Agricultural Economics Staff Paper

2020-2

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Revised October 2020

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AGRICULTURAL ECONOMICS

Exploring the Impact of Economic Integration Agreements Through Extreme Bounds Analysis

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Oct 28, 2020

Abstract

This paper provides an empirical strategy guided by the data to estimate the dynamics and effects 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 without researchers' discretion involved. We show that arbitrarily selected year intervals and starting year can result in non-robust estimates of transitional dynamics of the effects of EIAs on trade flows. The empirical strategy follows two steps: EBA firstly sifts lags and leads of EIAs robustly related to trade flows from candidates, then these are included in the gravity equation to estimate the effects of EIAs on trade. We find that various lags and leads are robustly and positively related to trade flows, and the lag and lead structure depends on the level of integration. Our results show that EIAs have a long-term effect of 64% on trade flows. Under the richer lag and lead structure, deep-integration agreements beyond the level of free trade agreements have a much higher impact on trade flows than free trade agreements do (112% versus 33%). The estimates of effects of EIAs obtained from EBA-based estimation have a smaller contemporaneous effect and larger phased-in effects compared to previous studies relying on the subjective choices of year intervals while similar results are observed with the decomposed EIAs.

JEL Classification: F1, C5

Keywords: Economic integration agreements; Extreme Bounds Analysis; Gravity equation

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1. Introduction

Our paper contributes to the literature assessing the dynamics and trade effects of Economic Integration Agreements (EIAs), by addressing the potential non-robustness of estimates of their trade effects. This paper provides an empirical strategy, guided by the data, to investigate the effects of EIAs on trade flows. The strategy uses Extreme Bounds Analysis (EBA) to guide the choice of lags and leads in the trade effects. This enables the exploration of the dynamics and transitional effects of EIAs. We show that arbitrarily selected intervals and starting year can result in non-robust estimates of the effects of EIAs on trade flows, distorting the dynamics of the effects. The empirical strategy follows two steps: EBA firstly sifts lags and leads of EIAs robustly related to trade flows from candidates, then these are included in the gravity equation to estimate the effects of EIAs on trade. Using the data of Baier and Bergstrand (2007), we find that various lags and one lead of EIAs are robustly related to trade flows, leading to a long-term increase in trade of 64%. Lag and lead structure can also vary according to the depth of integration of EIAs. Agreements deeper than the level of free trade agreements show richer lag and lead structure and exhibit a stronger long-term effect (112%) on trade than those from free trade agreements (33%). Our estimates show a smaller contemporaneous effect and larger phased-in effects compared to previous studies relying on subjective choices of year intervals.

With the proliferation of EIAs through regional and bilateral trade agreements and customs unions since the 1990s, 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 flow led to 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) avoided issues with instruments that violate the "exclusion restriction" condition for instrumental variables. They used pair fixed effects estimation that accounts for time-invariant and country-and-time varying unobservables in place 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% by using matching techniques. This magnitude is similar to those estimated by Baier and Bergstrand (2007). 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.

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 the lagged effects of EIAs that capture "phased-in" periods of EIAs. They 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. They 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 "year 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. While circumventing this critique, however, the intervals have been chosen at 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) 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. Based on these findings, they 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,[2] once negotiated and before they are ratified and enter into force officially (Moser and Rose, 2012; and 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

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[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] 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.

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 lagged and lead effects. As another example, Mexico reformed its economic policies in the 1980s and early 1990s to ensure acceptance in the GATT by gradually reducing tariffs, non-tariff barriers, and quotas (Hansen, 2000). This 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), signed in 1992 but ratified in 1994. A massive agricultural policy reform program, 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 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 with year intervals, 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 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.

2. An illustration of non-robustness

We illustrate the non-robustness of estimates of the effects of EIAs across the starting years within the year interval 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 different starting years (1962, 1963, 1964, 1965) by using a panel dataset from 1962-2000 of bilateral trade flows and EIAs.[3] 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, columns (1) – (4) show estimates of the effects of EIAs using 5-year intervals. First, one can find that the dynamics of EIAs depends on the starting years. For example, the lead effect of EIAs is significant with the starting year of 1964 while it does not with the starting years of 1962, 1963, and 1965. More importantly, the Chow test statistics show that many coefficients of lags in column (1) – (4) are statistically different across starting years. The test indicates that the estimated transitional dynamics of the effects of EIAs on trade flows might be distorted from using arbitrary starting years.

<Table 1 about here>

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

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

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 φ_{it}, θ_{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 5-year and 10-year lags respectively under 5-year intervals.

The non-robustness can be more clearly seen when dividing EIAs by their level of integration as done in Roy (2010) and Baier et al. (2014). We re-estimate the model with EIAs separated into free trade agreements (*FTA*) and agreements higher (deeper integration) than the level of FTA that combines customs unions, common markets, and economics unions (*CUCMECU*). While the estimated aggregate long-term effect of FTAs is quite stable across starting years, that of CUCMECUs varies significantly across the starting years as shown in column (5) – (8). It varies up to 42%p according to a selected starting year with 5-year intervals (column (6) and (8)). As a note, we also investigated the long-term effect with 4-year intervals and found that the estimates with 5-year intervals and with 4-year intervals can differ by up to 48%p. Moreover, differences in statistical significances and magnitudes of lags and leads of FTAs and CUCMECUs across starting years prop up our claim that both subjective choices of intervals and starting year can jointly contribute to weakening the robustness of estimates.

Therefore, we depart from using year intervals for the investigation of the effects of EIAs on trade flows. One possibility could be to include year-to-year lags and leads of EIA using the whole dataset without arbitrary choice involved. However, multicollinearity may be present from having many consecutive lag and lead changes in the model. For example, Magee (2008) suggested the possibility of multicollinearity that annual lags and leads of regional trade agreements are jointly significant as a group while most of them are individually insignificant. Similarly, 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.

We performed a pairwise correlation test with 10-year annual lags and 5-year annual leads. Results in Table 2 show evidence that there are statistically significant linear relationships between all lags and leads of EIA, which strongly suggests the possible multicollinearity bias.

Similar correlation relationships are found between all lags and leads of FTAs and CUCMECUs. Furthermore, the multicollinearity diagnostic of Belsley et al. (2004) produces a condition number of 28 for EIAs and 32 for FTAs and CUCMECUs, which is within the neighborhood that implies multicollinearity problems.

<Table 2 about here>

We apply EBA (Leamer, 1985; and Sala-i-Martin, 1997) to mitigate the multicollinearity bias by reducing the number of lags and leads of EIAs and select the appropriate lags and leads avoiding arbitrary choices of intervals. This step allows the dataset to determine which lags and leads of EIAs should be included in the model for the estimation of the effects 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 year intervals and starting year.

Our EBA-based empirical estimations indicate that various lags and one lead of EIAs have robust relationships with trade flows and lag and lead structure depends on the level of integration. This suggests that these lags and lead should not be disregarded at researchers' discretion to estimate the effects of EIAs. Our estimation shows that 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. When decomposing the EIAs according to their level of integration, agreements beyond the level of free trade agreements have a much higher impact on trade flows (112%) than free trade agreements (33%). Deeper-integration agreements also exhibit a richer lag and lead structure. Compared to the estimates using 5-year and 4-year intervals, the estimate of effects of EIAs based on EBA exhibits a different distribution of the transitional effects over time. The contemporaneous effect of EIAs is weaker and cumulative lagged effects of EIAs after their entry-into force are stronger, while similar results are observed with the decomposed EIAs.

These findings imply that specifications with arbitrary year intervals are likely to overstate the contemporaneous effect of EIAs, understate the phased-in effects of EIAs, resulting in biased estimates of the dynamics of transitional effects.

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 presents the main results and compares estimates based on EBA with those based on predetermined year intervals. Section 5 concludes with some suggestions for future research.

3. 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 Sala-i-Martin's EBA. The lags and leads found to be robustly related to bilateral trade flows in EBA are then used to estimate the effects of EIAs. This procedure not only identifies robust lagged and lead impacts of EIAs but also provides the foundation for estimating the long-term effect of EIAs. In addition, it reinforces the robustness of the estimates of the effects of EIAs because it does not require researchers' discretion on the selection of year intervals 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 ***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:

$$Y_j = \alpha_j + \boldsymbol{F}\beta_j + \gamma_j \mathrm{T} + \boldsymbol{D}\delta_j + \varepsilon_j. \tag{1}$$

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. The number of doubtful variables in ***D*** has conventionally limited up to three. For instance, if up to 3 doubtful variables are taken from a total of 4 variables in set *X*, the number of possible combinations is $C_0^4 + C_1^4 + C_2^4 + C_3^4 = 15$.

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 the 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 a different sign while all the remaining estimates 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 $\hat{\sigma}_j^2$, and w_j denotes weights. Sala-i-Martin (1997) applied weights proportional to the likelihoods, $w_j = L_j / \sum_i L_i$, 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 defined as above.

4. Empirical implementation

4.1. EBA using the gravity equation

Baier and Bergstrand (2007) established that estimated effects of EIAs could suffer from endogeneity bias because of the 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:

$$Y_{ijt} = exp(b_0 + b_1 EIA_{ijt} + \varphi_{it} + \theta_{jt} + \mu_{ij}) + \varepsilon_{ijt} \quad (2)$$

where $Y_{ijt}, \varphi_{it}, \theta_{jt}$, and μ_{ij} denote 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 lags and 5 leads of EIA dummy ($EIA_{ijt-1}, \ldots, EIA_{ijt-10}, EIA_{ijt+1}, \ldots, EIA_{ijt+5}$), which have been commonly covered in trade literature to see whether these lagged and lead effects are truly associated with trade flows. Therefore, given each focus variable taken from set *X*, up to 3 remaining doubtful variables in set *X* can be added to equation (2). For example, when the focus variable is EIA_{ijt-1} and one doubtful variable (EIA_{ijt-4}) is chosen from set *X*, equation (2) would be extended to:

$$Y_{ijt} = exp(b_0 + b_1 EIA_{ijt} + \gamma_1 EIA_{ijt-1} + \delta_1 EIA_{ijt-4} + \varphi_{it} + \theta_{jt} + \mu_{ij}) + \varepsilon_{ijt} \quad (3)$$

We resort to PPML to deal with heteroskedasticity in trade flows.[4] Therefore, clustered heteroskedasticity-robust standard errors are used to construct criteria for EBAs.

To sum up, estimation based on EBA follows two steps: EBA firstly chooses 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 3 doubtful variables taken from set *X* in the 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 weights.[5] However, the results of the unweighted version of Sala-i-Martin's EBA are used for 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, CDFs are calculated with no distribution assumption on coefficients of focus variables

[4] 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 the PPML estimator as a way to deal with this issue.
[5] 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.

because the kernel densities of coefficients of focus variables were not shown to follow the normal distribution. Histograms and densities are shown in the Appendix.

EBA is conducted using a modified "ExtremeBounds" package in R written by Hlavac (2016). This package can handle EBA with several estimation methods but it cannot deal with PPML and many pair-fixed effects at the same time.[6] 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.

4.2. 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.[7] Our study covers a total of 96 trading countries by following Baier and Bergstrand (2007).

For EIA variables, the Database on Economic Integration Agreements constructed by Baier and Bergstrand is used.[8] 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 by following Baier and Bergstrand (2007) and Anderson and Yotov (2016) and therefore construct a dichotomous EIA

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[6] 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.
[7] 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.
[8] The dataset is available at Bergstrand's website (https://www3.nd.edu/~jbergstr/).

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.

5. Results of EBA estimations

The upper panel of Table 3 shows the results of EBA with EIA variables. Results indicate that 1- to 7-year, 10-year lags, and 2-year lead of the EIA dummy have a significant relationship with trade flows as unweighted CDF(0)s of these variables are larger than 0.95. Results in the lower panel of Table 3 show EBA with EIAs decomposed into FTA and CUCMECU variables. Deeper integration (CUCMECU) has a richer lag and lead structure than simpler agreements (FTA). It shows that 1- to 10-year lags, 1-year, 2-year, and 5-year leads of CUCMECUs are robustly related to trade flows while only 1- to 5-year lags of FTAs do without lead effects.

<Table 3 about here>

The results show that various lags and leads contribute to explaining the trade effects of EIAs. They also strongly suggest that the level of integration interacts with the lag and lead structure. Leaving these at researchers’ discretion opens the door to non-robust estimates of the effects of EIAs. Therefore, the selection of lags and leads of EIAs should be guided empirically by the given dataset and variables, rather than being determined by researchers’ preconception.

Table 4 reports econometric results for estimated equation (2) with lags and lead of EIAs chosen by EBA using PPML. It is shown that 1- to 5-year lags, 10-year lag, and 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% ($e^{0.0614} \approx 1.06$) in anticipation of the benefits of EIAs. This significant lead (anticipatory) effect of EIAs is in line with the result of Magee (2008), which confirmed that regional trade agreements increase trade prior to their entry-into-force, albeit smaller than his estimate of 26%.

Compared with previous estimates, the estimate of the long-term effect is smaller than that of 114% found in Baier and Bergstrand (2007). As explained in Anderson and Yotov (2016), the difference possibly stems from the difference in the estimation methods. Baier and Bergstrand used OLS while we use PPML 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 effects of EIAs with our proposed approach.

<Table 4 about here>

Leads of EIAs are often regarded as insignificant and are mostly used to test the strict exogeneity assumption of EIAs by conducting a simple "strict exogeneity" test suggested by Wooldridge (2010)[9]. 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.

Table 5 shows estimates of the effects of FTA and CUCMECU. It indicates that all

[9] 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, the chosen lead effect (EIA_{ijt+2}) does not significantly change the contemporaneous and lagged effects of EIAs.

chosen lags of FTA are significant, meaning that FTAs have an impact on trade flows until 5 years after their enter-into-force with the long-term aggregate effect of 33%. On the other hand, the estimate of the long-term aggregate effect of CUCMECUs (112%) is much higher than that 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 5 years before and 10 years after their entry-into-force while trade-creating effects of FTAs exist until after 5-years from their entry-into-force.

<Table 5 about here>

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 12% from 5 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 the 1990s to accede to the EU and integrated with the EU in 2004. Furthermore, several deeper integration agreements are preceded by FTAs, motivating the long lead of CUCMECU. For example, Portugal had an interim FTA with the EU from 1973 until before it acceded to the EU in 1986. Likewise, Austria signed an FTA with the EU in 1972 before becoming an EU member 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.

5.1. 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). Therefore, 5-year and 10-year lags of the EIA dummy are added to equation (2):

$$Y_{ijt} = exp(b_0 + b_1 EIA_{ijt} + b_2 EIA_{ijt-5} + b_3 EIA_{ijt-10} + \varphi_{it} + \theta_{jt} + \mu_{ij}) + \varepsilon_{ijt} \quad (4)$$

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

$$Y_{ijt} = exp(b_0 + b_1 EIA_{ijt} + b_2 EIA_{ijt-4} + b_3 EIA_{ijt-8} + \varphi_{it} + \theta_{jt} + \mu_{ij}) + \varepsilon_{ijt} \quad (5)$$

We use the first available year as a starting year and therefore data from 1962 to 1997 (1962, 1967, …, 1997) and data from 1962 to 1998 (1962, 1966, …, 1998) are used for the estimation of equations (4) and (5), respectively.

Column (2) and (3) of Table 6 provide coefficient estimates of 5-year and 4-year interval specifications using EIA variables, respectively. Compared to the estimate of the long-term aggregate effect of EIAs on trade (64%) using EBA, the long-term aggregate estimates with year intervals are similar, 65% and 61% respectively. However, when we decompose the contemporaneous and the lagged (phased-in) impacts of EIAs on trade, we see that the distribution of transitional effects aggregated into the long-term effect of EIAs is different, even though estimated long-term aggregate effects of EIAs are close.

<Table 6 about here>

The contemporaneous effects of EIAs estimated with 5-year and 4-year intervals 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 12% and 21%, which is smaller than the corresponding cumulative effect of 30% estimated using EBA. Cumulative effects of EIAs from 6 to 10 years after entry-into-force of EIAs are similar. More importantly, estimation based on EBA finds the statistically significant lead effect while both specifications with intervals do not. This suggests that, even when models with year intervals successfully estimate the long-term effect of EIAs, there is a strong possibility to overstate the contemporaneous effect of EIAs and understate the "phased-in" effects of EIAs after they came into effect and distort the dynamics of transitional effects of EIAs.

Similar results are observed when comparing the effects of FTA and CUCMECU based on EBA with those based on year intervals. In Table 7, compared to the result based on EBA, the concurrent effects of FTA and CUCMECU are larger and phased-in effects tend to be smaller for the specifications with year intervals. Moreover, specification with 5-year intervals shows a significant 10-year lag of FTA that is found by EBA not to be robustly related to trade flows. In contrast, the 5-year interval specification finds an insignificant 5-year lead of CUCMECU in which EBA finds robustly related to trade flows. The contradictory findings reinforce our claim that relying on year intervals can distort the dynamics of transitional effects. Lastly, it is shown that the dynamics of the effects of FTA and CUCMECU can also be biased across year intervals. For instance, PPML results with 5-year intervals show the significant cumulative lagged effect (6-10) of FTA while the cumulative lagged effect (1-5) of FTA and the cumulative lead effect (1-5) of CUCMECU are not significant, which is the complete opposite of PPML result with 4-year intervals.

<Table 7 about here>

Our results put in question the claim of Cheng and Wall (2005) that the effects of EIAs are not fully captured with annual data, in favor of using data differenced over a long period to estimate the effect of EIAs. Based on Tables 6 and 7, however, the estimate of the "long-term" effect using annual data falls in the mid-range of the estimates using year-intervals, suggesting that the long-term effect can be appropriately captured with annual data. As we show, using data differenced over an arbitrarily selected period rather produces biased estimates of the dynamics of transitional effects of EIAs. Therefore, we argue that the data should guide the investigation of the dynamics of transitional effect without ex-ante exclusions.

6. Conclusion

The contribution of our paper is to provide an empirical strategy based on EBA and guided by the data to derive robust estimates of the effects of EIAs on trade flows. This strategy avoids potential shortcomings induced by arbitrary empirical decisions, leading to specific and non-robust results. The decisions refer to year intervals and starting year in datasets.

The estimation of the effects of EIAs through EBA followed two steps: EBA firstly sifts lags and leads of EIAs robustly related with trade flows from candidate lags and leads and then these lags and leads are in turn included in the gravity equation to estimate the effects of EIAs on trade.

We find that various lags and one lead of EIAs exhibit a robust relationship with trade flows and the lag and lead structure can vary according to the level of EIAs. These lags and leads should not be ignored at researchers' discretion. The following estimation indicates that EIAs increase bilateral trade by 64% in the long run. Under the richer lag and lead structure, deeper integration agreements beyond free trade agreements have a stronger long-term effect of 112% than free trade agreements have of 33%.

Estimation based on EBA provides evidence that the lead effects of EIAs and those of deep-integration agreements (CUCMECU) significantly robustly increase trade flows. This suggests that 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 transitional effects of EIAs is different. The contemporaneous effect is smaller and phased-in effects are larger under EBA-based estimation. Furthermore, specifications with arbitrary year intervals capture lags and leads that are not robustly correlated with trade flows. This finding implies that using arbitrary year intervals might result in the upward-biased contemporaneous effect and downward-biased phased-in effects of EIAs, distorting the dynamics 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. 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 the effects of EIAs can be used to evaluate the 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.

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Table 1. PPML results with 5-year intervals and different starting years

	(1) 1962-1997	(2) 1963-1998	(3) 1964-1999	(4) 1965-2000
EIA_{ijt}	[a]0.256***	0.198***	[a]0.158***	0.219***
	(0.0375)	(0.0317)	(0.0334)	(0.0349)
EIA_{ijt-5}	[bc]0.113***	[d]0.138***	[bd]0.212***	[c]0.184***
	(0.0270)	(0.0267)	(0.0283)	(0.0279)
EIA_{ijt-10}	[e]0.129***	[fg]0.190***	[f]0.0804***	[eg]0.0574**
	(0.0294)	(0.0323)	(0.0270)	(0.0282)
EIA_{ijt+5}	0.00493	0.0348	[h]0.0729**	[h]-0.0163
	(0.0399)	(0.0433)	(0.0330)	(0.0371)
Long-term (EIA)	65%	69%	69%	58%
N	44134	42699	44524	45077
R^2	0.994	0.995	0.995	0.995

	(5) 1962-1997	(6) 1963-1998	(7) 1964-1999	(8) 1965-2000
FTA_{ijt}	0.203***	0.155***	0.128***	0.180***
	(0.0378)	(0.0325)	(0.0336)	(0.0351)
FTA_{ijt-5}	[ab]0.0441	[cd]0.0828***	[ac]0.191***	[bd]0.159***
	(0.0283)	(0.0260)	(0.0282)	(0.0280)
FTA_{ijt-10}	[ef]0.0692**	[gh]0.0996***	[eg]-0.00166	[fh]-0.0155
	(0.0312)	(0.0320)	(0.0276)	(0.0307)
FTA_{ijt+5}	-0.00966	0.0189	[i]0.0551*	[i]-0.0386
	(0.0402)	(0.0435)	(0.0331)	(0.0385)
$CUCMECU_{ijt}$	[jk]0.361***	[j]0.270***	[kl]0.232***	[l]0.348***
	(0.0393)	(0.0369)	(0.0359)	(0.0418)
$CUCMECU_{ijt-5}$	0.264***	[m]0.294***	0.249***	[m]0.187***
	(0.0470)	(0.0452)	(0.0366)	(0.0316)
$CUCMECU_{ijt-10}$	0.105**	0.191***	0.167***	0.135***
	(0.0429)	(0.0415)	(0.0460)	(0.0449)
$CUCMECU_{ijt+5}$	0.0547	0.106**	0.138***	0.0652
	(0.0502)	(0.0520)	(0.0452)	(0.0469)
Long-term (FTA)	31%	40%	38%	40%
Long-term (CUCMECU)	108%	137%	119%	95%
N	44134	42699	44524	45077
R^2	0.995	0.995	0.995	0.995

Notes: Supercripts a-m indicate that two corresponding coefficients are statistically different at significance level of 10% in the Chow test. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2. Pairwise Correlations

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	EIA_{ijt}	1.000															
(2)	EIA_{ijt-1}	0.964*	1.000														
(3)	EIA_{ijt-2}	0.928*	0.963*	1.000													
(4)	EIA_{ijt-3}	0.891*	0.925*	0.961*	1.000												
(5)	EIA_{ijt-4}	0.856*	0.889*	0.923*	0.961*	1.000											
(6)	EIA_{ijt-5}	0.821*	0.851*	0.884*	0.921*	0.958*	1.000										
(7)	EIA_{ijt-6}	0.787*	0.816*	0.846*	0.881*	0.918*	0.958*	1.000									
(8)	EIA_{ijt-7}	0.754*	0.782*	0.811*	0.843*	0.878*	0.917*	0.957*	1.000								
(9)	EIA_{ijt-8}	0.725*	0.752*	0.779*	0.811*	0.842*	0.879*	0.919*	0.960*	1.000							
(10)	EIA_{ijt-9}	0.701*	0.726*	0.752*	0.782*	0.813*	0.847*	0.885*	0.926*	0.964*	1.000						
(11)	EIA_{ijt-10}	0.678*	0.702*	0.728*	0.756*	0.786*	0.819*	0.853*	0.893*	0.930*	0.965*	1.000					
(12)	EIA_{ijt+1}	0.965*	0.930*	0.895*	0.859*	0.827*	0.793*	0.760*	0.729*	0.701*	0.677*	0.655*	1.000				
(13)	EIA_{ijt+2}	0.932*	0.898*	0.865*	0.831*	0.800*	0.767*	0.735*	0.705*	0.678*	0.655*	0.634*	0.967*	1.000			
(14)	EIA_{ijt+3}	0.902*	0.869*	0.838*	0.805*	0.775*	0.743*	0.713*	0.683*	0.657*	0.635*	0.614*	0.935*	0.968*	1.000		
(15)	EIA_{ijt+4}	0.872*	0.841*	0.811*	0.780*	0.750*	0.720*	0.690*	0.662*	0.636*	0.615*	0.595*	0.905*	0.937*	0.968*	1.000	
(16)	EIA_{ijt+5}	0.840*	0.810*	0.781*	0.751*	0.722*	0.693*	0.665*	0.637*	0.613*	0.592*	0.573*	0.872*	0.902*	0.932*	0.964*	1.000

Notes: Bonferroni-adjusted standard errors are used to test the significance of correlation coefficients. * $p < 0.05$

Table 3. Results of Sala-i-Martin's EBA

	Unweighted CDF(0)	Robust / Fragile
EIA_{ijt-1}	0.999	Robust
EIA_{ijt-2}	0.999	Robust
EIA_{ijt-3}	1.000	Robust
EIA_{ijt-4}	1.000	Robust
EIA_{ijt-5}	0.999	Robust
EIA_{ijt-6}	0.969	Robust
EIA_{ijt-7}	0.953	Robust
EIA_{ijt-10}	0.999	Robust
EIA_{ijt+2}	0.988	Robust

	Unweighted CDF(0)	Robust / Fragile
FTA_{ijt-1}	0.995	Robust
FTA_{ijt-2}	0.995	Robust
FTA_{ijt-3}	0.999	Robust
FTA_{ijt-4}	0.999	Robust
FTA_{ijt-5}	0.991	Robust
$CUCMECU_{ijt-1}$	0.999	Robust
$CUCMECU_{ijt-2}$	0.999	Robust
$CUCMECU_{ijt-3}$	1.000	Robust
$CUCMECU_{ijt-4}$	0.999	Robust
$CUCMECU_{ijt-5}$	0.999	Robust
$CUCMECU_{ijt-6}$	0.998	Robust
$CUCMECU_{ijt-7}$	1.000	Robust
$CUCMECU_{ijt-8}$	0.995	Robust
$CUCMECU_{ijt-9}$	0.999	Robust
$CUCMECU_{ijt-10}$	0.997	Robust
$CUCMECU_{ijt+1}$	0.999	Robust
$CUCMECU_{ijt+2}$	0.973	Robust
$CUCMECU_{ijt+5}$	0.962	Robust

Notes: Only robust variables from EBA are presented. Full results are available in the Appendix. Up to 3 doubtful variables are used. No distribution assumption is imposed on the coefficients of focus variables to calculate CDFs because kernel densities of the coefficients are different from the normal distribution. Histograms and densities are available in the Appendix.

Table 4. Main PPML results with EIA

	(1)
EIA_{ijt}	0.0593***
	(0.0146)
EIA_{ijt-1}	0.0812***
	(0.0198)
EIA_{ijt-2}	0.0247**
	(0.0102)
EIA_{ijt-3}	0.0724***
	(0.0137)
EIA_{ijt-4}	0.0397***
	(0.0104)
EIA_{ijt-5}	0.0453***
	(0.0113)
EIA_{ijt-6}	0.00631
	(0.00935)
EIA_{ijt-7}	0.00505
	(0.0172)
EIA_{ijt-10}	0.101***
	(0.0237)
EIA_{ijt+2}	0.0614**
	(0.0291)
Long-term effect	**64%**
N	216154
R^2	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 5. Main PPML results with FTA and CUCMECU

	(1)
FTA_{ijt}	0.0779***
	(0.0267)
FTA_{ijt-1}	0.0664***
	(0.0202)
FTA_{ijt-2}	0.0152
	(0.0104)
FTA_{ijt-3}	0.0626***
	(0.0144)
FTA_{ijt-4}	0.0355***
	(0.0106)
FTA_{ijt-5}	0.0402**
	(0.0182)
$CUCMECU_{ijt}$	0.124***
	(0.0228)
$CUCMECU_{ijt-1}$	0.0956***
	(0.0217)
$CUCMECU_{ijt-2}$	0.0320***
	(0.0122)
$CUCMECU_{ijt-3}$	0.0808***
	(0.0138)
$CUCMECU_{ijt-4}$	0.0532***
	(0.0140)
$CUCMECU_{ijt-5}$	0.0450**
	(0.0190)
$CUCMECU_{ijt-6}$	0.0144
	(0.0130)
$CUCMECU_{ijt-7}$	0.0922***
	(0.0289)
$CUCMECU_{ijt-8}$	-0.00204
	(0.0199)
$CUCMECU_{ijt-9}$	0.0382***
	(0.0128)
$CUCMECU_{ijt-10}$	0.0769**
	(0.0369)
$CUCMECU_{ijt+1}$	0.0474***
	(0.0120)
$CUCMECU_{ijt+2}$	0.0143
	(0.0181)
$CUCMECU_{ijt+5}$	0.0663**
	(0.0320)
Long-term effect (FTA)	**33%**
Long-term effect (CUCMECU)	**112%**
N	216154
R^2	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 6. PPML results using EBA and year intervals

	(1) EBA-based	(2) 5-year intervals (1962-1997)	(3) 4-year intervals (1962-1998)
EIA_{ijt}	0.0593***	0.258***	0.189***
	(0.0146)	(0.0376)	(0.0334)
Contemporaneous effect	**6%**	**29%**	**21%**
EIA_{ijt-1}	0.0812***		
	(0.0198)		
EIA_{ijt-2}	0.0247**		
	(0.0102)		
EIA_{ijt-3}	0.0724***		
	(0.0137)		
EIA_{ijt-4}	0.0397***		0.187***
	(0.0104)		(0.0280)
EIA_{ijt-5}	0.0453***	0.113***	
	(0.0113)	(0.0270)	
Cumulative effect (1-5)	**30%**	**12%**	**21%**
EIA_{ijt-6}	0.00631		
	(0.00935)		
EIA_{ijt-7}	0.00505		
	(0.0172)		
EIA_{ijt-8}			0.101***
			(0.0286)
EIA_{ijt-9}			
EIA_{ijt-10}	0.101***	0.128***	
	(0.0237)	(0.0293)	
Cumulative effect (6-10)	**11%**	**14%**	**11%**
EIA_{ijt+2}	0.0614**		
	(0.0291)		
Cumulative lead effect (1-5)	**6%**	**0%**	**0%**
Long-term effect	**64%**	**65%**	**61%**
N	216154	44134	54413
R^2	0.994	0.994	0.995

Notes: Lead effects are not included in column (2) and (3) due to a statistical insignificance. 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 7. PPML results with FTA and CUCMECU

	(1) EBA-based	(2) 1962-1997 (5-year intervals)	(3) 1962-1998 (4-year intervals)
FTA_{ijt}	0.0779***	0.201***	0.133***
	(0.0267)	(0.0374)	(0.0320)
Contemporaneous effect	**8%**	**22%**	**14%**
FTA_{ijt-1}	0.0664***		
	(0.0202)		
FTA_{ijt-2}	0.0152		
	(0.0104)		
FTA_{ijt-3}	0.0626***		
	(0.0144)		
FTA_{ijt-4}	0.0355***		0.168***
	(0.0106)		(0.0268)
FTA_{ijt-5}	0.0402**	0.0440	
	(0.0182)	(0.0284)	
Cumulative lag effect (1-5)	**23%**	**0%**	**18%**
FTA_{ijt-6}			
FTA_{ijt-7}			
FTA_{ijt-8}			-0.00683
			(0.0263)
FTA_{ijt-9}			
FTA_{ijt-10}		0.0789***	
		(0.0305)	
Cumulative lag effect (6-10)	**0%**	**8%**	**0%**
FTA_{ijt+1}			
FTA_{ijt+2}			
FTA_{ijt+3}			
FTA_{ijt+4}			0.0304
			(0.0392)
FTA_{ijt+5}			
Cumulative lead effect (1-5)	**0%**	**0%**	**0%**
Long-term (FTA)	**33%**	**32%**	**35%**

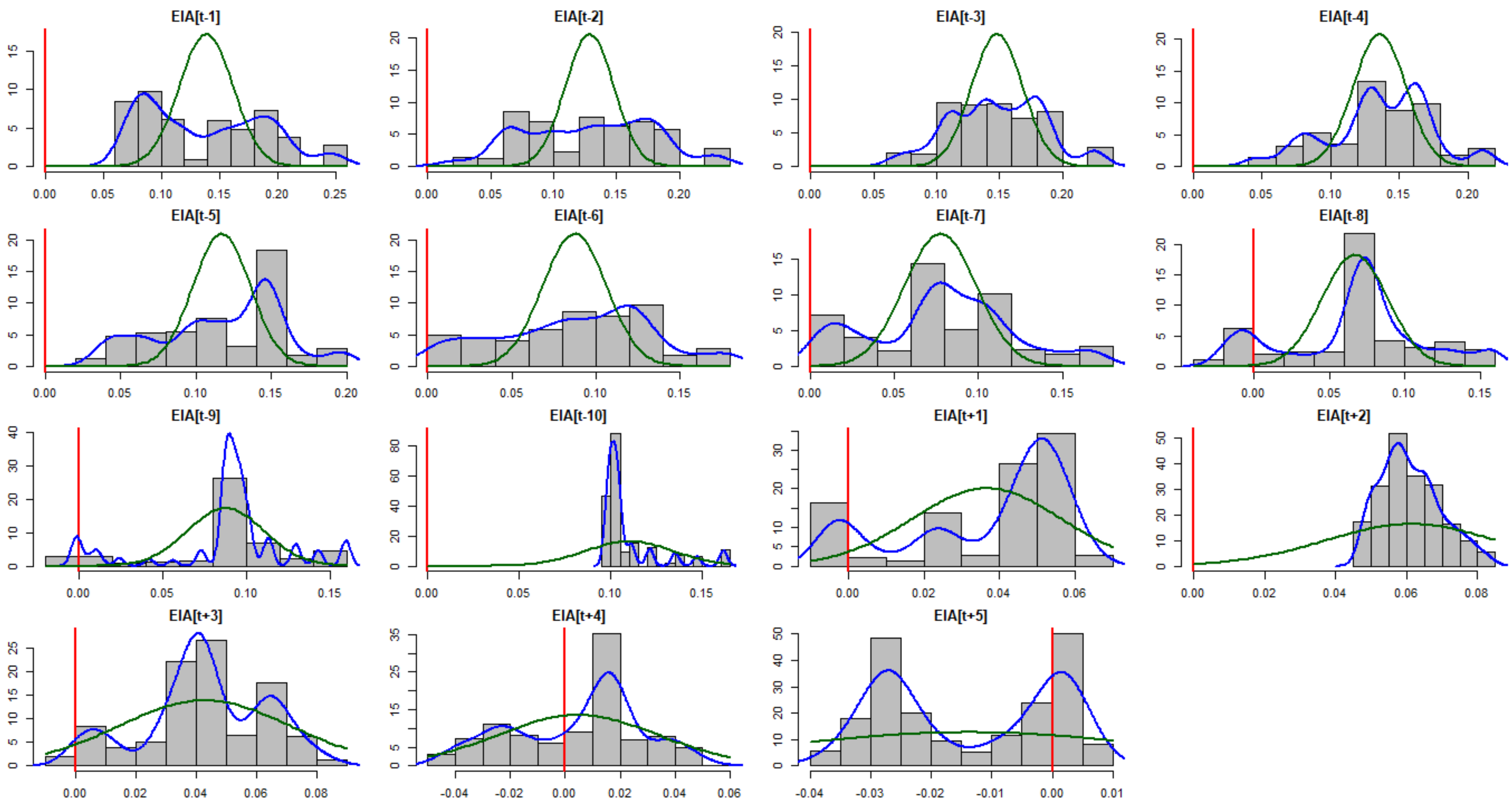
Table 7. PPML results with FTA and CUCMECU (Continued)

	(1) EBA-based	(2) 1962-1997 (5-year intervals)	(3) 1962-1998 (4-year intervals)
$CUCMECU_{ijt}$	0.124^{***}	0.361^{***}	0.225^{***}
	(0.0228)	(0.0393)	(0.0325)
Contemporaneous effect	**13%**	**43%**	**25%**
$CUCMECU_{ijt-1}$	0.0956^{***}		
	(0.0217)		
$CUCMECU_{ijt-2}$	0.0320^{***}		
	(0.0122)		
$CUCMECU_{ijt-3}$	0.0808^{***}		
	(0.0138)		
$CUCMECU_{ijt-4}$	0.0532^{***}		0.242^{***}
	(0.0140)		(0.0374)
$CUCMECU_{ijt-5}$	0.0450^{**}	0.258^{***}	
	(0.0190)	(0.0465)	
Cumulative lag effect (1-5)	**36%**	**29%**	**27%**
$CUCMECU_{ijt-6}$	0.0144		
	(0.0130)		
$CUCMECU_{ijt-7}$	0.0922^{***}		
	(0.0289)		
$CUCMECU_{ijt-8}$	-0.00204		0.218^{***}
	(0.0199)		(0.0474)
$CUCMECU_{ijt-9}$	0.0382^{***}		
	(0.0128)		
$CUCMECU_{ijt-10}$	0.0769^{**}	0.104^{**}	
	(0.0369)	(0.0427)	
Cumulative lag effect (6-10)	**23%**	**11%**	**24%**
$CUCMECU_{ijt+1}$	0.0474^{***}		
	(0.0120)		
$CUCMECU_{ijt+2}$	0.0143		
	(0.0181)		
$CUCMECU_{ijt+3}$			
$CUCMECU_{ijt+4}$			0.111^{**}
			(0.0472)
$CUCMECU_{ijt+5}$	0.0663^{**}		
	(0.0320)		
Cumulative lead effect (1-5)	**12%**	**0%**	**12%**
Long-term (CUCMECU)	**112%**	**106%**	**128%**
N	216154	44134	54413
R^2	0.994	0.995	0.995

Notes: Lead effects are not included in column (2) due to a statistical insignificance. Coefficient estimates for country-and-time and bilateral fixed effects are not reported for brevity. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix (not intended for publication)

Appendix Figure 1. Histogram and densities of coefficients of focus variables (Blue line: kernel density, Green line: normal density)



Appendix Table 1. Full Results of Sala-i-Martin's EBA (*EIA*)

	Unweighted CDF(0)	Robust / Fragile
EIA_{ijt-1}	0.999	Robust
EIA_{ijt-2}	0.999	Robust
EIA_{ijt-3}	1.000	Robust
EIA_{ijt-4}	1.000	Robust
EIA_{ijt-5}	0.999	Robust
EIA_{ijt-6}	0.969	Robust
EIA_{ijt-7}	0.953	Robust
EIA_{ijt-8}	0.870	Fragile
EIA_{ijt-9}	0.948	Fragile
EIA_{ijt-10}	0.999	Robust
EIA_{ijt+1}	0.874	Fragile
EIA_{ijt+2}	0.988	Robust
EIA_{ijt+3}	0.884	Fragile
EIA_{ijt+4}	0.561	Fragile
EIA_{ijt+5}	0.657	Fragile

Notes: Up to 3 doubtful variables are used. No distribution assumption is imposed on coefficients of focus variables to calculate CDFs because kernel densities of the coefficients are different from the normal distribution.

Appendix Table 2. Full Results of Sala-i-Martin's EBA (*FTA* and *CUCMECU*)

	Unweighted CDF(0)	Robust / Fragile
FTA_{ijt-1}	0.995	Robust
FTA_{ijt-2}	0.995	Robust
FTA_{ijt-3}	0.999	Robust
FTA_{ijt-4}	0.999	Robust
FTA_{ijt-5}	0.991	Robust
FTA_{ijt-6}	0.903	Fragile
FTA_{ijt-7}	0.766	Fragile
FTA_{ijt-8}	0.666	Fragile
FTA_{ijt-9}	0.736	Fragile
FTA_{ijt-10}	0.901	Fragile
FTA_{ijt+1}	0.574	Fragile
FTA_{ijt+2}	0.871	Fragile
FTA_{ijt+3}	0.742	Fragile
FTA_{ijt+4}	0.617	Fragile
FTA_{ijt+5}	0.842	Fragile
$CUCMECU_{ijt-1}$	0.999	Robust
$CUCMECU_{ijt-2}$	0.999	Robust
$CUCMECU_{ijt-3}$	1.000	Robust
$CUCMECU_{ijt-4}$	0.999	Robust
$CUCMECU_{ijt-5}$	0.999	Robust
$CUCMECU_{ijt-6}$	0.998	Robust
$CUCMECU_{ijt-7}$	1.000	Robust
$CUCMECU_{ijt-8}$	0.995	Robust
$CUCMECU_{ijt-9}$	0.999	Robust
$CUCMECU_{ijt-10}$	0.997	Robust
$CUCMECU_{ijt+1}$	0.999	Robust
$CUCMECU_{ijt+2}$	0.973	Robust
$CUCMECU_{ijt+3}$	0.892	Fragile
$CUCMECU_{ijt+4}$	0.928	Fragile
$CUCMECU_{ijt+5}$	0.962	Robust

Notes: Up to 3 doubtful variables are used. No distribution assumption is imposed on coefficients of focus variables to calculate CDFs because kernel densities of the coefficients are different from the normal distribution.

Appendix Table 3. 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

Appendix Table 4. List of Economic Integration Agreements

<u>**ECONOMIC UNIONS**</u>

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

<u>**COMMON MARKETS**</u>

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

<u>**CUSTOMS UNION**</u>

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

<u>**FREE TRADE AGREEMENTS**</u>

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

Appendix Table 4. (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 using the online appendix of Baier et al. (2018).