ABSTRACT

PARK, BYUNGYUL. International Trade and Economic Integration Agreements in Goods and Education Services (Under the direction of Drs. John Beghin and Kathryn Boys).

This dissertation investigates international trade and the effects of Economic Integration Agreements on trade in goods and higher education services. Chapter 1 provides an empirical strategy guided by the data to estimate the long-term effect of Economic Integration Agreements (EIAs) on trade flows. The strategy uses Extreme Bounds Analysis (EBA) to guide the choice of lags and leads in the effects, the periodicity of time intervals if any, and a starting year and associated data exclusions. We show that arbitrarily selected intervals and the starting year can result in non-robust estimates of the long-term effect of EIAs on trade. The empirical strategy follows two steps: EBA firstly sifts lags and leads of EIAs robustly related with trade flows from candidates and then these are in turn included in the gravity equation to estimate the long-term aggregate effect of EIAs on trade. we find that various lags and leads are robustly related to trade flows, leading to the long-term effect of 64%. The long-term estimate obtained from EBA-based estimation has a larger contemporaneous effect and smaller lagged effects compared to previous studies relying on subjective choices of lags and leads and periodicity. Further analysis indicates that deep-integration agreements have stronger and longer impacts on trade than simpler free trade agreements, revealing a richer lead and lag structure under the former.

Chapter 2 analyzes bilateral exports of higher education services between OECD countries and Asia, using a gravity equation approach, panel data from 1998 to 2016, and PPML regression. The approach treats higher education consumption by Asian countries as a consumable durable good reflecting investment in human capital. Asian Students come to OECD countries to obtain degrees from their universities. Structurally, the flow of students from Asian country *j* to OECD country *i* depends on the higher-education capacity of *i*, the perceived quality

of universities in *i*, expected earnings in *i*, a series of bilateral transaction costs between *i* and *j*, the income per capita in *j*, school-age demographics in *j*, and the usual multilateral trade resistance terms. We find that bilateral flows of students are strongly influenced by wage levels in the host country, bilateral distance, importers' income, demographics, common language, the visa regime prevailing in bilateral country pairs, and the network of migrants from *j* in *i*. These results hold through a variation of specifications, proxies, and estimation methods. We find mixed evidence on the role of tertiary education capacity in OECD countries and no evidence of a country's universities reputations explaining the flow of students. The evolution over time of education capacity, earnings, visa regimes, migrant networks, strong income growth and changes in demographics in nearby export markets explain the emergence of Australia, Canada, Korea, and New Zealand and the loss of market share by the US, which still strongly dominates international trade in higher education services.

Chapter 3 examines the impact of EIAs on trade in Higher Education Services (HES). I discover empirical evidence that EIAs have a long-term effect of 42% on trade in Higher Education Services (HES) by using bilateral movements of students as a proxy for HES exports. The two-step estimation strategy using Extreme Bounds Analysis avoids arbitrary decisions with respect to lags and leads in the impacts, the periodicity of time intervals, and data exclusions from choosing a starting year. A counterfactual analysis indicates that gains from EIAs are taken mostly by EU countries that have industriously endeavored to reduce costs through EIAs. Further analysis additionally confirms that countries can enjoy more benefits in terms of increased international students flows from deeper integration by committing to the removal of restrictions on HES. The impact of deeper integration through commitments to HES is stronger and longer than basic integration without commitments to HES has.

International Trade and Economic Integration Agreements in Goods and Education Services

by
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DEDICATION

To my parents and my brother for their unconditional supports.

BIOGRAPHY

Byungyul Park was born in Seoul, South Korea. He received his Bachelor of Arts degree in Economics from Sejong University and his Master of Arts degree in Economics from Korea University. After graduation, he began his Ph.D. in Economics at North Carolina State University with his deep interests in economics.

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CHAPTER 1

Exploring the Impact of Economic Integration Agreements through Extreme Bounds Analysis

1.1. Introduction

With the proliferation of EIAs since the 1990s, through regional and bilateral trade agreements and custom unions, a large trade literature has investigated the effect of EIAs on merchandise trade. Early investigations reached two opposite conclusions, with an eventual rejoinder on their limitations. Some investigations found statistically insignificant or negligible effects of EIAs on trade flows (see for example, Tinbergen, 1962; Bergstrand, 1985; and Frankel et al., 1995). Other investigations found significant effects, sometimes negative, of EIAs on trade (e.g., Aitken, 1973; Abrams, 1980; and Brada and Mendez, 1985).

These opposite findings and variability of the estimated effects of EIAs on trade flows led addressing the suspected endogeneity of EIAs and trade flows. Unobservables correlated with trade flows can cause the EIA variables to be endogenous and seriously bias estimated effects when one overlooks the endogeneity issue. Baier and Bergstrand (2002) relied on control function techniques to deal with the endogeneity using several instruments for the EIA variable. They found that the estimated positive trade effect of EIAs quadrupled from 23% to 92%. Magee (2003) used 2SLS and found strong evidence of larger and positive trade effects. Similarly, Egger et al. (2011) used a two-way fixed effects model to find similar evidence of downward bias in conventional estimates.

In an important departure, Baier and Bergstrand (2007) avoid issues with instruments that violate the “exclusion restriction” condition for instrumental variables. They used pair fixed effects estimation that account for time-invariant and country-and-time varying unobservables in

lieu of instrumental variable estimation. In addition, Baier and Bergstrand (2009) focused on selection bias with observables and estimated average long-run effects of EIAs on trade flows of 100%. This magnitude is similar to those estimated by Baier and Bergstrand (2007), by using matching techniques. A similar nonparametric method (difference in difference) is used in Egger et al. (2008), who found a 4% effect of EIAs on intra-industry trade shares.

A more recent evolution in this literature deals with the "long-term" effects of EIAs on trade as trade agreements take time to be implemented. Notably, Baier and Bergstrand (2007) introduced lagged effects of EIAs that capture "phased-in" periods of EIAs and discovered that EIAs have not only a contemporaneous effect, but also lagged effects on bilateral trade, which can integrate economies more deeply than suggested by the contemporaneous effect. Baier and Bergstrand (2007) highlighted much stronger effects of EIAs than those found in previous studies that increase trade by about 114% after 10 years. This lagging approach has been widely adopted (e.g., Roy, 2010; and Anderson and Yotov, 2016).

To address the implementation length of EIAs, economists have also used "intervals" by leaving out years between observations to account for the EIA implementation time.[1] The motivation to apply the intervals has been to avoid the critique of Cheng and Wall (2005) that bilateral trade would not instantaneously respond to EIAs in a single year's time.[2] While circumventing this critique, however, the intervals have been chosen at the researchers' discretion without solid grounding or a consensus view on the proper interval, leading to incongruent year intervals among existing papers. For example, Baier and Bergstrand (2007)

[1] For example, when 5-year intervals are used with data for 1990 - 2005, only the years 1990, 1995, 2000, and 2005 are used with 5-year and 10-year lags of EIAs included in the model.
[2] In the past, the use of intervals was often due to the unavailability of annual trade data (See Baier and Bergstrand, 2007). However, recent trade literature still utilizes different year intervals, not based on this reason, but to avoid this critique (See Baier et al. 2014; Anderson and Yotov, 2016; Baier et al. 2018).

used 5-year intervals, Anderson and Yotov (2016) used 4-year intervals, and Trefler (1993) used 3-year intervals. Olivero and Yotov (2012) found that the estimates of the effects of EIAs obtained with 3-year and 5-year intervals are similar while these estimates are about twice as large as those obtained with yearly data, and recommended 3-year intervals as it contains more information than 5-year intervals.

Many investigations ignore lead effects, or use leads as a test of unaddressed endogeneity. EIAs take time to be negotiated and have various phases, such as "scrubbing" regulations, or zero-for-zero phases,[3] once negotiated and before they are ratified and enter into force officially (Moser and Rose, 2012; Wright et al., 2020). This possibility has been recognized by Frankel (1997), Magee (2008) and Roy (2010). Hence, we posit that lead effects are plausible, to reflect the fact that trade integration is well on its way before the official starting date of an EIA and that expectations of various economic agents have adjusted before the official starting date of most EIAs. To illustrate, the EU-Korea free trade agreement took 7 rounds of negotiations lasting more than 2 years, followed by nearly 2 years of time before its provisional application, and then almost five years to be fully implemented after that (Wright et al. 2020), suggesting both lead and lagged effects. As another example, Mexico reformed its economic policies in the 1980s and early 1990s to ensure acceptance in GATT by gradually reducing tariffs, non-tariff barriers, and quota (Hansen, 2000). It enabled Mexico to sign a free trade agreement with Chile in 1991, which came into effect in 1999. In addition, Mexico implemented a series of market reforms leading to the North American Free Trade Agreement (NAFTA), being signed in 1992 but ratified in 1994. A massive agricultural policy reform program,

[3] Scrubbing regulation refers to a phase of preparing respective regulations to be consistent with the forthcoming EIA. Zero for zero refers to agreeing to reduce specific distortions, such as border taxes or regulation, in a reciprocal fashion to zero levels.

PROCAMPO, started in 1993 to help cope with the surge of imports and adapt to competitive markets (Hansen, 2000). Similarly, Poland performed a massive economic transformation to an open market economy in early 1990 before its interim agreement with the EEC in 1992. They implemented a regime of free trade by allowing firms to import and export freely and by setting a unified exchange rate to support trade with Western Europe. As a result, their exports increased by 20% in 1990 (Sachs and Lipton, 1990) compared to 1989.

Our last contention has to do with the starting year of the empirical investigation, which is often chosen arbitrarily, adding to specific findings conditioned on these subjective choices. For example, bilateral trade data between 2000 – 2015 could lead to choosing 4-year intervals and 2000 as the starting year, and therefore would estimate their model with 4 periods (2000, 2004, 2008, 2012). It is uncertain, however, that the estimates of the effects of EIAs from this model and data provide the accurate and robust findings, because different sets of years can also be used for estimation according to different starting years, such as 2001, 2002 and 2003 in this example.

1.1.1. An illustration of non-robustness

We illustrate the non-robustness of estimates of the effects of EIAs across the year intervals and the starting years in a simple analysis. Using Poisson Pseudo Maximum Likelihood (PPML) with pair-fixed effects estimation technique, we estimate the gravity bilateral trade model by following Baier and Bergstrand (2007) and their data, with the same 5-year intervals but with different starting years (1962, 1963, 1964, 1965) by using a panel dataset from 1962-2000 of bilateral trade flows and EIAs.[4] In the same way, we also estimate the model with the same 4-

[4] Baier and Bergstrand (2007) used pair-fixed effects to account for the potential endogeneity of EIAs as following:

$$Y_{ijt} = exp(\beta_0 + \beta_1 EIA_{ijt} + \beta_2 EIA_{ijt-1} + \beta_3 EIA_{ijt-2} + \varphi_{it} + \theta_{jt} + \gamma_{ij}) + \varepsilon_{ijt}.$$

year intervals but with different starting years (1962, 1963, 1964). Note that we merely use different starting years within the same dataset, and therefore, all estimations with the same intervals have the same data points but with different sets of years.

In Table 1.1, columns (1) – (4) show estimates of effects of EIAs using 5-year intervals and column (5) – (7) show estimates using 4-year intervals. One can clearly see that the estimates of the long-term effects of EIAs rely on the starting year even with the same year intervals. It varies by up to 26% according to a selected starting year with 5-year intervals (column (2) and (4)) and up to 17% in case of 4-year intervals (column (5) and (7)). The estimates with 5-year intervals and with 4-year intervals can differ by up to 38% (see column (2) and (7)). Both these subjective choices of intervals and starting year can jointly contribute to weakening the robustness of estimates.

We depart from the literature by applying EBA (Leamer, 1985; and Sala-i-Martin, 1997) to select appropriate lags and leads of EIAs avoiding arbitrary choices of intervals and starting years. This step allows the dataset to determine which lags and leads of EIAs should be included in the model for the estimation of the long-term effect of EIAs. Since the full dataset is used with EBA, it also eliminates the issue of the possible lack of robustness that stems from the arbitrary selection of lags, intervals, and the starting year.

Our EBA-based estimations indicate that various lags and one lead of EIAs have robust relationships with trade flows, suggesting that these lags and lead should not be disregarded at the researcher's discretion to estimate the long-term effect of EIAs. Our estimation shows that

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Here, Y_{ijt} is bilateral trade flows between countries *i* and *j*, EIA_{ijt} is a binary variable that equals to 1 if countries *i* and *j* have an economic integration agreement and 0 otherwise, and $\varphi_{it}, \theta_{jt}$, and γ_{ij} are pair-fixed effects that capture unobservables possibly correlated with EIAs. EIA_{ijt-1} and EIA_{ijt-2} denote lagged levels of the EIA dummy. Note that EIA_{ijt-1} and EIA_{ijt-2} are 4-year (5-year) and 8-year (10-year) lags respectively under 4-year (5-year) intervals.

EIAs increase bilateral trade by 64% in the long run, from 2-years before and up to 10 years after entry-into-force of EIAs. Compared to the estimates using 5-year and 4-year intervals, the estimate of long-term effect of EIAs based on EBA exhibits a different distribution of the effects over time. The contemporaneous effect of EIAs is weaker, and cumulative lagged effects of EIAs (after 5 years and between 5 to 10 years) after their entry-into force are stronger. These findings imply that specifications with arbitrary year intervals are likely to overstate the contemporaneous effect of EIAs and understate the "phased-in" effects of EIAs.

Section 2 describes the EBA of Leamer (1980) and Sala-i-Martin (1997). Section 3 provides the two-step estimation method using EBA for the long-term effect of EIAs. Section 4 provides main results and addresses the comparison between estimates based on EBA with those based on predetermined year intervals. Section 5 concludes with some suggestions for future research.

1.2. Extreme Bounds Analysis

EBA is a sensitivity analysis that identifies explanatory variables that robustly affect the dependent variable in presence of model uncertainty related to a set of candidate variables to include or not. Many researchers have used EBA to determine the inclusion or exclusion of additional variables to obtain findings that are more robust.

EBA has been used before to investigate regional trade agreements (RTAs), by Ghosh and Yamarik (2004). Similarly, Yamarik and Ghosh (2005) used Leamer's EBA to evaluate the robustness of variables commonly used as control variables in the gravity model literature and identified determinants, Baxter and Kouparitsas (2006) also tested the robustness of variables commonly used by prior researchers using both Leamer's and Sala-i-Martin's EBA. They

showed that fixed exchange rates, the level of development, and current account restrictions are robustly related to trade.

In light of the above literature that tested the robustness of variables commonly used in the gravity model using EBA, we test the robustness of lags and leads of EIAs commonly used in the gravity model through both Leamer's and Sala-i-Martin's EBA. Lags and a lead found to be robustly related to bilateral trade flows in each EBA are then used to estimate the long-term effect of EIAs. This procedure not only identifies robust lagged impacts of EIAs but also provides the foundation for estimating the long-term effect of EIAs. In addition, it reinforces the robustness of the estimate of the long-term effect of EIAs because it does not require researcher's discretion on the selection of intervals, lags, and the starting year.

The basic idea of EBA is to find out explanatory variables that strongly correlate with the dependent variable from all candidate explanatory variables (set X) by running many possible regressions. Each regression model consists of the dependent variable Y, a vector of free variables $\boldsymbol{F}$ included in every regression, a focus variable T to be tested, and a vector of doubtful variables $\boldsymbol{D}$ taken from set X. Note that free variables always appear in every regression so that these variables are considered important.

Each regression j has the following form:

$$Y = \alpha_j + F\beta_j + \gamma_j T + D\delta_j + \varepsilon. \tag{1}$$

The estimated coefficients (γ) and standard errors (σ) of the focus variable (T) for M possible combinations of $D \subset X$ are used to construct a criterion to select explanatory variables that robustly correlate with the dependent variable. For instance, if up to 2 doubtful variables are taken from a total of 4 variables in set X, the number of possible combinations is $C_0^4 + C_1^4 + C_2^4 = 11$.

Leamer (1985)'s EBA focuses on extreme bounds of coefficient estimates of the focus variable. The lower extreme bound is defined as the minimum value of $\hat{\gamma}_j - \tau\hat{\sigma}_j$ across M possible estimations, where $\hat{\gamma}_j$, $\hat{\sigma}_j$ and τ denote the coefficient of the focus variable, the corresponding standard error, and the critical value for the confidence level respectively. In case of the 95 percent confidence level, τ is 1.96 approximately. Likewise, the upper extreme bound is the maximum value of $\hat{\gamma}_j + \tau\hat{\sigma}_j$. If the lower and upper extreme bounds have the same signs, the corresponding focus variable is deemed "robust," meaning that the focus variable has a robust relationship with the dependent variable with similar directional impact (negative or positive). On the other hand, if the two extreme bounds have opposite signs, the focus variable is considered "fragile" so that the variable should not be included in the model as estimates of the focus variable vary significantly according to which doubtful variables are added to the model.

Leamer's EBA uses a stringent criterion for the focus variable to pass the test. The focus variable can be deemed "fragile" even if only one extreme bound has the different sign while all of the remaining estiamtes have the same signs. This demanding criterion might result in very few robust focus variables. On this point, Sala-I-Martin (1997) proposed a moderated version of EBA to admit a larger number of "robust" focus variables. His approach pays attention to the cumulative distribution function (CDF) of coefficients of the focus variable. That is, the more the fraction of the cumulative distribution of a focus variable lies on the same side of zero, the more correlated with the dependent variable the focus variable is believed to be. In practice, the tested focus variable is regarded as being robustly related to the dependent variable if 95 percent of the density function of the focus variable (CDF(0)) lies on the same side of zero.

Assuming that the regression coefficients (γ) follow the normal distribution, the cumulative distribution function (CDF) in Sala-i-Martin's EBA is given by

$$\gamma \sim N(\bar{\gamma}, \bar{\sigma}), \textit{ where } \bar{\gamma} = \sum_j w_j \hat{\gamma}_j \textit{ and } \bar{\sigma}^2 = \sum_j w_j \hat{\sigma}_j^2.$$

Here, $\bar{\gamma}$ is the weighted mean of regression coefficients $\hat{\gamma}_j$ and $\bar{\sigma}^2$ is the weight mean of the variances $\hat{\sigma}_j^2$, where w_j denotes weights. Sala-I-Martin (1997) applied weights proportional to the likelihoods, $\mathrm{w_j} = L_j / \sum_i L_i$, which gives more weight to models with a better fit. Other measures of goodness of fit such as R squared, and McFadden's likelihood ratio index can also be used as weights. Considering that γ may not follow the normal distribution, Sala-i-Martin also suggested a generic model in which γ does not follow any particular distribution. In this case, an individual CDF of each regression model is calculated first and then an aggregate CDF is obtained from the weighted average of these CDFs:

$$\Phi(0) = \sum_j w_j \phi_j(0|\hat{\gamma}_j, \hat{\sigma}_j^2),$$

where w_j is weights the same as above.

1.3. Empirical Implementation

1.3.1. EBA using the Gravity Equation

Baier and Bergstrand (2007) established that estimated effects of EIAs could suffer from endogeneity bias because of self-selection of country-pairs into EIAs and suggested incorporating bilateral fixed and country-time fixed effects in the gravity equation as a way to deal with the endogeneity bias. By following their approach, we include bilateral fixed and country-time fixed effects in the gravity equation:

$$Y_{ijt} = exp(\beta_0 + \beta_1 EIA_{ijt} + \varphi_{it} + \theta_{jt} + \gamma_{ij}) + \varepsilon_{ijt} \qquad (2)$$

where $Y_{ijt}, \varphi_{it}, \theta_{jt}, and\ \gamma_{ij}$ denotes bilateral trade flow between *i* and *j* at time *t*, time-varying exporter dummies, time-varying importer dummies, and time-invariant country-pair fixed effects, respectively. These fixed effects absorb all bilateral time-invariant, importer-time

variant, and exporter-time variant covariates in addition to multilateral price resistance terms of the gravity equation, and therefore account for time-varying and time-invariant unobservables that possibly correlate with the error term in equation (2).

For EBA, we consider the contemporaneous effect of EIAs (EIA_{ijt}) as a most important effect and thus set this effect to be a free variable, which appears in every regression. Set X of doubtful variables incorporates 10 annual lagged effects of EIAs ($EIA_{ijt-1}, \ldots, EIA_{ijt-10}$), which have been commonly covered in trade literature to see whether these lagged effects are truly associated with trade flows. Therefore, given each focus variable taken from set *X*, up to 9 remaining doubtful variables in set *X* can be added to equation (2). For example, when the focus variable is EIA_{ijt-1} and two doubtful variables (EIA_{ijt-2}, EIA_{ijt-4}) are chosen from set *X*, equation (2) would be extended to:

$$Y_{ijt} = exp(\beta_0 + \beta_1 EIA_{ijt} + \beta_2 EIA_{ijt-1} + \beta_3 EIA_{ijt-2} + \beta_4 EIA_{ijt-4} + \varphi_{it} + \theta_{jt} + \gamma_{ij}) + \varepsilon_{ijt}.$$

Finally, to examine possible lead effects of EIA on trade flows, a second set of EBAs is conducted by extending set *X* to have 10 annual lags and 10 annual leads of the EIA dummy ($EIA_{ijt-1}, \ldots, EIA_{ijt-10}, EIA_{ijt+1}, \ldots, EIA_{ijt+10}$).

We resort to PPML to deal with heteroskedasticity in trade flows.[5] Therefore, clustered heteroskedasticity-robust standard errors are used to construct criterions for EBAs.

To sum up, estimation based on EBA follows two steps: EBA firstly choose lags and leads of EIAs robustly associated with trade flows from candidates and then these are in turn included in the gravity equation (2). Each regression of EBA includes a free variable (EIA_{ijt}), a focus variable taken from set *X*, and up to available 9 doubtful variables taken from set *X* in the

[5] Silva and Tenreryro (2006) argued that the log linear OLS approach produces inconsistent estimates since it does not account for zero trade flows and heteroskedasticity in trade flows, and proposed PPML estimator as a way to deal with this issue.

first set of EBAs while up to 7 doubtful variables are used for the second set of EBAs.[6] Therefore, the number of regressions for each focus variable is $\sum_{i=0}^{9} C_i^9 = 512$ for the first set of EBAs and $\sum_{i=1}^{7} C_i^{19} = 94184$ for the second set of EBAs.

By following Sala-i-Martin (1997), an unweighted version of CDFs is computed to compare results with a weight version of CDFs for which R-squared of each regression is used as weight.[7] However, the results of the unweight version of Sala-i-Martin's EBA are used for an analysis to take account of the unexpected endogeneity even after including the pair-fixed effects. Weighted and unweighted versions of Sala-i-Martin's EBA produced comparable results. Lastly, for Sala-i-Martin's EBA, CDFs are calculated with no distribution assumption on coefficients of focus variables because the kernel density of coefficients of focus variables were not shown to follow the normal distribution. Histograms and densities are shown in the Appendix A.

EBA is conducted using a modified "ExtremeBounds" package in R written by Hlavac (2016). This package can handle both Leamer's and Sala-i-Martin's EBA with several estimation methods but it cannot deal with PPML and many pair-fixed effects at the same time.[8] Hence, we manually fixed the internal code of "ExtremeBounds" package in R to efficiently perform PPML with many pair-fixed effects as these fixed effects play a critical role in dealing with the endogeneity bias of EIA variables.

[6] Even though up to 19 doubtful variables can be added to equation (2) in the second set of EBAs, up to 7 doubtful variables are allowed to be added because of the computational difficulty. The second set of EBAs took about 5 weeks with our computer.
[7] Sala-i-Martin (1997) suggested conducting an unweighted version of EBA because unreasonably higher weights can be given to models that contain endogenous variables in case of a weighted version of EBA.
[8] STATA also has a function "eba" but it only performs Leamer's EBA. To our knowledge, there is still no package that can computationally efficiently perform EBA with many pair-fixed effects.

1.3.2. Data

Annual bilateral trade flows from the NBER-United Nations trade data constructed by Feenstra et al. (2005) are used for the dependent variable. This dataset covers aggregate non-zero trade flows of 149 countries for 1962-2000.[9] Our study covers a total of 96 trading countries by following Baier and Bergstrand (2007). Even though more recent trade data are available, we rely on this dataset because we want to compare our results with Baier and Bergstrand (2007) who covered bilateral trade flows from 1960 – 2000.[10]

For EIA variables, the Database on Economic Integration Agreements constructed by Baier and Bergstrand is used.[11] Their dataset provides records of the economic integration of bilateral countries from 1950 through 2012. It specifies the level of economic integration by ranking: No Agreement (0), One-way Preferential Trade Agreement (1), Two-way Preferential Trade Agreement (2), Free Trade Agreement (3), Customs Union (4), Common Market (5), and Economic Union (6). For estimation, we only consider full EIAs and therefore construct a dichotomous EIA variable to be "1" if the level of economic integration is equal to or higher than Free Trade Agreement (3).

Combining these two large datasets, we have a large panel of annual bilateral trade flows and corresponding status of EIA for 1962 – 2000 that covers 96 countries. In principle, the full data set has 355,680 observations (96 exporters * 95 importers * 39 years), but 216,154 observations are used for the estimation because of data gap issues for bilateral trade flows.

[9] The fact that the dataset only includes positive trade flows might cast doubt on possible conservative results. However, Silva and Tenreyro (2006) confirmed that estimates obtained with PPML vary little when only positive trade flows are used.
[10] See the United Nation's COMTRADE database for recent trade data (https://comtrade.un.org/) and WTO's Regional Trade Agreements database for recent EIA data (http://rtais.wto.org/UI/PublicMaintainRTAHome.aspx).
[11] The dataset is available at Bergstrand's website (https://www3.nd.edu/~jbergstr/).

1.4. Results of EBA estimations

The upper panel of Table 1.2 shows results of the first set of EBAs with 10 lags of the EIA dummy. In Leamer's EBA, lower and upper extreme bounds of 1- to 5-year and 10-year lags of the EIA dummy have the same sign at a significance level of 5%, meaning that these lags appear to robustly relate with trade flows. Sala-i-Martin's EBA produces the same result that 1- to 5-year and 10-year lags of the EIA dummy have a significant relationship with trade flows as unweighted CDF(0)s of these variables are larger than 0.95.

The lower panel of Table 1.2 includes results of the second set of EBAs with 10 lags and 10 leads of the EIA dummy to investigate the existence of lead effects of EIAs. Leamer's EBA shows the same result as in the first set of EBAs that 1- to 5-year and 10-year lags of the EIA dummy are of robust relationships with trade flows. On the other hand, Sala-i-Martin's EBA finds an additional 2-year lead of the EIA dummy that have robust relationships with trade flows.

The results from two sets of EBAs show that various lags and lead contribute to explaining the trade effects of EIAs. Leaving these at the researcher's discretion opens the door to a biased estimate of the long-term effect of EIAs. Therefore, the selection of lags and leads of EIAs should be guided empirically by the given dataset, rather than by researchers' preconception.

In sum, two sets of EBAs discover two different sets of lags and leads robustly correlated with bilateral trade flows:

$$\text{Set 1: } (EIA_{ijt-1}, EIA_{ijt-2}, EIA_{ijt-3}, EIA_{ijt-4}, EIA_{ijt-5}, EIA_{ijt-10})$$

$$\text{Set 2: } (EIA_{ijt-1}, EIA_{ijt-2}, EIA_{ijt-3}, EIA_{ijt-4}, EIA_{ijt-5}, EIA_{ijt-10}, EIA_{ijt+2}).$$

Set 1 includes lags that have robust relationships with trade flows discovered from the first set of EBAs and Leamer's EBA of the second set of EBAs. Set 2 accommodates lags and a lead that

are of robust relationships with trade flow indicated by Sala-i-Martin's EBA of the second set of EBA. These two different sets of lags and leads are in turn added to equation (2) to test statistical significances to estimate the long-term effect of EIAs.

Table 1.3 reports results of estimating equation (2) with lags and lead in Set 1 and Set 2 using PPML. In column (1), which includes estimates of lags in Set 1, all chosen lags are significant, leading to the long-term effect of 62%. Compared with previous estimates, the estimate of the long-term effect is smaller than estimate of the long-term effect of 114% found in Baier and Bergstrand (2007). As explained in Anderson and Yotov (2016), the difference possibly stems from the difference in estimation method as Baier and Bergstrand used OLS while we use PPML estimation technique as in Anderson and Yotov. In the next section, we re-estimate equation (2) with year intervals, as done in previous trade literature, using the same data and PPML estimation technique. This provides a more valid comparison in estimates of the long-term effects of EIAs.

Column (2) shows estimates of lags and the lead of Set 2. It indicates that 1- to 5-year and 10-year lags, and the 2-year lead are significant, leading to the long-term effect of 64%. The statistically significant lead effect of EIAs indicates that trade increases by 6% ($e^{0.0615} \approx 1.06$) in anticipation of the benefits of EIAs. This significant lead (anticipatory) effect of EIAs is in line with the result of Magee (2008) who confirmed that regional trade agreements raise trade prior to their entry-into-force, albeit smaller than its estimate of 26%.

As we have argued, the positive lead effect of EIAs on trade flows is not surprising when one thinks about a long process of EIAs. Leads of EIAs are often regarded as not central and just used to test the strict exogeneity assumption of EIAs by conducting a simple "strict exogeneity"

test suggested by Wooldridge (2010)[12]. However, a mechanical and simplistic interpretation of leads of EIAs as a test of the strict exogeneity abstracts from the lengthy genesis of EIAs with their prerequisite policy reforms enhancing trade before ratification. We argue for leads of EIAs to be carefully examined to reflect trade expansion in the "preparatory" period of the EIAs.

1.4.1. Comparison with estimates using year intervals

In this section, we estimate the gravity equation (2) with year intervals as in previous trade literature but with the same data and the same PPML estimation technique to compare estimates more precisely. The first specification is the gravity equation with 5-year intervals as in Baier and Bergstrand (2007) and therefore 5-year and 10-year lags of the EIA dummy ($EIA_{ijt-5}, EIA_{ijt-10}$) are added to equation (2):

$$Y_{ijt} = exp(\beta_0 + \beta_1 EIA_{ijt} + \beta_2 EIA_{ijt-5} + \beta_3 EIA_{ijt-10} + \varphi_{it} + \theta_{jt} + \gamma_{ij}) + \varepsilon_{ijt} \quad (3)$$

Likewise, the second specification is the gravity equation with 4-year intervals that includes 4-year and 8-year lags of the EIA dummy (EIA_{ijt-4}, EIA_{ijt-8}) as in Anderson and Yotov (2016):

$$Y_{ijt} = exp(\beta_0 + \beta_1 EIA_{ijt} + \beta_2 EIA_{ijt-4} + \beta_3 EIA_{ijt-8} + \varphi_{it} + \theta_{jt} + \gamma_{ij}) + \varepsilon_{ijt} \quad (4)$$

Both specifications are estimated with PPML using the same data. Cross section years for each specification are chosen to overlap cross section years used in the studies above. As a result, using available years in our dataset (1962 – 2000), data from 1965 to 2000 (1965, 1970, …, 2000) and data from 1962 to 1998 (1962, 1966, …, 1998) are used for the estimation of

[12] Wooldridge (2010) suggests that the feedback effect (lead effect) should not be statistically significant to satisfy the strict exogeneity assumption. One might cast doubt on the assumption of strict EIA exogeneity because of the statistically significant lead effect of EIAs. However, Leamer's EBA with 10 lags and 10 leads (the second set of EBAs) shows that all lead effects of EIAs are not robustly correlated with trade flows and therefore should not be included in the gravity equation (2). Furthermore, even relying on Sala-i-Martin's EBA, the chosen lead effect (EIA_{ijt+2}) does not significantly change the contemporaneous and lagged effects of EIAs as shown in Table 3.

equations (3) and (4), respectively.

Column (2) and (3) of Table 1.4 provide coefficient estimates of 5-year and 4-year interval specifications, respectively. Compared to the estimate of the long-term effect of EIAs on trade (62%) using EBA, the long-term estimates from equation (3) and (4) with year intervals are qualitatively similar, 57% and 61% respectively. However, when we separately see the contemporaneous and the lagged (phased-in) impacts of EIAs on trade, one can find that the distribution of the long-term effect of EIAs is different, even though estimated long-term effects of EIAs are qualitatively close.

The contemporaneous effects of EIAs estimated from equations (3) and (4) are larger than that estimated using EBA. Cumulative effects of EIAs on trade, from 1 to 5 years after their entry-into-force, are estimated to be about 20%, which is smaller than the corresponding cumulative effect of 31% estimated using EBA. Cumulative effects of EIAs from 6 to 10 years after entry-into-force of EIAs also tend to be smaller in equation (3) and (4). This suggests that, even when models with year intervals successfully estimate the long-term aggregate effect of EIAs, there is a strong possibility to overstate the contemporaneous effect of EIAs and understate "phased-in" effects of EIAs after they came into effect.

1.5. An investigation into effects of different levels of EIAs

Following Baier et al. (2014), we decompose the EIA binary variable into two separate variables, *FTA* (level 3) and *CUCMECU* (level 4,5,6), to examine effects of different levels of trade integration on trade flows. *CUCMECU* is defined as a combination of customs union (level 4), comment markets (level 5), and economic unions (level 6) and therefore considered "deeper integration."

Leamer's EBA and Sala-i-Martin's EBA are re-performed with these variables. As above,

the concurrent effects of FTAs and CUCMECUs ($FTA_{ijt}, CUCMECU_{ijt}$) are free variables and thus included in every regression. Set *X* now incorporates 10 lags and 10 leads of FTAs and CUCMECUs, therefore a total of 40 doubtful variables. For each regression in EBAs, up to 3 doubtful variables are allowed to be added to equation (2) due to the computational difficulty. Unweighted CDFs are again only presented for Sala-i-Martin's EBA considering the possible endogeneity of *FTA* and *CUCMECU* but note that there was no remarkable difference in the results between weighted and unweighted CDFs. In addition, no distribution assumption is imposed on coefficients of focus variables because kernel density curves of the coefficients were not close to the normal distribution.

Table 1.5 displays results of EBAs. EBAs produce different results about robustness of focus variables. 1 lag of FTAs (FTA_{ijt-3}), 5 lags of CUCMECUs ($CUCMECU_{ijt-1}, \ldots,$ $CUCMECU_{ijt-4}$, $CUCMECU_{ijt-7}$), and 1 lead of CUCMECUs ($CUCMECU_{ijt+10}$) have robust relationships with trade flows under Leamer's EBA while Sala-i-Martin's EBA additionally finds 4 lags of FTAs (FTA_{ijt-1}, FTA_{ijt-2}, FTA_{ijt-4}, FTA_{ijt-5}), 1 lead of FTAs (FTA_{ijt+10}), 5 lags of CUCMECUs ($CUCMECU_{ijt-5}$, $CUCMECU_{ijt-6}$, $CUCMECU_{ijt-8}$, $CUCMECU_{ijt-9}$, $CUCMECU_{ijt-10}$), and 2 leads of CUCMECUs ($CUCMECU_{ijt+1}$, $CUCMECU_{ijt+9}$). These lags and leads found robust in each EBA are in turn added to equation (2) to estimate the long-term effect of FTAs and CUCMECUs.

PPML results with lags and leads chosen from each EBA are shown in Table 1.6. Column (1) and (2) display PPML results with lags and leads chosen from Leamer's EBA and chosen from Sala-i-Martin's EBA respectively. In column (1) and (2), the long-term effect of FTAs is estimated to be 30% and 26% at a significance level of 5%. These long-term aggregate effects are slightly different according to the type of EBA. On the other hand, the estimate of the long-

term aggregate effect of CUCMECUs (133% and 132%) is much higher than those of FTAs, which indicates that deeper integration on average creates more trade. These results are in accordance with, for example, those found by Baier et al. (2014) and Roy (2010). In addition, deeper integration (*CUCMECU*) has longer effects than FTAs have since CUCMECUs increase trade 10 years before and after their entry-into-force while trade-creating effects of FTAs exist until after 4-years from their entry-into-force.

One can find the significant lead effects of CUCMECUs, meaning that trade flows tend to increase before CUCMECUs officially enter into force, while this trade-creating effect prior to the entry-into-force does not apply to FTAs. The aggregate lead effect of CUCMECUs on trade from the EBAs is on average 21% from 10 years before entry-into-force of CUCMECUs. One possible explanation is that it takes much more time for deeper integration than for FTAs and countries already gear up towards integrating and changing policies long beforehand with the intention to achieve deeper integration. For instance, as mentioned above, Poland reduced its trade barriers in 1990s to accede to the EU and integrated with the EU in 2004. Likewise, Argentina and Brazil eliminated their quantitative restrictions on imports and exports and lowered their tariff by signing the Iguaçu Declaration (1985) before their establishment of MERCOSUR (Southern Common Market) in 1995. It suggests that trade could change long before the entry-into-force of CUCMECUs due to countries' long preparatory period for deeper integration.

1.6. Conclusion

The contribution of our paper is to provide an empirical strategy based on EBA and guided by the data to estimate the robust long-term effect of EIAs on trade flows, and avoiding potential

shortcomings induced by arbitrary decisions, leading to specific and non-robust results. The decisions refer to EIA lags, the periodicity of time intervals and a starting year in datasets.

The estimation of the long-term aggregate effect of EIAs through EBA followed two steps: EBA firstly, sifts lags of EIAs robustly related with trade flows from candidate lags and leads and then these lags (and lead) are in turn included in the gravity equation to estimate the long-term aggregate effect of EIAs on trade.

We find that various lags and one lead of EIAs exhibit a robust relationship with trade flows. These lags and leads should not be ignored at the researcher's discretion. The following estimation indicates that EIAs increase bilateral trade by 64% in the long run. Estimation based on EBA provides evidence that a 2-year lead of EIAs significantly robustly increases trade flows. EIAs increase trade before their entry-into-force. We argue that trade investigations should also examine leads of EIAs to fully capture the impact of the long process of an EIA on trade flows beyond their simple usage for strict exogeneity test.

The estimate of the long-term effect of EIAs on trade obtained from EBA-based estimation is of a comparable magnitude to those from specifications with arbitrary year intervals; however, the distribution of the long-term effect of EIAs is different. The contemporaneous effect is smaller and "phased-in" effects are larger. This finding implies that using arbitrary year intervals might result in the upward-biased contemporaneous effect and downward-biased phased-in effects of EIAs.

EBA may help resolve several problems, which several papers have encountered. For example, Baier et al. (2014) could not find systematically significant trade effects when they estimate their model with consecutive lags and leads of EIAs, using annual data. Collinearity may be present from having many consecutive lag and lead changes in the model. Magee (2008)

found that annual lags and leads of regional trade agreements are jointly significant as a group while most of them are individually insignificant, which suggests possible collinearity. The refinement through EBA could mitigate the risk of the collinearity by narrowing the number of lags and leads of EIAs included in the model.

We only considered the aggregate effect of EIAs on trade flows and therefore future research can apply this method to disaggregated sectors. Furthermore, the estimates of effects of EIAs can be used to evaluate welfare implications of trade, such as national gains and efficiency of trade in light of the well-defined gravity equation foundation. Anderson and Yotov (2016) extended the gravity model and suggested a simulation approach to calculate the terms of trade, national gains, and global efficiency. Future research might want to follow this approach and reevaluate such welfare indexes using estimates of effects of EIAs based on EBA. Finally, the two-step estimation can be conducted with different types of EIAs to investigate a lead and lag structure, and the long-term effect of heterogeneous EIAs on which we will be working.

Table 1.1. PPML results with year intervals and different starting years

5-year intervals (8 data points)				
	(1) 1962-1997	(2) 1963-1998	(3) 1964-1999	(4) 1965-2000
EIA_{ijt}	0.258***	0.214***	0.194***	0.212***
	(0.0376)	(0.0324)	(0.0351)	(0.0352)
EIA_{ijt-5}	0.113***	0.139***	0.213***	0.183***
	(0.0270)	(0.0267)	(0.0283)	(0.0279)
EIA_{ijt-10}	0.128***	0.189***	0.0788***	0.0580**
	(0.0293)	(0.0323)	(0.0268)	(0.0282)
Long-term	65%	72%	63%	57%
N	44134	42699	44524	45077
R^2	0.994	0.995	0.995	0.995
4-year intervals (10 data points)				
	(5) 1962-1998	(6) 1963-1999	(7) 1964-2000	
EIA_{ijt}	0.189***	0.209***	0.176***	
	(0.0334)	(0.0360)	(0.0321)	
EIA_{ijt-4}	0.187***	0.169***	0.170***	
	(0.0279)	(0.0250)	(0.0235)	
EIA_{ijt-8}	0.101***	0.0899***	0.0733***	
	(0.0286)	(0.0275)	(0.0266)	
Long-term effect	61%	60%	52%	
N	54413	56025	55643	
R^2	0.994	0.995	0.995	

Notes: Coefficient estimates for country-and-time and bilateral fixed effects are not reported for brevity. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.2. Results of Leamer's and Sala-i-Martin's EBA

	With 10 lags (up to 9 doubtful variables)				
	Leamer's EBA			Sala-i-Martin's EBA	
	Lower Extreme Bound	Upper Extreme Bound	Robust / Fragile	Unweighted CDF(0)	Robust / Fragile
EIA_{ijt-1}	0.036	0.304	Robust	0.999	Robust
EIA_{ijt-2}	0.001	0.280	Robust	0.997	Robust
EIA_{ijt-3}	0.036	0.278	Robust	1.000	Robust
EIA_{ijt-4}	0.021	0.263	Robust	1.000	Robust
EIA_{ijt-5}	0.015	0.248	Robust	0.999	Robust
EIA_{ijt-6}	-0.024	0.230	Fragile	0.887	Fragile
EIA_{ijt-7}	-0.034	0.220	Fragile	0.847	Fragile
EIA_{ijt-8}	-0.046	0.211	Fragile	0.558	Fragile
EIA_{ijt-9}	-0.034	0.213	Fragile	0.799	Fragile
EIA_{ijt-10}	0.051	0.215	Robust	0.999	Robust

	With 10 lags and 10 leads (up to 7 doubtful variables)				
	Leamer's EBA			Sala-i-Martin's EBA	
	Lower Extreme Bound	Upper Extreme Bound	Robust / Fragile	Unweighted CDF(0)	Robust / Fragile
EIA_{ijt-1}	0.035	0.311	Robust	0.999	Robust
EIA_{ijt-2}	0.000	0.284	Robust	0.999	Robust
EIA_{ijt-3}	0.036	0.280	Robust	1.000	Robust
EIA_{ijt-4}	0.018	0.263	Robust	1.000	Robust
EIA_{ijt-5}	0.014	0.248	Robust	0.999	Robust
EIA_{ijt-6}	-0.025	0.230	Fragile	0.930	Fragile
EIA_{ijt-7}	-0.036	0.221	Fragile	0.889	Fragile
EIA_{ijt-8}	-0.047	0.211	Fragile	0.666	Fragile
EIA_{ijt-9}	-0.036	0.214	Fragile	0.875	Fragile
EIA_{ijt-10}	0.051	0.216	Robust	0.999	Robust
EIA_{ijt+1}	-0.029	0.114	Fragile	0.818	Fragile
EIA_{ijt+2}	-0.007	0.129	Fragile	0.997	Robust
EIA_{ijt+3}	-0.062	0.135	Fragile	0.918	Fragile
EIA_{ijt+4}	-0.109	0.096	Fragile	0.493	Fragile
EIA_{ijt+5}	-0.102	0.070	Fragile	0.742	Fragile
EIA_{ijt+6}	-0.086	0.062	Fragile	0.730	Fragile
EIA_{ijt+7}	-0.069	0.061	Fragile	0.513	Fragile
EIA_{ijt+8}	-0.060	0.062	Fragile	0.643	Fragile
EIA_{ijt+9}	-0.060	0.061	Fragile	0.533	Fragile
EIA_{ijt+10}	-0.063	0.045	Fragile	0.693	Fragile

Notes: No distribution assumption is imposed on coefficients of focus variables to calculate CDFs because kernel densities of the coefficients are different from normal distribution. Histogram and densities are available in Appendix A.

Table 1.3. Main PPML Results

	(1)	(2)
EIA_{ijt}	0.107***	0.0594***
	(0.0272)	(0.0146)
EIA_{ijt-1}	0.0813***	0.0817***
	(0.0199)	(0.0199)
EIA_{ijt-2}	0.0216**	0.0241**
	(0.0100)	(0.0102)
EIA_{ijt-3}	0.0712***	0.0725***
	(0.0139)	(0.0139)
EIA_{ijt-4}	0.0426***	0.0396***
	(0.0104)	(0.0104)
EIA_{ijt-5}	0.0535***	0.0528***
	(0.0161)	(0.0161)
EIA_{ijt-10}	0.103***	0.105***
	(0.0243)	(0.0244)
EIA_{ijt+2}		0.0615**
		(0.0291)
Long-term effect	62%	64%
N	216154	216154
R^2	0.994	0.994

Notes: Coefficient estimates for country-and-time and bilateral fixed effects are not reported for brevity. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.4. PPML results using EBA and year intervals

	(1) EBA-based	(2) Eq. (3) 5-year intervals (1965-2000)	(3) Eq. (4) 4-year intervals (1962-1998)
EIA_{ijt}	0.107***	0.212***	0.189***
	(0.0272)	(0.0352)	(0.0334)
Contemporaneous effect	11%	24%	21%
EIA_{ijt-1}	0.0813***		
	(0.0199)		
EIA_{ijt-2}	0.0216**		
	(0.0100)		
EIA_{ijt-3}	0.0712***		
	(0.0139)		
EIA_{ijt-4}	0.0426***		0.187***
	(0.0104)		(0.0279)
EIA_{ijt-5}	0.0535***	0.183***	
	(0.0161)	(0.0279)	
Cumulative effect (1-5)	31%	20%	21%
EIA_{ijt-8}			0.101***
			(0.0286)
EIA_{ijt-10}	0.103***	0.0580**	
	(0.0243)	(0.0282)	
Cumulative effect (6-10)	11%	6%	11%
Long-term effect	62%	57%	61%
N	216154	45077	54413
R^2	0.994	0.995	0.994

Notes: Coefficient estimates for country-and-time and bilateral fixed effects are not reported for brevity. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.5. Results of Leamer's and Sala-i-Martin's EBA (FTAs and CUCMECUs)

	Leamer's EBA			Sala-i-Martin's EBA	
	Lower Extreme Bound	Upper Extreme Bound	Robust / Fragile	Unweighted CDF(0)	Robust / Fragile
FTA_{ijt-1}	-0.017	0.258	Fragile	0.997	Robust
FTA_{ijt-2}	-0.018	0.233	Fragile	0.997	Robust
FTA_{ijt-3}	0.001	0.236	Robust	0.999	Robust
FTA_{ijt-4}	-0.021	0.227	Fragile	0.999	Robust
FTA_{ijt-5}	-0.044	0.224	Fragile	0.991	Robust
$CUCMECU_{ijt-1}$	0.014	0.394	Robust	0.999	Robust
$CUCMECU_{ijt-2}$	0.006	0.370	Robust	0.999	Robust
$CUCMECU_{ijt-3}$	0.022	0.379	Robust	1.000	Robust
$CUCMECU_{ijt-4}$	0.012	0.378	Robust	0.999	Robust
$CUCMECU_{ijt-5}$	-0.010	0.382	Fragile	0.999	Robust
$CUCMECU_{ijt-6}$	-0.016	0.382	Fragile	0.999	Robust
$CUCMECU_{ijt-7}$	0.027	0.400	Robust	1.000	Robust
$CUCMECU_{ijt-8}$	-0.043	0.372	Fragile	0.997	Robust
$CUCMECU_{ijt-9}$	-0.002	0.354	Fragile	0.999	Robust
$CUCMECU_{ijt-10}$	-0.010	0.336	Fragile	0.998	Robust
$CUCMECU_{ijt+1}$	-0.014	0.199	Fragile	0.996	Robust
$CUCMECU_{ijt+9}$	-0.058	0.266	Fragile	0.993	Robust
$CUCMECU_{ijt+10}$	0.006	0.285	Robust	0.999	Robust

Note: Only robust variables from at least 1 EBA are presented. Full results are available in Appendix A. Up to 3 doubtful variables are used.

Table 1.6. PPML Results with FTA and CUCMECU

	(1) Leamer	(2) Sala-i-Martin
FTA_{ijt}	0.119***	0.0767***
	(0.0280)	(0.0267)
FTA_{ijt-1}		0.0653***
		(0.0201)
FTA_{ijt-2}		0.00965
		(0.0106)
FTA_{ijt-3}	0.143***	0.0595***
	(0.0241)	(0.0147)
FTA_{ijt-4}		0.0331***
		(0.0107)
FTA_{ijt-5}		0.0350*
		(0.0183)
Long-term (FTA)	30%	26%
$CUCMECU_{ijt}$	0.195***	0.125***
	(0.0295)	(0.0228)
$CUCMECU_{ijt-1}$	0.0491***	0.0957***
	(0.0180)	(0.0217)
$CUCMECU_{ijt-2}$	0.0212**	0.0290**
	(0.00957)	(0.0122)
$CUCMECU_{ijt-3}$	0.140***	0.0797***
	(0.0198)	(0.0139)
$CUCMECU_{ijt-4}$	0.0440***	0.0528***
	(0.0162)	(0.0139)
$CUCMECU_{ijt-5}$		0.0421**
		(0.0192)
$CUCMECU_{ijt-6}$		0.0152
		(0.0130)
$CUCMECU_{ijt-7}$	0.225***	0.103***
	(0.0432)	(0.0291)
$CUCMECU_{ijt-8}$		-0.00293
		(0.0198)
$CUCMECU_{ijt-9}$		0.0389***
		(0.0128)
$CUCMECU_{ijt-10}$		0.0861**
		(0.0370)
$CUCMECU_{ijt+1}$		0.0476**
		(0.0210)
$CUCMECU_{ijt+9}$		0.0276
		(0.0278)
$CUCMECU_{ijt+10}$	0.171***	0.143***
	(0.0415)	(0.0342)
Long-term (CUCMECU)	133%	132%
N	216154	216154
R^2	0.994	0.994

Notes: Coefficient estimates for country-and-time and bilateral fixed effects are not reported for brevity. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

CHAPTER 2

The Exports of Higher Education Services from OECD Countries to Asian Countries, A Gravity Approach

2.1. Introduction

International trade in services has been increasing globally. OECD countries have been particularly adept at exporting services to other and often poorer countries. In particular, trade in higher education services has been on the rise globally, and especially in OECD countries which have been very successful at increasing their exports of education services. This trade has more than doubled in the last two decades. About 3.5 million foreign students enroll in OECD countries' universities (OECD, 2018) of which, a majority, nearly 2 million students, comes from Asia (see Figure 2.1 and 2.2).

Higher-education trade flows have taken place in several forms (Bashir, 2007). Some OECD universities open campuses in other countries, but more predominantly, foreign students from Asia come to OECD countries to acquire degrees representing about 55% of the OECD trade in higher education services. Some OECD students also study overseas but mostly within the OECD countries, and the latter trade flows represent about 28% of the OECD trade in higher education services and take place mostly with students from European countries (see Figure 2.2).

The dominant form of exports remains the flow of university students from Asian countries to OECD countries (Bashir, 2007; OECD, 2018). Other countries in Africa and Latin America only represent 8% and 3% of foreign students enrolled in OECD countries' universities. In our investigation, we focus on the large Asian component of higher-education trade and explain its evolution since 1998.

Competition in the provision of higher education has increased considerably. Foreign

students contribute disproportionately to tuition revenues in higher education.[13] The dominance of US universities remains but has decreased, in terms of their market share, to the benefit of other OECD countries such as Australia, Canada, Korea, Turkey, several EU countries, and New Zealand. Almost all OECD countries have experienced a dramatic increase in foreign enrollment despite this competition among providers. The growth in foreign student enrollment has been fueled by rising affluence in many Asian countries both through expectation of higher income coming from education and through the demand for higher education as consumable durable goods and the associated nonpecuniary benefits. The appeal of studying abroad remains powerful.

Growing demographics in parts of Asia, and a global decrease in visa restrictions, and an increase in the size of the higher education sector in OECD countries could explain the growth as well. Substantial migrant networks facilitate the decision to study abroad and might have helped easing the decision to study abroad. Our investigation explores these conjectures and brings rationalization to the rich and contrasting patterns that have emerged in the last 20 years.

This growth in trade in higher education services through foreign students coming to OECD countries has been organic in the sense that international trade policy and multilateral trade agreements have played a moderate role. The Global Agreement on Trade in Services (GATS) of the WTO covers trade in higher education services, but in practice, signing members of the GATS have mostly focused on liberalizing foreign investment regimes in higher education in importing countries (Knight, 2015). The GATS sets up principles and guidelines to progressively liberalize services. In higher education, it is less clear how this is done. GATS centers on national treatment, market access, Most Favored Nation, and transparency issues.

[13] For example, foreign students contribute more than $9 billion or about 28% of tuition revenues in US public universities but represent only 12% of enrollment in recent years (Loudenback, 2016).

Given the dominance of OECD universities, national treatment and market access are relevant issues for OECD universities trying to establish campuses in non-OECD markets, not the opposite.

Knight (2006) identifies the following minor trade liberalization issues for the "consumption abroad" segment of higher education: restriction on travel abroad based on discipline or area of study, restriction on export of currency and exchange, a quota on the number of students proceeding to a county or institution, and prescription of minimum standards or attainments. Some countries also subsidize a restricted number of students as governments recognize the multiple benefits of having better-skilled labor force (Institute for International Education).

Income growth, demographics, the strong return on higher education, and other factors have genuinely fostered the growing international trade between Asian countries and OECD providers of higher education. Visa regimes have been liberalized in all countries and that has fostered the flow of international students as we explain later in our investigation.

The economics literature sees the demand for higher education made of two components. First, there is an investment demand to acquire human capital (a production durable based on a net return to investment) and then there is a consumable durable element to derive non-market benefits from higher education (e.g., Willis and Rosen, 1979; Becker, 1964; Schultz, 1961; and Campbell and Siegel, 1967). In practice, because it is difficult to gather data on expected net return to higher education, the two approaches are often used in confluence with similar price/unit cost and income argument (e.g., Campbell and Siegel, 1967; Beine et al., 2014; and Perkins and Neumayer, 2014).

There is also a large political science and sociological literature looking at the

globalization of higher education, often from a critical perspective of the "commoditization" of higher education (e.g., Altbach and Knight, 2007; and Tilak, 2011). Education scholars have looked at factors influencing the number of foreign students in a country (e.g., Wei, 2013). There are investigations exploring the geography and migration of international students using reduced forms based on heuristics of cost and benefits of acquiring foreign education (Perkins and Neumayer, 2014; Abbott and Silles, 2016; and Beine et al., 2014 for a formal approach). Beine et al. (2012) develop a migration model using a random utility model, which leads to a bilateral migration flow equation with determinants capturing the costs of migrating, living and education, expected return to skills, and nonpecuniary benefits as proxied by university ranking. They apply the model to 13 destinations countries for years 2004-2007 but fixing many variables to a given year. The latter investigation is the most related to our investigation, although it uses a limited panel, and a migration model rather than a bilateral trade flow model leading to account for fewer transaction and trade costs such as trade costs related to visas and foreign exchange.

McMahon (1992) estimated reduced form equations to assess "push and pull" factors explaining bilateral flows of foreign students coming to the US. Naidoo (2007) used a reduced form to look at factors influencing Asian students to attend UK universities such as access to their own universities, tuition, exchange rate, income and integration in the global economy.

Our contribution is to spell out an international-trade approach based on education consumption to acquire human capital in OECD countries and to systematically analyze exports of higher education services and their economic determinants. In addition, our analysis takes place in a larger global context than previous investigations, using a much larger panel dataset. Finally, we account for a more comprehensive set of transaction costs than in previous investigations. We then use our parameters estimate to decompose the change over time in

student flows between key countries based on variation in their determinants. We also use our estimates to explain the observed decrease in Chinese students coming to the US in recent years.

More specifically, our quantitative approach investigates the determinants of bilateral flows of university students from 51 Asian countries to 34 OECD countries using a gravity equation approach and Poisson Pseudo Maximum likelihood (PPML) estimation applied to panel data from 1998 to 2016. The approach treats higher education consumption by Asian countries as human capital consumption decisions. Asian Students come to OECD countries to enroll and obtain degrees from these OECD universities based on perceived costs and benefits of attending a particular OECD country. We derive a sectoral structural model based on Constant Elasticity of Substitution (CES) preferences for these services and higher education capacity in OECD countries. A market equilibrium is formalized in higher education markets in OECD countries, under these assumptions. This step leads to a well-specified gravity equation approach to bilateral exports of higher education services. In the empirical investigation, we explore the potential endogeneity of the supply of higher education services in OECD countries and we account for perceived reputation heterogeneity among OECD countries and their influence on bilateral export demand. Further, we account for an array of transaction and trade costs between importing and exporting countries, including the effect of migrant network, cost of obtaining visas, cultural costs, and the usual costs associated to distance and language.

In our econometric investigation, we find that bilateral flows of students are strongly influenced by the level of wages in OECD destinations, the existing network of migrants from their own country in OECD countries, bilateral distance, income of the importer, demographics of college-age population in the importer's country, common language, and the visa regime prevailing in bilateral country pairs. We find a mixed evidence of a systematic effect of the size

of the higher education sector in OECD countries depending on the proxy used to characterize capacity of the tertiary education sector. As reported in Appendix B, endogeneity of capacity with exports does not appear to be the cause of the mixed result. We also find no significant effect of the perceived reputation of universities in OECD countries.

In the following sections, we first spell out a simple human capital approach to education consumption leading to an aggregate demand in each Asian country for a particular OECD university system. Then, we derive our sectoral model of higher education services based on export demand for these services in Asian countries, and the provision of these services in OECD countries and then the equilibrium between demand and supply. Next, we describe our empirical implementation including, the specification used, the panel data used, and a series of diagnostic tests. We follow with a presentation of the regression results, the decomposition of trade flows over time for key country pairs, and the recent decrease in the flow of Chinese students coming to the US. We also present robustness checks and the investigation of potential endogeneity of higher education capacity in OECD countries. We draw some implications for service trade policy. Appendix B presents additional results on endogeneity tests and robustness checks.

2.2. A Sectoral approach

The approach parallels the gravity equation of Anderson (1979) and Anderson and Van Wincoop (2003), but with distinct features. First, we start from a simple human capital approach (Willis and Rosen, 1979) to the consumption of higher education considered a tradable good. Then, we make use of the result established by Anderson, De Palma, and Thisse (1989) mapping discrete choices into CES preferences. The latter authors characterize the discrete choice as a two-step process in which the consumer first choose the specific variety of the good and then the level of

consumption. Anderson, De Palma, and Thisse show the equivalence of the logit discrete choice and the CES utility function.[14] We also use a sectoral approach to the gravity equation rather than an aggregate GDP, as suggested in Anderson 1979 (his footnote 14).

In addition, our bilateral trade variable is a physical measure of consumption (the number of students from Asian country *j* going enrolled in OECD country *i* in a given year). Further, in our model, trade costs are borne mostly by the importer (in country *j*) who must come to country *i* to consume the exportable service. This assumption is consistent with the preponderant real-world stylized facts explained in the introduction.

Foreign students in country *j* choose a university training consumption level in country *i* (destination and numbers of years) that optimizes the following choice $c_{ij} = \text{Max}(V_{1j}, V_{2j}, \ldots, V_{mj})$ for *m* possible higher education destinations which are in the feasible set of these students. Value function V_{ij} expresses the value students in *j* put on education option *i*. Function *V* is increasing in expected earnings from the gained education. It is also increasing in non-pecuniary benefits associated with the same higher education choice; and finally, it is decreasing in the costs associated with the destination choice. We have *V=V*(*expected earnings*, *non-pecuniary benefits*, *costs associated with the school choice*).

Non-pecuniary benefits are, for example, the quality and reputation of the school and the attractiveness of the foreign location as in Beine et al. (2014). Costs include economic and cultural costs. Difficulty to obtain a visa, travel cost to the destination country, fees, and cost of living are the main economic costs. Cultural costs are associated with language barriers (absence of common language), religious differences between the home and destination country, the lack

[14] The authors spell out conditions sufficient to reconcile a class of models including the logit and the CES for a representative consumer and characteristics approaches to product differentiation. There is a parallel justification to use a CES to represent discrete choices. McFadden has established a closely related equivalence between aggregated discrete choices and a representative consumer CES utility function (McFadden 1978 and 1981; and Feenstra, 2004).

of potential network of nationals as captured by formal colonial links, contiguity (proximity), and immigrant networks from the home country present in the destination country.

We then invoke Anderson, De Palma, and Thisse (1989), to characterize these higher education discrete choices as coming from maximizing utility maximization with CES preferences. Assume agents in country *j* have homothetic preferences assumed CES and choose to purchase higher-education services in country *i* to maximize their utility. These higher education services are differentiated by country of origin (i.e., OECD countries' higher education sectors in our empirical investigation). Denote c_{ij} the consumption of higher education services of OECD country *i* by students coming from country *j*. Consumers in country *j* maximize utility

$$(1)\ U_j = \left(\sum_{i=1}^{m} \beta_{ij}^{\frac{1-\sigma}{\sigma}} c_{ij}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

subject to income constraint (2) $\sum_{i=1}^{m} p_{ij} c_{ij} = Y_j$,

where β_{ij} is the taste parameter for perceived returns, quality and reputation of higher education services in country *i* by consumer *j* (β_{ij}= β_{ij}(*expected earnings, non-pecuniary benefits* (*quality*$_i$)); σ is the constant elasticity of substitution of consumers, p_{ij} is the price of higher education services of country *i* for students in country *j*, and Y_j is consumer income in country *j*. The price for education service *i* p_i (at the border of *i*) varies by importing country *j* (p_{ij}) because of economic and cultural trade costs between *i* and *j*, linked to distance, visa cost, cultural cost, such as language, religion, and other differences, and real exchange rate capturing the relative cost of living.

These costs are made explicit in $p_{ij} = p_i\, t_{ij}$, with t_{ij} denoting the bilateral trade cost factor between *i* and *j*. Here, the trade cost is born by the importer *j* moving to country *i* to consume the higher education services. Taste parameters β_{ij} are unobserved but assumed to be increasing in perceived quality. Later in the empirical investigation, we use a reputation proxy for perceived

quality as an explanatory variable.

Maximizing utility (1) subject to (2) leads to export demand from country *j* for higher education service *i*:

$$(3)\ c_{ij} = \left(\frac{\beta_{ij} p_i^{-\frac{\sigma}{1-\sigma}} t_{ij}^{-\frac{\sigma}{1-\sigma}}}{P_j}\right)^{(1-\sigma)} Y_j, \text{ with price index } P_j,\ P_j = \left(\sum_{i=1}^{m} \left(\beta_{ij} p_i t_{ij}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}.$$

Index *i* covers *m* OECD countries. Because we follow a sectoral approach, we can safely adopt the assumption of specialization in a single service sector as in Anderson and van Wincoop (2003).

Denote the supply of higher education services in *i* as C_i. This variable represents the capacity in the tertiary education sector in country *i* in a given year. We assume the capacity is pre-determined and investigate the potential endogeneity of the supply in the empirical investigation. We have an equilibrium condition equating this capacity with the sum of demands for higher education services from all countries:

$$(4)\ C_i(p_i) = \sum_{j=1}^{all} c_{ij} = p_i^{-\sigma} \sum_{j=1}^{all} t_{ij}{}^{-\sigma} \beta_{ij}^{1-\sigma} \left(\frac{Y_j}{P_j^{1-\sigma}}\right).$$

Equation (4) can be solved for scaled price $p_i^{-\sigma}$ as a function of capacity C_i, trade cost factor t_{ij}, income Y_j, taste parameters β_{ij}, σ, and price index P_j. Substituting the scaled price into equation (3), yields

$$(5)\ c_{ij} = C_i \left(\frac{\beta_{ij}\, t_{ij}^{-\frac{\sigma}{1-\sigma}}}{P_j P_i}\right)^{(1-\sigma)} (pop_j y_j) \text{ with } P_i = \left(\sum_{j=1}^{all} t_{ij}^{-\sigma} Y_j \left[\frac{\beta_{ij}}{P_j}\right]^{1-\sigma}\right)^{\frac{1}{1-\sigma}}.$$

Equation (5) expresses the equilibrium consumption of higher education services in OECD country *i* consumed by country *j* as a function of the capacity of higher education in *i*, C_i, bilateral trade cost factor t_{ij}, preference parameter β_{ij} for schooling in OECD country *i* as a

function of expected earnings, perceived quality and cost of attending universities in *i*, the sectoral equivalent of the multilateral trade resistance terms faced by *i* and *j*, P_i and P_j, and income of consumers in country *j*, Y_j. The latter is decomposed into its income per capita component y_j, and demographic component pop_j.

With more structure, the two trade resistance terms can be solved eventually, as a function of trade cost factors, income, and shares of total income and total OECD higher education supply (see Anderson and Van Wincoop (2003), their equations (10) through (12)). In the empirical investigation, the trade resistance terms are captured by country fixed effects (Thibault, 2015). These effects are not central to our economic investigation. These fixed effects for exporters may also capture some of the non-pecuniary attributes of the OECD destination not captured by the other determinants.

Equation (5) is the base of our empirical implementation. The preference parameters β_{ij} will reflect expected earnings from being schooled in country *i*, non-pecuniary benefits from location *i*, that is, perceived quality and the size of the facilitating migrant network. Trade cost factors are expressed as a power function of bilateral distance, *d*, four cultural dimension variables (with dichotomous variables common language, *cl*, geographical contiguity, *cont*, colonial ties, *col*, and a continuous variable reflecting religion heterogeneity, *reli*), the difficulty to obtain a visa, *visa*, real exchange rate, *rer*, capturing the cost of living differential (purchase power rate of exchange), and a scaling factor *h*, with subscripts *i* and *j* as previously defined. It is:

$$(6)\ t_{ij} = {hd_{ij}}^{\alpha 1}\left(1 + cl_{ij}\right)^{\alpha 2}(1 + cont_{ij})^{\alpha 3}(1 + col_{ij})^{\alpha 4} reli^{\alpha 5} {visa_{ij}}^{\alpha 6} {rer_{ij}}^{\alpha 7}.$$

Equation (6) is then substituted into equation (5) as well as the variables reflecting the benefits of the destination to reflect all explanatory variables. This step is presented in the next section. The

trade cost factor is time varying through the time variation of *visa* and *rer*. The benefits of the OECD destination are time varying in OECD wages and perceived quality/reputation. Capacity in tertiary education is also time varying.

We use equations (5) and (6) in exponential form to accommodate zero bilateral trade flows which is consistent with the PPML estimation method used here. This is unlike logarithmic specifications and their known drawbacks. Since we use panel data, we also add a time subscript *k* to time-varying variables and add time fixed effects T_k. These added features lead to bilateral trade flows between countries *i* and *j* at time *k* expressed as

(7) $c_{ijk} = exp\big(\lambda_0 + \lambda_1 lnC_{ik} + \lambda_2 lnReputation_{ik} + \lambda_3 lnE_{ik} + \lambda_4 lnN_{ijk} + \lambda_5 lnd_{ij} + \lambda_6 cl_{ij} + \lambda_7 cont_{ij} + \lambda_8 col_{ij} + \lambda_9 lnreli_{ij} + \lambda_{10} lnvisa_{ijk} + \lambda_{11} lnrer_{ijk}\big) \times exp\big(\lambda_{12} lny_{jk} + \lambda_{13} lnpop_{jk} + \lambda_{14} Foreign_k + P_i + P_j + T_k\big) + \varepsilon_{ijk}$.

Variable *Reputation* represents the perceived quality of the higher education sector in country *i* by students from country *j*; *E* represents expected future earnings in year *k* from enrolling in higher education in country *i*; variable *N* represents the size of the network of immigrants from country *j* in *i*.

Variable $Foreign_k$ is dichotomic and equal to 1 if the data used refers to foreign students is used in year *k*, as opposed to data on international (non-resident) students as will be explained in the data section. Our dataset comprises a mix of foreign and international students. This dummy variable captures the difference between foreign and international students. Our export equation is of the form $I = exp(\lambda' X)$, with *X* denoting the vector of determinants in (7), other than $Foreign_k$. International students, *I*, are a subset of foreign students, *F*, which also includes students who are resident of the host country. Define the share of international students, $\alpha = I/F$. Then, we have: $F = I/\alpha = exp(\lambda' X - ln(\alpha))$. Therefore, we can append the foreign

student data from countries, which do not disaggregate their *I* subset by using a dummy variable ($Foreign_k$) which corrects for the data inflation ($-ln(\alpha)$). In this case, parameter α captures the average proportion of *I* in *F*, across exporters. We expect the effect of this variable *Foreign* on trade flow to be positive because international students are a fraction of foreign students as will be explained in the data section.

Variable ε denotes a random term with mean zero and conditional variance assumed proportional to the conditional mean ($E(y|x) \propto V(y|x)$). These are the typical assumptions to motivate the PPML estimation approach used here. PPML has been widely used in the estimation of bilateral trade flows for some key reasons. It can handle zero observations, even when they are present in large numbers (Santos Silva and Tenreyro, 2006 and 2011). The PPML estimation method provides regression estimates that are not biased unlike those obtained from a double log specification. In addition, the estimates tend to be more efficient than those from other methods for which the conditional variance $V(y_i|x)$ is proportional to higher order terms of the conditional mean. The latter puts too much weight on large observations, which often are noisier (Santos Silva and Tenreyro, 2006). Heteroskedasticity often increases with the conditional mean and PPML addresses this potential heteroskedasticity. Trade data are characterized by their variance increasing with larger observations of trade flows. The logarithm approach cannot accommodate this characteristic and provides inconsistent estimates. The PPML method is implemented using Stata. Given the panel nature of our dataset, we use clustered errors based on the bilateral distance variable.

The potential endogeneity of variable C_{ik} is approached as follows. We use a control function with PPML to endogenize C_{ik} and account for potential omitted variables generating the possible endogeneity. This approach yields consistent estimators and provides a way to test

endogeneity (Wooldridge, 1997). We also consider the instrumental variable approach in Stata (the IVPoisson command) (Windmeijer and Silva 1997). However, the estimators in this approach suffer from the incidental parameter problem and will be inconsistent as we have fixed effects for importer, exporter and time and the approach uses GMM (Cameron and Trivedi 2013). As a third way to investigate endogeneity, we use direct instruments for C_{ik}. All three approaches are considered.

For additional robustness check on the estimation methods and specifications, we also provide results for truncated non-zero data using a double log specification, double log specification for $(c_{ij} + 1)$ with OLS, and negative binomial PML (NBPML).

2.3. Data

Dependent variable

For our dependent variable, we use OECD data on international student enrollment covering 51 Asian countries and 34 OECD countries for years 1998 to 2016. The country coverage is shown in Table 2.1. OECD countries report the number of international students according to three categories: Foreign (Non-citizen) students, Non-resident students, and students with prior education outside the reporting country. Foreign students are defined as *students who are not citizens of the country in which they are enrolled and where the data are collected* (OECD, 2018). International students are defined either as non-resident students or as students with prior education outside the reporting country. Non-resident students are those with permanent residence outside the reporting country, which means *holding a student visa or permit, or electing a foreign country of domicile in the year prior to entering the education system of the country reporting the data* (OECD, 2018) in practice. The country of prior education is defined

as *the country in which students obtained their upper secondary or the qualification required to enroll in their current level of education* (OECD, 2018).

There are two large data sets for international students flows. The first one covers 1998 – 2012, and the second covers 2013-2016. In the first set, only the number of foreign students is available prior to 2004 and both foreign and international student categories are available from 2004 to 2012 for many countries, but not all values for these categories are available. For example, the United States only reported the number of international students while United Kingdom reported both the number of foreign and international students during this period. The second set only provides the number of international students regardless of the category and is based on updated criteria used for defining international students. These criteria are available in the annex of *Education at a Glance 2018* (OECD, 2018).

Using the number of foreign students as a proxy for the number of international students overestimates the number of mobile students because it accommodates long-term residents who came to the reporting country as a result of prior migration. However, the exclusion of the number of foreign-students data leads to a loss of most observations for important markets in international higher education, such as Czech Republic, Finland, France, Greece, Hungary, Israel, Italy, Japan, Korea, Norway, and Turkey. Not to lose these observations, we account for both categories (International and Foreign) and control for the difference between categories by including the dummy variable *Foreign*, as explained in the model section. International students are a subset of foreign students (OECD, 2018). For example, we use the number of international students (i.e., non-resident or prior education category) if it is reported. However, the number of foreign students is used as a measure of international students with the dummy variable if only

the Foreign (Non-citizen) category is available.[15]

Because of data gap issues for both the enrollment and explanatory variables, we drop Mexico, North Korea, and Palestine. In principle, we have (34 OECD x 51 Asia x 19 years) 32,946 data points. The panel is unbalanced with different time coverage for different countries, although for key markets we have 19 years. Because of missing data for several countries and because of the countries that are dropped, we have 25,265 bilateral trade flow observations including 5,616 zero flows. Hence, the share of observations that are equal to zero is about 22%. This is well within the range of zeros handled by PPML. Because of missing data for some explanatory variables, we eventually use 21,238 of these observations of which 3,428 are zeros, or about 16%. Summary data information is shown in Table 2.2.

Explanatory variables

The same database of the OECD provides total college-age (15-24) population for OECD countries, which we use as a first variable to approximate the supply of higher education services, *C*. We predict the college-age population variable using a reduced form including all the exogenous variables included the bilateral trade flow equation (7), and death rate per 1,000 people as an instrument for the college-age population. We also use total population per OECD country and total tertiary education enrollment for OECD countries as alternative proxies of tertiary education capacity, as well as lagged values of college-age population. Presumably, OECD population, especially of college-age, is predetermined to the tertiary education capacity in the same countries.

For the *Reputation* variable (perceived quality of universities in each country), we use the

[15] If both non-resident and prior education categories are available, the number of students in the non-resident category is used.

country count of universities in the top 100 universities of the Shanghai university ranking (Shanghai university ranking). The ranking was originally known as the Academic Ranking of World Universities computed by Shanghai Jiao Tong University. Since 2009, the ranking has been published by ShanghaiRanking Consultancy. It is based on Clarivate Analytics (formerly Web of Science) information and other honorific and reputational metrics. The ranking is available from 2003 to 2016. For years prior to 2003, we use 2003 values. Despite the lack of values for early years, the index shows variation over time. The US dominates the ranking, especially for the top 20 universities, but other countries have been progressively improving their standing, gaining a significant chunk of the top 100 universities. The index is also available for top 500 universities. The latter was used as an alternate proxy in some of the specifications. This Shanghai ranking indicator has been used in previous analyses of the global competition in higher education (Marginson, 2006; Beine et al., 2014). Beine et al. normalized the ranking by the number of students enrolled in the country, which seems to us peculiar given the non-rival nature of the reputation effect.

For the OECD earning variable (*E*), we use the OECD Employment database, which provide wages time series in OECD countries. The earnings are properly deflated by the country CPI and expressed in local currency units.

For the network variable (*N*), we use three alternative proxies. First, we use the Global Bilateral Migration Database from the World Bank. We use the bilateral migrant stock variable. This dataset is for 2000 and is time invariant, which is a major drawback. The advantage is that the variable is available for many countries and minimize the loss of observations. Second, we use the Docquier, Lowell, and Marfouk (DLM) dataset available from Marfouk's website (http://www.abdeslammarfouk.com/dlm-database.html). This dataset has been used frequently to

capture migrant networks. We rely on the stock of migrants by country of origin. Zeros are dropped for the log transformation with the consequence of having a smaller dataset. The dataset contains only 20 countries.[16] The data is for 2000 (no time variation). The total number of observations is 16,898. The third source comes from the Brucker, Capuano and Marfouk (BCM) dataset (http://www.abdeslammarfouk.com/bcm-database.html). In the latter, the total number of foreign-born individuals is used as a proxy for the migrant network. Only 20 countries are available, also in 5-year intervals. We use 1995 values are used for 1998-1999, 2000 values are used for 2000-2004, 2005 is used for 2005-2009, and so on.

For transaction costs linked to geographical and cultural distances, we use the CEPII Geodist database (CEPII; and Mayer and Zignago, 2011), which provides geographical distances between countries (*d*) and dichotomous variables for a pair of contiguous countries (*cont*), countries with a common language (*cl*), and countries with colonial ties (*col*). These variables are fixed over time. Contiguous countries include 7 countries around Turkey and 3 countries around Israel. Common language includes English and French-speaking countries, and then, Portuguese, Greek, and Turkish languages. Colonial ties originate with the UK, France, and then Turkey, Portugal, Greece, Spain, and the United States. Colonial ties capture some cultural familiarity and likely network effects from the colony's population in the former colonizing country not captured by the network variable.

To capture further cultural costs, we look at the effect of religion heterogeneity on the decision of students to choose the country to study (*reli*). We construct a religion heterogeneity variable between origin and destination countries. We do so using the Religious Diversity Index

[16] Thus, Belgium, Czech Republic, Estonia, Hungary, Iceland, Israel, Italy, Japan, Korea, Poland, Slovak Republic, Slovenia, and Turkey (13 countries in total) are dropped to use this network variable.

Scores from the Pew Research Center.[17] Pew reports percentage shares of each religious group in populations by country for 2010. We measure religion heterogeneity as the sum of the squares of the differences in shares of five major world religions (Christian, Muslim, Hindu, Buddhist, and Jewish) between exporter and importer countries. The variable varies between zero and two and increases with heterogeneity in shares between the two countries.

We use Henley's Passport Index (Henley) to capture transaction cost linked to visas[18]. The index counts the number of countries the passport holder can travel visa-free. It is based on International Aviation Travel Association (IATA) raw data. The index is reported from 2005 to 2016. Most countries exhibit a rising index over time, suggesting a better integration and freer movement of people over time. For example, Denmark, which has been consistently ranked among the countries with the highest index, had an index of 130 in 2005, which reached 187 in 2016. Japan's index increased from 128 to 190 during the same period. The ranking has changed quite significantly over time for countries such as Korea, which has moved from top 30 to top 5, with a jump in its index from 115 to 188. To capture the change in bilateral cost linked to visas we multiply the scores of the two countries. The product behaves as expected (increasing in the number of visa-free destinations for each country in the pair). For the years 1998 to 2004, we use the 2005 value of the index. For 2008, we use the average of the index values for 2007 and 2009. A direct measure of actual bilateral restrictions would be a more exhaustive way to capture the trade cost of visas, but this would require prohibitive work to be collected manually using primary IATA data (see Neumayer, 2011).

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[17] Available at http://www.pewforum.org/2014/04/04/religious-diversity-index-scores-by-country/

[18] We check if the passport index is an appropriate proxy for student visa. Due to the unavailability of data for the number of student visas issued by countries covered in this chapter, we partially investigate a correlation between passport index and nonimmigrant visa (F1) issue of USA by country for 2006 – 2016. There is a strong correlation of 0.99 between the F1 issue and passport index. The F1 visa data are obtained from U.S Department of State – Bureau of Consular Affairs (https://travel.smtate.gov/content/travel/en/legal/visa-law0/visa-statistics/nonimmigrant-visa-statistics.html).

We rely on The World Bank WDI database to obtain exchange rates and GDP deflators to derive real exchange rates (*rer*). For exporters other than the US, bilateral exchange rates are obtained by using the ratio of US dollar exchange rates of the two countries involved in bilateral trade. Income per capita of the importer (*y*) is approximated by GDP per capita, expressed in real LCU based in 2004 prices. The data come from The World Bank WDI database. Exchange rates and GDP deflators were described before. Population data focus on the population in or near college-age (15 to 24 years old) in Asian countries and in OECD countries. The former is the population shifter of the demand for higher education in importing countries (*pop*). The latter was explained above and related to OECD capacity in higher education. Our database and Stata codes are available upon request.

2.4. Results

Before we estimate equation (7), we run collinearity diagnostics for explanatory variables. We follow Besley et al. (2004)'s approach, computing condition indices and a variance decomposition proportions to identify potential numerical problems indicating near collinearity among our explanatory variables. Collinearity issue can potentially be exacerbated by the large number of fixed effects (time, importer, and exporter) and the presence of time-invariant bilateral dichotomous variables (contiguity, common language, and colonial link) and the time-invariant distance and religion heterogeneity variables. Results indicate that when we exclude Iceland (as STATA selects) there is a correlation between the ln(wage) variable and the constant and also between importer fixed effects (Japan and Kazakhstan). However, when we exclude the exporter USA and importer Kazakhstan dummies, there was no significant collinearity issue found with extreme variance inflation in two or more explanatory variables per high condition index. The

inflation remains much below any alarming level as per recommended by Besley et al. (2004). Besley et al. suggest that a condition index larger than 30 with more than 80% of the variance of two or more coefficients indicate an underlying near dependency among explanatory variables, which leads to degraded estimates. We do not encounter numerical issues when we estimate the regressions.

Following the preliminary check, the central results are presented in Table 2.3. Tertiary education capacity in OECD countries (as proxied by OECD college-age population) appears to be significantly linked to the trade flow of foreign students in one of the three runs presented in Table 2.3 (see last column). The three runs present results for three proxies of migrants' network effects and with varying datasets as explained in the data section. The third column shows results for the smaller of the three datasets with migrant networks being time varying. The elasticity is quite high and much larger than for the two other runs. In any case this result is mixed as the significance of the capacity proxy disappears in the estimations shown in columns (1) and (2) and with the magnitude varying so much across runs but with the sign being as expected.

The next issue is the potential endogeneity of the supply of tertiary education in OECD universities. The college-age population could be endogenous to its foreign student component in that we do not specify the public funding and tuition revenues due to unavailability of the data. To check the possible endogeneity, we run an endogeneity test using the control function approach (Wooldridge, 1997). It is done by first predicting the college-age population as a function of the other explanatory variables included in (7) and an additional exogenous variable specific to OECD countries (death rate in the OECD country). The estimated residuals from this regression are then used as an additional regressor in the PPML estimation. If they are significantly linked to the bilateral trade variable, then they provide evidence that the proxy is

endogenous. The results indicate that residuals obtained from the control function are not endogenous to the dependent variable, which means it does not suffer from an omitted variables bias.[19] We also use another instrumental variable approach using the IVPOISSON command in Stata considering the potential endogeneity bias created by simultaneity. The IVPOISSON, however, suffers from the incidental parameter problem as mentioned previously. Nevertheless, the same conclusion holds and no evidence of endogeneity created by simultaneity is found with IVPOISSON since the college-age population is found insignificant as well. Finally, we also use three direct instruments (OECD total populations, foreign enrollment and lagged college-age population). However, none of these proxies was significant. The detailed results of the endogeneity investigation are shown in Table B.1.

The perceived quality/reputation of universities does not matter statistically in all the PPML runs. We also tried rankings based on top 300 and top 500, without success. The ranking represents the right tale of the distribution of universities and may not represent the reputation of the whole university systems at the national level. Results for the alternative proxies are available upon request. The findings of Beine et al. (2014) cannot be confirmed with our larger dataset and we keep in mind their normalization of reputation. In addition, we have a panel as the latter authors use 2007 data.

Expected earnings as captured by OECD wages appear significant and positively related to bilateral flows of students in all PPML runs presented in Table 2.3 and B.1. The implied elasticity is high between 1.7 and 2.7 in Table 2.3, and it persists in the PPML runs in Appendix B. These high elasticities are smaller than those found by Beine et al. (2014), which were as high as 5.5. Wages in the latter investigation were for workers with tertiary education. In any case,

[19]To implement the control function approach, we use bootstrap standard errors (1000 iterations). Each pair of countries are resampled over clusters based on the bilateral distance variable.

these results on wages are also consistent with those found by Rosenzweig (2008). As a note of caution, we tried GNI per capita in OECD countries and relative GNI per capita between exporter and importer and could not find systematic significance with these alternative proxies.

Next, network effects are positive and significant for the three measures used, and with elasticities in the range of .24 to 0.43, depending on the migrant network measure. These results hold for all PPML runs and appear solid. These results and magnitudes confirm findings by Beine et al. (2014) in their smaller dataset for 2007.

As found in many investigations of merchandise trade, distance matters significantly for exports in education services with a response between -.77 and -1.02, depending on the specification. Again all PPML runs confirm the negative role of distance. These values in Table 2.3 are near the median of estimates analyzed in Disdier and Head (around -0.9), and larger than magnitudes found by Beine et al. (2014).

Common language is also important with a significant response between roughly between 1.0 and 1.2 Using the Halvorsen-Palmquist formula [(exp(beta)-1) x100], this common language coefficient (1.228) in column (1) is equivalent to an effect of 241% on the flow of students! Common language has a very strong effect on these foreign students flows, in line with results of existing papers (Abbott and Silles, 2016; Beine et al., 2014; Perkins and Neumayer, 2014). This effect captures the important role of English, but also of French, Greek and Portuguese among these countries. Contiguity and the former colonial ties are not statistically significant. This absence of effect holds through all PPML runs.

Cultural distance as captured by religion dissimilarity does not appear to create cost to students. The religious profile of OECD countries does not seem to play a significant role in a choice of country to study. In the robustness check section, we investigate another dimension of

religion, and found some temporary influence post 2001. (See that section below).

The elasticity of trade with respect to the bilateral trade cost linked to visas is strong and around 1. These results are verified through all the PPML runs. Countries can further integrate and improve their bilateral visa regimes to facilitate the flow of foreign students. OECD countries have increased their passport access by 43% on average between 2003 and 2016. Some countries have improved by great strides (Turkey, and Korea). Similarly, some Asian countries sending their students have been improving their access, by 85% on average. They are still lagging on OECD countries and could do more. This is actionable.

The real exchange rate variable is not statistically significant in columns 1 and 2, and marginally significant in column 3. The real exchange rate has the expected negative impact on bilateral trade in higher education. The estimated standard deviations are relatively high. This mixed to inconclusive result on real exchange rates follow the inconclusive findings of Abbott and Silles (2016), who found a statistically insignificant but positive effect of real exchange rate on the number of international student migrants.

Furthermore, demand shifters in importing countries are significant. Income per capita shows an estimated elasticity in the range (0.63 to 0.745). The population of college-age shows a comparable magnitude for its elasticity with the range (0.535 to .760) with a small loss of significance in column 3. These two results hold through all the PPML runs. The income shifter is the major drive of the growth of this trade in higher education service. Changes in demographics have been smaller on average with strong growth in India, and Malaysia, smaller growth in Indonesia and reductions in China, given its tight control policy on household size. China's income growth has been phenomenal, and that effect swamps the negative impact of the contraction of the college-age population over the period analyzed. Below we look at the recent

development in China's demographic and income to analyze the projected flow of Chinese students in the US in 2017.

Lastly, the coefficient of $Foreign_k$ is significantly positive in all PPML runs. Using the first estimation in column (1) of Table 2.3, we have $-ln(\alpha) = 0.373$, leading to $\alpha = exp(-0.373) \approx 69\%$. It indicates that international students on average represent 69% of foreign students. This proportion is quite close to the average proportion of 71% reported in OECD (2007).

2.4.1. Prediction of Chinese Student Flows to the US for 2017

Using the available variables (visa, real exchange rate, GDP, and population) for 2017, we predict the number of students from China to the US by using predicted coefficients with other variables being constant in 2016. The number of international students coming from China to the US is predicted to decrease by 1% in 2017, which is a smaller effect in absolute value than the actual decrease of 6.6% in 2017 (Hackman and Belkin, 2018). The predicted decrease is mostly driven by the decrease in college-age population of China despite of a decrease in real exchange rate and despite an increase in visa regime and GDP of China. Furthermore, the number of students from China to US might continue to decrease by 2022 based on the decreasing population of China as predicted by UNESCO, with other variables held constant. The estimation does not account for the recent tightening of immigration by the Trump administration.

2.4.2. The Effect of 9/11

The aftermath of the US tragedy of September 11, 2001 may also have influenced the choice of university destination. There were some restrictions imposed on visa seekers and some public anti-foreign and Muslim sentiments, especially in the US (Neiman and Swagel, 2009). We further investigate how the 9/11 event affected bilateral trade in education, in terms of a relationship between Muslim proportion and bilateral trade in education after 9/11. We interact the Muslim proportion of importing countries (i.e., Asian countries) from the data of Pew Research Center with year dummies from 2001 to 2016 and add these variables ($pctmus * year\ dummy$) to our model specification (7).

Table 2.4 shows the estimated effect of 9/11 event from 2001 on. At a 5% significance level, there are statistically significant and negative relationships between Muslim population proportion of importing countries and the bilateral trade in education from 2002 to 2009. Two interpretations are possible and not mutually exclusive. Exporting countries were reluctant to accept students from countries that have higher proportion of Muslims after 9/11 and students from these countries may have felt less welcome in OECD countries following the event. This contraction reached an apex in 2005 and weakened from 2006 on. The negative impact of 9/11 on trade in education appears to be insignificant from 2011 on, indicating that the effect of 9/11 has persisted almost 8 years but has subsided since 2011.

2.5. Robustness checks

To check the robustness of our results, we ran alternative specifications including double-log on truncated and original data adding an arbitrary small number to zeros, and NBPML with 2 different data scaling. Results are shown in Table B.2 for two proxies of OECD tertiary

education capacity and using the WB network proxy. Silva and Tenreyro (2006) point out that parameters of interests are likely to be biased because the log-normal specification does not treat zero-value observations and from the presence of heteroskedasticity. Furthermore, even if we accommodate zero-value observations in the log-normal specification by manually adding a small positive number, the magnitude of parameter estimates depends on the number added to zero-value observations (King, 1988). Nevertheless, results in double log confirm many results except for the estimated parameters of the enrollment variable (significantly negative), the reputation variable (significantly positive), contiguity (significantly negative), colonial link (significantly positive), visa (not significant), and population changes in Asian countries (insignificant). The explanatory power is not as good as the PPML approach and the zero observations are not rationalized properly.

The NBPPML results are shown in column (3) and (4) of Table B.2. They exhibit the poorest explanatory power of all the runs with an obvious issue with scaling. Scaling down the dependent variable by 100 improves the fit considerably but still falls short of the PPML explanatory power. The scale dependency of NBPML is a well-known drawback. We focus on the latter run since the fit is better. Results are at odds with PPML results for the OECD enrollment (significantly negative), reputation (significant), contiguity (significantly negative), and colonial link (significantly positive). Nevertheless, the results confirm many of the PPML results but with some variations in some magnitudes of the effects.

The last robustness check concerns the *Foreign* correction for the inflation in the count of international students when using Foreign data. We modify equation (7) to allow for some variation in the (F/I) correction for as many countries as possible. Six countries have all F or all I data (see Appendix B). We allow for country-specific effect for the remaining 27 countries.

Results are reported in Table B.3. The results show that there is variation in the value of these country-specific *Foreign* data correction, although many are around the range of values obtained for the common Foreign correction in the previous runs. Luxembourg exhibits a negative correction which is at odds with the fact that I is comprised in F. Luxembourg has very small bilateral flows of foreign students and many zeros or near zeros. The latter element may be source of the poor fit, as PPML estimations tend to "overestimate" small values near zero.

2.6. Decomposition

Following Heien and Wessells (1988), we decompose the percentage change in the number of students involved in bilateral trade between notable exporters and importers into the elasticity sum of the percentage changes in the time-varying explanatory variables. For the decomposition, we choose exporters (Australia, Canada, United Kingdom and the United States) and importers (China, India, Japan, Korea, and Malaysia). Since only the number of foreign students is available prior to 2004, we use two points (2004, 2016) to compare the annual growth rate of actual international students with that of predicted international students.

From the equation (7), the annual compound rate of growth of international students ($\hat{r}$) between two points can be derived as:

$$(8)\ \hat{r} = \frac{1}{T}\left(ln\hat{c}_{ijk} - ln\hat{c}_{ijk-T}\right) = \frac{1}{T}\hat{\lambda}_1(lnC_{ik} - lnC_{ik-T}) + \frac{1}{T}\hat{\lambda}_2(top100_{ik} - top100_{ik-T}) + \frac{1}{T}\hat{\lambda}_3(wage_{ik} - wage_{ik-T}) + \frac{1}{T}\hat{\lambda}_{10}\left(lnvisa_{ijk} - lnvisa_{ijk-T}\right) + \frac{1}{T}\hat{\lambda}_{11}\left(lnrer_{ijk} - lnrer_{ijk-T}\right) + \frac{1}{T}\hat{\lambda}_{12}\left(lny_{jk} - lny_{jk-T}\right) + \frac{1}{T}\hat{\lambda}_{13}\left(lnpop_{jk} - lnpop_{jk-T}\right) + \frac{1}{T}\hat{\lambda}_{14}(Foreign_k - Foreign_{k-T}) + + \frac{1}{T}(\hat{\alpha}_k - \hat{\alpha}_{k-T}),$$

where $\hat{\alpha}$ denotes the coefficient of time dummy with T=13 in this case.

Table 2.5 shows the results of decomposition.[20] Overall, the annual compound rates of growth of international students between 2004 and 2016 are well-predicted in the sense that an average predicted change for these 19 bilateral flows is nearly similar to an actual change (3.73% actual, 3.32% predicted). Directions of predicted and actual changes are similar, except for Australia-Malaysia, Canada – Japan, Japan-Malaysia, and UK-Korea. Overall, the decomposition reveals that GDP of an importing country and visa regime between an exporting country and an importing country are the most important contributors for the changes in the bilateral flow of international students. The OECD wages perceived by importers is also important, except for Japan (as a destination), which has experienced stagnant wages. Demographic changes in Asian countries are important for China, Malaysia and Japan (as an importer). Other time-varying variables are less important because, either their elasticity is small or the change in the variable is limited or both.

Looking at salient elements, for Australia, Canada and the US, visa regimes, income growth of importers, and wage growth have driven the changes in the number of international students they host. Importers' income growth and visa regimes play an important role for the change for the UK destination. Changes in the number of international students are in general over-predicted for the US and to a lesser extent the UK. However, a change in the number of international students flows between US and China is very well predicted.

For importers, China has increased its imports from the four exporters from 2004 to 2016. Its changes in the number of international students are estimated to have increased by about 10%, driven by a liberalization of visa regimes and GDP growth, and this despite of a decrease in college-age population. Improvements in visa regime, GDP, and population in India also lead to

[20] The annual rates of change of top100 for Canada and US are zero because the number of top100 universities in 2004 does not differ from that in 2016, while showing some variations between 2004 and 2016.

a large increase in imports for India (8%). Korea shows a moderate increase in total higher education imports over the period (2%), despite a large increase in students going to Canada and to a lesser extent Australia. The decomposition under-predicts actual changes in Korea's imports for the key destinations shown in the Table 2.5. The flow of students to Japan has sharply decreased driven by stagnant Japanese wages, and the reduced capacity in Japan. Finally, the decomposition shows that Japan has reduced its imports from the four exporters consistently with the actual changes, partly driven by the contraction of the college-age population.

2.7. Conclusion

This growth of the flows of foreign students coming to OECD countries has been remarkable in the last two decades with more than a doubling of foreign students coming to OECD countries. The lion share of these students is from Asia. The growth has affected most OECD countries positively but with increasing market share for Australia, the UK, France, Korea, Canada, and NZ, and more recently declining market shares for the US and Japan (OECD, 2018). Most countries have experienced strongly increasing enrollment of foreign students despite the competition for these students. The US and UK still dominate the market but with a large competitive fringe of other OECD countries. Further, some Asian countries like China are experiencing a demographic transition with a shrinking population in college-age. This is affecting exports of higher education, especially in the US, which has historically received a large share of Chinese students. US Universities will have to find students in other countries.

Our results suggest that the growth has principally been fueled organically by rising income and changes in demographics in some importing countries like India and Indonesia, decreasing transaction costs to enroll and cross borders (our visa proxy shows increasing

mobility across countries). Wages in OECD countries provide a pull and influence foreign students to come. Distance remains a strong impediment, which benefits Japan, Korea, and Turkey as host countries.

Common language strongly benefits especially Anglo-Saxon universities (US, Canada, UK, Australia, NZ, and Ireland) with their connection to large export markets in Hong Kong, India, Israel, Pakistan, the Philippines, and Singapore. Communality in religion appears not to matter, but we found that countries with larger populations of Muslim international students flows experienced reduced flow for several years following the tragedy of September 11, 2001. In our analysis, we cannot address specific trade or education policy issues directly because we have gross measures of trade costs. Nevertheless, we find that visa restrictions have a significant role in constraining the consumption abroad of higher education. The policy prescription if any is for Asian (and other) with limited international mobility to increase the ease of access to OECD markets for their students.

Figure 2.1. Growth of enrollment of foreign students

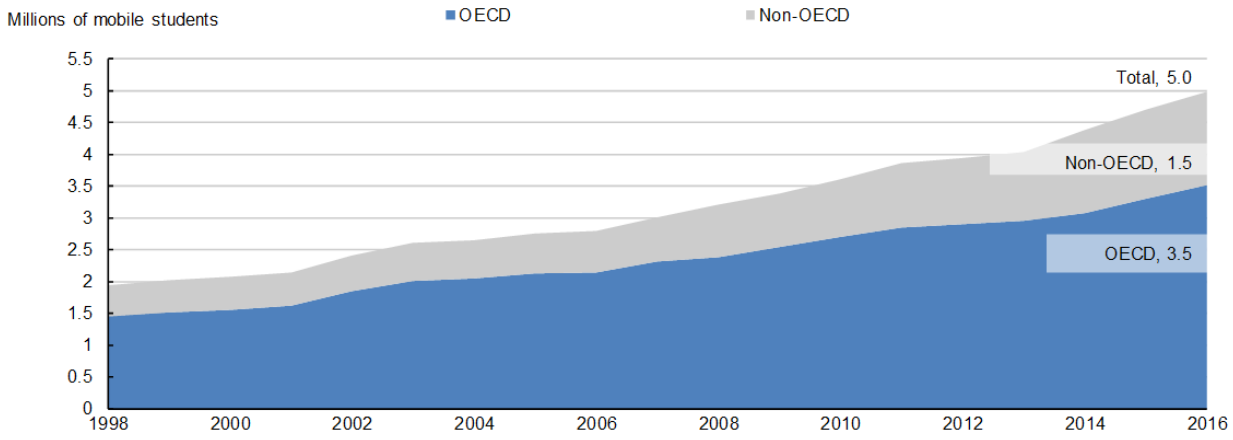

Figure 2.2. Distribution of international students by region of origin

Country	Total tertiary	Short-cycle tertiary	Bachelor's or equivalent	Master's or equivalent	Doctoral or equivalent
Asia	55	66	55	57	42
Europe	24	14	25	22	32
Africa	8	7	8	9	10
Latin America & Carribean	5	5	5	6	8
North America	3	2	3	3	4
Oceania	1	1	1	0	1
Rest of the World (non allocated	3	6	4	3	3

	Total tertiary education	Short-cycle tertiary	Bachelor's or equivalent	Master's or equivalent	Doctoral or equivalent
Total	3,521,004	206,200	1,751,923	1,320,635	242,246
Asia	1,946,054	135,408	960,529	749,351	100,765

Table 2.1. Country list in the OECD database

OECD Exporters	Asian Importers	
Australia	United Arab Emirates	Oman
Austria	Afghanistan	Pakistan
Belgium	Armenia	Palestine, State of
Canada	Azerbaijan	Philippines
Chile	Bangladesh	Qatar
Czech Republic	Bahrain	Russian Federation
Denmark	Brunei Darussalam	Saudi Arabia
Estonia	Bhutan	Singapore
Finland	China	Syrian Arab Republic
France	Cyprus	Tajikistan
Germany	Georgia	Thailand
Greece	Hong Kong, China	Timor-Leste
Hungary	Indonesia	Turkey
Iceland	Israel	Turkmenistan
Ireland	India	Uzbekistan
Israel	Iraq	Viet Nam
Italy	Iran, Islamic Republic of	Yemen
Japan	Jordan	
Korea	Japan	
Luxembourg	Kyrgyzstan	
Mexico	Cambodia	
Netherlands	North Korea	
New Zealand	Korea, Republic of	
Norway	Kuwait	
Poland	Kazakhstan	
Portugal	Laos	
Slovak Republic	Lebanon	
Slovenia	Sri Lanka	
Spain	Macao	
Sweden	Malaysia	
Switzerland	Maldives	
Turkey	Mongolia	
United Kingdom	Myanmar	
United States	Nepal	

Table 2.2. Summary Statistics

	Obs.	Non-zero Obs.	Mean	Std. Dev.	Min	Max
Student	25,625	19,921	842.04	6451.93	0	309837.30
OECDpop	25,625	25,625	4728.44	7951.86	42.39	44434.69
Top100	25,625	12,583	3.30	9.81	0	57
Wage	24,774	24,774	39779.30	11820.49	15070.25	64551.55
Network	25,625	22,032	16179.70	99558.17	0	2008979
Log(distcap)	25,625	25,625	8.72	0.58	4.71	9.86
Common language	25,625	815	0.03	0.18	0	1
Contiguity	25,625	200	0.01	0.09	0	1
Colony	25,625	666	0.03	0.16	0	1
Religious dissimilarity	25,625	25,625	0.93	0.51	0.00005	1.94
Visa	25,625	25,625	8032.10	6304.93	624	30621
RER	25,625	25,625	752.90	2494.86	.0001	28829.32
GDPasia	25,625	25,625	20957.76	52568.50	6.07	284136.50
POPasia	25,625	25,625	16042.31	45124.91	54.50	243092.40

Table 2.3. PPML results with 3 proxies of network effects

	(1) PPML	(2) PPML	(3) PPML
OECD college-age pop	0.209	0.375	2.354***
	(0.465)	(0.478)	(0.720)
University reputation	0.0183	0.0195	0.0229
	(0.0174)	(0.0171)	(0.0180)
Ln OECD wage	2.699***	2.566***	1.698*
	(0.801)	(0.834)	(0.939)
Ln network migration WB	0.239***		
	(0.0483)		
Ln network DLM total		0.387***	
		(0.0579)	
Ln network Marfouk			0.436***
			(0.0658)
Ln distance	-1.027***	-0.784***	-0.767***
	(0.154)	(0.146)	(0.154)
Common language	1.228***	1.072***	1.011***
	(0.265)	(0.256)	(0.277)
Contiguity	0.0634	0.262	-0.113
	(0.457)	(0.491)	(0.627)
Colonial link	-0.123	-0.336	-0.120
	(0.235)	(0.252)	(0.354)
Ln religious dissimilarity	-0.0758	-0.0926	0.0460
	(0.105)	(0.101)	(0.143)
Ln visa free	1.035***	1.028***	1.021***
	(0.262)	(0.257)	(0.269)
Ln real exchange rate	-0.125	-0.136	-0.165*
	(0.0828)	(0.0834)	(0.0993)
Ln GDP per capita Asia	0.744***	0.745***	0.630***
	(0.222)	(0.212)	(0.215)
Ln Asia college-age population	0.760**	0.739**	0.535*
	(0.300)	(0.294)	(0.303)
Foreign data correction	0.373***	0.389***	0.368***
	(0.0714)	(0.0713)	(0.0903)
Constant	-41.23***	-41.44***	-39.72***
	(9.365)	(9.176)	(12.16)
N	21238	16898	14321
R^2	0.927	0.925	0.924

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4. The effects of 9/11 on Asian Students' enrollment in OECD Countries

OECD college-age pop	0.266	pctMus x 2003	-0.489***
	(0.464)		(0.126)
University reputation	0.0210	pctMus x 2004	-0.786***
	(0.0173)		(0.215)
Ln OECD wage	2.723***	pctMus x 2005	-0.841***
	(0.742)		(0.227)
Ln network migrants WB	0.239***	pctMus x 2006	-0.815***
	(0.0482)		(0.234)
Ln distance	-1.029***	pctMus x 2007	-0.646***
	(0.154)		(0.240)
Common language	1.226***	pctMus x 2008	-0.593**
	(0.265)		(0.256)
Contiguity	0.0759	pctMus x 2009	-0.555**
	(0.447)		(0.271)
colony	-0.123	pctMus x 2010	-0.561*
	(0.235)		(0.290)
Ln religious dissimilarity	-0.0759	pctMus x 2011	-0.529*
	(0.106)		(0.296)
Ln visa free	1.108***	pctMus x 2012	-0.516*
	(0.252)		(0.313)
Ln real exchange rate	-0.157*	pctMus x 2013	-0.469
	(0.0875)		(0.326)
Ln gdp per capita Asia	0.661***	pctMus x 2014	-0.464
	(0.229)		(0.347)
Ln Asia college age population	0.811**	pctMus x 2015	-0.450
	(0.338)		(0.366)
Foreign data correction	0.357***	pctMus x 2016	-0.399
	(0.0702)		(0.377)
pctMus x 2001	-0.134*	Constant	-42.57***
	(0.0686)		(9.503)
pctMus x 2002	-0.271**		
	(0.106)		
		N	21238
		R^2	0.926

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5. Decomposition of trade flows over time (between 2004 and 2016)

Exporter	Importer	OECD capacity	Reputation	Visa regime	Real exchange rate	Asian GDP per capita	Asian college population	OECD wage	Foreign correction	Actual changes	Predicted change	(actual - predicted)
Australia	China	0.20%	0.28%	10.86%	0.31%	5.87%	-1.59%	2.32%	0.00%	10.60%	10.28%	0.32%
Australia	India	0.20%	0.28%	8.56%	-0.03%	4.14%	0.59%	2.32%	0.00%	8.30%	8.09%	0.21%
Australia	Japan	0.20%	0.28%	5.13%	-0.37%	0.50%	-1.16%	2.32%	0.00%	-4.58%	-1.07%	-3.51%
Australia	Korea	0.20%	0.28%	5.93%	-0.13%	2.02%	-0.38%	2.32%	0.00%	3.37%	2.28%	1.09%
Australia	Malaysia	0.20%	0.28%	5.21%	-0.03%	2.04%	1.16%	2.32%	0.00%	-0.38%	3.21%	-3.59%
Canada	China	0.07%	0.00%	10.68%	0.45%	5.87%	-1.59%	3.77%	0.00%	15.68%	11.27%	4.40%
Canada	India	0.07%	0.00%	8.37%	0.10%	4.14%	0.59%	3.77%	0.00%	21.16%	9.08%	12.08%
Canada	Japan	0.07%	0.00%	4.94%	-0.24%	0.50%	-1.16%	3.77%	0.00%	1.35%	-0.08%	1.43%
Canada	Korea	0.07%	0.00%	5.75%	0.01%	2.02%	-0.38%	3.77%	0.00%	9.49%	3.27%	6.22%
Canada	Malaysia	0.07%	0.00%	5.03%	0.10%	2.04%	1.16%	3.77%	0.00%	5.39%	4.20%	1.18%
Japan	China	-0.32%	-0.14%	10.54%	0.68%	5.87%	-1.59%	0.42%	-2.87%	0.04%	4.62%	-4.58%
Japan	India	-0.32%	-0.14%	8.23%	0.34%	4.14%	0.59%	0.42%	-2.87%	6.95%	2.43%	4.52%
Japan	Korea	-0.32%	-0.14%	5.61%	0.24%	2.02%	-0.38%	0.42%	-2.87%	-4.51%	-3.38%	-1.13%
Japan	Malaysia	-0.32%	-0.14%	4.89%	0.34%	2.04%	1.16%	0.42%	-2.87%	1.53%	-2.45%	3.98%
UK	China	0.03%	-0.28%	10.63%	0.70%	5.87%	-1.59%	0.38%	0.00%	4.82%	7.76%	-2.94%
UK	India	0.03%	-0.28%	8.32%	0.35%	4.14%	0.59%	0.38%	0.00%	1.00%	5.56%	-4.56%
UK	Japan	0.03%	-0.28%	4.89%	0.01%	0.50%	-1.16%	0.38%	0.00%	-5.97%	-3.60%	-2.37%
UK	Korea	0.03%	-0.28%	5.70%	0.26%	2.02%	-0.38%	0.38%	0.00%	2.82%	-0.25%	3.07%
UK	Malaysia	0.03%	-0.28%	4.98%	0.35%	2.04%	1.16%	0.38%	0.00%	2.97%	0.68%	2.28%
US	China	0.10%	0.00%	10.46%	0.42%	5.87%	-1.59%	1.98%	0.00%	9.69%	9.26%	0.43%
US	India	0.10%	0.00%	8.15%	0.07%	4.14%	0.59%	1.98%	0.00%	4.09%	7.07%	-2.98%
US	Japan	0.10%	0.00%	4.72%	-0.27%	0.50%	-1.16%	1.98%	0.00%	-7.48%	-2.09%	-5.39%
US	Korea	0.10%	0.00%	5.53%	-0.02%	2.02%	-0.38%	1.98%	0.00%	1.09%	1.26%	-0.17%
US	Malaysia	0.10%	0.00%	4.81%	0.07%	2.04%	1.16%	1.98%	0.00%	2.03%	2.19%	-0.16%

CHAPTER 3

The Effect of Economic Integration Agreements on the Exports of Higher Education Services, A Gravity and Extreme Bounds Analysis

3.1. Introduction

Over the last three decades, EIAs have proliferated through regional trade agreements and also through multilateral trade liberalization with the GATT/WTO. WTO recognized the importance of trade in services along with trade in goods, and consequently, the General Agreement on Trade in Services (GATS) was signed during the Uruguay Round of the WTO and came into effect in 1995. Similar to the goal of the GATT, GATS aims at trade liberalization in services, covering 12 different services sectors including education services and 155 sub-sectors. Specifically, four different ways of providing international services are treated under GATS: cross-border supply, consumption abroad, commercial presence, and presence of natural persons. Of these four ways, the focus of this essay is consumption abroad (mode 2), meaning that consumers or firms making use of services in another country. In the context of the education services sector, it directly indicates students going to another country for the purpose of studying.

Education services sector is unique in the sense that it relates with the acquisition of human capital. It is well known that education is an important way to invest in human capital and contribute to productivity growth and income growth even after adjusting for various costs for education (Becker, 1964). The significance and potential benefits of human capital have been noticed by many countries, leading to a global increase in international students flow to OECD countries as shown in Beghin and Park (2019). However, the nominal value of trade in education services is difficult to be accurately measured in practice and thus data on trade flows in education services are limited. This is supported by the fact that data on trade in education

services are not available to date while those on trade in other services have recently become available. As a result, economic research on education services has not been active in comparison with other service sectors. In particular, the effects of EIAs on higher education services (HES) exports have not been estimated to my knowledge, which motivates me to fill this gap.

In this paper, I look at the impact EIAs have had on education exports as characterized by bilateral movements of students between countries involved or not in EIAs. An EIA can affect trade flows in the education sector with leads and lags. That is, even though an EIA legally comes into effect, its economic effect cannot be fully captured in the concurrent year only because EIAs have a "phased-in" period over some years (Baier and Bergstrand, 2007). Furthermore, countries may change the volume of trade in expectation of an approaching agreement and some policy changes may precede the full agreement. For instance, some EIAs include pre-EIA phases within which some partial policy changes take place, such as zero for zero agreements to liberalize some markets prior to the full EIA. Therefore, I also investigate these "phase-in" and "feedback" effects of EIAs. With the estimated effects of EIAs on HES exports, I perform a counterfactual EIA experiment to examine what could happen to exporter countries without EIAs. For estimation, I follow the approach developed by Baier and Bergstrand (2007) and perfected by Anderson and Yotov (2016) in a two-step procedure described in the model section. Lastly, I further divide EIAs into EIAs with and without commitments to HES sector that guarantee to impose no restrictions and analyze the separate effects. The latter step allows to capture the deeper integration achieved by some EIAs.

I argue and show that arbitrarily selecting periodicity (year intervals) in the investigation of EIAs can lead to a distorted estimated long-term effect of EIAs in that the estimates vary by

the periodicity and the starting year even under the same periodicity. Therefore, I suggest avoiding using arbitrary periodicity and rely on Extreme Bounds Analysis, developed by Leamer (1985) and refined by Sala-I-Martin (1997), as a means of selecting valid lags and leads of EIAs. I use R to implement Sala-I-Martin's approach to EBA with fixed effects.

I find that EIAs in goods and services have no significant contemporaneous impact on the trade in education services but have significant lagged and lead effects. EIAs increase international students flows by about 15% after 5 years from their entry-into-force and by 24% 3 years before their entry-into-force. Leads in EIAs are motivated by partial agreements and long negotiations taking place prior to the EIA signature or ratification. Finally, various trade cost variables recovered from a two-step procedure (Anderson and Yotov, 2016) confirm the result of Beghin and Park (2019). The counterfactual experiment indicates that total trade flows in HES would decrease by 18% without EIAs, inducing a big decrease in exports for EU member countries. Lastly, the effect of deeper integration is stronger and longer than that of basic integration (without HES commitments), which shows a long-term effect of 98% and 22% respectively. In other words, deeper integration greatly magnifies the integration effect of basic EIA by a factor of about 4.5.

3.2. Literature Review

Numerous studies have been done on the impacts of EIAs on trade flows of goods. Many of the investigations broadly reached two opposite conclusions of either statistically significant or insignificant effects of EIAs on trade flows. For example, Tinbergen (1962) estimated the effects of EIAs for the first time and found negligible and insignificant impacts of EIAs on trade flows. His results showed that membership in the British Commonwealth and Benelux trade agreements

increase trade flows by a small amount of 5% and 4% respectively. Bergstrand (1985) and Frankel et al. (1995) confirmed this early finding of statistically insignificant impacts of EIAs. Bergstrand (1985) revealed that the European Economic Community (EEC) has a statistically insignificant effects on trade flows, while Frankel et al. (1995) demonstrated insignificant effects of trading blocs on trade flows such as EFTA, NAFTA, and MERCOSUR[21]. On the other hand, Aitken (1973) found the statistically significant effects of EEC and EFTA on trade flows and Brada and Mendez (1985) found significant impacts of several trading blocs across all cross-section years. Abrams (1980) also highlighted the statistically significant and positive effects of EIAs from pooled time series cross-section data in support of Brada and Mendez (1985).

Although numerous studies have tried to investigate the effect of EIAs on trade flows, their findings have diverged and many of these investigations have found the effects of EIAs to be variable over time. For example, the estimated effects of EIAs are not statistically significant (Bergstrand, 1985; Frankel et al., 1995) while they are statistically significant (Aitken, 1973; Brada and Mendez, 1985) and even some studies show the unexpected negative effects (Aitken, 1973) in some cross-section years.

These discrepancies in findings and instability of the effects of EIAs on trade stem from ignoring the endogeneity of the EIA dichotomic variables. The EIA variables might be possibly correlated with an error term in the standard gravity model because a variable unobservable to researchers but related to the EIA variables such as unmeasurable domestic regulations will be absorbed in the error term representing unobservable policy barriers as long as it is not accounted for as an explanatory variable (Baier and Bergstrand, 2007). For example, unmeasured domestic regulations that hinder trade would cause the error term to be negative while render higher

[21] EFTA: European Free Trade Association, NAFTA: North American Free Trade Agreement, MERCOSUR: Southern Common Market.

likelihood of the two countries' selecting into an EIA because two countries that have such regulations are likely to create new bilateral trade through an EIA. In other words, these unmeasured domestic regulations produce negative correlation between EIAs and the error term, causing the EIA coefficients to be underestimated. This highlights the importance of dealing with the endogeneity of EIAs to obtain consistent estimates of EIAs.

The endogeneity of a trade policy variable has been recognized by many researchers. In dealing with the endogeneity of trade policies, Trefler (1993) showed that controlling for the endogeneity of trade policies results in estimates of effects of trade protection policies on importers 10 times larger than estimates treating the trade policies exogenously. It suggests that the effect of trade policy can be severely underestimated if the endogeneity is not properly controlled for. Lee and Swagel (1997) also corroborated the importance of considering endogeneity. Covering broader range of countries, they find that taking into account the endogeneity leads to two to three times larger effect of trade policy on imports.

Likewise, Baier and Bergstrand (2007) found the endogeneity of EIA variables by showing that estimates of the EIAs are highly unstable across years, suggesting that the most plausible way to deal with the endogeneity is to include bilateral fixed and country-and-time fixed effects, which captures the potential endogeneity bias created by unobserved time-invariant bilateral variables and time-varying multilateral price terms. In doing so, while losing all other variables unfortunately, more accurate estimates of the effects of EIAs are obtained. These EIA effects could be underestimated by 80% without handling the endogeneity properly. The authors indeed reveal the larger effect of EIAs, doubling the bilateral trade after 10 years, than previously estimated effects of EIAs. Anderson and Yotov (2016) confirmed the statistically positive effects of EIAs while estimates are smaller than those of Baier and Bergstrand (2007).

The inherent endogeneity issue of EIAs in goods would apply similarly to the EIAs in services. In the context of higher education exports, EIA in services might be correlated with unobservable trade costs in the sense that education services are controlled under each country's own domestic regulations and therefore some countries are more likely to pursue liberalization in education services through EIA in services according to the extent of existing barriers. Furthermore, the fact that EIAs in services are generally made in tandem with EIAs in goods supports the possible endogeneity of EIAs in services.

Several recent studies have looked at bilateral trade in services as data on services trade become available. For example, Kimura and Lee (2006) found determinants of bilateral trade in services similar to those of bilateral trade in goods. Most importantly, the cost of transport proxied by geographical distance is larger for services trade than for goods trade. Head et al. (2009) supported this result by finding strong distance effect in services trade. However, in regard to effects of EIAs, most literature have explored the effects confined to the regional organization such as the EU and NAFTA, not encompassing EIAs among countries. For instance, Kimura and Lee (2006) discovered the positive effect of regional trade agreements and Francois and Hoekman (2010) found the positive impact of European Union on trade flows in line with the result of Park (2002) that highlighted the positive effect of free trade agreements falling only on the EU, not on other agreements such as NAFTA, MERCOSUR, and the Andean pact. Regarding the education services sector, only Abbott and Silles (2016) recently revealed the positive effect of the EU on the flow of international students.

In sum, while many studies have investigated the effects of EIAs on trade in goods, there have been no studies that assess the comprehensive effects of EIAs in services on trade in HES to the best of my knowledge. It is important to understand the effects of EIAs in services on

bilateral trade flows between countries as trade in services comprises a significant share of global trade nowadays. According to WTO, trade in services has reached $4.8 trillion in 2014, representing 21% of world trade in goods and services.

3.3. Year Intervals in Trade Literature

Trade econometric estimations are sometimes criticized when data are pooled over consecutive years. For example, Trefler (2004) claimed that trade flows are not fully adjusted in a single year's time and Cheng and Wall (2005) favored this opinion in a broader perspective that economic specifications that use fixed effects and data pooled over consecutive years can be criticized because a dependent variable would not instantaneously respond to independent variables. In order to avoid these critiques, existing studies have employed panel data with intervals (i.e. leaving years between observations) and take into account possible lagged effects of EIAs. For instance, Anderson and Yotov (2016) used 4-year intervals, Baier and Bergstrand (2007) used 5-year intervals, and Trefler (1993, 2004) used 3-year intervals.

However, the intervals in the existing literatures have chosen at researchers' discretion without a valid justification for which intervals should be used to estimate the effects of EIAs on trade flows. In other words, how many years should be left between observations have not been dealt with. Regarding this point, Olivero and Yotov (2012) revealed that estimates of the long-term effect of EIAs obtained with 3-year and 5-year intervals are similar while these estimates are about twice as large as those obtained with the yearly data. From this result, they recommended 3-year intervals because it contains more information than 5-year intervals.

Nevertheless, it brings about other questions whether estimates are robust regardless of the starting year for the same intervals. If estimated effects of EIAs differ according to the

starting year chosen for the intervals, it means that the estimates depend on a data set of each study and therefore, might not be considered true effects of EIAs, leading to a distorted estimate of the long-term effect of EIAs. In addition, trade flows toward each destination country might be adjusted for different periods of time after the entry-into-force of EIA according to each country's extent of existing barriers or policy changes before and after the EIA. It also indicates that arbitrarily ignoring different time-lagged effects of EIAs would not accurately capture the long-term effect of EIAs.

These unanswered questions lead me to explore the robustness of estimates of EIAs obtained with intervals through a simple analysis. I estimate the following gravity model of Baier and Bergstrand (2007) with 5-year and 4-year periodicity (intervals):

$$(1)\ c_{ijt} = exp(\beta_0 + \beta_1 EIA_{ijt} + \varphi_{it} + \theta_{jt} + \gamma_{ij}) + \varepsilon_{ijt},$$

where $c_{ijt}, \varphi_{it}, \theta_{jt}, and\ \gamma_{ij}$ denotes bilateral trade flow in HES between *i* and *j* at time *t*, time-varying exporter dummies, time-varying importer dummies, and time-invariant country-pair fixed effects, respectively. With 5-year (4-year) periodicity, $EIA_{ij,t-5}$ and $EIA_{ij,t-10}$ ($EIA_{ij,t-4}$ and $EIA_{ij,t-8}$) are used as lags and added to equation (1).

Table 3.1 shows estimates of impacts of EIAs with the same intervals but with the different starting year. For example, estimates in column (1) are obtained by applying 5-year intervals with the starting year of 2001 so that cross section years 2001, 2006, 2011, 2016 are used while 2000, 2005, 2010, and 2015 are used in column (2). It is clear that magnitudes and significance of estimates depend on a set of years used for the estimation, leading to the different estimated long-term effect of EIAs. EIAs have a statistically significant 5-year lagged effect on trade flow in column (1) and (3) while they have not in column (2) and (4). These different

results generate inconsistent long-term effects of EIA. The long-term effect of EIA is estimated as 18% in column (1), 31% in column (2), and even 0% in column (4).

These unstable estimates are also confirmed by results under 4-year intervals as shown in column (5)-(7). Different starting years yield divergent long-term effects: 24%, 18%, and 0%. Furthermore, even when the starting year is the same, different intervals produce different long-term effects as seen in column (2) and column (5). This implies that findings of Olivero and Yotov (2012) that estimates are consistent across intervals might be a coincidence or might not pertain to education services.

This fragility in estimates of effect of EIAs obtained by using intervals alludes that arbitrary truncation of a data set for intervals might cause vulnerable estimates of the long-term effect of EIAs. Therefore, while admitting the importance of the critiques from Trefler (2004) and Cheng and Wall (2005), I claim that using arbitrary data points without a valid justification for intervals can rather lead to distorted estimates. In order to avoid this problem, I propose Extreme Bounds Analysis (EBA) as a means of selecting valid lags and leads of the EIA variables. With EBA, since the full dataset is used without resorting to researcher's discretion, the possible non-robustness of the estimate due to the arbitrary selection of lags, intervals and a starting year would vanish.

3.4. Extreme Bounds Analysis

EBA is a sensitivity analysis that identifies explanatory variables that robustly affect the dependent variable in presence of model uncertainty related to a set of candidate variables to include or not. It has been used by many researchers to demonstrate the robustness of their

results by determining inclusion or exclusion of additional variables to obtain more robust results.

The basic idea of EBA is to find out explanatory variables that strongly correlate with the dependent variable from all candidate explanatory variables (set *X*) by running many possible regressions. Each regression model consists of the dependent variable *Y*, a vector of free variables ***F*** included in every regression, a focus variable T to be tested, and a vector of doubtful variables ***D*** taken from set *X*. Note that free variables always appear in every regression so that these variables are considered important.

Each regression *j* has the following form:

$$Y = \alpha_j + F\beta_j + \gamma_j T + D\delta_j + \varepsilon.$$

The estimated coefficients (γ) and standard errors (σ) of the focus variable (T) for M possible combinations of $D \subset X$ are used to construct a criterion to select explanatory variables that robustly correlate with the dependent variable. For instance, if up to 2 doubtful variables are taken from a total of 4 variables in set *X*, the number of possible combinations is $C_0^4 + C_1^4 + C_2^4 = 11$.

Leamer (1985)'s EBA focuses on extreme bounds of coefficient estimates of the focus variable. The lower extreme bound is defined as the minimum value of $\hat{\gamma}_j - \tau\hat{\sigma}_j$ across M possible estimations, where $\hat{\gamma}_j$, $\hat{\sigma}_j$ and τ denote the coefficient of the focus variable, the corresponding standard error, and the critical value for the confidence level respectively. In case of the 95 percent confidence level, τ is 1.96 approximately. Likewise, the upper extreme bound is the maximum value of $\hat{\gamma}_j + \tau\hat{\sigma}_j$. If the lower and upper extreme bounds have the same signs, the corresponding focus variable is deemed "robust," meaning that the focus variable has a robust relationship with the dependent variable with similar directional impact (negative or

positive). On the other hand, if the two extreme bounds have opposite signs, the focus variable is considered "fragile" so that the variable should not be included in the model as estimates of the focus variable vary significantly according to which doubtful variables are added to the model.

Leamer's EBA has a quite stringent criterion for the focus variable to pass the test in that the focus variable can be regarded "fragile" even if only one extreme bound has the different sign while all of the remainder have the same signs. This demanding criterion might result in very few robust focus variables. On this point, Sala-I-Martin (1997) found that only one, out of 59 tested variables, passes Leamer's EBA and proposed a moderated version of EBA to admit a larger number of "robust" focus variables. His approach pays attention to the cumulative distribution function (CDF) of coefficients of the focus variable. That is, the more the fraction of the cumulative distribution of a focus variable lies on the same side of zero, the more correlated with the dependent variable the focus variable is believed to be. In practice, the tested focus variable is regarded as being robustly related to the dependent variable if 95 percent of the density function of the focus variable (CDF(0)) lies on the same side of zero.

Assuming that the regression coefficients (γ) follow the normal distribution, the cumulative distribution function (CDF) in Sala-i-Martin's EBA is given by

$$\gamma \sim \mathrm{N}(\bar{\gamma}, \bar{\sigma}), \text{ where } \bar{\gamma} = \sum_{\mathrm{j}} \mathrm{w_j} \hat{\gamma}_{\mathrm{j}} \text{ and } \bar{\sigma}^2 = \sum_{\mathrm{j}} \mathrm{w_j} \hat{\sigma}_j^2.$$

Here, $\bar{\gamma}$ is the weighted mean of regression coefficients $\hat{\gamma}_{\mathrm{j}}$ and $\bar{\sigma}^2$ is the weight mean of the variances $\hat{\sigma}_j^2$, where $\mathrm{w_j}$ denotes weights. Sala-I-Martin (1997) applied weights proportional to the likelihoods, $\mathrm{w_j} = L_j / \sum_i L_i$, which gives more weight to models with a better fit. Other measures of goodness of fit such as R squared, and McFadden's likelihood ratio index can also be used as weights. Considering that γ may not follow the normal distribution, Sala-i-Martin also suggested a generic model in which γ does not follow any particular distribution. In this case, an

individual CDF of each regression model is calculated first and then an aggregate CDF is obtained from the weighted average of these CDFs:

$$\Phi(0) = \sum_j w_j \phi_j(0|\hat{\gamma}_j, \hat{\sigma}_j^2),$$

where w_j is weights the same as above.

3.5. Empirical Implementation

3.5.1. Economic Specification

Following the approach of Beghin and Park (2019), the consumption of higher education services of country *i* by students coming from country *j* can be expressed as:

$$(2)\ c_{ij} = C_i \left(\frac{\beta_{ij} t_{ij}^{-\sigma/(1-\sigma)}}{P_j P_i} \right)^{(1-\sigma)} Y_j,$$

$$\text{where } P_i = \left(\sum_{j=1}^{all} t_{ij}^{-\sigma} Y_j \left[\frac{\beta_{ij}}{P_j} \right]^{1-\sigma} \right)^{\frac{1}{1-\sigma}},\ P_j = \left(\sum_{i=1}^{m} (\beta_{ij} p_i t_{ij})^{1-\sigma} \right)^{\frac{1}{1-\sigma}}.$$

The EIA effects on bilateral trade flows in education services are considered as a part of the unobservable trade costs, thereby expressed as:

$$(3)\ t_{ij}^{-\sigma} = exp(\alpha_1 EIA_{ij} + \alpha_2 lndist_{ij} + \alpha_3 cl_{ij} + \alpha_4 cont_{ij} + \alpha_5 col_{ij} + \alpha_6 lnreli_{ij}).$$

Here, EIA_{ij} is a dummy variable that indicates whether exporter *i* and importer *j* have a economic integration trade agreement ($EIA_{ij} = 1$ if so), $lndist_{ij}$ is a logarithm of bilateral distance, and $cl_{ij}, cont_{ij}, col_{ij}$ and $lnreli_{ij}$ capture the presence of common language, contiguous borders, colonial ties, and religion heterogeneity, respectively. By substituting (3) into (2) and expanding the equation with an error term, the economic specification in a panel context for the empirical estimation is derived as:

$$(4)\ c_{ijt} = exp(\gamma_1 lnC_{it} + \gamma_2 ln\beta_{it} + \alpha_1 EIA_{ijt} + \alpha_2 lndist_{ij} + \alpha_3 comlang_{ij} + \alpha_4 cont_{ij} + \alpha_5 col_{ij} + \alpha_6 lnreli_{ij} + \gamma_3 lnP_{jt} + \gamma_4 lnP_{it} + \gamma_5 lnY_{jt}) + \varepsilon_{ijt}.$$

Following in the spirit of Baier and Bergstrand (2007), I control for the endogeneity of EIAs by including bilateral fixed and country-and-time fixed effects:

$$(5)\ c_{ijt} = exp(\beta_0 + \beta_1 EIA_{ijt} + \varphi_{it} + \theta_{jt} + \gamma_{ij}) + \varepsilon_{ijt},$$

where $\varphi_{it}, \theta_{jt}, and\ \gamma_{ij}$ denotes time-varying exporter dummies, time-varying importer dummies, and time-invariant country-pair fixed effects. These fixed effects absorb all bilateral time-invariant, importer-time variant, and exporter-time variant covariates in addition to multilateral price resistance terms in equation (4).

Some bilateral fixed effects ($\hat{\gamma}_{ij}$) are not identified for pairs of countries that did not trade during the period of investigation. In the counterfactual experiment section, I follow a two-step procedure proposed by Anderson and Yotov (2016) to recover these unidentified bilateral fixed effects. The missing estimates of the bilateral fixed effects are replaced with predicted value from a second-stage regression that projects estimated bilateral fixed effects on time-invariant trade costs:

$$(6)\ \hat{\gamma}_{ij} = exp(\delta_1 lndist_{ij} + \delta_2 comlang_{ij} + \delta_3 cont_{ij} + \delta_4 col_{ij} + \delta_5 lnreli_{ij}) + \varepsilon_{ij}.$$

3.5.2. Estimation

Estimation of the effects of EIAs through EBA follows two steps: EBA firstly chooses variables robustly associated with trade flows from candidate lags and leads and then these in turn included in the gravity equation (5).

For EBA, I consider the contemporaneous effect of EIAs (EIA_{ijt}) as a most important effect and thus set this effect to be a free variable, which appears in every regression. Set *X* of

doubtful variables consists of ten lagged variables ($EIA_{ijt-1}, \ldots, EIA_{ijt-10}$), which have been commonly used in several existing papers, and three possible lead variables ($EIA_{ijt+1}, EIA_{ijt+2}, EIA_{ijt+3}$). To accommodate zero trade flows, PPML is used for the estimation and clustered heteroskedasticity-robust standard errors are used for EBA. Each regression includes a focus variable, a free variable (EIA_{ijt}) and up to available 12 doubtful variables taken from set X. Therefore, the number of regressions for each focus variable is $\sum_{i=1}^{12} C_i^{12} = 4096$. Lastly, an unweighted version of CDF is computed to compare results with a weight version of CDF for which R-squared of each regression are used as weights. However, results of the unweight version of Sala-i-Martin's EBA are used for an analysis to take account of the unexpected endogeneity even after including the pair-fixed effects. As a note, both weighted and unweighted version of Sala-i-Martin's EBA produced almost the same CDFs

3.5.3. Data

For the dependent variable, OECD data on international student enrollment for 1998 – 2016 which covers 33 OECD countries[22] as exporter countries and importer countries. The dataset for other countries is also available but it only contains unilateral trade flows toward OECD countries (e.g., from Afghanistan to Australia). To accurately measure the effects of EIAs on bilateral trade flows in HES, these unilateral flow data are excluded.

OECD countries report international students as broadly two categories: Foreign (non-citizen) students and international students (non-resident students or students with prior education outside the reporting country). Since using only international students would lead to a

[22] 33 OECD countries are Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, and United States.

loss of data, I use both types of students but instead dummy out the difference between foreign and international students, based on the fact that international students are in general a subset of foreign students as determined in Beghin and Park (2019). In the end, the dummy variable is absorbed by exporter-time varying dummy variable. For explanatory variables, I construct economic integration agreement dichotomic variables using data from the World Trade Organization (WTO) website. The WTO reports all economic integration agreements among countries with date of entry-into-force. For the EIA variables, only economic integration agreements in goods and services are considered. In other words, economic integration agreements that only cover goods are excluded. EIAs used in the estimation are listed in Table 3.2. Overall, my data consist of 18,061 points including 1,001 zero flows, which represents 5% of the observations.

3.6. Results

Table 3.3 shows results of Leamer's EBA and Sala-I-Martin's EBA. Leamer's EBA indicates that EIA_{t-5} and EIA_{t+3} have robust relationships with trade in HES. However, 3 lagged variables (EIA_{t-1}, EIA_{t-5}, EIA_{t-6}) and one lead variable (EIA_{t+3}) pass the Sala-I-Martin's EBA under the assumption of normal distribution while EIA_{t-1}, EIA_{t-5} and EIA_{t+3} do without the normal distribution assumption as more than 95 percent of coefficients for these variables lies to the one side of zero. On the other hand, CDFs from the weighted and unweighted version of Sala-I-Martin's EBA are nearly the same because R-squared of all regressions are nearly similar (around 0.98), which eventually gives the same weight to all regressions identical to the unweighted version.

To determine variables for the next step, I produce a set of histograms of focus variables to see whether coefficients actually follow the normal distribution. Figure 3.1 shows the histograms. In the histogram, a blue line represents the kernel density of each coefficient while a green line shows the normal distribution of the corresponding coefficient. We can clearly find that the blue kernel densities are different from the green normal distributions. Thus, imposing the assumption of normal distribution on the coefficients of focus variables does not seem to be sensible because the coefficients are not normally distributed.

In sum, I follow the Sala-I-Martin's less stringent version of EBA without the assumption of normally distributed coefficients because it embraces more explanatory variables and has been widely used by many researchers. As a result, for estimation, EIA_{t-1}, EIA_{t-5}, and EIA_{t+3} chosen by Sala-i-Martin's EBA are added to equation (5) and (7) for estimation and simulation.

Table 3.4 provides results of the PPML estimation. EIAs have no contemporaneous impact on trade in education services but they have statistically significant lagged and lead effects, leading to the long-term effect of 42%. The estimated coefficient of EIA_{t-1} is statistically insignificant while that of EIA_{t-5} is statistically significant at a significance level of 5%. A possible explanation for this result is the time required for students to prepare for studying abroad. Even after students decide to study abroad, for example, students would spend some time investigating environment of the destination country, taking exams required to apply for universities, and requesting a visa. This implies that the entry-into-force of EIAs might not immediately lead to an increase in international students flows in a short period of time after entry-into-force of EIA.

PPML estimation also provides evidence of a feedback effect of EIAs. It indicates that EIAs elevate trade in HES by 24% 3 years before the entry-into-force. The lead effect of EIAs

can be interpreted that trade in education services increases in anticipation of an upcoming EIA (see footnote 22 of Baier and Bergstrand (2007)). This is reasonable when one thinks about a long process of EIAs. Countries typically make some policy reforms to prepare for an upcoming EIA or to cushion the impact of an upcoming EIA. This policy changes could lead to trade changes before an EIA officially comes into effect.

Another interpretation of the significant lead effect is that trade might cause EIA formations. Baier and Bergstrand (2004) pointed out that factors that explain bilateral trade flows also tend to explain the selection of country-pair into EIAs. Based on this possible selection effect, Baier at al. (2014) explained that trade might lead EIA and found statistically significant lead effects of EIAs. In trade in HES, the selection effect can be explained by network effects that increase students' migration. Beine et al. (2014) found that the network that have been built by previous migrants from the origin country living at the destination country helps students settle in the destination country, and therefore, decreases students' migration costs. On the other hand, Wilson and Yilmaz (2018) revealed that more migration leads to a greater probability of EIAs. These studies imply that the network effect that stems from the stock of migrants can explain both trade in HES and the selection of country-pairs into EIAs, which prop the existence of lead effect of EIAs.

3.6.1. A Counterfactual Experiment without Economic Integration Agreements

In the estimation of equation (5), bilateral fixed effects for 62 observations are not identified because these pairs of countries did not trade at all during the period of investigation. The missing estimates for these observations are replaced with predicted values from the second stage PPML estimates of equation (6) and then bilateral trade costs recovered from equation (7)

with the lags chosen from EBA for the counterfactual experiment. With the full set of fixed effects, hypothetical trade flows in education services without EIA are predicted by:

$$\hat{c}_{ijt}^{NOEIA} = exp(\hat{\beta}_0 + \hat{\varphi}_{it} + \hat{\theta}_{jt} + \hat{\gamma}_{ij}).$$

To examine changes in trade flows without EIAs, the hypothetical trade flows are compared to trade flows predicted from:

$$\hat{c}_{ijt}^{EIA} = exp(\hat{\beta}_0 + \hat{\beta}_1 EIA_{ijt} + \hat{\beta}_2 EIA_{ij,t-1} + \hat{\beta}_3 EIA_{ij,t-5} + \hat{\beta}_4 EIA_{ij,t+3} + \hat{\varphi}_{it} + \hat{\theta}_{jt} + \hat{\gamma}_{ij}).$$

Table 3.5 shows second stage gravity estimates. Estimates of the effects of bilateral distance, common language, colonial ties, contiguous borders, and religion heterogeneity have the same signs with the estimates in Beghin and Park (2019) while showing smaller effects for bilateral distance and common language and significant effects for colonial ties and contiguous borders. One possible explanation for this difference is the data set covering different countries. The data set in this paper covers trade flows between OECD countries while trade flows from Asian countries to OECD are used for Beghin and Park (2019). One can expect that students in OECD countries, compared to Asian students, are less responsive to bilateral distance, common language and more responsive to colonial ties and contiguous borders while these factors still play an important role in decision of students crossing the borders. The insignificant and smaller effect of religion heterogeneity might be because OECD countries are quite homogeneous on this front compared to the set of countries in Beghin and Park (2019). Indeed, the average religion heterogeneity is much larger for between OECD and Asia countries than for between OECD countries.

Results of the counterfactual experiment are shown in Table 3.6. It indicates that trade flows among OECD countries in terms of the number of international students flows could decrease by about 18% without EIAs. Furthermore, the benefits of EIA mostly fall on EU

countries. On average, trade flows in HES among EU countries are reduced by 25% without EIAs, which is much larger than for other countries. This is because the EU has actively tried to reduce trade costs by removing visa restrictions limiting the movement among member countries and by providing the Erasmus program which enables students to study in other EU member countries with financial assistance. Other countries such as Australia, Canada, Korea, New Zealand and the United States also have enjoyed nontrivial benefits of EIA as HES trade flows increase by about 9% with EIAs.

3.6.2. The Effects of Deeper Integration through Commitments to HES on Trade

WTO countries can make commitments to specific services sectors that promise the extent of limitation on the corresponding services sector. Many countries involved in EIAs have not yet made commitments to integrate the education sector. As of April 2019, only 62 of the 164 WTO countries listed as EIA members have included commitments to education in their schedule, while 52 of the 62 countries made commitments to higher education. Countries that have included commitments to higher education sector in their schedule generally impose less limitations on mode 2 (consumption abroad), directly related to international student flows, than any other modes of supply in education services (Knight, 2006). More importantly, most of the 52 countries have made unconditional commitments on higher education sector to integrate the higher education sector without any limitation.

In this section, I distinguish effects of EIA with and without commitments to higher education and consider the former as a deeper integration and the latter as a basic integration in HES to estimate separate effects on trade in higher education services. For example, EIA_{ijt} is decomposed into $deeperEIA_{ijt}$ and $basicEIA_{ijt}$ where $deeperEIA_{ijt}$ equals 1 if countries that

have an EIA in time *t* both list commitments on higher education[23]. The variable $basicEIA_{ijt}$ is equal to 1 if countries have an EIA without listing HES commitments. With these variables, EBAs are reperformed. That is, set X of doubtful variables now extends to incorporate 10 lags and 3 leads of deeper and basic EIAs, a total of 26 variables. For each regression in EBA, up to 3 doubtful variables are allowed to be added.

Table 3.7 displays results of EBAs. Leamer's EBA indicates only $deeperFTA_{ijt+3}$ and $basicFTA_{ijt+3}$ are robustly relate with trade flows while Sala-i-Martin's EBA additionally discover 1- to 4-year lag of deeper FTAs. These lags and leads are in turn used to estimate the effects of EIAs trade in HES.

Table 3.8 shows PPML estimates. With the leads chosen from Leamer's EBA (column (1)), basic integration increases trade in HES by 21% 3 years before it officially comes into effect while deeper integration has the concurrent and the 3-year lead effects with the long term effect of 92%. Estimates with the lags and leads chosen from Sala-i-Martin's EBA exhibit similar results (column (2)). The basic integration only has a positive impact on trade flows 3 years before entry-into-force of EIA, leading to a long-term effect of 21%. On the other hand, at a significance level of 5%, a 67% of trade-creating effect of the deeper integration exists from 3 years before and 2 years after its entry-into-force. In sum, the deeper integration in general shows richer lag and lead structure than the basic integration.

The effect of basic integration can be interpreted as an indirect effect of integration of other goods and services sectors and other subsectors in educational services on trade flows in HES. In the same way, the effect of deeper integration can be seen as a direct effect of HES

[23] Countries that have made commitments to higher education are Austria, Canada, Chile, Finland, France, Iceland, Israel, Korea, Netherlands, Sweden, and United States.

integration on trade flows. In terms of the long-term effect, the direct effect is much stronger and longer than the indirect effect, which suggests the need for WTO countries to officially commit liberalization in higher education sector to promote trade in education services.

3.7. Discussion

One may argue that determinants of trade in services is different from trade in goods. However, Kimura and Lee (2006) demonstrate that goods and services share the similar determinants and that the gravity model can even explain trade in services better than trade in goods. Their finding is also confirmed by the significant effect of distance, language, colonial ties, and contiguity on trade in HES, which have been regarded as conventional determinants of trade in goods.

One may also claim that EIAs in services have a little impact on international students flows because GATS excludes services supplied in the exercise of governmental authority. However, the HES sector is hybrid, part public, part private. The exclusion does not apply to privately funded education services and furthermore, liberalization in several service sectors through EIA in services is likely to positively affect the education service sector in the sense that all sectors function organically (Francois and Hoekman, 2010). For instance, increased cooperation and integration in transport, telecommunication, and financial services between countries would reduce trade cost for students going abroad for the purpose of studying by facilitating international transfers of money and entrance to the destination country. This indirect effect of other services sectors on trade flows in HES is partially confirmed by statistically significant effects of basic integration as shown above. The fact that education services share factors that affect trade in other services sectors, such as distance and language (see Kandilov and Grennes, 2010), also suggests possible correlation among services sectors.

EBA suggested in this paper might find a clue to several problems in which various papers have encountered. For example, Baier et al. (2014) could not find systematic significant effects when they estimate the model with consecutive lagged and lead effects by using annual data. This might be because some of lagged and lead effects are not robustly related to trade flow, which should be selected through EBA before included in the model. The refinement through EBA also resolves the potential risk of multicollinearity from having many consecutive lag and lead changes in the model as mentioned in Magee (2008). Furthermore, manual selection of intervals implicitly means that all countries on average have the *regular* lagged effects. However, this implicit assumption should also be tested through EBA before the lagged effects are tested whether they have statistically significant effects because we do not know how irregularly EIAs affect the trade flow.

I ascertain stronger and longer effects of decreasing trade costs through the commitments to higher education in EIAs. Many countries to date still place limitations on higher education sector and education sector is one of least committed sectors, not in accordance with the objective of GATS: liberalization in trade in services. These countries are often reluctant to fully liberalize their education sector on account of the protection of local universities. However, my results indicate that guaranteeing the liberalization in HES through commitments can encourage "bilateral" international student flows, which benefits both exporter and importer countries by increasing income of local universities and human capital. Provided that education sector can be a stepping-stone to other key sectors, liberalization in education sector would be a crucial task for WTO countries to boost aggregate trade in services (Knight, 2006).

3.8. Conclusion

Compared to other services sectors, little is known about trade in the HES sector due to the restricted data on this sector. In this paper, using bilateral movements of student as a proxy for HES exports, I discover empirical evidence that EIAs has a long-term effect of 42% on trade in HES. The gain from EIAs is taken mostly by EU countries that have industriously endeavored to reduce costs through EIAs. Further analysis provides evidence that countries can enjoy more benefits in terms of increased international students flows from deeper integration by committing to the removal of restrictions on HES. The impact of deeper integration through commitments to HES is stronger and longer than basic integration without commitments to HES has, showing richer lag and lead structure.

The estimated long-term impact of EIAs on HES exports is smaller than that on trade in goods, for example, the estimated increase of 114% from EIAs in Baier and Bergstrand (2007). Possible explanation for this difference is that the indirect effect of EIAs that only cover goods on HES exports. Even though educational services sector is not treated, Zhou and Whalley (2014) find that "only goods" RTAs can indirectly promote bilateral services trade. Given that all service sectors might be correlated, this finding might also apply to education services sector, which amplify the impact of EIAs on trade in HES. Because only "goods and services" EIAs are considered in this paper, future research should therefore take into account this indirect effect of "only goods" EIAs.

Barriers in service sectors are characterized as non-tariff barriers (NTBs) and thus it is difficult for countries to establish policy to liberalize service sectors. For instance, according to Knight (2006), the commonly recognized barriers to education services are (i) *Restriction on travel abroad based on discipline or area of study,* (ii) *Restriction on export of currency and*

exchange, (iii) *Quota on the number of students proceeding to a country or institution*, (iv) *prescription of minimum standards or attainments*, and (v) *generic barriers such as absence of transparency in regulatory policies and discriminatory treatment on foreign providers or students*. These NTBs are not as transparent as tariffs in goods, suggesting the need to develop effective instruments to control NTBs as tariff policies in goods trade for further integration in education services.

This paper only covered 33 countries mostly EU countries, due to the lack of bilateral data. Based on the findings from Beghin and Park (2019) that the number of Asian students going to OECD countries and EIA between OECD and non-OECD countries have increased over the last 20 years, much more countries should be included in future studies to capture more extensive effects of EIA on trade in HES. Data improvement in education services would be the key for this analysis.

Figure 3.1. Histogram of coefficients of focus variables

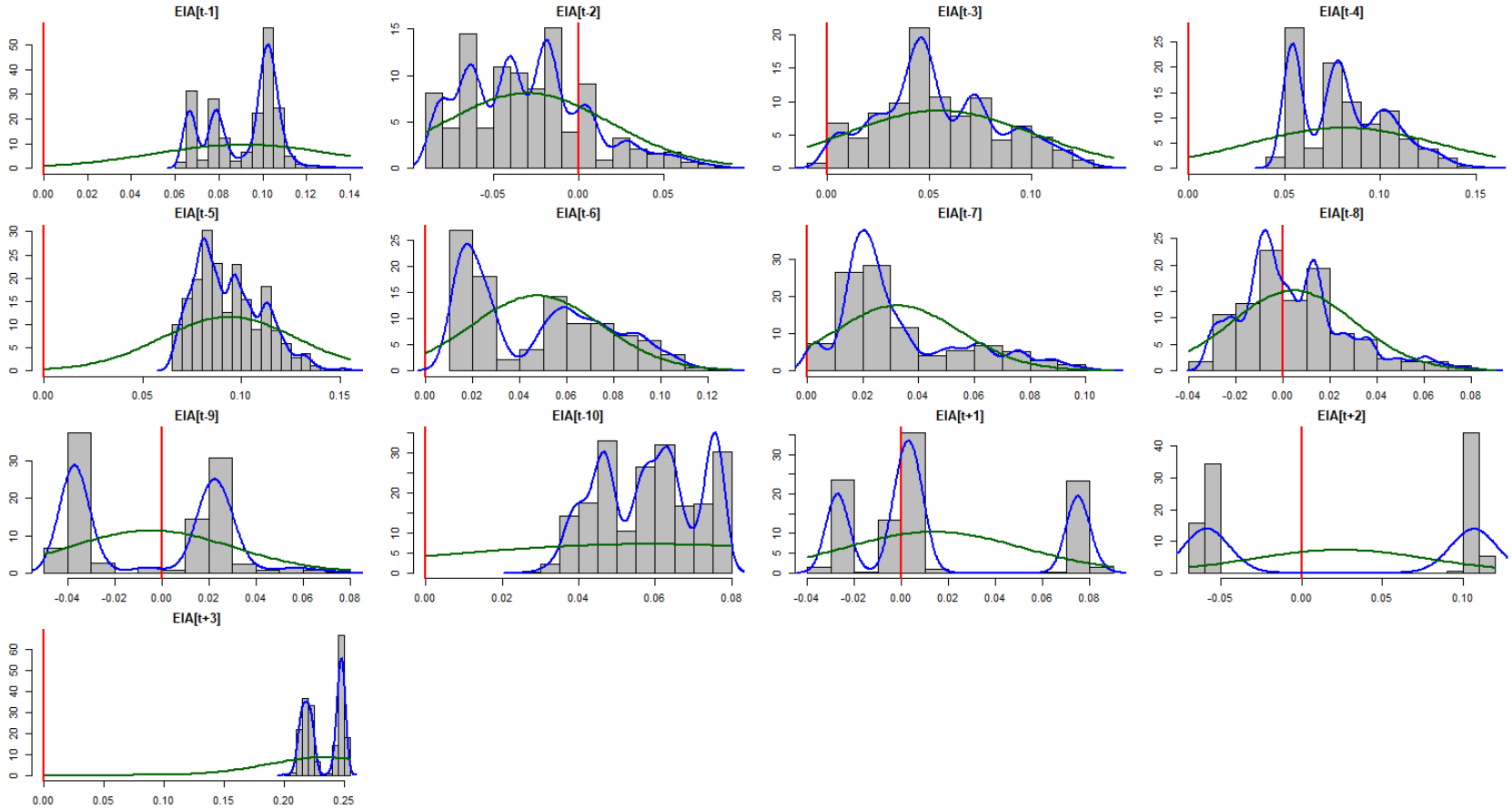

Table 3.1. PPML results with different starting years

	5-year intervals			
	(1) 2001-2016	(2) 2000-2015	(3) 1999-2014	(4) 1998-2013
EIA_{ijt}	0.0780	0.285***	0.132	0.160
	(0.0898)	(0.104)	(0.176)	(0.127)
EIA_{ijt-5}	0.165**	0.100	0.271**	0.0743*
	(0.0832)	(0.117)	(0.117)	(0.0415)
EIA_{ijt-10}	0.0115	0.0250	0.0850	0.0486
	(0.0596)	(0.0511)	(0.0524)	(0.0755)
Long-term	18%	33%	31%	0%
N	3833	3851	3647	3618
R^2	0.987	0.987	0.987	0.989
	4-year intervals			
	(5) 2000-2016	(6) 1999-2015	(7) 1998-2014	
EIA_{ijt}	0.0268	0.162**	0.117	
	(0.0858)	(0.0731)	(0.137)	
EIA_{ijt-4}	0.217**	0.123*	0.0766	
	(0.0864)	(0.0657)	(0.105)	
EIA_{ijt-8}	0.0429	0.0656	0.0677	
	(0.0511)	(0.0440)	(0.0496)	
Long-term	24%	18%	0%	
N	4810	4682	4643	
R^2	0.987	0.987	0.988	

Table 3.2. A list of Economic Integration Agreements in Services

European Union (EU, 1958): Belgium, France, Germany, Italy, Luxembourg, Netherlands, Denmark (1973) , Ireland (1973), United Kingdom (1973), Greece (1981), Portugal, Spain (1986), Austria (1995), Finland (1995), Sweden (1995), Cyprus (2004), Czech Republic (2004), Estonia (2004), Hungary (2004), Poland (2004), Slovak Republic (2004), Slovenia (2004)
European Free Trade Association (EFTA, 1960): Austria (until 1995), Finland (1986-1995), Iceland (1970), Norway, Sweden (until 1990), Switzerland
European Economic Area (EEA, 1994): EU – EFTA agreement
North American Free Trade Agreement (NAFTA, 1994): Canada, Mexico, United States
Canada – Chile (1997)
EU – Chile (2003)
United States – Chile (2004)
Korea – Chile (2004)
EFTA – Chile (2004)
United States – Australia (2005)
Trans-Pacific Strategic Economic Partnership (TPP, 2006): Chile, New Zealand
EFTA – Korea (2006)
Australia – Chile (2009)
Japan – Switzerland (2009)
ASEAN – Australia – New Zealand (2010): Australia, New Zealand
EU – Korea (2011)
Korea – United States (2012)
Korea – Australia (2014)
Canada – Korea (2015)
Japan – Australia (2015)
Korea – New Zealand (2015)
EU – Canada (2017)
Comprehensive and Progressive Agreement for Trans-Pacific Partnership (CPTPP, 2018): Australia, Canada, Chile, Japan, New Zealand
EU – Japan (2019)

Notes: Only economic integration agreements between countries in the sample that covers both goods and services are shown in chronological order.
Source: WTO RTA database (http://rtais.wto.org/UI/PublicMaintainRTAHome.aspx)

Table 3.3. Results of Leamer's and Sala-I-Martin's EBA

	Leamer's EBA		
	Lower Extreme Bound	Upper Extreme Bound	Robust / Fragile
EIA_{t-1}	-0.042	0.276	Fragile
EIA_{t-2}	-0.168	0.231	Fragile
EIA_{t-3}	-0.086	0.274	Fragile
EIA_{t-4}	-0.066	0.293	Fragile
EIA_{t-5}	0.004	0.258	Robust
EIA_{t-6}	-0.040	0.217	Fragile
EIA_{t-7}	-0.057	0.188	Fragile
EIA_{t-8}	-0.092	0.171	Fragile
EIA_{t-9}	-0.096	0.170	Fragile
EIA_{t-10}	-0.087	0.185	Fragile
EIA_{t+1}	-0.116	0.202	Fragile
EIA_{t+2}	-0.177	0.239	Fragile
EIA_{t+3}	0.106	0.347	Robust

	Sala-i-Martin's EBA			
	Weights		No Weights	
	(1) Normal	(2) Generic	(3) Normal	(4) Generic
EIA_{t-1}	0.983*	0.962*	0.983*	0.972*
EIA_{t-2}	0.728	0.714	0.728	0.714
EIA_{t-3}	0.875	0.848	0.875	0.848
EIA_{t-4}	0.944	0.936	0.944	0.936
EIA_{t-5}	0.996*	0.996*	0.996*	0.996*
EIA_{t-6}	0.952*	0.894	0.952*	0.894
EIA_{t-7}	0.911	0.876	0.911	0.876
EIA_{t-8}	0.561	0.561	0.561	0.561
EIA_{t-9}	0.547	0.632	0.547	0.632
EIA_{t-10}	0.852	0.846	0.852	0.846
EIA_{t+1}	0.630	0.562	0.630	0.562
EIA_{t+2}	0.667	0.553	0.667	0.553
EIA_{t+3}	1.000*	1.000*	1.000*	1.000*

* denotes CDF(0) larger than 0.95

Table 3.4. Main PPML results

	(1)
EIA_{ijt}	-0.0337
	(0.0495)
EIA_{ijt-1}	0.0762
	(0.0596)
EIA_{ijt-5}	0.141^{***}
	(0.0500)
EIA_{ijt+3}	0.212^{***}
	(0.0484)
Long-term effect	42%
N	17999
R^2	0.987

Notes: dependent variable is the number of students coming from origin country to destination country. Long-term effects are calculated as *exp(total effect)*. For example, $\exp(0.141 + 0.212) \approx 1.42$. Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5. PPML results for the second stage gravity estimates

	(1)
$lndist$	-0.282***
	(0.00245)
$comlang$	0.797***
	(0.0290)
$colony$	0.615***
	(0.0393)
$contig$	0.582***
	(0.0307)
$lnreli$	-0.00271
	(0.00446)
N	17999
R^2	0.302

Note: dependent variable is predicted pair fixed effects.
Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6. Counterfactual experiment results

Exporters	Obs.	Predicted	No EIA	% Change
Australia	576	906.38	829.45	-8.49%
Austria	608	1074.61	773.99	-27.97%
Belgium	576	559.89	385.45	-31.16%
Canada	480	767.20	661.73	-13.75%
Chile	470	17.68	13.91	-21.32%
Czech Republic	607	525.31	379.22	-27.81%
Denmark	607	328.83	232.57	-29.27%
Estonia	384	30.37	21.80	-28.22%
Finland	608	113.31	85.02	-24.97%
France	608	1479.43	1123.20	-24.08%
Germany	608	2498.82	1990.82	-20.33%
Greece	416	42.27	32.22	-23.78%
Hungary	575	241.58	189.07	-21.74%
Iceland	608	18.70	13.69	-26.79%
Ireland	608	206.36	163.49	-20.77%
Israel	224	106.25	106.25	0.00%
Italy	608	470.10	356.02	-24.27%
Japan	608	782.18	780.18	-0.26%
Korea	608	74.18	68.19	-8.07%
Luxembourg	352	51.75	35.36	-31.67%
Netherlands	576	678.19	471.80	-30.43%
New Zealand	606	236.18	214.19	-9.31%
Norway	608	149.88	107.68	-28.16%
Poland	605	152.61	120.05	-21.34%
Portugal	480	100.93	72.89	-27.78%
Slovak Republic	544	140.20	98.63	-29.65%
Slovenia	256	7.93	5.77	-27.24%
Spain	608	530.67	375.03	-29.33%
Sweden	608	329.73	240.28	-27.13%
Switzerland	607	765.96	761.67	-0.56%
Turkey	608	76.74	76.74	0.00%
United Kingdom	608	4233.58	3199.92	-24.42%
United States	608	5930.11	5439.53	-8.27%
Total	18061	780.26	641.34	-17.80%

Note: predicted and No EIA value is mean of students in destination countries

Table 3.7. Results of Leamer's and Sala-i-Martin's EBA (Deeper and Basic integration)

	Leamer's EBA			Sala-i-Martin's EBA	
	Lower Extreme Bound	Upper Extreme Bound	Robust / Fragile	Unweighted CDF(0)	Robust / Fragile
$deeperEIA_{ijt-1}$	-0.031	0.809	Fragile	0.990	Robust
$deeperEIA_{ijt-2}$	-0.019	0.769	Fragile	0.987	Robust
$deeperEIA_{ijt-3}$	-0.048	0.711	Fragile	0.986	Robust
$deeperEIA_{ijt-4}$	-0.082	0.520	Fragile	0.984	Robust
$deeperEIA_{ijt+3}$	0.067	0.422	Robust	0.999	Robust
$basicEIA_{ijt+3}$	0.020	0.393	Robust	0.999	Robust

Note: Only robust variables from at least 1 EBA are presented. No distribution assumption imposed on coefficients of focus variables and unweighted CDFs are used for Sala-i-Martin's EBA. Up to 3 doubtful variables are allowed to be added to each regression.

Table 3.8. PPML results for deeper and basic integration

	(1) Leamer	(2) Sala-i-Martin
$deeperEIA_{ijt}$	0.411***	0.0215
	(0.142)	(0.0887)
$deeperEIA_{ijt-1}$		0.125***
		(0.0441)
$deeperEIA_{ijt-2}$		0.125**
		(0.0613)
$deeperEIA_{ijt-3}$		0.186*
		(0.112)
$deeperEIA_{ijt-4}$		0.0665
		(0.0683)
$deeperEIA_{ijt+3}$	0.239***	0.264***
	(0.0576)	(0.0565)
Long-term (deeper EIA)	92%	67%
$basicEIA_{ijt}$	-0.0698	-0.0626
	(0.0792)	(0.0800)
$basicEIA_{ijt+3}$	0.191***	0.194***
	(0.0574)	(0.0570)
Long-term (basic EIA)	21%	21%
N	17999	17999
R^2	0.988	0.988

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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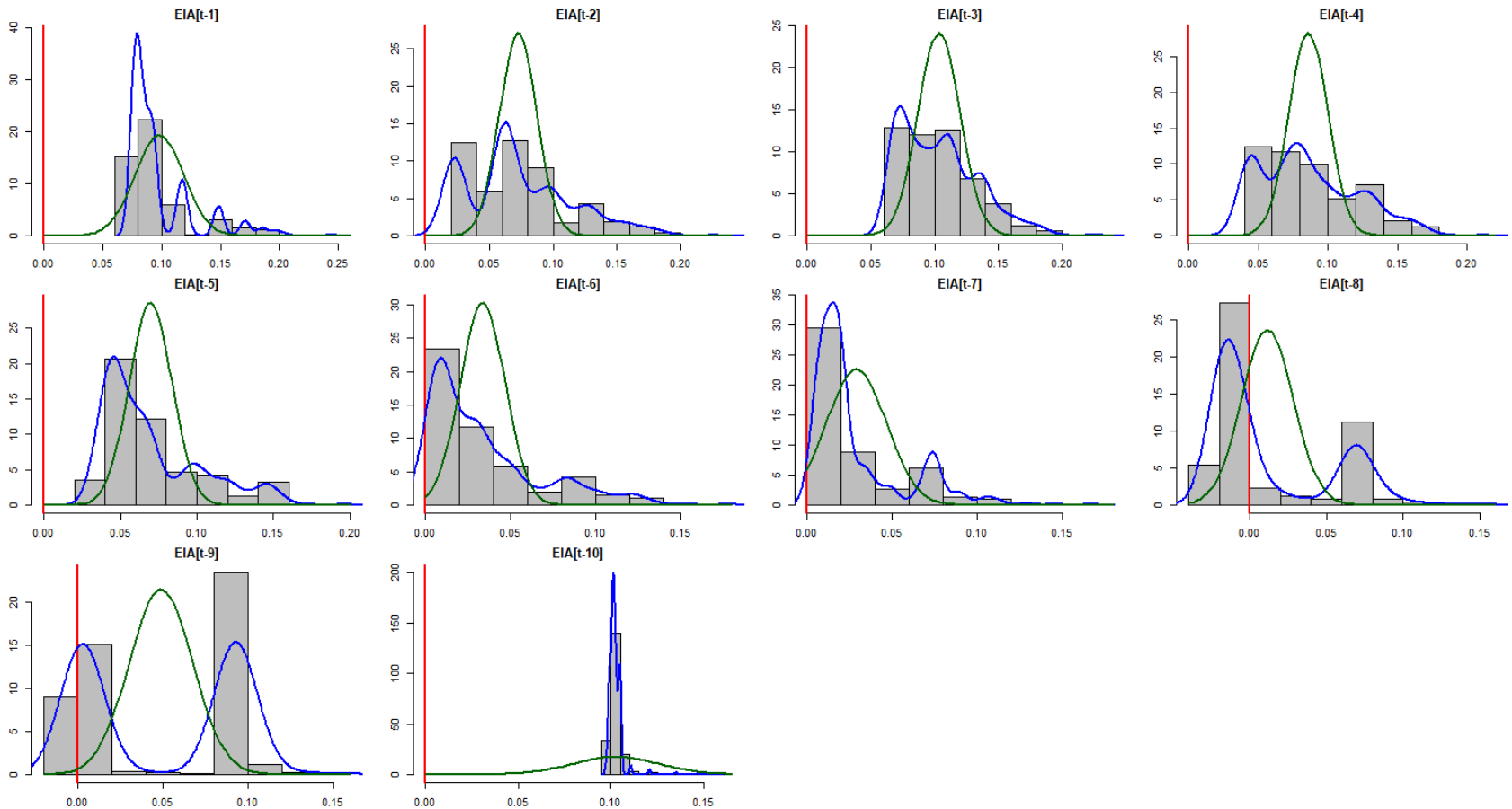
APPENDICES

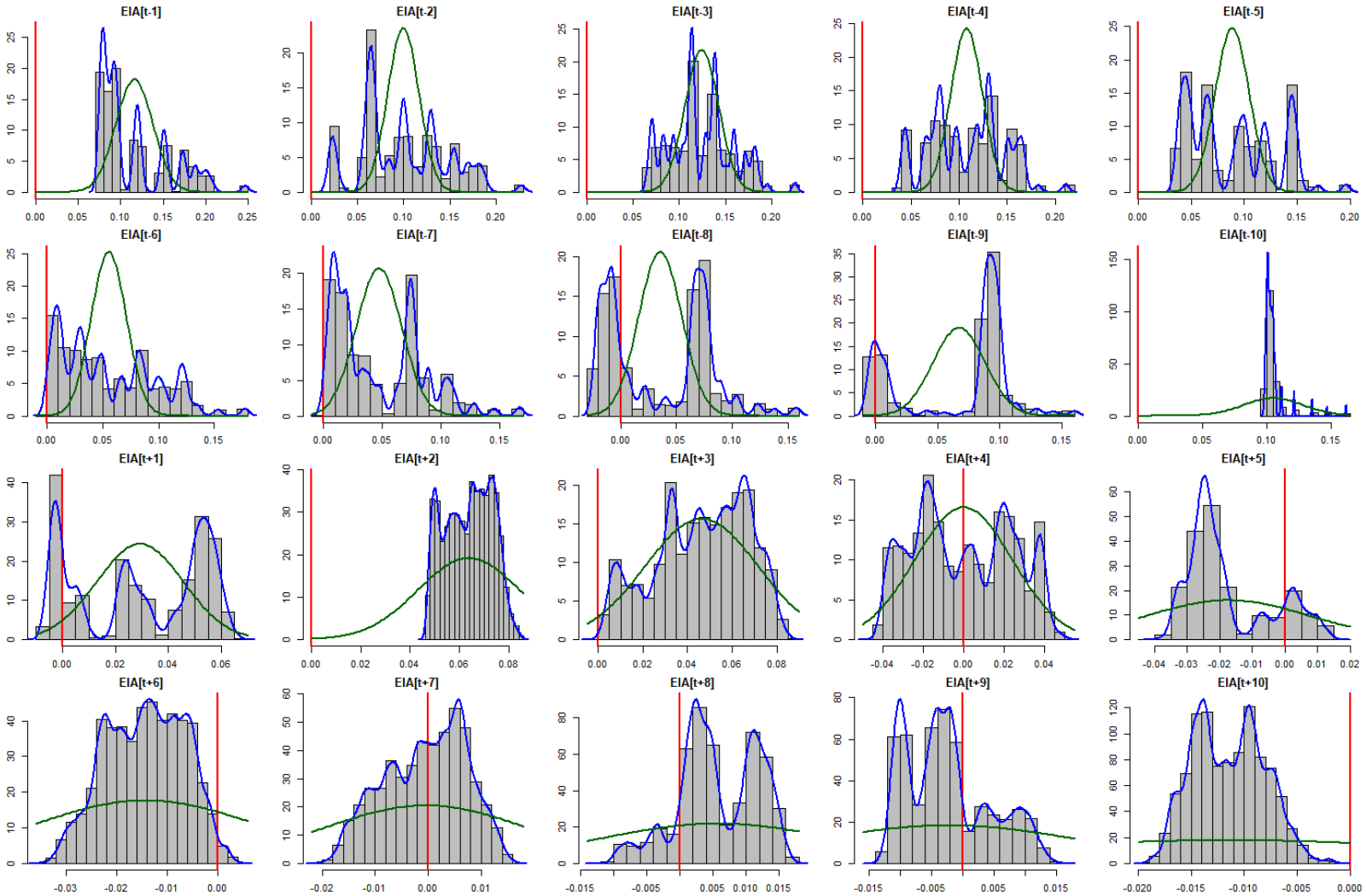
Appendix A: Appendix for Chapter 1

Figure A.1. Histogram of coefficients of focus variables (10 lags)



Note: blue lines exhibit kernel density curve and green lines show normal distribution.

Figure A.2. Histogram of coefficients of focus variables (10 lags and 10 leads)



Note: blue lines exhibit kernel density curve and green lines show normal distribution.

Table A.1. List of Countries

Austria	Chile	Hong Kong
Belgium	Colombia	Indonesia
Denmark	Ecuador	Iran
Finland	Guyana	Israel
France	Paraguay	Pakistan
Germany	Peru	Singapore
Greece	Uruguay	Sri Lanka
Ireland	Venezuela	Syria
Italy	Australia	China
Netherlands	New Zealand	Albania
Norway	Bulgaria	Bangladesh
Portugal	Hungary	Burkina Faso
Spain	Poland	Cameroon
Sweden	Romania	Cyprus
Switzerland	Egypt	Ivory Coast
United Kingdom	India	Ethiopia
Canada	Japan	Gabon
Costa Rica	Philippines	Gambia
Dominican Republic	Thailand	Guinea-Bissau
El Salvador	Turkey	Madagascar
Guatemala	Korea	Malawi
Haiti	Algeria	Malaysia
Honduras	Angola	Mali
Jamaica	Ghana	Mauritania
Mexico	Kenya	Mauritius
Nicaragua	Morocco	Niger
Panama	Mozambique	Saudi Arabia
Trinidad and Tobago	Nigeria	Senegal
United States	Tunisia	Sierra Leone
Argentina	Uganda	Sudan
Bolivia	Zambia	Congo, Dem. Rep. of
Brazil	Zimbabwe	Congo, Republic of

Table A.2. List of Economic Integration Agreements

ECONOMIC UNIONS

Euro Area (1999): Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain

West African Economic and Monetary Union (UEMOA/WAEMU) (2000): Burkina Faso, Guinea-Bissau, Ivory Coast, Mali, Niger, Senegal

Economic and Monetary Community of Central Africa (CEMAC) (2000): Cameroon, Congo. Rep, Gabon

COMMON MARKETS

European Economic Area (EEA) (1993): Austria (1994), Belgium, Denmark, Finland (1994), France, Germany, Greece, Ireland, Italy, Netherlands, Norway (1994), Portugal, Spain,
Sweden (1994), UK

CUSTOMS UNION

Andean Community 1 (1995): Bolivia, Colombia, Ecuador, Peru, Venezuela

Caribbean Community and Common Market (CARICOM) (1975): Guyana, Jamaica, Trinidad and Tobago

Central American Common Market (CACM1) (1966-1969): Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua

European Economic Community (EEC) (1962-1992): Belgium, Denmark (1973), France, Germany, Greece (1981), Ireland (1973), Italy, Netherlands, Portugal (1986), Spain (1986),
UK (1973)

European Union Customs Union (EUCU): EU-Cyprus (1993)

Mercado Común del Sur (MERCOSUR) (1995): Argentina, Brazil, Paraguay, Uruguay

West African Economic and Monetary Union (WAEMU) (1995-1999): Burkina Faso, Guinea-Bissau (1997), Ivory Coast, Mali, Niger, Senegal

FREE TRADE AGREEMENTS

I. PLURILATERAL AGREEMENTS

Andean Community 2 (1993-1994): Bolivia, Colombia, Ecuador, Venezuela

Arab Common Market (ACM) (1965): Egypt, Syria

Association of Southeast Asian Nations (ASEAN) (2000): Indonesia, Malaysia, Philippines, Singapore, Thailand

Caribbean Free Trade Agreement (CARIFTA) (1968-1974): Guyana, Jamaica, Trinidad and Tobago

Central American Common Market (CACM2) (1951-1965): Costa Rica (1963), El Salvador, Guatemala (1955), Honduras (1957), Nicaragua

Central American Common Market (CACM3) (1993): Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua

Central European Free Trade Area (CEFTA) (1993): Hungary (1993-2004), Poland (until 2004), Romania (1997-2006)

European Free Trade Association (EFTA 1960): Austria (until 1995), Denmark (until 1973), Finland (1986-1995), Norway, Portugal (until 1986), Sweden (until 1995), Switzerland, United Kingdom (until 1973)

European Union (EU) (1958): Austria (1995), Belgium, Denmark (1973), Finland (1995), France, Germany, Greece (1981), Ireland (1973), Italy, Netherlands, Portugal (1986), Spain (1986), Sweden (1995), United Kingdom (1973)

NAFTA (North American Free Trade Agreement 1994): Canada, Mexico, US

Pan-Arab Free Trade Area (1998) (PAFTA/GAFTA): Egypt, Morocco, Saudi Arabia, Syria

West African Monetary Union (WAMU) (1962-1965): Burkina Faso, Mali, Mauritania, Niger, Senegal

Table A.2. (Continued)

II. BILATERAL AGREEMENTS
Australia-New Zealand (1983-2009)
Bolivia-Chile (1996-2004)
Bolivia-Mexico (1995)
CACM3-Dominican Republic (1998)
Cameroon-Gabon (1966-1999)
Canada-Chile (1997)
Canada-Israel (1997)
Canada-USA (1989-1993)
CARICOM-Dominican Republic (1998)
CEFTA-Bulgaria (1993-1998)
Chile-Mexico (2000)
Colombia-Mexico (1995-2009)
Congo, Republic of-Gabon (1966)
Costa Rica-Mexico (1995-2000)
EEC-Israel (1975-1992)
EEA-Israel (1993)
EFTA-Bulgaria (1994-2006)
EFTA-Hungary (1994-2004)
EFTA-Israel (1993)
EFTA-Morocco (2000)
EFTA-Poland (1994)
EFTA-Romania (1994-2006)
EU-Bulgaria (1994-2006)
EU-Cyprus (1988-2004)
EU-EFTA (Agreement/European Economic Area 1973/1994)
EU-Hungary (1992-2004)
EU-Israel (2000)
EU-Mexico (1998)
EU-Poland (1992-2004)
EU-Romania (1993-2006)
EU-Tunisia (1999)
Hungary-Israel (1998-2004)
India-Sri Lanka (1999-2005)
Israel-Poland (1998-2004)
Israel-USA (1986)
MERCOSUR-Bolivia (1996-2004)
MERCOSUR-Chile (1996)
Mexico-Colombia (1995)
Mexico-Nicaragua (1999)
Mexico-Venezuela (1995)

Notes: Only economic integration agreements that involve countries in the sample are listed. This table is constructed on the basis of the online appendix of Baier et al. (2018).

Table A.3. Full Results of Leamer's and Sala-i-Martin's EBA (FTA and CUCMECU)

	Leamer's EBA			Sala-i-Martin's EBA	
	Lower Extreme Bound	Upper Extreme Bound	Robust / Fragile	Unweighted CDF(0)	Robust / Fragile
FTA_{ijt-1}	-0.017	0.258	Fragile	0.997	Robust
FTA_{ijt-2}	-0.018	0.233	Fragile	0.997	Robust
FTA_{ijt-3}	0.001	0.236	Robust	0.999	Robust
FTA_{ijt-4}	-0.021	0.227	Fragile	0.999	Robust
FTA_{ijt-5}	-0.044	0.224	Fragile	0.991	Robust
FTA_{ijt-6}	-0.087	0.204	Fragile	0.911	Fragile
FTA_{ijt-7}	-0.130	0.128	Fragile	0.768	Fragile
FTA_{ijt-8}	-0.110	0.118	Fragile	0.660	Fragile
FTA_{ijt-9}	-0.110	0.121	Fragile	0.704	Fragile
FTA_{ijt-10}	-0.076	0.135	Fragile	0.849	Fragile
FTA_{ijt+1}	-0.055	0.098	Fragile	0.640	Fragile
FTA_{ijt+2}	-0.038	0.133	Fragile	0.908	Fragile
FTA_{ijt+3}	-0.065	0.130	Fragile	0.821	Fragile
FTA_{ijt+4}	-0.107	0.100	Fragile	0.523	Fragile
FTA_{ijt+5}	-0.112	0.071	Fragile	0.712	Fragile
FTA_{ijt+6}	-0.104	0.070	Fragile	0.760	Fragile
FTA_{ijt+7}	-0.101	0.069	Fragile	0.821	Fragile
FTA_{ijt+8}	-0.100	0.075	Fragile	0.843	Fragile
FTA_{ijt+9}	-0.108	0.055	Fragile	0.926	Fragile
FTA_{ijt+10}	-0.107	0.037	Fragile	0.945	Fragile
$CUCMECU_{ijt-1}$	0.014	0.394	Robust	0.999	Robust
$CUCMECU_{ijt-2}$	0.006	0.370	Robust	0.999	Robust
$CUCMECU_{ijt-3}$	0.022	0.379	Robust	1.000	Robust
$CUCMECU_{ijt-4}$	0.012	0.378	Robust	0.999	Robust
$CUCMECU_{ijt-5}$	-0.010	0.382	Fragile	0.999	Robust
$CUCMECU_{ijt-6}$	-0.016	0.382	Fragile	0.999	Robust
$CUCMECU_{ijt-7}$	0.027	0.400	Robust	1.000	Robust
$CUCMECU_{ijt-8}$	-0.043	0.372	Fragile	0.997	Robust
$CUCMECU_{ijt-9}$	-0.002	0.354	Fragile	0.999	Robust
$CUCMECU_{ijt-10}$	-0.010	0.336	Fragile	0.998	Robust
$CUCMECU_{ijt+1}$	-0.014	0.199	Fragile	0.996	Robust
$CUCMECU_{ijt+2}$	-0.062	0.193	Fragile	0.921	Fragile
$CUCMECU_{ijt+3}$	-0.087	0.182	Fragile	0.765	Fragile
$CUCMECU_{ijt+4}$	-0.090	0.171	Fragile	0.754	Fragile
$CUCMECU_{ijt+5}$	-0.110	0.174	Fragile	0.739	Fragile
$CUCMECU_{ijt+6}$	-0.123	0.188	Fragile	0.737	Fragile
$CUCMECU_{ijt+7}$	-0.100	0.218	Fragile	0.880	Fragile
$CUCMECU_{ijt+8}$	-0.092	0.240	Fragile	0.938	Fragile
$CUCMECU_{ijt+9}$	-0.058	0.266	Fragile	0.993	Robust
$CUCMECU_{ijt+10}$	0.006	0.285	Robust	0.999	Robust

Note: the number of doubtful variables added to each regression is limited up to 3 due to a computational difficulty.

Appendix B: Appendix for Chapter 2

Table B.1. Investigation of endogeneity of OECD college-age population as proxy for capacity and other proxies for the supply of higher education

	(1) CF	(2) IVPOISSON	(3) PPML	(4) PPML	(5) PPML
Ln OECD pop 15-24	1.010	0.887			
	(0.797)	(0.564)			
Ln OECD total pop			1.516		
			(1.252)		
Ln OECD enrollment				-0.103	
				(0.23)	
Ln OECD pop 15-24 lagged					0.164
					(0.451)
University reputation	0.00493	0.0209	0.0150	0.0164	0.0157
	(0.0210)	(0.0176)	(0.018)	(0.0174)	(0.0178)
Ln OECD wage	2.917***	1.987**	2.291***	2.744***	2.771***
	(0.922)	(0.882)	(0.733)	(0.870)	(0.798)
Ln network migrant WB	0.240***	0.240***	0.239***	0.237***	0.236***
	(0.0561)	(0.0484)	(0.0483)	(0.0486)	(0.0481)
Ln distance	-1.019***	-1.023***	-1.027***	-1.045***	-1.022***
	(0.224)	(0.154)	(0.154)	(0.155)	(0.154)
Common language	1.227***	1.228***	1.229***	1.265***	1.227***
	(0.315)	(0.265)	(0.266)	(0.271)	(0.266)
contiguity	0.0738	0.0728	0.0650	0.0577	0.0750
	(0.802)	(0.457)	(0.459)	(0.458)	(0.456)
Colonial link	-0.122	-0.128	-0.125	-0.127	-0.128
	(0.406)	(0.235)	(0.235)	(0.236)	(0.235)
Ln religious dissimilarity	-0.0802	-0.0828	-0.0778	-0.0814	-0.0701
	(0.154)	(0.106)	(0.105)	(0.107)	(0.105)
Ln visa free	1.148***	1.042***	1.053***	1.036***	1.011***
	(0.264)	(0.260)	(0.259)	(0.269)	(0.260)
Ln real exchange rate	-0.112	-0.143	-0.144*	-0.0922	-0.142*
	(0.0810)	(0.0874)	(0.0875)	(0.0808)	(0.0826)
Ln per capita gdp Asia	0.758***	0.745***	0.728***	0.741***	0.658***
	(0.236)	(0.215)	(0.217)	(0.233)	(0.228)
Ln Asia pop24	0.747**	0.734**	0.739**	0.795***	0.725**
	(0.311)	(0.303)	(0.302)	(0.300)	(0.320)
Foreign correction	0.447***	0.406***	0.361***	0.349***	0.356***
	(0.105)	(0.0758)	(0.0677)	(0.0728)	(0.0676)
residuals	-1.290				
	(0.962)				
Constant	-52.60***	-38.74***	-44.59***	-32.43***	-40.18***
	(14.21)	(8.955)	(10.29)	(10.01)	(9.759)
N	21238	21238	21238	20714	20278
R^2	0.926	0.927	0.927	0.927	0.928

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2. Truncated OLS and Negative Binomial PML with OECD college-age population as capacity proxy

	(1) Truncated OLS	(2) Truncated OLS $log(c_{ij}+1)$	(3) NBPML	(4) NBPML $(c_{ij}/100)$
Ln OECD college pop	0.158	0.205	0.719**	-0.0880
	(0.215)	(0.185)	(0.284)	(0.279)
University reputation	0.0640***	0.0707***	0.0661***	0.0404***
	(0.0141)	(0.0146)	(0.0167)	(0.0148)
Ln OECD wage	-0.0849	-0.344	-0.269	1.474***
	(0.281)	(0.239)	(0.375)	(0.399)
Ln network Migrant WB	0.294***	0.267***	0.323***	0.239***
	(0.0207)	(0.0194)	(0.0210)	(0.0292)
Ln distance	-1.420***	-1.392***	-1.415***	-1.414***
	(0.110)	(0.107)	(0.124)	(0.123)
Common language	0.678***	0.810***	0.762***	0.884***
	(0.177)	(0.183)	(0.182)	(0.185)
contiguity	-1.272***	-1.267**	-1.220*	-0.987*
	(0.491)	(0.525)	(0.625)	(0.504)
Colonial link	0.876***	0.981***	1.197***	0.832***
	(0.257)	(0.259)	(0.229)	(0.228)
Ln religious dissimilarity	-0.0292	-0.0259	-0.00684	0.0137
	(0.0486)	(0.0447)	(0.0497)	(0.0643)
Ln visa free	-0.0268	0.142	0.0672	0.784***
	(0.136)	(0.131)	(0.165)	(0.135)
Ln real exchange rate	-0.0652***	-0.0747***	-0.0213	-0.0614**
	(0.0252)	(0.0255)	(0.0298)	(0.0304)
Ln per capita gdp Asia	0.588***	0.468***	0.545***	0.504***
	(0.0957)	(0.0823)	(0.101)	(0.102)
Ln Asian pop 15-24	-0.0769	0.00548	0.0821	0.579***
	(0.113)	(0.0965)	(0.139)	(0.129)
Foreign correction	0.374***	0.336***	0.303***	0.306***
	(0.0418)	(0.0370)	(0.0496)	(0.0472)
Constant	9.681***	8.905***	4.028	-19.55***
	(3.683)	(3.065)	(6.016)	(5.468)
N	17810	21238	21238	21238
R^2	0.797	0.809	0.321	0.677

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3. Disaggregated effects of foreign students by country

Capacity proxy college pop	0.615	Foreign_FIN	-0.323
	(0.697)		(0.257)
University reputation	-0.0112	Foreign_FRA	0.314***
	(0.0271)		(0.0877)
ln OECD wage	1.884**	Foreign_DEU	1.037***
	(0.843)		(0.288)
Ln network migrant WB	0.239***	Foreign_HUN	0.266*
	(0.0482)		(0.148)
ln distance	-1.028***	Foreign_ISL	-0.309
	(0.154)		(0.234)
common language	1.226***	Foreign_IRL	0.135
	(0.266)		(0.275)
contiguity	0.0556	Foreign_JPN	0.311***
	(0.460)		(0.118)
colonial link	-0.110	Foreign_LUX	-1.184***
	(0.235)		(0.296)
ln religion dissimilarity	-0.0730	Foreign_NLD	0.473
	(0.106)		(0.335)
ln visa free	1.075***	Foreign_NZL	0.128
	(0.260)		(0.263)
ln real exchange rate	-0.128	Foreign_NOR	0.568***
	(0.0834)		(0.189)
ln gdp per capita Asia	0.705***	Foreign_POL	-0.271
	(0.219)		(0.280)
ln Asian pop 15-24	0.738**	Foreign_PRT	-0.212
	(0.295)		(0.262)
Foreign_AUS	0.387*	Foreign_SVK	0.143
	(0.211)		(0.257)
Foreign_AUT	0.339*	Foreign_ESP	0.181
	(0.177)		(0.214)
Foreign_BEL	1.222***	Foreign_SWE	0.369
	(0.214)		(0.295)
Foreign_CAN	-0.0966	Foreign_CHE	0.454**
	(0.217)		(0.201)
Foreign_CHL	1.733***	Foreign_GBR	0.244
	(0.233)		(0.169)
Foreign_CZE	0.753***	Foreign_USA	0.676***
	(0.283)		(0.209)
		Constant	-32.30***
			(9.509)
N			21238
R^2			0.930

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.4. Data categories used in each year

Country	1998-2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013-2016
Australia	F	I	I	I	I	I	I	I	I	I	I
Austria	F	F	F	F	F	F	F	F	F	I	I
Belgium	F	I	I	I	I	I	I	I	I	I	I
Canada	F	I	X	I	I	I	I	I	I	I	I
Chile	F	X	F	X	F	I	I	I	I	I	I
Czech	F	F	F	F	F	F	F	F	F	F	F
Denmark	F	I	I	I	I	I	I	I	I	I	I
Estonia	X	X	I	I	I	I	I	I	I	I	I
Finland	F	F	F	F	F	F	F	F	F	F	I
France	F	F	F	F	F	F	F	F	F	F	I
Germany	F	I	I	I	I	I	I	I	I	I	I
Greece	F	F	F	F	F	F	X	F	F	F	F
Hungary	F	F	F	F	F	F	I	I	I	I	F
Iceland	F	F	F	F	I	I	I	I	I	I	I
Ireland	F	I	I	I	I	I	I	I	I	I	I
Israel	X	X	X	X	X	X	X	F	F	F	F
Italy	F	F	F	F	F	F	F	F	F	F	F
Japan	F	F	F	F	F	F	F	F	F	F	I
Korea	F	F	F	F	F	F	F	F	F	F	F
Luxembourg	F	X	X	F	X	F	I	I	X	I	I
Netherlands	F	I	I	I	I	I	I	I	I	I	I
New Zealand	F	I	I	I	I	I	I	I	I	I	I
Norway	F	F	F	F	F	F	F	F	F	F	I
Poland	F	F	F	F	F	F	F	F	I	I	I
Portugal	F	F	F	F	F	I	I	I	I	I	I
Slovak	F	I	I	I	I	I	I	I	I	I	F
Slovenia	X	X	I	I	I	I	I	I	I	I	X
Spain	F	I	I	I	I	I	I	I	I	I	I
Sweden	F	I	I	I	I	I	I	I	I	I	I
Switzerland	F	I	I	I	I	I	I	I	I	I	I
Turkey	F	F	F	F	F	F	F	F	F	F	F
United Kingdom	F	I	I	I	I	I	I	I	I	I	I
United States	F	I	I	I	I	I	I	I	I	I	I

1) F: Foreign (Non-Citizen) students, I: International students (non-resident or prior education outside the reporting country), X: none of the categories are available.