged dummies. The results are reported in Table 3. In this table, the results for the whole sample are shown in columns (1) to (4), and those for the sample without the US are shown in columns (5) to (8). Compared to Table 2, the estimated coefficients do not change much, though the magnitude of the coefficients of the RTA dummies (RTA, FTA, and CU) and the WTO dummies (WTO and ITA) tends to reduce slightly, and their significance level tends to fall slightly as we take longer lags. However, we notice that the ITA dummy becomes insignificant in the estimation without the US. As indicated at the bottom of the table, the Hausman test again rejects the null hypothesis that the RENB is the preferred model in all cases of RTA and WTO dummies with lags. In terms of robustness, the results in Table 3 indicate that the FXNB estimates reported in Table 2 are quite robust.

5 Conclusions

In this paper, we investigated empirically whether RTAs enhance technology spillovers among member countries. We used patent citation data from the USPTO as a proxy for technology spillovers. We found that RTAs have a positive and significant effect on technology spillovers in the sense that pairs of countries belonging to the same RTA have more patent citations. This finding is robust for different estimation techniques (i.e., NB and FXNB). The estimated results from the FXNB suggest that there is no significant difference in the effects of FTA and CU on technology spillovers. We also found that the membership of GATT/WTO enhances technology spillovers between member countries and that participation in the ITA of the WTO also facilitates technology spillovers.

The finding in this paper suggests that on average RTAs (both FTAs and CUs) enhance technology spillovers among members of the same RTAs. The contribution of this paper is important in the sense that we found a positive and significant effect of RTAs on patent citations in the sample, including medium- and low-income countries/regions as well as high-income countries/regions, and covering most of the relevant RTAs. The coverage of our analysis is much more comprehensive in both countries and RTAs than in previous papers such as Peri (2005) and Jinji et al. (2013). However, we still found the average effect of RTAs on technology spillovers to be significantly positive. Countries usually form RTAs to facilitate trade in goods and services among member countries. If RTAs also increase knowledge flows among members (which our study actually confirmed), countries can expect an improvement in the productivity of domestic firms and an increase in their research and development activities by signing RTAs. These effects will be particularly important for medium- and low-income countries, in which indigenous firms try to absorb superior technology from firms in technologically advanced countries.

Another important implication from our analysis is that economic distance actually affects the localization of technology spillovers. Although countries cannot change geographical distance to the source of new technology (i.e., a technologically advanced country), they can control economic distance to it by implementing trade and industrial policies. RTA formation and WTO participation are included in such policies. Thus, our finding suggests an active role for governments to facilitate technology spillovers across countries.

Since the above results are based on the USPTO data, it is worthwhile to check the robustness of the results by analyzing other patent data from, for example, EPO and JPO. Moreover, our analysis is not enough to completely understand the role of economic distance in the localization of technology spillovers. A detailed study on other aspects of economic distance will be included in our future study.

Appendix Fixed and Random Effects Negative Binomial Models

Let C_{kt} be the number of patent citations by the k^{th} pair of the citing and cited countries/regions in time t. As shown in Allison and Waterman (2002), the FXNB function proposed by Hausman et al. (1984) can be written as

$$f(C_{kt}|\eta_{kt},\lambda_k) = \frac{\Gamma(\eta_{kt}+C_{kt})}{\Gamma(\eta_{kt})\Gamma(C_{kt}+1)}\left(\frac{\lambda_k}{1+\lambda_k}\right)^{\eta_{kt}}\left(\frac{1}{1+\lambda_k}\right)^{C_{kt}}, \tag{A.1}$$

where Γ is the gamma function and λ_k is an unknown dispersion parameter, which is assumed to be constant over time for the pair of citing and cited countries/regions. The parameter η_{kt} is assumed to depend on covariates for regressors by an exponential function:

$$\eta_{kt} = \exp\left(\boldsymbol{x}'_{kt}\boldsymbol{\beta}\right), \tag{A.2}$$

where $\boldsymbol{x}_{kt}$ is a vector of regressors, which may include time–invariant regressors, and $\boldsymbol{\beta}$ is a vector of unknown parameters. The mean and variance of C_{kt} are given by

$$E(C_{kt}) = \eta_{kt}/\lambda_k, \quad \text{and} \quad V(C_{kt}) = \eta_{kt}(1+\lambda_k)/(\lambda_k)^2, \tag{A.3}$$

respectively. Thus, the ratio of the variance to the mean is $(1+\lambda_k)/\lambda_k$, which can vary across pairs but is constant over time. We assume that $\lambda_k = (\tilde{\lambda}_{ij})^{-1}$ holds, where $\tilde{\lambda}_{ij}$ is a time–invariant individual effect that appears in Eqs. (3), (5), and (6).

As shown in Cameron and Trivedi (2005: 806), the parameter λ_k can drop out of the conditional joint density for the k^{th} observation, which is given by

$$\begin{aligned} f(C_{k1},\ldots,C_{kT}|\sum_t C_{kt}) &= \frac{\Gamma(\sum_t \eta_{kt})\Gamma(\sum_t C_{kt}+1)}{\Gamma(\sum_t \eta_{kt}+\sum_t C_{kt})} \\ &\quad \times \prod_t \frac{\Gamma(\eta_{kt}+C_{kt})}{\Gamma(\eta_{kt})\Gamma(C_{kt}+1)}. \end{aligned} \tag{A.4}$$

Since the conditional maximum likelihood FXNB estimator of $\boldsymbol{\beta}$ maximizes the log-likelihood function based on Eq. (A.4), consistent estimation of $\boldsymbol{\beta}$ in the presence of fixed effects is feasible (Cameron and Trivedi, 2005).

This property of the FXNB allows us to simultaneously estimate coefficients for the geographic factors such as $\ln(Dist)$ and $Lang$ in $\boldsymbol{x}_{kt}$ and the individual effects (λ_k) in the FXNB. However, it means that the FXNB is different from the fixed effects models in the usual sense (Allison and Waterman, 2002). In general, Eq. (A.4) is obtained only if a specific functional relationship holds between the individual fixed effect and the parameter λ_k (Guimarães, 2008). Simulations by Guimarães (2008) indicate that this condition is reasonably satisfied when the sample size is sufficiently large and the time horizon is not too short.

We next consider the RENB. Following Hausman et al. (1984), we now assume that the parameter λ_k takes the form $\lambda_k = \xi_k/e^{\mu_k}$, which is randomly distributed across the pair of the citing and cited countries/regions, independent of $\boldsymbol{x}_{kt}$. Parameters ξ_k and μ_k vary across the pair of countries.

Since we need a two-parameter distribution for λ_k, we assume that the ratio $z_k \equiv \lambda_k/(1+\lambda_k) = 1/(1+e^{\mu_k}/\xi_k)$ is distributed as a beta random variable with parameters (a, b) and hence z_k has a density function:

$$f(z) = [B(a,b)]^{-1} z^{a-1}(1-z)^{b-1}, \tag{A.5}$$

where $B(\cdot)$ is the beta function. Using the beta density, the conditional joint density for the k^{th} observation in the RENB model is given by

$$\begin{aligned} f(C_{k1},\ldots,C_{kT}|\eta_{k1},\ldots,\eta_{kT},a,b) &= \frac{\Gamma(a+b)\Gamma(a+\sum_t \eta_{kt})\Gamma(b+\sum_t C_{kt})}{\Gamma(a)\Gamma(b)\Gamma(a+b+\sum_t \eta_{kt}+\sum_t C_{kt})} \\ &\quad \times \prod_t \frac{\Gamma(\eta_{kt}+C_{kt})}{\Gamma(\eta_{kt})\Gamma(C_{kt}+1)}, \end{aligned} \tag{A.6}$$

where η_{kt} is given by Eq. (A.2) (Hausman et al., 1984; Cameron and Trivedi, 2005: 803–804). Although the last term on the right-hand side of Eq. (A.6) is the same as the term in FXNB (A.4), we estimate additional parameters a and b from the beta distribution, which describe the distribution of the parameter λ_k across pairs of the citing and cited countries/regions.

In our estimations, we use Stata command `xtnbreg` with options `fe` and `re` to estimate the FXNB and RENB models, respectively.

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Table 1: NB Model: The Effects of RTAs on Technology Spillovers

Dependent Variable: C_{ijt}	(1) Full Sample	(2) Full Sample	(3) Without US	(4) Without US
$\ln(P_i)$	0.91^{***}	0.91^{***}	0.87^{***}	0.87^{***}
	(149.79)	(149.92)	(190.66)	(191.78)
$\ln(P_j)$	0.96^{***}	0.96^{***}	0.95^{***}	0.95^{***}
	(233.23)	(233.40)	(255.34)	(256.58)
$\ln(Dist)$	-0.04^{***}	-0.05^{***}	-0.11^{***}	-0.12^{***}
	(-4.47)	(-4.85)	(-11.91)	(-12.3)
$Lang$	0.39^{***}	0.38^{***}	0.31^{***}	0.31^{***}
	(19.23)	(18.90)	(15.63)	(15.3)
RTA	0.18^{***}		0.22^{***}	
	(7.62)		(9.51)	
FTA		0.22^{***}		0.27^{***}
		(7.27)		(8.94)
CU		0.13^{***}		0.16^{***}
		(4.61)		(6.28)
WTO	-0.17^{***}	-0.17^{***}	-0.08^{***}	-0.08^{***}
	(-5.50)	(-5.48)	(-2.92)	(-2.90)
ITA	0.12^{***}	0.12^{***}	0.20^{***}	0.20^{***}
	(5.32)	(5.47)	(9.64)	(9.84)
No. of Obs.	286128	286128	281378	281378
Log pseudolikelihood	-108659.8	-108653.9	-86414.3	-86404.7

Notes: (1) Estimations are implemented using Stata's command `nbreg`.

(2) "***", "**", and "*" denote 1%, 5%, and 10% significance levels, respectively.

(3) Values in parentheses are t-statistics.

(4) The regressions include year dummies and constant terms.

Table 2: FXNB Model: The Effects of RTAs on Technology Spillovers

Dependent Variable: C_{ijt}	(1) Full Sample	(2) Full Sample	(3) Without US	(4) Without US
$\ln(P_i)$	0.51^{***}	0.51^{***}	0.54^{***}	0.54^{***}
	(102.57)	(102.59)	(86.86)	(86.86)
$\ln(P_j)$	0.43^{***}	0.43^{***}	0.49^{***}	0.49^{***}
	(81.92)	(81.88)	(75.83)	(75.78)
$\ln(Dist)$	-0.19^{***}	-0.20^{***}	-0.13^{***}	-0.13^{***}
	(-12.73)	(-12.88)	(-8.05)	(-7.99)
$Lang$	-0.16^{***}	-0.16^{***}	0.20^{***}	0.20^{***}
	(-4.78)	(-4.82)	(4.56)	(4.55)
RTA	0.10^{***}		0.14^{***}	
	(6.71)		(8.70)	
FTA		0.12^{***}		0.14^{***}
		(6.61)		(6.99)
CU		0.07^{***}		0.14^{***}
		(3.06)		(6.13)
WTO	0.27^{***}	0.27^{***}	0.22^{***}	0.22^{***}
	(11.49)	(11.50)	(7.88)	(7.89)
ITA	0.07^{***}	0.07^{***}	0.03^{*}	0.03^{*}
	(4.63)	(4.82)	(1.84)	(1.84)
No. of Obs.	62816	62816	58238	58238
Log likelihood	-76858.7	-76857.1	-62122.6	-62122.6
Hausman test	2707.1^{***}	2750.3^{***}	2185.5^{***}	2199.0^{***}

Notes: (1) Estimations are implemented using Stata's command `xtnbreg` with option `fe`.

(2) "***", "**", and "*" denote 1%, 5%, and 10% significance levels, respectively.

(3) Values in parentheses are t-statistics.

(4) The regressions include year dummies and constant terms.

(5) The Hausman test statistic is distributed χ^2 with degrees of freedom equal to the number ofregressors in the model.

Table 3: FXNB Model: RTA and WTO Dummies with Lags

Dependent Variable: C_{ijt}	(1) Full Sample	(2) Full Sample	(3) Full Sample	(4) Full Sample	(5) Without US	(6) Without US	(7) Without US	(8) Without US
$\ln(P_i)$	0.51***	0.51***	0.51***	0.51***	0.53***	0.53***	0.53***	0.53***
	(98.54)	(98.57)	(94.77)	(94.77)	(82.41)	(82.41)	(78.70)	(78.69)
$\ln(P_j)$	0.43***	0.43***	0.42***	0.42***	0.49***	0.49***	0.48***	0.48***
	(78.32)	(78.31)	(74.79)	(74.80)	(72.15)	(72.12)	(68.31)	(68.31)
$\ln(Dist)$	−0.20***	−0.21***	−0.20***	−0.21***	−0.14***	−0.14***	−0.15***	−0.15***
	(−12.96)	(−13.15)	(−12.66)	(−12.7)	(−8.68)	(−8.68)	(−8.70)	(−8.61)
$Lang$	−0.15***	−0.15***	−0.13***	−0.13***	0.19***	0.19***	0.19***	0.19***
	(−4.37)	(−4.41)	(−3.72)	(−3.73)	(4.12)	(4.10)	(4.04)	(4.05)
RTA_{t-1}	0.07***				0.10***			
	(4.78)				(6.07)			
RTA_{t-2}			0.06***				0.08***	
			(3.82)				(4.88)	
FTA_{t-1}		0.10***				0.11***		
		(5.05)				(5.05)		
FTA_{t-2}				0.07***				0.08***
				(3.71)				(3.64)
CU_{t-1}		0.04*				0.09***		
		(1.80)				(4.11)		
CU_{t-2}				0.04*				0.09***
				(1.87)				(3.74)
WTO_{t-1}	0.29***	0.29***			0.25***	0.25***		
	(12.61)	(12.61)			(9.23)	(9.23)		
WTO_{t-2}			0.28***	0.28***			0.23***	0.23***
			(12.02)	(12.02)			(8.71)	(8.71)
ITA_{t-1}	0.06***	0.06***			0.02	0.03		
	(3.95)	(4.14)			(1.41)	(1.45)		
ITA_{t-2}			0.05***	0.05***			0.02	0.02
			(3.38)	(3.46)			(1.40)	(1.37)
No. of Obs.	58804	58804	54877	54877	54496	54496	50854	50854
Log likelihood	−73350.8	−73348.9	−69866.3	−69865.8	−59383.9	−59383.8	−56678.2	−56678.1
Hausman test	2638.7***	2675.4***	2587.5***	2608.5***	2154.6***	2165.3***	2126.5***	2133.9***

Notes: (1) Estimations are implemented using Stata's command `xtnbreg` with option `fe`.

(2) "***", "**", and "*" denote 1%, 5%, and 10% significance levels, respectively.

(3) Values in parentheses are *t*-statistics.

(4) The regressions include year dummies and constant terms.

(5) The Hausman test statistic is distributed χ^2 with degrees of freedom equal to the number of regressors in the model.

Table A.1: Sampled Countries/Regions

No.	Country/Region	No.	Country/Region	No.	Country/Region	No.	Country/Region
1	ALBANIA	37	ECUADOR	74	LAO PEOPLE'S	111	SENEGAL
2	ALGERIA	38	EGYPT		DEM. REP.	112	SIERRA LEONE
3	ANGOLA	39	EL SALVADOR	75	LATVIA	113	SINGAPORE
4	ANTIGUA AND	40	ESTONIA	76	LEBANON	114	SLOVAK REPUBLIC
	BARBUDA	41	ETHIOPIA	77	LIBERIA	115	SLOVENIA
5	ARGENTINA	42	FIJI	78	LIBYA	116	SOLOMON ISLANDS
6	ARMENIA	43	FINLAND	79	LITHUANIA	117	SOUTH AFRICA
7	AUSTRALIA	44	FRANCE	80	LUXEMBOURG	118	SPAIN
8	AUSTRIA	45	GABON	81	MACEDONIA	119	SRI LANKA
9	AZERBAIJAN	46	GAMBIA	82	MADAGASCAR	120	ST.LUCIA
10	BAHAMAS	47	GEORGIA	83	MALAWI	121	SURINAME
11	BAHRAIN	48	GERMANY	84	MALAYSIA	122	SWAZILAND
12	BANGLADESH	49	GHANA	85	MALI	123	SWEDEN
13	BARBADOS	50	GREECE	86	MALTA	124	SWITZERLAND
14	BELARUS	51	GRENADA	87	MAURITIUS	125	SYRIA
15	BELGIUM	52	GUATEMALA	88	MEXICO	126	TANZANIA
16	BELIZE	53	GUINEA	89	MOLDVA	127	THAILAND
17	BERMUDA	54	GUYANA	90	MOROCCO	128	TRINIDAD
18	BOLIVIA	55	HAITI	91	NAMIBIA		&TOBAGO
19	BOTSWANA	56	HONDURAS	92	NEPAL	129	TUNISIA
20	BRAZIL	57	HONG KONG	93	NETHERLANDS	130	TURKEY
21	BULGARIA	58	HUNGARY	94	NEW ZEALAND	131	UGANDA
22	CAMBODIA	59	ICELAND	95	NICARAGUA	132	UKRAINE
23	CAMEROON	60	INDIA	96	NIGER	133	UNITED KINGDOM
24	CANADA	61	INDONESIA	97	NIGERIA	134	UNITED STATES
25	CHAD	62	IRAN	98	NORWAY	135	URUGUAY
26	CHILE	63	IRAQ	99	OMAN	136	UZBEKISTAN
27	CHINA	64	IRELAND	100	PAKISTAN	137	VANUATU
28	COLOMBIA	65	ISRAEL	101	PANAMA	138	VENEZUELA
29	CONGO DEM.	66	ITALY	102	PARAGUAY	139	VIETNAM
	REP. OF (ZAIRE)	67	JAMAICA	103	PERU	140	YEMEN REPUBLIC
30	COSTA RICA	68	JAPAN	104	PHILIPPINES		OF
31	CROATIA	69	JORDAN	105	POLAND	141	YUGOSLAVIA
32	CYPRUS	70	KAZAKHSTAN	106	PORTUGAL		SOCIALIST FED.
33	CZECH REPUBLIC	71	KENYA	107	QATAR		REP. OF
34	DENMARK	72	KOREA	108	ROMANIA	142	ZIMBABWE
35	DOMINICA	73	KUWAIT	109	RUSSIA		
36	DOMINICAN REP.			110	SAUDI ARABIA		

Table A.2: List of RTAs

RTA Name	RTA Type
ASEAN Free Trade Area (AFTA)	FTA
Australia - New Zealand (ANZCERTA)	FTA&EIA
Central American Common Market (CACM)	CU
Canada - Chile	FTA&EIA
Canada - Costa Rica	FTA
Canada - Israel	FTA
Andean Community (CAN)	CU
Caribbean Community and Common Market (CARICOM)	CU&EIA
Economic and Monetary Community of Central Africa (CEMAC)	CU
Common Economic Zone (CEZ)	FTA
Commonwealth of Independent States (CIS)	FTA
Chile - China	FTA&EIA
Chile - Costa Rica	FTA&EIA
Chile - Japan	FTA&EIA
Chile - Mexico	FTA&EIA
Chile - El Salvador	FTA&EIA
China - Hong Kong China	FTA&EIA
Common Market for Eastern and Southern Africa (COMESA)	CU
Colombia - Mexico	FTA&EIA
Costa Rica - Mexico	FTA&EIA
Dominican Republic - Central America	FTA&EIA
Dominican Republic - Central America - United States Free Trade Agreement (CAFTA-DR)	FTA&EIA
East African Community (EAC)	CU
Eurasian Economic Community (EAEC)	CU
EC Treaty	CU&EIA
Economic Community of West African States (ECOWAS)	CU
EFTA - Chile	FTA&EIA
EFTA - Croatia	FTA
EFTA - Israel	FTA
EFTA - Jordan	FTA
EFTA - Korea Republic of	FTA&EIA
EFTA - Lebanon	FTA
EFTA - Morocco	FTA
EFTA - Former Yugoslav Republic of Macedonia	FTA
EFTA - Mexico	FTA&EIA
EFTA - Singapore	FTA&EIA
Central European Free Trade Agreement (CEFTA) 2006	FTA
European Free Trade Association (EFTA)	FTA&EIA
EFTA - Tunisia	FTA
EFTA - Turkey	FTA
Egypt - Turkey	FTA
EU - Albania	FTA
EU - Chile	FTA
EU - Croatia	FTA
EU - Algeria	FTA
EU - Egypt	FTA
EU - Israel	FTA
EU - Iceland	FTA
EU - Jordan	FTA
EU - Lebanon	FTA
EU - Morocco	FTA
EU - Former Yugoslav Republic of Macedonia	FTA&EIA
EU - Mexico	FTA&EIA
EU - Norway	FTA
EU - Switzerland - Liechtenstein	FTA
EU - Tunisia	FTA
EU - Turkey	CU
EU - South Africa	FTA
Gulf Cooperation Council (GCC)	CU
Georgia - Azerbaijan	FTA
Georgia - Kazakhstan	FTA
Georgia - Russian Federation	FTA
Georgia - Ukraine	FTA
Israel - Mexico	FTA
India - Singapore	FTA&EIA
Jordan - Singapore	FTA&EIA
Japan - Mexico	FTA&EIA
Japan - Malaysia	FTA&EIA
Japan - Singapore	FTA&EIA
Japan - Thailand	FTA&EIA
Korea Republic of - Chile	FTA&EIA
Korea Republic of - Singapore	FTA&EIA
Southern Common Market (MERCOSUR)	CU&EIA
Mexico - Guatemala	FTA&EIA
Mexico - Honduras	FTA&EIA
Mexico - Nicaragua	FTA&EIA
Mexico - El Salvador	FTA&EIA
North American Free Trade Agreement (NAFTA)	FTA&EIA
New Zealand - Singapore	FTA&EIA
Pan-Arab Free Trade Area (PAFTA)	FTA
Panama - Singapore	FTA&EIA
Panama - El Salvador	FTA&EIA
Pacific Island Countries Trade Agreement (PICTA)	FTA
Pakistan - China	FTA&EIA
Southern African Development Community (SADC)	FTA
South Asian Free Trade Agreement (SAFTA)	FTA
Singapore - Australia	FTA&EIA
Thailand - Australia	FTA&EIA
Thailand - New Zealand	FTA&EIA
Trans-Pacific Strategic Economic Partnership	FTA&EIA
Turkey - Croatia	FTA
Turkey - Israel	FTA
Turkey - Morocco	FTA
Turkey - Former Yugoslav Republic of Macedonia	FTA
Turkey - Tunisia	FTA
Ukraine - Azerbaijan	FTA
Ukraine - Belarus	FTA
Ukraine - Kazakhstan	FTA
Ukraine - Moldova	FTA
Ukraine - Former Yugoslav Republic of Macedonia	FTA
Ukraine - Russian Federation	FTA
Ukraine - Uzbekistan	FTA
US - Australia	FTA&EIA
US - Bahrain	FTA&EIA
US - Chile	FTA&EIA
US - Israel	FTA
US - Jordan	FTA&EIA
US - Morocco	FTA&EIA
US - Singapore	FTA&EIA
West African Economic and Monetary Union (WAEMU)	CU

Source: The web page of the WTO. http://rtais.wto.org/UI/PublicMaintainRTAHome.aspx

Note: (1) The listed RTAs are all RTAs notified to WTO that entered into force by 2006 and of which at least two countries/regions in our sample are signatories are included in the sample.

(2) RTA types are free trade agreements (FTA), customs unions (CU), and economic integration agreements (EIA).

Table A.3: Descriptive Statistics

Variable	No. of Obs	Mean	Std. Dev.	Min	Max
C_{ijt}	286128	35.89	1423.17	0.00	206459
$\ln(P_i)$	286128	2.25	5.63	-13.82	13.37
$\ln(P_j)$	286128	2.25	5.63	-13.82	13.37
$\ln(Dist)$	286128	8.19	0.81	4.02	9.42
$Lang$	286128	0.19	0.39	0.00	1.00
RTA	286128	0.067	0.25	0.00	1.00
FTA	286128	0.032	0.18	0.00	1.00
CU	286128	0.034	0.18	0.00	1.00
WTO	286128	0.63	0.48	0.00	1.00
ITA	286128	0.090	0.29	0.00	1.00

Table A.4: Correlations of the Variables

	C_{ijt}	$\ln(P_i)$	$\ln(P_j)$	$\ln(Dist)$	$Lang$	RTA	FTA	CU	WTO	ITA
C_{ijt}	1.000									
$\ln(P_i)$	0.042	1.000								
$\ln(P_j)$	0.042	−0.028	1.000							
$\ln(Dist)$	0.007	−0.003	−0.003	1.000						
$Lang$	0.002	−0.013	−0.013	−0.047	1.000					
RTA	0.005	0.074	0.074	−0.416	0.115	1.000				
FTA	0.008	0.064	0.064	−0.221	0.055	0.682	1.000			
CU	−0.001	0.039	0.039	−0.354	0.104	0.708	−0.034	1.000		
WTO	0.019	0.207	0.207	0.087	0.128	0.084	0.017	0.098	1.000	
ITA	0.064	0.228	0.228	−0.122	−0.053	0.257	0.153	0.204	0.228	1.000