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Quantile Gravity: Economic Integration Agreements, Least Traded Goods, and Less Developed Economies

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ABSTRACT

Gravity-equation estimates of the elasticity of trade with respect to bilateral trade costs – or of coefficient estimates of binary variables for the presence or absence of economic integration agreements (EIAs) – are central to determining quantitatively economic welfare impacts of trade-policy liberalizations. Despite decades of study, trade economists have largely focused on *conditional mean* estimates of a (constant) trade elasticity or of an EIA dummy variable's (common) effect in a "gravity-equation" specification. In this paper, we provide a novel panel-data *quantile regression* approach to estimating EIAs' partial effects across (conditional) quantiles that avoids Jensen's Inequality, avoids the incidental parameters problem associated with three-way fixed effects, and allows zeros. To motivate the potential economic usefulness of our approach, we examine two distinct "cases." First, using quantile regressions across a broad swath of country-pairs and EIAs at the disaggregated trade-flow level, we provide systematic evidence that supports the Arkolakis (2010) proposition; trade-flow growth effects of any type of EIA are larger for goods with lower initial sales. Second, we show that the partial effects of EIAs on trade flows are considerably larger for developing countries' exporters across quantiles.

JEL Classification: F1, F13, F63, O10, O24

> "*In cases where either the requirements for mean regression, such as homoscedasticity, are violated or interest lies in the outer regions of the conditional distribution, quantile regression can explain dependencies more accurately than classical methods.*"
>
> (Waldmann (2018), p. 1).

1 | Introduction and Motivation

One of the hallmarks of the New Quantitative Trade models in international trade is the ability to estimate the economic welfare gains from trade-policy liberalizations using medium-sized general equilibrium structures and minimal parameter estimates. Indeed, gravity-equation estimates of the elasticities of trade with respect to *ad valorem* variable trade costs – or of coefficient estimates of binary variables for the presence or absence of an economic integration agreement (EIA) – are *central* to determining quantitatively the economic welfare impacts of trade-policy liberalizations using the New Quantitative Trade models, compare, Head and Mayer (2014).[1] As an example, there is now an entire sub-literature using gravity equations to estimate the welfare impacts on the United Kingdom – as well as other countries – of Brexit using EIA dummies' partial effects.[2] Even the 2016 and 2021 comprehensive analyses of the U.S. economic effects of U.S. free trade agreements by the U.S. International Trade Commission employed EIA dummy variable coefficient estimates to analyze their trade and economic welfare effects, compare, United States International Trade Commission (2016) and United States International Trade Commission (2021).

The vast bulk of these empirical studies uses some variant of the specification established in Baier and Bergstrand (2007) – "Do Free Trade Agreements *Actually* Increase Members' International Trade?" – to estimate the conditional mean (partial) effect of an EIA on bilateral trade flows. While that paper employed ordinary least squares (OLS) for estimation with three-way fixed effects, the literature has now moved to a three-way fixed-effects specification employing Poisson pseudo maximum likelihood (PPML) to estimate the conditional mean effect. Santos Silva and Tenreyro (2006) questioned the long-standing use of OLS to estimate trade gravity equations, citing Jensen's Inequality that $E(\ln X|\mathbf{Z}) \neq \ln E(X|\mathbf{Z})$. They suggested instead a PPML estimator to resolve the issue, as well as to accommodate zeros in trade. Though some economists have suggested other distributions (such as the Gamma and Negative Binomial distributions), PPML has surfaced in recent years as the new workhorse estimator, compare, Baier, Kerr, and Yotov (2018) and Baier et al. (2019).

However, recent theory and evidence using panel data and conditional mean estimation suggest that EIAs may have *heterogeneous* effects across the distribution of trade. A natural source of heterogeneous effects is, of course, the *depth* of agreements. For instance, Baier et al. (2014) and Egger and Nigai (2015) examined the various degrees of depth of an agreement as a source of heterogeneous EIA effects. Among numerous results, Baier et al. (2014) found that one-way or two-way preferential trade agreements had lower impacts than free trade agreements, and the latter had lower impacts than deeper agreements. Egger and Nigai (2015) found evidence that the larger the number of provisions in an agreement – suggesting more trade liberalization – the larger was the impact.

Although depth of agreements is an important source of heterogeneous EIA (partial) effects, there is now some evidence of considerable heterogeneity in EIA effects even *within* various types of agreements (e.g., free trade agreements, common markets, etc.). For instance, Baier et al. (2015) used a "random coefficients" approach in a standard three-way fixed effects OLS gravity equation to demonstrate heterogeneous effects of EIAs across country pairs within types of agreements. That study showed that – even though deeper agreements had larger (conditional mean) partial effects than shallower agreements – the heterogeneity of partial effects across the distribution of bilateral trade flows *far exceeded* the average treatment effects between types of agreements. The study using conventional conditional mean (PPML) estimates most closely related to our present paper is Chen and Novy (2022).[3] In their analysis of a large panel dataset, Chen and Novy (2022) provide conditional mean estimates of the effects of EIAs using a conventional three-way fixed-effects approach. By interacting the EIA estimate with set values for the *predicted* import share, they show that the effects range from 0.77 at the 10th percentile of the predicted import share to 0.22 at the 90th percentile.[4] However, the inclusion (in column 1 of their Table 7) of pair-specific fixed effects precludes simultaneously including other trade-cost variables (e.g., distance, etc.). Because of their approach, when such other trade-cost variables are included (see other columns in their Table 7), they cannot control for pair-specific unobservable heterogeneity. We address these limitations in our paper using a novel quantile regression approach employing correlated random effects.

In this paper, we consider the use of *quantile regressions* (QRs) to examine heterogeneous EIA partial effects across the *entire* (conditional) *distribution* of trade flows of numerous country-pairs over time.[5] One of the characteristics of quantile regressions is that they are *local* measures of location (unlike conditional mean estimates which are based upon the global distribution). Consequently, QR estimates are notably invariant to perturbations in the tails of the distribution; QR estimates depend only on the properties of the distribution around the quantile of interest.[6] Furthermore, up to now, there has been minimal use of quantile regressions of gravity equations to examine the potential heterogeneous impacts of EIAs, and it is arguable that those estimates may have suffered from the "incidental parameters problem."

Our intent in this paper is to make three potential contributions. First, we introduce a novel QR econometric approach to estimate the partial effects of EIAs across *all* (conditional) *quantiles*, using data with numerous years, country-pairs, and EIAs. One of the major contributions is that our technique yields estimates of partial effects of EIAs – *alongside* estimates of partial effects of distance, contiguity, common official language, common legal origin, common official religion, and common colonial history – while still accounting for unobservable multilateral price (or resistance) terms *and* pair-specific unobservable heterogeneity (using correlated random effects).[7]

Note that unlike the conditional mean approach used in numerous studies from Baier and Bergstrand (2007) to Weidner and Zylkin (2021) using three-way fixed effects for conditional mean estimates, researchers using QRs have yet to establish that QRs with three-way fixed effects can provide unbiased coefficient estimates. As discussed shortly, at most two-way fixed effects can be used, and even that requires specific conditions and assumptions. Accordingly, to avoid the incidental parameters problem (IPP), we provide an alternative to a three-way fixed effects QR approach used previously.[8] Borrowing from Baier and Bergstrand (2009a) and Baier and Bergstrand (2010), we use their (unweighted) "*Bonus Vetus*" (BV) methodology to account for (unobservable) exporter and importer multilateral price terms; the technique, motivated by a first-order Taylor-series approximation, effectively "de-means" bilateral trade-cost variables. This approach eliminates the need for exporter-year and importer-year fixed effects in the QRs. Furthermore, to account for country-pair-specific unobservable heterogeneity but avoid a pair fixed effect, we use the correlated random effects (CRE) approach of Chamberlain-Mundlak (CM). As will be discussed, Santos Silva (2019) argues that "Estimation of QR with fixed effects is difficult because there is **no transformation** that can be used to eliminate the incidental parameters. Therefore, due to the **incidental parameter problem**, consistency requires that both $N \to \infty$ and $T \to \infty$. For fixed T, the only realistic option is the '**correlated random effects**' (Mundlak) estimator." Hence, for positive trade flows, we employ this "BVQCM" approach. Furthermore, to account for zeros, we nest our approach inside a novel adaptation of the three-step approach in Galvao et al. (2013), which we discuss later.[9] Furthermore, by employing the *Bonus Vetus* technique, we are able to provide coefficient estimates across quantiles of *all* the bilateral trade-cost variables (including time-invariant ones), which can then be compared to previous QR studies that used only a cross section, compare, Baltagi and Egger (2016).

Having established a novel QR methodology to provide estimates of EIA (partial) effects across conditional quantiles, we introduce two "cases" to motivate the relevance of our approach for economic insights. Our first "case" uses our methodology to shed light (and potential confirmation using a broad sample of country-pairs, years, and the *virtual universe* of EIAs) on the Arkolakis (2010) proposition. Arkolakis (2010) provided a theoretical model for the differential growth effects on the trade expansion between partners from a free trade agreement (FTA) across the trade-flow distribution and the paper made two significant contributions. First, on the theoretical side, Arkolakis (2010) extended the canonical Melitz model of trade, with *ad valorem* variable trade costs and fixed trade costs, to allow for increasing marginal market-penetration (IMMP) costs. Second, in the presence of IMMP costs, Arkolakis (2010) showed, using a calibration exercise, that the effect on trade flows from a trade liberalization was largest for the least productive firms that had the smallest level of (previously traded) goods; moreover, the trade-expansion effect *declined monotonically* as the levels of previous trade increased, as shown in Figure 1 (from Arkolakis (2010)). Although Kehoe and Ruhl (2013) was the first paper to examine this empirically for the case of NAFTA (see their Section 3.C.) and French and Zylkin (2024) examined this using PPML conditional mean estimation for a large number of country-pairs, years, and EIAs, ours is the first paper to examine the Arkolakis hypothesis systematically using *quantile regression*, accounting for unobservable multilateral price terms and pair-specific unobservable heterogeneity, for the virtual universe of EIAs over multiple decades.[10]

Beyond this first case, there are other potential reasons for larger EIA partial effects at the lower portions of the conditional distribution. For instance, growth dynamics are a possible source. Mix (2023) examines theoretically and empirically the relationship between export churning and the aggregate trade response to trade policy. Specifically, his theoretical model posits that exporters that liberalize trade with minor (in size) destinations should experience larger bilateral export growth than liberalizations with major destinations; his empirical work using the Baier-Bergstrand specification supports the theory. In this spirit, our second case addresses whether or not *developing countries'* exporters benefit relatively more or less from EIAs than developed countries' exporters.[11] Although motivating formally theoretically the inclusion of an interaction of exporter per capita GDP and the EIA dummy variable is beyond the scope of this paper, we provide systematic evidence *across quantiles* that EIA partial effects are larger the *lower* is the exporter's per capita GDP; all else constant, developing countries' exporters have larger export effects from an EIA. A likely mechanism is that developing countries' tend historically to have larger tariff and non-tariff barriers;

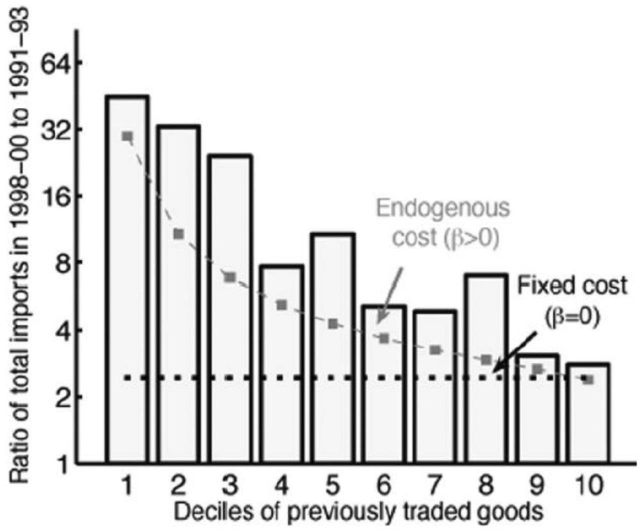

FIGURE 1 | Predicted and actual ratio of U.S. imports from Mexico in 1998–2000 to that in 1991–1993 for each decile of previously traded goods. (Arkolakis, JPE, 2010).

the International Monetary Fund and World Bank estimate that developing countries' tariffs on industrial products are "three to four times" those of developed economies.[12] Consequently, tariff rate reductions of developing exporters associated with EIAs may be much larger than those of developed economies.[13] Beyond the cases just discussed, other reasons for larger EIA effects at the lower portions of the conditional distribution could include the removal of uncertainty related to trade flows between country pairs, as examined and discussed in Figueiredo and Lima (2020).

The remainder of this paper is as follows. Section 2 summarizes the related literature. Section 3 provides theoretical context for our econometric analysis. Section 4 addresses the econometric specification based upon the BV approach to account for exporter-year and importer-year multilateral resistance terms and using correlated random effects to account for unobserved pair-specific heterogeneity. This section also provides quantile regression results using only positive trade flows. Section 5 discusses our novel adaptation of the three-step implementation of Galvao et al. (2013) to account for zeros in trade and provides a robustness analysis. Section 6 examines the Arkolakis proposition using disaggregate trade data and previous period's sales shares. Section 7 demonstrates that developing country exporters have benefited significantly more from EIAs than developed country exporters. Section 8 illustrates the positive relationship between conditional and unconditional quantile predictions. Section 9 concludes.

2 | Related Literature

We separate the related literature into two sections. The first section examines studies having provided OLS or PPML estimates of heterogeneous effects of EIAs. We will not focus on the literature of shallow versus deep agreements, but rather on heterogeneous effects associated with the *level* of bilateral trade. The second section examines previous QR studies using a gravity-equation framework. We will show that there is only one previous (unpublished) study that uses QR to estimate partial effects of EIAs across the entire (conditional) distribution of bilateral trade flows, accounting for unobservable time-varying exporter and importer multilateral price (resistance) terms *and* for pair-specific unobservable heterogeneity; that study's results may have been compromised by the IPP.

2.1 | Heterogeneous Effects of EIAS

Several studies have used traditional conditional mean estimation to explain and estimate heterogeneous effects of EIAs according to the level of trade. Novy (2013) is one of two early studies to examine departures from standard assumptions in the New Quantitative Trade Models to motivate such heterogeneous effects. Appealing instead to a transcendental logarithmic (translog) utility function, Novy (2013) motivates a structural gravity equation where the absolute value of the trade elasticity increases with the exogenous number of origin country goods exported and decreases with the share of destination country income spent on the trade flow from country i to country j. Using a cross section of bilateral trade flows, Novy (2013) shows empirically that the absolute values of the (intensive margin) elasticities are negatively related to the imports of j from i as a share of j's expenditures, as the theory predicts. Chen and Novy (2022) extend Novy (2013) by using panel data and PPML to estimate the standard three-way fixed effects model. Consistent with Novy (2013), Chen and Novy (2022) find statistically significant and economically plausible effects of currency unions and economic integration agreements on trade, with trade effects declining with the level of the import share of domestic expenditures divided by the total number of product exported by i (or intensive margin trade flow share).[14]

Spearot (2013) is a second of two 2013 studies to motivate variable trade elasticities. This paper argues theoretically and demonstrates empirically that a common-sized trade-cost reduction can increase low revenue varieties (in an industry) by more than high revenue varieties. A key assumption is varying demand elasticites, which, similar to Novy (2013) and Chen and Novy (2022), generates a demand-side intensive-margin argument.[15]

2.2 | Quantile Regression Studies Using Gravity Frameworks

In a series of papers, Erik Figueiredo and Luiz Renato Lima have used QRs to analyze trade and migration flows using panel data, typically examining the effects of EIAs on such flows. Figueiredo, Lima, and Schaur (2016) focused on estimating the Euro's impact on European Union trade along with an EIA dummy using a panel and a specification that accounted for time-varying multilateral price terms. However, the study did not account for the potential endogeneity bias from the Euro and EIA dummies by using pair fixed effects, as raised in Baier and Bergstrand (2007); instead they included standard bilateral gravity variables such as bilateral distance and time-invariant dummies. In their study of the effects of EIAs on bilateral migration flows using panel data, Figueiredo, Lima, and Orefice (2016) also do not account for endogeneity of EIAs using pair fixed effects, using instead bilateral distance and time-invariant dummies. However, Figueiredo and Lima (2020) use a new three-stage technique to estimate the effects of EIAs on improving trade predictability that involves computations of internal instrumental variables for the EIA variable used in the group QRs. The goal is to account effectively for exporter-year, importer-year, and pair fixed effects using a three-step method; however, this particular paper omits zeros in trade. Finally, the sole paper among this sub-literature that actually examined – as in this paper – the partial effects of EIAs on bilateral trade flows across conditional quantiles was Figueiredo et al. (2014). This paper used a three-step panel approach originally suggested by Chernozhukov and Hong (2002), or CH, and adapted by Galvao et al. (2013), or GLL, to address jointly the issues of unknown error structure, time-varying multilateral price terms, country-pair fixed effects, *and* zeros in trade. The first step predicts the probability of observations with zeros using a logit regression with all three types of fixed effects and any time-varying bilateral variables (such as an EIA dummy) to create propensity scores.[16] Using sub-samples determined by the propensity scores for which the probability of positive trade ranges across sub-samples from high to low, the second step estimates a linear fixed-effects QR to obtain fixed-effects estimates and partial effects of the time-varying bilateral variables. Step 3 re-estimates the step-2 parameters to guarantee efficiency using a reduced subset of observations from step 2. As noted by CH and GLL, this type of three-step estimator "allows for some misspecification" in the estimation of the propensity scores.

Note that the three-stage GLL technique as applied in Figueiredo et al. (2014) uses a linear three-way fixed-effects QR specification in the second and third stages.[17] Researchers have long questioned the consistency of results using a large number of multiple fixed effects in QR estimation due to the incidental parameters problem (IPP), compare, Wooldridge (2010), Galvao and Monte-Rojas (2017), and Santos Silva (2019). Galvao and Monte-Rojas (2017) provide guidance as to consistency of estimates under various cases with three dimensions; in all 4 three-dimensional cases, at most only two effects can be controlled for. To the authors' knowledge, consistency has not yet been proven in QR panel cases with three dimensions and three-way effects. As Santos Silva (2019) notes, there is no transformation in the context of QRs with fixed effects that can be used to eliminate the incidental parameters (with small T); he states "due to the incidental parameter problem, consistency requires $N \to \infty$ and $T \to \infty$."

Accordingly, our novel approach will be to combine a first-stage logit (or Cloglog or linear probability) model to calculate the propensity scores that determine the "informative subsets" of observations for which the conditional quantiles are above the censoring point (Chernozhukov and Hong 2002; Tang et al. 2012; Galvao et al. 2013). Note that this method is distinct from Helpman et al. (2008), which is based on a Heckman latent variable model. A specification suggested in Baier and Bergstrand (2009a) and Baier and Bergstrand (2010) is used at every stage of our suggested method (without fixed effects in the benchmark specifications). The purpose of the first stage is to determine the informative subset for each quantile to use for the second stage. For example, following GLL at a low conditional quantile (say, $q = 0.10$), we determine the subset for which the propensity score is larger than $1 - q - c_N$, that is, the probability of positive flow is high but note the actual flow could be zero.[18]

Using these various informative sub-samples at each quantile, the second step uses the same regressors (and, as in the first step, a Chamberlain-Mundlak-based correlated-random-effects approach to account for unobserved heterogeneity) in the estimation of the parameters of interest – notably, EIA partial effects – at various conditional quantiles. The third-step re-estimates step 2 (with an adjusted sample) to guarantee efficiency. As Santos Silva (2019) concludes, to avoid the incidental parameters problem (with small T) the "only realistic option is the correlated random effects (Mundlak) estimator."[19]

3 | Theoretical Context

There is a large literature on the theoretical foundations for the gravity equation in international trade. Much of this has been summarized comprehensively in numerous surveys, such as Anderson and van Wincoop (2004), Bergstrand and Egger (2011), and Baier, Kerr, and Yotov (2018).

Following Baier, Kerr, and Yotov (2018), we can express a standard trade gravity equation as:

$$X_{ijt} = (W_{it}L_{it})(W_{jt}L_{jt})\left(\frac{\tau_{ijt}}{\Pi_{it}\Phi_{jt}}\right)^{-\epsilon_\tau} f_{ijt}^{-\epsilon_f} \qquad (1)$$

where X_{ijt} is the nominal trade flow from exporter i to importer j in year t, $W_{it}L_{it}$ ($W_{jt}L_{jt}$) is nominal aggregate income (expenditure) in country i (j) in year t, τ_{ijt} (> 1) represents *ad valorem* (iceberg) bilateral trade costs (including time-invariant and time-varying elements), f_{ijt} represents (bilateral) export fixed costs (conceptually, measured in terms of units of labor), Π_{it} is country i's "outward" multilateral price (or resistance) term in year t, Φ_{jt} is country j's "inward" multilateral price term in year t, ϵ_τ is the *ad valorem* trade-cost "trade elasticity," and ϵ_f is the elasticity of trade with respect to export fixed costs. In the cases of the Anderson-van Wincoop (Armington) and Baier-Bergstrand (Krugman) models without export fixed costs (f_{ijt}), $\epsilon_\tau = \sigma - 1$, where σ is the elasticity of substitution in a constant-elasticity-of-substitution (CES) utility function. In the case of the Eaton-Kortum (Ricardian) model also excluding f_{ijt}, $\epsilon_\tau = \theta$, where θ is the (inverse) index of heterogeneity of firms' productivities. In the case of Melitz (2003) (with the export fixed costs, f_{ijt}), $\epsilon_\tau = \theta$, $\epsilon_f = \frac{\theta}{\sigma-1} - 1$, and σ and θ are defined as above.[20]

For empirical work on estimating the partial effects of economic integration agreements (EIAs), using *ad valorem* tariff rates creates a potential mis-specification bias as a result of omitting a measure of export fixed costs. The difficulty of measuring changes in f_{ijt} from EIAs has led researchers increasingly to use binary variables to capture the changes in $\tau_{ij}^{-\theta} f_{ijt}^{1-\frac{\theta}{\sigma-1}}$ resulting from EIAs, compare, Footnote 2. This suggests:

$$X_{ijt} = \left(\frac{(W_{it}L_{it})(W_{jt}L_{jt})}{\Pi_{it}\Phi_{jt}}\right) \exp(\beta EIA_{ijt})\eta_{ijt} \qquad (2)$$

where β is the partial equilibrium effect of an EIA and η_{ijt} is a non-negative error term.

As discussed earlier, several studies have suggested theoretical rationales for possible heterogeneous partial effects of EIAs. Such studies suggest non-constant trade elasticities depending upon the conditional quantiles. In this paper, we focus upon estimation of the partial effects of an EIA (and potentially in subsequent work of *ad valorem* trade-cost trade elasticities) across conditional quantiles. In the context of the notation and discussion above, we can rewrite Equation (2) as:

$$X_{ijt}^q = \left(\frac{(W_{it}L_{it})^q(W_{jt}L_{jt})^q}{\Pi_{it}^q\Phi_{jt}^q}\right) \exp(\beta^q EIA_{ijt}^q)\eta_{ijt}^q \qquad (3)$$

where q denotes the conditional quantile.

As we will discuss later, treatment of zeros in quantile regressions is more difficult. Zeros may be generated by the existence of export fixed costs. However, zeros may be generated by censoring of the data by institutional organizations reporting the data, whether at the national or international level. Accordingly, we will be agnostic about the source. In the quantile regression literature for panel data, Chernozhukov and Hong (2002), Galvao et al. (2013), and Galvao and Kato (2018) suggest a three-step quantile regression procedure to handle censoring of zeros allowing unobserved heterogeneity. The key to the approach – which is distinct from the two-stage Heckman approach specific to a two-part DGP – is determining sub-samples from the distribution for each (conditional) quantile, determined using the same regressors as in the second and third stages. The propensity scores from the first stage are used to restrict observations and create *informative first-step subsets of observations* (for the second and third steps) where the conditional quantile is above the censoring point. In the second stage, quantile regression is used on the entire sub-sample of observations including censored values, for which the true qth conditional quantile is above the censoring point. The third step repeats the second step to ensure efficiency.

4 | Quantile Regression Methodology and Empirical Results For Positive Trade Flows

We offer an alternative econometric approach to evaluating the partial effects of an EIA. As noted in Section 2, this study is not the first to employ QRs to estimate gravity equations. However, we are the first to use QRs to generate EIA treatment effects across quantiles that are robust to various levels of economic integration, heteroskedasticity bias, endogeneity bias, mis-specification bias (owing to accounting for unobserved effects), and – as addressed in later sections – to censoring at zero. Furthermore, as noted in the introduction, QRs allow us to estimate EIA partial effects at various conditional quantiles of the trade-flow distribution.

4.1 | Quantile Regression

Since many trade researchers may be unfamiliar with QRs, we provide a brief overview of the benefits of QRs relative to conditional mean estimators.[21] QRs split the data (here, bilateral trade flows) into proportions q below and $1 - q$ above conditional quantile q. QR then minimizes the least absolute deviations, that

TABLE 1 | Comparison of linear regression and quantile regression.

Linear regression	Quantile regression
1. Predicts the conditional mean $E(Y\|X)$	Predicts conditional quantiles $Q_\tau(Y\|X)$
2. Often assumes normality	Is distribution agnostic
3. Does not preserve $E(Y\|X)$ under transformation	Preserves $Q_\tau(Y\|X)$ under transformation
4. Is sensitive to outliers	Is robust to response outliers
5. Applies when n is small	Needs sufficient data
6. Is computationally inexpensive	Is computationally intensive

Note: Source: Rodriguez and Yao (2017).

is, $\sum_{ij}|\epsilon_{ij}|$. QR minimizes a sum that gives asymmetric penalties $(1-q)|\epsilon_{ij}|$ for overprediction and $q|\epsilon_{ij}|$ for underprediction.

The first advantage is that QR is *invariant to monotonic transformations*, such as logarithmic transformations. Given the earlier discussion, the importance of this consideration cannot be overstated. The quantiles, Q_q, of $\ln(X_{ij})$ – a monotonic transform of X_{ij} – are $\ln(Q_q(X_{ij}))$. Moreover, the inverse transformation may be used to translate the results back to (conditional) X_{ij}. Hence, the limitation of Jensen's inequality – the primary motivation for the Santos Silva and Tenreyro (2006) introduction of PPML to gravity equations – is removed.

Second, standard conditional mean estimators summarize the average relationship between a set of regressors and the outcome variable based on the conditional mean function $E(X_{ij}|\mathbf{Z}_{ij})$. QRs provide an opportunity to examine the relationship *at different points* in the conditional distribution of X_{ij}. This will be useful later to address the hypothesis in Arkolakis (2010).

Table 1, reproduced (with minor modifications) from Rodriguez and Yao (2017), highlights several factors that suggest why QRs may be very useful for the context of gravity equations with large data sets. First, as just mentioned above, OLS and PPML can only predict conditional means of the trade flows; QRs can predict conditional quantiles of the trade flows across an array of quantiles. Second, linear regression cannot preserve $E(X|Z)$ under monotonic transformations, such as logarithmic transformations, whereas QR can preserve quantiles of X conditional on Z under monotonic transformations. Third, linear regression is much more sensitive to outliers, whereas QR is less sensitive. The last two lines of Table 1 highlight the shortcomings of QRs relative to linear regressions; however, neither of these is a problem for our context. Linear regression applies even when the sample size is small, whereas QRs require a large number of observations. In our case, our data will potentially have nearly 250,000 observations, using unidirectional bilateral trade flows among (potentially) 180 countries with 10 years of data at 5-year intervals; in a robustness analysis, we will find similar results using annual data. QRs are more computationally intensive than linear regressions. However, with modern techniques introduced in Stata, this is not a severe impediment, as we will discuss.

In reality, the world is not so generous as to provide precise measures of Π_{it}, Φ_{jt}, τ_{ijt} and f_{ijt} for a large sample of nearly 200 countries (and 40,000 unidirectional flows) over a 50-year period. Consequently, researchers have either used proxies for these variables or introduced various fixed effects, applying various estimators. Traditional proxies for τ_{ijt} and f_{ijt} include the logarithm for bilateral distance ($\ln DIST_{ij}$) and dummy variables for the presence or absence of an EIA (EIA_{ijt}), common land border ($CONTIG_{ij}$), common language ($LANG_{ij}$), common legal origin ($LEGAL_{ij}$), common official religion ($RELIG_{ij}$), and common colonial background ($COMCOL_{ij}$).

Regarding econometric specification, it is useful to note that Head and Mayer (2014) offered a Monte Carlo analysis to conduct a "horse race" between seven alternative (conditional mean) methods introduced over the years to generate consistent estimates of coefficients of various traditional proxies for variables identified in theoretical Equation (1), such as the logarithm of bilateral distance ($\ln DIST_{ij}$) and a dummy variable for the presence or absence of an EIA (EIA_{ij}).[22] Although the Monte Carlo horse race of Head and Mayer (2014) considered seven methods, they noted only three methods – least squares with country dummy variables (LSDV), double de-meaning of LHS and RHS variables (DDM), and the Baier and Bergstrand (2009a) and Baier and Bergstrand (2010) theory-motivated method of (unweighted) de-meaning of RHS bilateral trade-cost variables described as "*Bonus Vetus* OLS" (BVU) – had consistent estimates of distance and EIA elasticities, even after random censoring of up to 50 percent of the observations.[23] However, all three of the methods LSDV, DDM, and BVU are effectively "de-meaning" approaches.[24]

4.2 | Quantile Regressions Ignoring Unobserved Heterogeneity and Zeros

In this section, we ignore pair-specific unobserved heterogeneity. First, we will apply the (unweighted) BV technique of Baier and Bergstrand (2010) to account for the unobservable exporter-year and importer-year multilateral prices, Π_{it} and Φ_{jt} in Equation (3), respectively. In the traditional BV approach, all bilateral (trade-cost) variables are de-meaned as described below. As explained in Baier and Bergstrand (2009a) and Baier and Bergstrand (2010), these two papers provide general equilibrium foundations for the "BV" approach using a first-order Taylor-series expansion of the Anderson-van Wincoop model and structural gravity Equation (1).[25] For our initial specification using positive trade flows, we consider first a "traditional" BV approach, as suggested in Baier and Bergstrand (2010), ignoring here unobserved pair-specific heterogeneity. This specification takes the following form:

$$\begin{aligned} Quant_q(\ln X_{ijt}) = {} & \beta_0^q + \beta_1^q \ln GDP_{it}^q + \beta_2^q \ln GDP_{jt}^q + \beta_3^q EIABV_{ijt}^q \\ & + \beta_4^q DISTBV_{ij}^q + \beta_5^q CONTIGBV_{ij}^q + \beta_6^q LANGBV_{ij}^q \\ & + \beta_7^q LEGALBV_{ij}^q + \beta_8^q RELIGBV_{ij}^q + \beta_9^q COMCOLBV_{ij}^q \\ & + \sum_{t=1}^{T} \alpha_t^q (INTER_{ij} \times YEAR\_t)q + \ln \eta_{ijt}^q \end{aligned} \tag{4}$$

where $EIABV_{ijt}^q = EIA_{ijt}^q - \frac{1}{N}\sum_{k=1}^N EIA_{ikt}^q - \frac{1}{N}\sum_{l=1}^N EIA_{ljt}^q + \frac{1}{N^2}\sum_{k=1}^N\sum_{l=1}^N EIA_{klt}^q$, $DISTBV_{ij}^q = \ln DIST_{ij}^q - \frac{1}{N}\sum_{k=1}^N \ln \times$

$DIST^q_{ik} - \frac{1}{N}\sum_{l=1}^{N} \ln DIST^q_{lj} + \frac{1}{N^2}\sum_{k=1}^{N}\sum_{l=1}^{N} \ln DIST^q_{kl}$, and so forth. Let $q = 0.10, 0.20, \ldots, 0.90$. Following Bergstrand et al. (2015), the specification above includes a variable $(INTER \times YEAR)^q$, which interacts a dummy taking the value of 1 (0) for inter- (intra-) national trade and YEAR denotes year dummies. Estimation includes data on intra-national trade flows.

4.3 | Specification Accounting For Unobserved Heterogeneity

The widespread acceptance of the three-way FE specification is premised upon the literature's focus on evaluating empirically the relationship between *bilateral* trade costs and (bilateral) trade flows. Yet, often trade costs can only be measured on a *country-specific* level. For instance, countries' institutional governance indexes are often reported as country specific. Also, researchers may be interested in the effects of an exporting country's or importing country's per capita income on bilateral trade. The three-way FE specification cannot accommodate such questions without additional adjustments. These adjustments include interacting the country-specific effect with another variable – such as a time-invariant binary variable indicating intra-national trade flows or border effects, as in Heid et al. (2021) – or using the multi-stage empirical model discussed in Head and Mayer (2014). By contrast, the BV specifications can address country-specific effects in a manner founded upon the formal theoretical foundation in Baier and Bergstrand (2009a) and Baier and Bergstrand (2010). Furthermore, while OLS can easily accommodate three-way fixed effects for conditional mean estimation, only recently did Weidner and Zylkin (2021) show the conditions under which PPML with three-way fixed effects will generate unbiased conditional mean estimates of the partial effects of EIA_{ijt}.

As noted, specification (4) does not account for unobserved heterogeneity (except accounting for the BV terms). In this section, we address the rationale for using a standard (and well established) Chamberlain-Mundlak-based (CM) correlated random effects (CRE) methodology for accounting for unobserved heterogeneity. Econometricians have long faced problems using fixed effects (FEs) in QRs. Excellent sources of discussion on the topic are found in Wooldridge (2010) (Section 12.10.3), Galvao and Monte-Rojas (2017), and Galvao and Kato (2018), with the latter an exceptional discussion of the issues with FEs in QRs using panel data and the suitability of correlated random effects for QRs with panel data.

The basic problem with using FEs in QRs is the "incidental parameters problem" (IPP). As Galvao and Monte-Rojas (2017) state, "there is no general transformation that can suitably eliminate" the incidental parameters. The IPP arises because the number of parameters estimated is proportional to the number of cross-section observations (say, N). If the number of time periods (say, T) is fixed, then the number of observations available for estimation is comparable to the number of parameters, preventing consistent estimation of the common parameter (say, the coefficient on $EIABV$). Accordingly, econometricians have appealed to asymptotic theory. However, as discussed formally in Kato et al. (2012), existing sufficient conditions under which the asymptotic bias of QR with FEs is negligible require T strictly greater than N ($T >> N$). Moreover, the non-differentiability of the QR objective function (i.e., the "check function") complicates the asymptotic analysis of QRs with FEs. As discussed in Galvao and Monte-Rojas (2017), certain restrictions can be applied to generate consistent estimates with QRs. However, as those authors note, with three dimensions (or three-way FEs, such as addressed in gravity specifications in Section 5), no theory exists to demonstrate consistency of estimates of a common parameter; at best, one can only control for two effects (cf., their scenario iv).

Alternative estimation methods have surfaced beyond the conventional QRs with FEs, such as penalized estimation, minimum-distance estimation, and two-step estimation. However, all such alternative approaches have limitations. Koenker (2004) proposed the penalized estimation method where individual effects are treated as pure location-shift parameters common to all quantiles and subject to the "l_1 penalty." However, QR restrictions on estimation and asymptotic properties show that the "large T" requirement must hold for consistency. Galvao and Wang (2015) proposed a minimum distance estimator for panel QRs with FEs. The authors demonstrated asymptotic normality of the estimator under sequential and simultaneous asymptotics. However, for simultaneous asymptotics, the requirement $T, N \to \infty$ must hold; hence, this approach does not work for fixed T. Canay (2011) proposed a "two-step" estimation approach for panel QRs with FEs. However, as noted in Galvao and Monte-Rojas (2017), no individual FE is allowed to change across quantiles; moreover, his approach requires an additional restriction on the conditional average. Furthermore, Santos Silva (2019) notes that an assumption in the approaches in Koenker (2004) and Canay (2011) goes against the "spirit of QR." Thus, as Santos Silva (2019) concludes, "Estimation of QR with FEs is difficult because there is **no transformation** that can be used to eliminate the incidental parameters. Therefore, due to the **incidental parameter problem**, consistency requires that both $N \to \infty$ and $T \to \infty$. For fixed T, the only realistic option is the '**correlated random effects**' (Mundlak) estimator."

Wooldridge (2010) (Section 12.10.3), Galvao and Monte-Rojas (2017), and Galvao and Kato (2018) all provide convincing arguments for using the Chamberlain-Mundlak-based correlated random effects (CRE) approach to control for unobserved heterogeneity using panel data in QRs, as suggested by Santos Silva (2019); all noted the paper by Abrevaya and Dahl (2008). In the spirit of Chamberlain (1982), the CRE approach views the unobservable effects as a linear projection onto observables plus an error term; the intuition is that a rich set of covariates is capable of explaining unobserved heterogeneity, with the error term assumed independent of the covariates, compare, Galvao and Monte-Rojas (2017). As Galvao and Kato (2018) note, the key distinction between CRE and FE models is that one is able to avoid the IPP with CRE, allowing T to be fixed.

As Wooldridge (2010), Section 12.10.3 concisely describes, consistent estimates of a common parameter of interest can be obtained in a panel with variation in i and t by regressing the LHS variable (say, y_{it}) on an intercept, the RHS covariates (say, $\mathbf{x}_{it}$), and the time-averaged values of $\mathbf{x}_{it}$ – denoted $\overline{\mathbf{x}}_i$; the error term u_{it} is assumed independent of $\mathbf{x}_i$. In the context of our BV specifications, the QR specification is:

$$
\begin{aligned}
Quant_q(\ln X_{ijt}) = {} & \beta_0^q + \beta_1^q \ln GDP_{it}^q + \beta_2^q \ln GDP_{jt}^q \\
& + \beta_3^q EIABV_{ijt}^q + \beta_4^q DISTBV_{ij}^q \\
& + \beta_5^q CONTIGBV_{ij}^q + \beta_6^q LANGBV_{ij}^q \\
& + \beta_7^q LEGALBV_{ij}^q + \beta_8^q RELIGBV_{ij}^q \\
& + \beta_9^q COMCOLBV_{ij}^q + \sum_{t=1}^{T} \alpha_t^q (INTER_{ij} \times YEAR_t)^q \\
& + \beta_{10}^q \overline{\ln GDP}_i^q + \beta_{11}^q \overline{\ln GDP}_j^q \\
& + \beta_{12}^q \overline{EIABV}_{ij}^q + \eta_{ijt}^q \qquad (5)
\end{aligned}
$$

where $q = 0.10, 0.20, \ldots, 0.90$. The bars over variables in Equation (5) denote the time-averages of the underlying variables. Note that several BV variables such as $DISTBV_{ij}$ are time-invariant; consequently, their time-averaged means are subsumed in the intercept.

4.4 | Data

The data on nominal bilateral trade flows comes from the UN Comtrade data base (in thousands of U.S. dollars).[26] We converted these data into (actual) U.S. dollars by multiplying positive flows by 1000. Following Baier and Bergstrand (2007), Baier et al. (2014), and Baier, Bergstrand, and Clance (2018), we use annual trade flows for every 5 years: 1965, 1970, …, 2010. Hence, in our sample $T = 10$.[27] The potential number of countries in our sample in 2010 is 180; however, the number of countries in a previous year may be smaller because some of these 180 countries are not recognized under the Soviet Union and some African countries did not report trade flows or other information until later in the sample. Including intra-national trade, the total number of bilateral observations is 249,705. Excluding intra-national trade (which we will address in a robustness analysis), the number of uni-directional nominal bilateral trade-flow observations for the 10 years is 248,123.

The data for the dummy variable for economic integration agreements is from the National Science Foundation-Kellogg Institute for International Studies Database on Economic Integration Agreements constructed by Jeffrey Bergstrand and Scott Baier and available at https://sites.nd.edu/jeffrey-bergstrand/. This database provides a unidirectional multichotomous index of EIAs for pairings of 195 countries annually from 1950 to 2012 (April 2017 version). The index is defined as: no EIA (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 this study, we use "EIA" to denote a free trade agreement, customs union, common market, or economic union. The definitions are conventional, based upon Frankel (1997), and are defined explicitly in the data set.

Table 2 provides useful summary statistics for the data employed. Table 3 provides a useful decomposition of EIAs by type of agreement, which will be addressed in later results.

4.5 | Results

Table 4 provides our first set of QR empirical results; we label these specifications BVQ. Specification (4) is estimated in this subsection using only positive trade flows and ignores unobserved heterogeneity. We note three important results in this section. First, at the median (Q50), the coefficient estimate for $EIABV_{ijt}$ (0.385) is identical to a (conditional mean) three-way fixed effects OLS estimate (reported in Table A1 of the Appendix).

Second, and consistent with findings such as in Chen and Novy (2022) and Bas et al. (2017), the partial effects of an EIA are largest at the lowest quantiles and the partial effects (or percentage increases in trade from an EIA) generally decline as conditional quantiles increase.[28]

Third, one of the benefits of the BV model is that it allows estimates of coefficients of time-invariant bilateral variables, such as distance, that might otherwise be omitted using pair fixed effects. Examining bilateral distance, we find the absolute values of the coefficient estimates decline monotonically with increases in conditional quantiles.

Fourth, the BV approach is useful also because – not only does it account for the exporter and importer multilateral resistance terms – it allows coefficient estimates of exporter- and importer-specific variables. We note the exporter (importer) GDP elasticities decline monotonically from about 1.4 to 0.8 (about 1.1 to 0.8) as conditional quantiles increase. While there is no theoretical conjecture for this, we note the distinctive result in Santos Silva and Tenreyro (2006) that PPML generates GDP elasticities significantly less than one. Our results for the 90th quantile indicate lower income elasticities.

Table 5 provides results of estimating specification (5) for the same nine quantiles as in Table 4 using the same positive trade flows, but now accounting for unobserved heterogeneity using CREs; we label this specification BVQCM. First, we note that, including CREs rather than excluding CREs (as in Table 4), the coefficient estimates for $EIABV$ are different. At the (conditional) median, Q50, of the positive flows, the $EIABV$ effect with (without) CREs is 0.537 (0.385). Furthermore, this 0.537 estimate is above a conditional mean OLS coefficient estimate with three-way fixed effects of 0.385 but is identical to an OLS coefficient estimate using CREs for positive flows and close to the PPML estimate using CREs and positive flows (reported in Table A1 of the Appendix).

Second, the results are consistent with similar findings in Chen and Novy (2022) and Bas et al. (2017). Specifically, at the 10th quantile the $EIABV$ effect is slightly larger with CREs, but at the highest quantile (Q90) the effect is considerably smaller. Interestingly, at the 90th quantile the coefficient estimate is 0.168. Moreover, the coefficient estimates for $EIABV$ are statistically significantly different from Q10 to Q90; see Table 7 later in Section 5.3.1. Hence, accounting for unobserved heterogeneity with CREs alters the partial effect estimates.

Third, we find in this case that several variables other than just $EIABV$ and $DISTBV$ have coefficient estimates that decline with increases in conditional quantiles.[29] In particular, with

TABLE 2 | Summary statistics decomposed by EIA vs. No EIA.

Variables	No EIA	EIA	Total
(1)	(2)	(3)	(4)
n (%)	237987 (95.9)	10136 (4.1)	248123 (100.0)
Trade if $T_{ij} > 0$, mean (st dev)	2.2e+08 (2.7e+09)	2.0e+09 (9.3e+09)	3.5e+08 (3.7e+09)
Trade if $T_{ij} \geq 0$, mean (st dev)	1.1e+08 (1.9e+09)	1.7e+09 (8.8e+09)	1.7e+08 (2.6e+09)
T_{ij}, mean (st dev)	0.47 (0.50)	0.89 (0.31)	0.49 (0.50)
ln(GDP), mean (st dev)	22.82 (2.46)	24.59 (2.35)	22.89 (2.48)
ln(DIST), mean (st dev)	8.83 (0.68)	7.36 (0.84)	8.77 (0.75)
CONTIG, mean (st dev)	0.01 (0.11)	0.13 (0.34)	0.02 (0.13)
LANG, mean (st dev)	0.16 (0.37)	0.32 (0.47)	0.17 (0.37)
LEGAL, mean (st dev)	0.35 (0.48)	0.44 (0.50)	0.35 (0.48)
RELIG, mean (st dev)	0.17 (0.24)	0.29 (0.32)	0.17 (0.25)
COMCOL, mean (st dev)	0.11 (0.31)	0.16 (0.37)	0.11 (0.31)
Trade Decile, n (%)			
10–50th	125615 (99.1)	1110 (0.9)	126725 (100.0)
50–60th	21905 (98.9)	244 (1.1)	22149 (100.0)
60–70th	24301 (97.9)	512 (2.1)	24813 (100.0)
70–80th	23784 (95.9)	1028 (4.1)	24812 (100.0)
80–90th	23014 (92.8)	1798 (7.2)	24812 (100.0)
90–100th	19368 (78.1)	5444 (21.9)	24812 (100.0)

Note: T_{ij} is a binary variable that is 1 if international trade is positive and 0 otherwise. The positive values begin at the 52th percentile. Intra-national (domestic) trade is omitted from statistics.

TABLE 3 | Agreements description.

Integration index	Count	Percent of total	Cumulative percent
(0) No agreement	237,987	95.91	95.91
(3) Free trade agreement	6,114	2.46	98.38
(4) Customs union	1,802	0.73	99.11
(5) Common market	1,456	0.59	99.69
(6) Economic union	764	0.31	100.00
Total	248,123	—	—

Note: Total observations are based upon 180 countries for 10 periods at 5 year intervals (1965–2010). Note that number in parentheses is the number coded in the data source at https://sites.nd.edu/jeffrey-bergstrand. Non-reciprocal (one-way) and reciprocal preferential (two-way partial) agreements are coded as not having an agreement (or 0) for this study.

CREs, the coefficient estimates for $LANGBV$, $RELIGBV$, and $COMCOLBV$ generally decline with increases in conditional quantiles.

Finally, we note that using BVQCM the coefficient estimates for the logs of exporter and importer GDPs in Table 5 are now relatively stable across quantiles, and all but three importer GDP elasticities (at the lowest conditional quantiles) are not statistically significantly different from unity.

4.6 | Discussion

One of the benefits of using our BV-CRE approach is that we can also estimate partial effects *of all other BV variables.* Examining $DISTBV$, we find a one percent fall in distance increases bilateral trade more for the lower conditional quantiles. This is consistent with the finding in Carrere et al. (2020). Furthermore, we also find systematic declines in partial effects across quantiles for $LANGBV$, $RELIGBV$ and $COMCOLBV$; for $DISTBV$, $RELIGBV$, and $COMCOLBV$ there are statistically significant differences between the partial effects for the 10th and 90th quantiles.

Figure 2, Panel A (on the left-hand-side) provides a useful depiction of the $EIABV$ partial effects at each of nine quantiles, 10-90. Note the decline in partial effects as conditional quantiles increase. Panel B (on the right-hand-side) illustrates the absolute value of the $DISTBV$ partial effects across quantiles.

5 | Quantile Gravity With Zeros

Section 5.1 discusses the methodology for accounting for zeros and unobserved heterogeneity. Section 5.2 provides the benchmark results accounting for zeros. Section 5.3 provides a robustness analysis.

5.1 | Methodology

Galvao et al. (2013) introduced a three-step method for "censored" quantile regression (in the presence of fixed effects). The estimation strategy of Galvao et al. (2013) suggests that the censored QR can be estimated by focusing on an "informative" subset of observations where the "true" qth conditional quantile line

TABLE 4 | BVQ positive.

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
ln(GDPex)	1.386***	1.303***	1.231***	1.163***	1.099***	1.034***	0.964***	0.884***	0.783***
	(0.009)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
ln(GDPim)	1.057***	1.025***	0.992***	0.962***	0.936***	0.909***	0.880***	0.843***	0.803***
	(0.010)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
EIABV	0.820***	0.590***	0.473***	0.420***	0.385***	0.363***	0.337***	0.310***	0.322***
	(0.093)	(0.063)	(0.055)	(0.048)	(0.044)	(0.043)	(0.043)	(0.043)	(0.054)
DISTBV	−1.558***	−1.470***	−1.410***	−1.361***	−1.327***	−1.283***	−1.248***	−1.189***	−1.121***
	(0.040)	(0.030)	(0.027)	(0.024)	(0.023)	(0.024)	(0.024)	(0.022)	(0.026)
CONTIGBV	−0.078	0.058	0.221**	0.344***	0.452***	0.546***	0.645***	0.706***	0.576***
	(0.125)	(0.110)	(0.108)	(0.106)	(0.098)	(0.107)	(0.102)	(0.095)	(0.115)
LANGBV	0.534***	0.487***	0.462***	0.452***	0.448***	0.460***	0.467***	0.454***	0.466***
	(0.077)	(0.062)	(0.058)	(0.054)	(0.052)	(0.053)	(0.054)	(0.053)	(0.059)
LEGALBV	0.171***	0.261***	0.273***	0.296***	0.300***	0.332***	0.348***	0.349***	0.319***
	(0.058)	(0.045)	(0.041)	(0.038)	(0.036)	(0.036)	(0.035)	(0.034)	(0.037)
RELIGBV	0.544***	0.507***	0.386***	0.282***	0.212***	0.131**	0.110*	0.080	0.043
	(0.113)	(0.084)	(0.073)	(0.068)	(0.060)	(0.059)	(0.062)	(0.061)	(0.072)
COMCOLBV	0.426***	0.463***	0.477***	0.487***	0.483***	0.476***	0.477***	0.464***	0.393***
	(0.104)	(0.087)	(0.077)	(0.072)	(0.069)	(0.066)	(0.064)	(0.063)	(0.068)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
INTER × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	No	No	No	No	No	No	No	No	No
Pseudo R2	0.639	0.641	0.642	0.643	0.643	0.642	0.641	0.638	0.629
Obs	122999	122999	122999	122999	122999	122999	122999	122999	122999

Note: Clustered standard errors by country-pair are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Only positive trade values (i.e., $T_{ij} > 0$) were used in the estimation. The quantile estimation is performed using the Frisch-Newton interior point method at each decile. BV indicates that the "Bonus Vetus" methodology described in Baier and Bergstrand (2009a) and Baier and Bergstrand (2010) was used. "INTER × Year FE" indicates the interaction of a dummy variable that is 1 if international trade and 0 otherwise, and a year dummy variable were included or not; "CRE" indicates whether correlated random effects were used or not. Following Machado et al. (2016), the squared correlation of $\ln X_{ijt}$ and the fitted values $Quant_q(\ln X_{ijt})$ are reported as the pseudo R^2.

exceeds the censoring points and then estimating a fixed effects QR on this subset.[30] The authors note this three-step method has several advantages; it allows for some mis-specification in the propensity score of the first stage, allows for unobserved heterogeneity to be nonseparable from the regressors, and requires shorter panels than other methods. In the context (and notation) of their paper adjusted to the gravity model, the minimization problem for censored QR is:

$$\beta_q(\varsigma_{it}, \vartheta_{jt}, \varrho_{ij}, RHS_{ijt}) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\rho_q\left(X_{ijt} - \varsigma_{it} - \vartheta_{jt} - \varrho_{ij} - RHS'_{ijt}\beta\right) \times I\left[\varsigma_{it0} + \vartheta_{jt0} + \varrho_{ij0} + RHS'_{ijt0}\beta > C_{ijt}\right] \quad (6)$$

where ς_{it}, ϑ_{jt}, and ϱ_{ij} are the exporter-year, importer-year, and country-pair unobserved heterogeneity, RHS'_{ijt} is a vector of other observed controls that vary over time, C_{ijt} is the known censoring point, and $I[\cdot]$ is an indicator function; this specification is asymptotically equivalent to that of Powell (1986) if only *one* individual fixed effect was considered, as in Galvao et al. (2013).

Since we use BV and CRE approach to handle the unobserved heterogeneity, we simplify the notation and use $\overline{\omega}$ to represent these terms. To obtain the portion in $I[\cdot]$, a binary model is estimated such that:

$$\pi_0 = Pr(\lambda_{ijt} = 1|RHS_{ijt}, \overline{\omega}, C_{ijt}) = Pr(u_{ijt} > -\overline{\omega}_0 - RHS'_{ijt0}\beta_0 + C_{ijt}|RHS_{ijt}, \overline{\omega}, C_{ijt}) \quad (7)$$

and

$$Pr(u_{ijt} > 0|RHS_{ijt}, \overline{\omega}, C_{ijt}) > 1 - q \quad (8)$$

where $\lambda_{ijt} = 1$ for uncensored observations and u_{ijt} is the innovation term (the qth conditional quantile is equal to zero). For further details, see Galvao et al. (2013). Note that the use of an indicator variable implies smaller sub-samples as q decreases.

In Galvao et al. (2013), the first stage is a binary choice model, such as a logit model.[31] In the second stage, Galvao et al. (2013) recommended "applying fixed effects QR" (p. 1077) to subsets of observations. However, in our gravity-equation context, three-way fixed effects QR will introduce the IPP. Consequently, we modify the Galvao et al. (2013) approach by using instead our Chamberlain-Mundlak-based CRE approach to avoid IPP. As in

TABLE 5 | BVQCM positive.

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
ln(GDPex)	0.996***	1.020***	1.024***	1.042***	1.061***	1.064***	1.042***	1.025***	0.965***
	(0.041)	(0.034)	(0.030)	(0.028)	(0.026)	(0.026)	(0.026)	(0.026)	(0.030)
ln(GDPim)	1.051***	1.022***	0.991***	0.989***	0.972***	0.976***	0.999***	0.992***	1.048***
	(0.037)	(0.030)	(0.027)	(0.025)	(0.023)	(0.024)	(0.024)	(0.025)	(0.031)
EIABV	0.579***	0.529***	0.553***	0.585***	0.537***	0.511***	0.423***	0.309***	0.168***
	(0.099)	(0.056)	(0.047)	(0.043)	(0.040)	(0.039)	(0.037)	(0.041)	(0.048)
DISTBV	−1.588***	−1.491***	−1.432***	−1.392***	−1.345***	−1.297***	−1.249***	−1.165***	−1.087***
	(0.045)	(0.034)	(0.030)	(0.027)	(0.025)	(0.026)	(0.025)	(0.024)	(0.028)
CONTIGBV	−0.015	0.138	0.279**	0.382***	0.444***	0.499***	0.563***	0.618***	0.465***
	(0.127)	(0.111)	(0.110)	(0.107)	(0.098)	(0.105)	(0.099)	(0.097)	(0.106)
LANGBV	0.543***	0.465***	0.465***	0.451***	0.445***	0.467***	0.463***	0.462***	0.448***
	(0.079)	(0.063)	(0.058)	(0.054)	(0.052)	(0.053)	(0.054)	(0.054)	(0.058)
LEGALBV	0.171***	0.268***	0.273***	0.290***	0.302***	0.332***	0.350***	0.356***	0.352***
	(0.060)	(0.045)	(0.041)	(0.038)	(0.036)	(0.036)	(0.035)	(0.034)	(0.036)
RELIGBV	0.603***	0.510***	0.387***	0.271***	0.222***	0.118**	0.094	0.037	−0.010
	(0.115)	(0.086)	(0.073)	(0.068)	(0.060)	(0.059)	(0.061)	(0.061)	(0.072)
COMCOLBV	0.538***	0.534***	0.522***	0.497***	0.482***	0.471***	0.458***	0.445***	0.370***
	(0.107)	(0.087)	(0.077)	(0.072)	(0.069)	(0.066)	(0.065)	(0.064)	(0.069)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
INTER × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.640	0.642	0.643	0.643	0.643	0.642	0.640	0.637	0.627
Obs	122999	122999	122999	122999	122999	122999	122999	122999	122999

Note: Clustered standard errors by country-pair in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Only positive trade values (i.e., $T_{ij} > 0$) were used in the estimation. The quantile estimation is performed using Frisch-Newton interior point method at each decile. BV indicates that the "Bonus Vetus" methodology described in Baier and Bergstrand (2009a) and Baier and Bergstrand (2010) was used. "INTER × Year FE" indicates the interaction of a dummy variable that is 1 if international trade and 0 otherwise, and a year dummy variable were included or not; "CRE" indicates whether correlated random effects were used or not. Following Machado et al. (2016), the squared correlation of $\ln X_{ijt}$ and the fitted values $Quant_q(\ln X_{ijt})$ are reported as the pseudo R^2. Note that CRE methodology would use the means of the "INTER × Year FE" terms but we have omitted here, but the results remain unchanged to their inclusion. Omission is due to the fact that INTER is time-invariant and the year dummies are highly correlated with the mean "INTER × Year FE" terms slowing estimation.

Galvao et al. (2013), the third stage is required simply to ensure efficiency of the estimates.

Formally, our novel modified Galvao et al. (2013) three-stage approach can be described as follows:

1. Estimate a logit model such that

$$z(RHS_{ijt}, \overline{\omega}, C_{ijt}) = Pr(X_{ijt} > 1 | RHS_{ijt}, \overline{\omega}, C_{ijt}) \quad (9)$$

where z is a propensity score function determining whether $\ln X_{ijt}$ is greater than 0, RHS_{ijt} represents all the RHS variables, and C_{ijt} represents the known censoring point.[32] Define a subset of observations

$$J_0 = \left\{(i, j, t \, : \, \hat{z}(RHS_{ijt}, \overline{\omega}, C_{ijt}) > 1 - q + c_N\right\} \quad (10)$$

where q is the quantile of interest $[q \in (0, 1)]$ and c_N is a small positive constant defined as:

$$c_N = \min(.05, \ (NT)^{1/5} \times q) \quad (11)$$

where N is the number of country-pair observations and T is number of years in the sample.[33]

2. Estimate the CRE quantile model in Equation (5) for $q = 0.1, \ldots, 0.9$ using the subset of observations J_0 to obtain the vector of coefficient estimates, which we label $\hat{\beta}^0(q)$. As discussed above, we use the CRE approach for first and second stages to avoid the IPP.

3. To guarantee efficiency, construct another subset of observations J_1 such that:

$$J_1 = \left\{(i, j, t \, : \, \hat{\beta}^0(q)) > \delta_{NT}\right\} \quad (12)$$

where δ_{NT} is calculated as:

$$\delta_{NT} = 1/3(NT)^{(-1/3)} \quad (13)$$

Then we estimate the quantile model once more on the sample J_1 using again the CRE estimator. This third stage guarantees efficiency as shown by Galvao et al. (2013).[34]

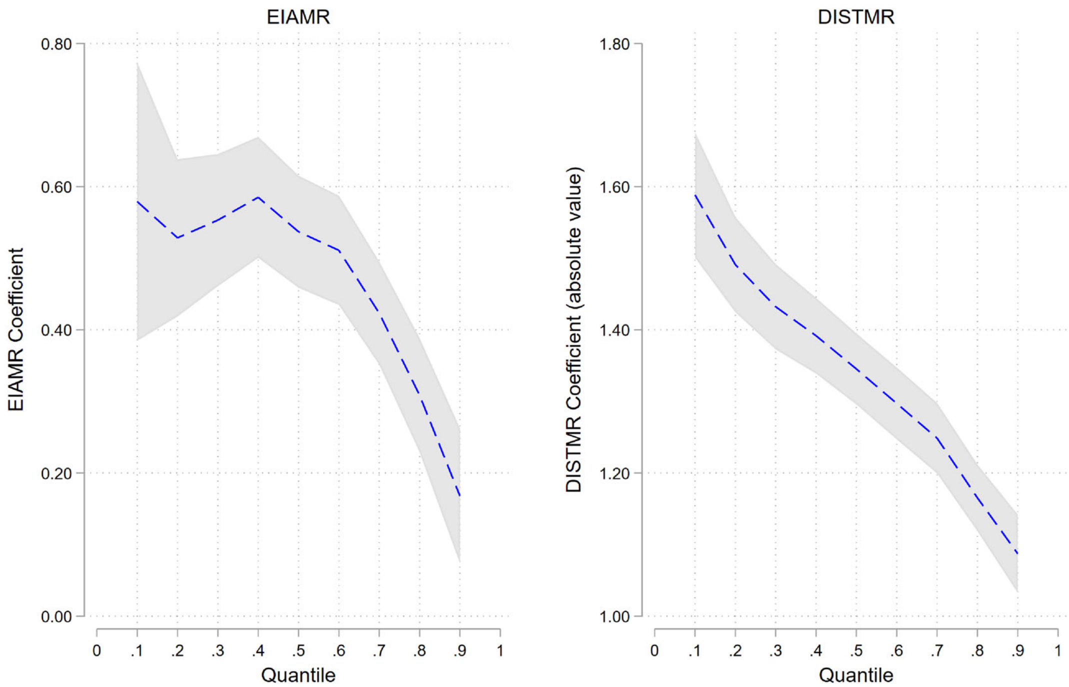

FIGURE 2 | Coefficients on $EIABV$ and $DISTBV$ at decile with 95% confidence interval. [Colour figure can be viewed at wileyonlinelibrary.com]

Intuitively, this procedure (essentially) suggests estimating (in the second and third stages) CRE Equation (5) on *informative subsets* of the full sample where – for various q – the estimated propensity score (that $\Pr(X_{ijt}) \geq 1$), $\hat{z}(RHS_{ijt}, \overline{\omega}, C_{ijt})$, exceeds $1 - q + c_N$. In the benchmark application, $C_{ijt} = 0$. However, since the full sample is sensitive to the cutoff value C_{ijt}, the second and third stage results may be sensitive to C_{ijt}; we explore this in a robustness analysis later.[35]

Finally, we address a concern raised in Machado et al. (2016) regarding mixed distributions and their implications for interpreting quantile regression (QR) partial effects across quantiles. In our three-stage censored QR approach, the estimated coefficients are not directly comparable across quantiles because each estimation uses a different subsample. This is because the subsamples include only observations where the propensity scores from the first-stage logit are greater than $1 - q + c_N$. To make the estimates comparable *across quantiles*, we calculate the "average partial effect" (APE) for each regressor, which accounts for the propensity scores from the first stage.[36] This adjustment allows us to accurately compare the influence of regressors at different points in the conditional distribution. Note that we report the average partial effects for all results using the three-stage censored approach; however, for brevity, we will henceforth refer to these simply as partial effects.

5.2 | Results

Table 6 provides the main empirical results across quantiles Q10-Q90 for estimating the partial EIA effects using our modified Galvao et al. (2013) three-step quantile approach with CREs; for brevity, we report only the results from the third-stage. As noted in Chernozhukov and Hong (2002), the farther away the conditional quantile function is from the censoring point improves the ability to create an informative subset defined by the condition that the propensity score function is above $1 - q$. At lower quantiles such as Q10, we will be more cautious in our interpretation since this condition is not likely to hold and indicates a less informative subset, or, as discussed by Chernozhukov and Hong (2002), an informative subset that is not *sufficiently rich*.

Several results are worth noting. First, like in Table 5 for positive flows with CREs, the partial effects of EIAs also decrease across conditional quantiles, consistent with our earlier results. For the reasons discussed above, lower quantiles, such as Q10, are less informative. This is confirmed by the large standard error on the partial effect at Q10. The partial effect at Q20 is 1.034; accounting for zeros has a substantive effect. Yet, at the 90th quantile the QR partial EIA effect is 0.164, which is only slightly lower than the partial effect for Q90 with only positive flows.

Second, if we focus on the conditional quantiles having more than 69,000 observations in their subsets, Q30-Q90, we find evidence of declining partial effects for other variables. For Q30-Q90, the partial effects for $LEGALBV$, $RELIGBV$, and $COMCOLBV$ all decline monotonically with higher conditional quantiles. For Q40-Q90, the partial effects for $DISTBV$ decline monotonically with higher conditional quantiles.

Finally, Figure 3 provides two graphs of the $EIABV$ effects at various conditional quantiles. The graph on the left includes quantiles Q10-Q90. Because of the large standard error at Q10 for reasons noted earlier, the scale on the LHS of this figure distorts the declining effect of $EIABV$ across the remaining quantiles. The graph on the right includes only quantiles Q20-Q90; this graph more clearly illustrates the monotonically declining effects.

TABLE 6 | Logit(BVCM)-BVQCM.

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
ln(GDPex)	0.777***	1.014***	1.013***	1.005***	0.955***	0.931***	0.886***	0.789***	0.638***
	(0.167)	(0.074)	(0.049)	(0.038)	(0.030)	(0.025)	(0.021)	(0.017)	(0.015)
ln(GDPim)	2.507***	1.551***	1.203***	1.081***	0.975***	0.861***	0.792***	0.703***	0.623***
	(0.291)	(0.099)	(0.057)	(0.042)	(0.032)	(0.027)	(0.022)	(0.019)	(0.016)
EIABV	2.282	1.034***	0.728***	0.565***	0.544***	0.482***	0.391***	0.231***	0.164***
	(1.438)	(0.131)	(0.080)	(0.057)	(0.047)	(0.042)	(0.036)	(0.031)	(0.031)
DISTBV	−0.576**	−0.874***	−1.084***	−1.164***	−1.155***	−1.115***	−1.049***	−0.982***	−0.888***
	(0.235)	(0.089)	(0.057)	(0.040)	(0.031)	(0.027)	(0.023)	(0.020)	(0.017)
CONTIGBV	−0.836	−0.228	0.042	0.216	0.410***	0.539***	0.623***	0.701***	0.687***
	(1.207)	(0.207)	(0.163)	(0.133)	(0.113)	(0.098)	(0.093)	(0.093)	(0.081)
LANGBV	0.268	0.278*	0.296***	0.377***	0.373***	0.438***	0.460***	0.435***	0.384***
	(0.520)	(0.164)	(0.106)	(0.075)	(0.062)	(0.056)	(0.049)	(0.043)	(0.039)
LEGALBV	0.581	0.458***	0.387***	0.319***	0.287***	0.252***	0.225***	0.220***	0.181***
	(0.885)	(0.107)	(0.074)	(0.054)	(0.043)	(0.038)	(0.033)	(0.029)	(0.025)
RELIGBV	0.026	0.446**	0.364***	0.353***	0.294***	0.242***	0.233***	0.252***	0.245***
	(0.605)	(0.214)	(0.132)	(0.097)	(0.078)	(0.067)	(0.057)	(0.050)	(0.046)
COMCOLBV	2.013	0.842***	0.701***	0.491***	0.379***	0.322***	0.277***	0.282***	0.333***
	(1.476)	(0.286)	(0.193)	(0.134)	(0.102)	(0.082)	(0.067)	(0.054)	(0.044)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
INTER × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.096	0.201	0.211	0.232	0.262	0.298	0.337	0.382	0.432
Obs	22744	47303	69033	89031	108901	130925	153708	178253	206294

Note: Clustered standard errors by country-pair are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The prefix "Logit(BVCM)-" indicates that the three-stage estimation procedure described by Galvao et al. (2013) was implemented to account for zeros in quantile regressions. The first stage is a logit model that uses "Bonus Vetus" (BV) methodology described in Baier and Bergstrand (2009a) and Baier and Bergstrand (2010) and correlated random effects (CM) using all trade pairs (i.e., $T_{ij} \geq 0$). The second and third stages are both quantile regressions using Frisch-Newton interior point method at each decile. "BV" and "CRE" indicate that "Bonus Vetus" and correlated random effects were used or not in the second and third stages. "INTER × Year FE" indicates the interaction of a dummy variable that is 1 if international trade and 0 otherwise, and a year dummy variable were included or not in all three stages. Following Machado et al. (2016), the squared correlation of $\ln X_{ijt}$ and the fitted values $Quant_q(\ln X_{ijt})$ are reported as the pseudo R^2. Note that CRE methodology would use the means of the "INTER × Year FE" terms but we have omitted here, but the results remain unchanged to their inclusion. Omission is due to the fact that INTER is time-invariant and the year dummies are highly correlated with the mean "INTER × Year FE" terms slowing estimation.

5.3 | Robustness Analysis

We conducted numerous robustness analyses along several dimensions. In the first robustness analysis, we test for differences between estimates of covariates between the lower and upper quantiles previously discussed in Tables 5 and 6; these are reported in Table 7. For brevity, the remaining robustness results are summarized in a single table with several panels reporting the partial effects across conditional quantiles for $EIABV$. Not surprisingly, for each alternative specification discussed below (which may use, for example, a different parametric model in the first stage to estimate the propensity score or the treatment of zeros), the relative magnitudes of partial effects differ. The results for $EIABV$ are provided in Table 8. For brevity, we report the results for all the coefficient estimates of this robustness analysis in the Appendix, due to the amount of material; those tables provide further information on the third-stage results across different specifications.

5.3.1 | Difference between Quantiles

For Tables 5 and 6, we conducted a bootstrap hypothesis test to assess whether the slope estimates of $EIABV$, $DISTBV$, and $LANGBV$ differ across conditional quantiles and the results are reported in Table 7. Columns 2 and 3 report the original results in Tables 5 and 6, and column 4 is the bootstrapped difference between columns 2 and 3.

In the top panel, we find that both $EIABV$ and $DISTBV$ are statistically different between Q_{10} and Q_{90} with the effects falling across conditional quantiles ($DISTBV$ in absolute

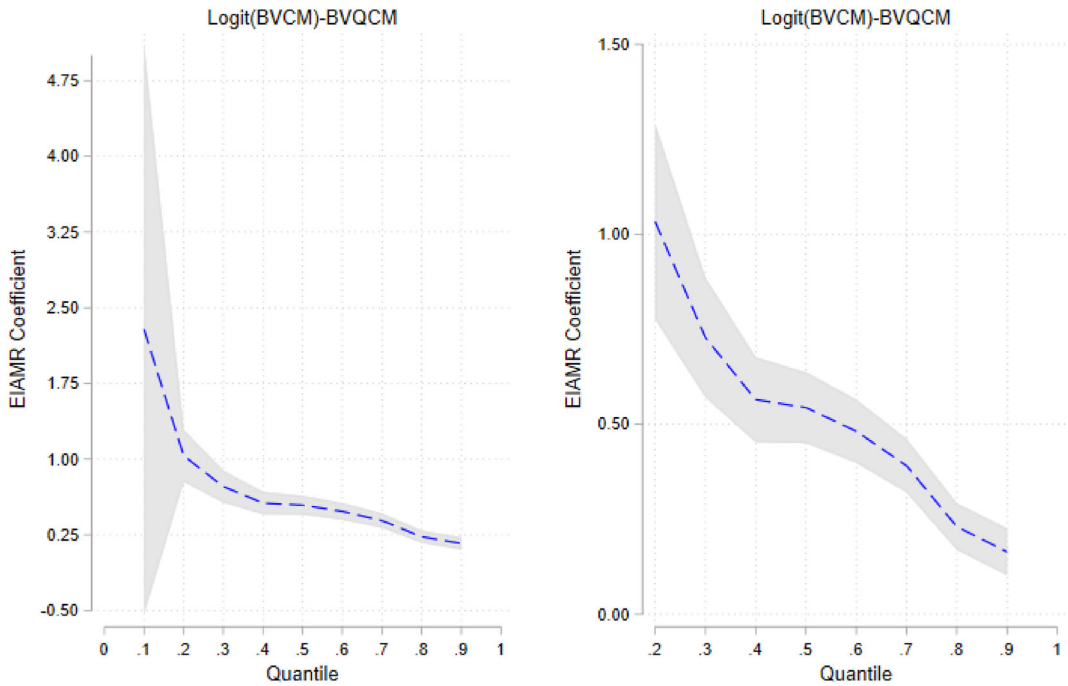

FIGURE 3 | Coefficients on $EIABV$ at decile with 95% confidence interval. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 7 | Bootstrap difference quantile results.

(1)	(2)	(3)	(4)
BVQCM positive (Table 5)	**Q10**	**Q90**	**Bootstrap Difference**
EIABV	0.579***	0.168***	−0.298***
	(0.099)	(0.048)	(0.096)
DISTBV	−1.588***	−1.087***	0.516***
	(0.045)	(0.028)	(0.051)
LANGBV	0.543***	0.448***	−0.052
	(0.079)	(0.058)	(0.093)
Logit(BVCM)-BVQCM (Table 6)	Q30	Q90	Bootstrap Difference
EIABV	0.728***	0.164***	−0.450***
	(0.080)	(0.031)	(0.086)
DISTBV	−1.084***	−0.888***	0.147***
	(0.057)	(0.017)	(0.062)
LANGBV	0.296***	0.384***	0.058
	(0.106)	(0.039)	(0.107)

Note: The quantile estimates for $EIABV$, $DISTBV$, and $LANGBV$ at the Q_{10} and Q_{90} are from Table 5 and Q_{30} and Q_{90} are from Table 6. The last column is the bootstrap difference between columns 2 and 3 using 500 replications.

terms). Although $LANGBV$ is negative in column 4, the results are not statistically significant. We find similar results in the bottom panel for each covariate using the Logit(BVCM)-BVQCM.

5.3.2 | Cloglog First-Stage Function

Panel A (Part A1) of Table 8 reports the $EIABV$ partial effects using a Cloglog specification for the first stage instead of the logit in the benchmark Logit(BVCM)-BVQCM specification. We label this specification Cloglog(BVCM)-BVQCM. The Cloglog specification is considered an asymmetric specification unlike the logit model, which is symmetric and implies different propensity scores. As indicated in Panel A1, the $EIABV$ partial effects decline monotonically as in Table 6 but with slightly lower effects across conditional quantiles relative to Table 6. Nevertheless, at Q50, the third-stage $EIABV$ partial effect using the logit (Cloglog) first-stage function is 0.54 (0.57); these average partial effects are quite similar.

TABLE 8 | Various robustness checks.

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
				Part A: First stage method					
				Part A1: Cloglog					
EIABV	1.622***	1.062***	0.742***	0.648***	0.567***	0.512***	0.374***	0.197***	0.141***
	(0.249)	(0.108)	(0.072)	(0.054)	(0.045)	(0.041)	(0.035)	(0.030)	(0.032)
				Part A2: LPM					
EIABV	1.926***	0.941***	0.680***	0.516***	0.469***	0.398***	0.282***	0.164***	0.138***
	(0.548)	(0.106)	(0.070)	(0.052)	(0.045)	(0.040)	(0.035)	(0.030)	(0.032)
				Part B: Dealing with missing observations					
				Part B1: Adding 1 to all trade values					
EIABV	2.287	1.034***	0.728***	0.565***	0.544***	0.482***	0.391***	0.231***	0.164***
	(1.439)	(0.131)	(0.080)	(0.057)	(0.047)	(0.042)	(0.036)	(0.031)	(0.031)
				Part B2: User defined minimum $10,000					
EIABV	2.259***	0.992***	0.660***	0.552***	0.520***	0.477***	0.384***	0.256***	0.171***
	(0.495)	(0.138)	(0.075)	(0.053)	(0.043)	(0.040)	(0.034)	(0.029)	(0.028)
				Part C: FTA vs. Deep agreements					
FTABV	2.115***	1.008***	0.709***	0.535***	0.482***	0.391***	0.274***	0.151***	0.116***
	(0.819)	(0.128)	(0.078)	(0.056)	(0.047)	(0.042)	(0.036)	(0.031)	(0.030)
CUCMECUBV	2.902***	1.143***	0.707***	0.563***	0.619***	0.559***	0.495***	0.426***	0.437***
	(1.064)	(0.195)	(0.120)	(0.087)	(0.071)	(0.061)	(0.052)	(0.048)	(0.065)
				Part D: First stage fixed effects					
				Part D1: Logit pair fixed effects					
EIABV	2.075***	0.920***	0.812***	0.704***	0.536***	0.349***	0.236***	0.156***	0.109**
	(0.324)	(0.192)	(0.158)	(0.117)	(0.089)	(0.077)	(0.066)	(0.056)	(0.051)
				Part D2: Logit exporter-year, Importer-year, Pair fixed effects					
EIABV	1.241***	0.891***	0.774***	0.672***	0.547***	0.387***	0.226***	0.180***	0.166**
	(0.193)	(0.138)	(0.113)	(0.100)	(0.080)	(0.072)	(0.068)	(0.062)	(0.066)
				Part D3: LPM pair fixed effects					
EIABV	0.797***	0.715***	0.647***	0.597***	0.493***	0.452***	0.353***	0.239***	0.180***
	(0.083)	(0.054)	(0.045)	(0.041)	(0.038)	(0.035)	(0.033)	(0.030)	(0.031)
				Part D4: LPM exporter-year, Importer-year, Pair fixed effects					
EIABV	0.784***	0.763***	0.716***	0.649***	0.566***	0.486***	0.359***	0.234***	0.207***
	(0.072)	(0.051)	(0.043)	(0.038)	(0.036)	(0.035)	(0.033)	(0.032)	(0.034)

Note: Clustered standard errors by country-pair are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The prefix "Cloglog", "LPM", and "Logit" indicate that the three-stage estimation procedure described by Galvao et al. (2013) was implemented and the first stage was estimated using a complementary log-log, linear probability, and logit model, respectively.

5.3.3 | Linear Probability Model First-Stage Function

Panel A2 of Table 8 reports the $EIABV$ partial effects using a linear probability model (LPM) specification for the first stage instead of the logit in the benchmark Logit(BVCM)-BVQCM specification. We label this specification LPM(BVCM)-BVQCM. The LPM specification estimates a linear version of the propensity score and Galvao et al. (2013) claim that the LPM works well in the first stage of their simulations. As indicated in Panel A2, the $EIABV$ partial effects decline monotonically as in Table 6, with effects very similar to those in Table 8's Panel A1. At Q50, the (third-stage) $EIABV$ partial effects using the logit or LPM first-stage function are similar, 0.54 versus 0.47.

5.3.4 | Approximations of Zeros

Methodology

The results of our estimation using the Logit(BVCM)-BVQCM technique may be sensitive to how we treat "zeros." We rationalized in our benchmark specification to accommodate (logs of) zeros by adding ones to all zeros in our benchmark case, following guidance from Cameron and Trivedi (2009), Wooldridge (2010), and Figueiredo et al. (2014). However, we provide two alternative methods for treating zeros in our estimation (which uses logarithms of flows for the LHS variable in the second and third stages). A less defendable choice is adding ones to all observations; we conduct one robustness analysis using this method. A second method, suggested in Martin and Pham (2020), is to use the minimum level of the trade flows in the sample. In our sample, the lowest non-zero value of trade flows is USD 1. In the spirit of robustness, we alternatively used a value of USD 10,000.[37]

Results

Panel B (Part B1) of Table 8 provides the results of the robustness analysis of adding ones to all trade flows instead of just the zeros. A comparison of the $EIABV$ partial effect results in Table 6 with those in Table 8 shows that the partial effects are quite similar using the alternative methods.

The second approach has two steps. First, we found all the observations that had values of trade less than USD 10,000 and considered them zeros. Second, we added ones to all zeros to be able to take the logs. Hence, in this approach, we have a larger percentage of "zeros" in the sample. Remarkably, as shown in Panel B2 of Table 8, using a minimum value of USD 10,000 does not have a material impact upon the results qualitatively or quantitatively.

5.3.5 | Varying Degrees of Economic Integration

Methodology

One of the benefits of using the NSF-Kellogg Institute Database on Economic Integration Agreements is that the database employs a multichotomous index of EIAs, notably allowing "deeper" trade agreements. Numerous papers have been exploring the trade impact of Deep Trade Agreements (DTAs). The conditional mean estimation of partial effects of EIAs of varying degrees of economic integration was explored systematically using panel data and OLS in Baier et al. (2014). None of the previous QR analyses noted in Section 2's literature summary has examined partial effects of EIAs *by type of agreement*. Similar to Baier et al. (2014), we examine partial effects of free trade agreements (FTAs) relative to those of customs unions (CUs), common markets (CMs), and economic unions (ECUs). However, like in Baier et al. (2014), due to the relatively few numbers of CUs, CMs, and ECUs in the data set, we combine the latter into one measure of "deep" trade agreements, labeled CUCMECU. The definitions of each type of agreement is described online in the EIA database as well as in Baier et al. (2014).

Results

In the interest of brevity, we present the results disaggregating EIAs by FTAs and CUCMECUs only for Logit(BVCM)-BVQCM, the benchmark specification. Panel C of Table 8 provides the estimates by type of EIA. First, as expected, note that the effect of CUCMECUs is larger than that for FTAs at every conditional quantile, except Q30 where $FTABV$ is larger by only 0.002. Deeper EIAs have larger partial effects.

Second, for the most part, we also find support for partial effects declining with higher conditional quantiles. For $FTABV$, partial effects decline monotonically with increases in conditional quantiles. For $CUCMECUBV$, partial effects decline (largely) monotonically from Q10-Q90, with a small and statistically insignificant uptick from Q40 to Q50 and a trivial uptick from Q80 to Q90.

5.3.6 | One Fixed Effect in First-Stage Logit and LPM

For robustness, we also consider a first stage logit (and LPM) model with a single country-pair fixed effect, instead of using CREs in the first stage; the second and third steps still used BVQCM.[38] The results are reported in Panels D1 and D3 of Table 8. Note that, due to the country-pair fixed effect, the estimation drops all perfectly predicted outcomes, which include intra-national trade observations. The rationale for this robustness check is to determine if a reduction in the number of country-pairs that always or never trade can influence (or even improve) the estimation of the propensity scores in the first stage. The first stage logit regression excludes 41,187 and 50,663 observations for which $T_{ij} = 0$ and $T_{ij} = 1$, respectively, in all years. We find that the standard errors of the partial effects at Q10 for both the logit and LPM models with a single pair fixed effect are considerably smaller, as expected. More importantly, for Q20-Q90 the $EIABV$ partial effects are not materially different from those in the benchmark Table 6 estimates.

5.3.7 | Three-Way Fixed Effects in First-Stage Logit and LPM

In the previous robustness analysis, we explored the sensitivity of the findings to a single country-pair fixed effect in the first step of the estimation. One of the notable findings of using a (single) pair fixed effect was that the results for the partial effects were not materially different across conditional quantiles than those in the benchmark results in Table 6. A concern initially for this study was the potential IPP problem with using *three-way* fixed effects in the first stage. In this section, we consider using three-way fixed effects in both the logit and LPM first stages, which are used *simply to create subsets*for the second (and third) step BVQCM quantile regressions.

The results are presented in Panels D2 and D4 of Table 8. The main conclusion is that – with the exception of Q10 – the third stage BVQCM results in Panel D2 are not materially different than those in Panel D1 using a single pair fixed effect in the first stage logit, nor those in Table 6 using Logit(BVCM) in the first stage.

Similarly, the results for the first stage LPMs are largely the same. In Panel D4, the partial effects of the third stage BVQCM with a first stage LPM with three-way fixed effects are not materially different than the BVQCM results in Panel D3 using a first stage logit with a single pair fixed effect.

5.3.8 | Annual Data

For robustness, we also ran the benchmark model using *annual data* over the same period of time. The results were robust to using annual data.

6 | Disaggregated Flows and the Arkolakis (2010) Proposition

Up to now, we have used only aggregate trade flows. However, the original empirical work in Arkolakis (2010) used 4-digit Standard International Trade Classification (SITC) data.

In this section, we examine empirically in more depth the Arkolakis proposition using 2-digit SITC data and our novel estimator.[39] Using such data moves estimation closer in spirit to the Arkolakis (2010) proposition that "goods with low volumes of trade prior to a trade liberalization episode grow more when trade costs decline" (p. 1153) and his use of disaggregated data. Second, we expand the specification of the QR to include two more variables. One variable is the previous period's share of country i's exports in two-digit sector s that are imported by country j. Given our 5-year intervals for our time series, these previous period (t-5) shares can be reasonably construed as exogenous to the current period trade flow. The second variable is an interaction of these previous period export shares with $EIABV$. Beyond showing the negative influence of the export shares, we will also calculate the marginal effects across quantiles of larger and larger export shares.[40]

6.1 | Methodology

First, consider disaggregated SITC Revision 1 trade at the 2-digit level for QR with non-negative trade flows and our three-step methodology with CREs. As we saw in the previous robustness analyses, the third-stage QR results are largely robust across various first-stage specifications for determining informative sub-samples. Due to the large number of zeros in 2-digit disaggregate data, we chose to use the Logit(BV1FE) specification for the first stage, due to the finding that it accounts better for zeros and the Arkolakis proposition focuses on "least traded goods" (not zeros). Yet, an implication of using the pair fixed effect in the first stage is that this effect removes intra-national trade from the estimation, as these observations are predicted perfectly.

As discussed in the introduction to this section, we extend the model to include the previous period's country i share of sector s exports to country j, $EXSH_{ij,t-5}$, and the interaction of this variable with $EIABV$, $EIABV_{ijt} * EXSH_{ij,t-5}$. In the context of our CRE approach (in the second and third steps), we include additionally the time-averaged mean of $EXSH_{ij,t-5}$.

Subject to the modifications just noted, the three-step estimation procedure is akin to that described in Section 5.1. This suggests the following specification for the (second and) third stage quantile regression:

$$\begin{aligned} Quant_q(\ln X_{ijst}) = {} & \beta_0^q + \beta_1^q \ln GDP_{it}^q + \beta_2^q \ln GDP_{jt}^q \\ & + \beta_3^q EIABV_{ijt}^q + \beta_4^q DISTBV_{ij}^q \\ & + \beta_5^q CONTIGBV_{ij}^q + \beta_6^q LANGBV_{ij}^q \\ & + \beta_7^q LEGALBV_{ij}^q + \beta_8^q RELIGBV_{ij}^q \\ & + \beta_9^q COMCOLBV_{ij}^q + \sum_{t=1}^{T} \alpha_t^q YEAR_t \\ & + \beta_{10}^q \overline{\ln GDP}_i^q + \beta_{11}^q \overline{\ln GDP}_j^q + \beta_{12}^q \overline{EIABV}_{ij}^q \\ & + \beta_{13}^q EXSH_{ijs,t-5}^q + \beta_{14}^q \overline{EXSH}_{ijs}^q \\ & + \beta_{15}^q (EIABV_{ijt} * EXSH_{ijs,t-5})^q + \sum_{s=1}^{S} \Upsilon_s + \eta_{ijst}^q \end{aligned} \quad (14)$$

where Υ_s represents a sector fixed effect and $\overline{EXSH}_{ijs}^q$ represents the mean sectoral export share for each bilateral country pair to control for unobserved bilateral heterogeneity by sector.

6.2 | Results

The results are presented in Table 9. Consistent with earlier results, we find that the partial effects decline with increases in conditional quantiles. It is important to note the significant increase in the sizes of the sub-samples that are used, due to the use of two-digit SITC trade flows. The sub-samples for Table 9 are *10 times* larger than those for our previous estimates using aggregate trade flows, compare, Table 6. For the majority of quantiles, the coefficient estimates for the interactions of $EIABV_{ijt}^q$ with $EXSH_{ijs,t-5}^q$ are signed as expected and statistically significant.

The partial effect of $EIABV_{ijt}$ is only higher than that in Table 8 (Panel D1) at higher quantiles. However, we should be comparing Table 8 (Panel D1) $EIABV_{ijt}$ partial effects with marginal effects. The negative coefficient estimates for $(EIABV_{ijt} * EXSH_{ijs,t-5})^q$ imply that the partial effect of an EIA decreases as the previous period's export share increases, consistent with the Arkolakis proposition. Moreover, this is readily apparent also from estimated marginal effects reported in Table 10. As conditional quantiles increase, the marginal effects decline; note that we use here the same procedure as discussed earlier to make all the marginal effects comparable across

TABLE 9 | SITC 2 Digit Logit(BV1FE)-BVQCM with $EXSH_{t-5}$.

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
ln(GDPex)	1.913***	1.293***	1.074***	0.913***	0.979***	0.927***	0.832***	0.709***	0.548***
	(0.165)	(0.079)	(0.052)	(0.038)	(0.035)	(0.028)	(0.024)	(0.020)	(0.015)
ln(GDPim)	1.661***	1.395***	1.241***	1.086***	1.205***	1.153***	0.989***	0.792***	0.617***
	(0.190)	(0.094)	(0.057)	(0.044)	(0.040)	(0.034)	(0.028)	(0.023)	(0.018)
EIABV	1.094***	1.015***	0.853***	0.721***	0.682***	0.605***	0.571***	0.498***	0.396***
	(0.184)	(0.097)	(0.078)	(0.065)	(0.061)	(0.054)	(0.045)	(0.039)	(0.032)
DISTBV	−1.116***	−0.944***	−0.836***	−0.725***	−0.713***	−0.638***	−0.614***	−0.541***	−0.420***
	(0.110)	(0.058)	(0.040)	(0.033)	(0.029)	(0.024)	(0.019)	(0.017)	(0.013)
CONTIGBV	0.511*	0.282	0.249*	0.242**	0.194*	0.142	0.113	0.025	−0.012
	(0.300)	(0.179)	(0.129)	(0.109)	(0.099)	(0.088)	(0.073)	(0.062)	(0.049)
LANGBV	0.502**	0.298***	0.143*	0.157**	0.120**	0.167***	0.200***	0.180***	0.162***
	(0.199)	(0.103)	(0.074)	(0.062)	(0.056)	(0.049)	(0.042)	(0.037)	(0.032)
LEGALBV	0.349**	0.271***	0.224***	0.217***	0.223***	0.186***	0.170***	0.135***	0.106***
	(0.159)	(0.085)	(0.061)	(0.049)	(0.042)	(0.036)	(0.030)	(0.026)	(0.022)
RELIGBV	−0.374	−0.204	−0.101	−0.093	−0.063	−0.041	−0.058	−0.066	−0.079**
	(0.236)	(0.135)	(0.095)	(0.080)	(0.072)	(0.062)	(0.051)	(0.044)	(0.036)
COMCOLBV	1.585***	0.400**	0.312***	0.200**	0.154**	0.160**	0.162***	0.154***	0.148***
	(0.344)	(0.169)	(0.116)	(0.088)	(0.078)	(0.065)	(0.054)	(0.045)	(0.035)
$EXSH_{t-5}$	0.085***	0.058***	0.042***	0.033***	0.030***	0.023***	0.019***	0.017***	0.014***
	(0.004)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$EIABV*EXSH_{t-5}$	−0.036***	−0.022***	−0.013***	−0.008***	−0.007***	−0.004**	−0.002	−0.001	−0.004***
	(0.008)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SITC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	234527	452827	651499	850013	1055536	1279976	1595144	1929410	2382178

Note: Clustered standard errors by country-pair are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The prefix "Logit(BV1FE)-" indicates that the three-stage estimation procedure described by Galvao et al. (2013) was implemented to account for zeros in quantile regressions. The first stage is a logit model with pair-sector fixed effects using all trade pairs (i.e., $T_{ij} \geq 0$). Note that using pair-sector fixed effects removes intra-national trade and any observations perfectly predicted by the pair-sector fixed effects. The second and third stages are both quantile regressions using Frisch-Newton interior point method at each decile. BV indicates that the "Bonus Vetus" methodology described in Baier and Bergstrand (2009a) and Baier and Bergstrand (2010) was used."Year FE" indicates whether year dummy variables were included or not in the second and third stages; "CRE" indicates whether correlated random effects were used or not in the second and third stages. $EXSH_{t-5}$ denotes the share of sector s exports of country i to country j in the previous period. The three-stage model used trade values at a 2 digit SITC disaggregation level. Following Machado et al. (2016), the squared correlation of $\ln X_{ijt}$ and the fitted values $Quant_q(\ln X_{ijt})$ are reported as the pseudo R^2.

conditional quantiles. Furthermore, we see going down Table 10 across rows that, as the export share in sector s of country i's exports to country j increases, the marginal effects decline. Along with French and Zylkin (2024), this is one of the first studies to provide systematic empirical support of the Arkolakis proposition across time, across country-pairs, and across a *vast array* of EIAs.

7 | Have Developing-Country Exporters Benefited More From Eias Than Developed-Country Exporters?

Baier, Bergstrand, and Clance (2018), or BBC, examined the heterogeneous effects of EIAs on country-pairs' trade flows using conditional mean (OLS) estimation including interaction terms. Based upon their theoretical extension of the Melitz general equilibrium model of trade with heterogeneous firms, BBC argued that variable-cost and fixed-cost trade elasticities associated with trade liberalizations are heterogeneous and endogenous to levels of country-pairs' bilateral policy and non-policy, variable and fixed trade costs (even allowing for constant-elasticity-of-substitution preferences and an untruncated Pareto distrituion of productivities). Using associated comparative statics, BBC provided several explicit predictions of the heterogeneous EIA dummies' partial effects allowing for variations in country-pairs' bilateral (trade-cost-related) characteristics, and confirmed the predictions empirically.

However, in one of their robustness analyses, BBC could not show that the trade effects of an EIA were sensitive to the *level* of either

TABLE 10 | Logit(BV1FE)-BVQCM marginal effects: Previous sales share.

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
EIABV									
Share 0.0%	1.085***	1.013***	0.852***	0.721***	0.682***	0.605***	0.571***	0.498***	0.396***
	(0.182)	(0.097)	(0.078)	(0.065)	(0.061)	(0.054)	(0.045)	(0.039)	(0.032)
Share 0.50%	1.068***	1.003***	0.846***	0.716***	0.678***	0.603***	0.570***	0.497***	0.394***
	(0.185)	(0.096)	(0.078)	(0.064)	(0.060)	(0.054)	(0.045)	(0.039)	(0.032)
Share 1.0%	1.052***	0.992***	0.840***	0.712***	0.675***	0.601***	0.569***	0.497***	0.392***
	(0.182)	(0.096)	(0.078)	(0.064)	(0.060)	(0.053)	(0.045)	(0.038)	(0.031)
Share 2.5%	1.002***	0.960***	0.821***	0.700***	0.665***	0.596***	0.566***	0.495***	0.386***
	(0.185)	(0.095)	(0.077)	(0.064)	(0.059)	(0.053)	(0.044)	(0.038)	(0.031)
Share 5.0%	0.917***	0.906***	0.790***	0.679***	0.647***	0.586***	0.561***	0.492***	0.377***
	(0.186)	(0.096)	(0.077)	(0.063)	(0.058)	(0.052)	(0.043)	(0.037)	(0.031)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
INTER × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.146	0.123	0.130	0.123	0.127	0.124	0.126	0.131	0.141
Obs	234522	452825	651498	850012	1055536	1279976	1595144	1929410	2382178

Note: Clustered standard errors by country-pair are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The coefficients reported are the average marginal effects. Note that using pair-sector fixed effects removes intra-national trade and any observations perfectly predicted by the pair-sector fixed effects. For all remaining trade values, the percentiles of $\ln(X)$ at 50th, 75th, 90th, and 95th correspond to previous export shares at 0%, 0.01%, 0.51%, and 2.79%. Following Machado et al. (2016), the squared correlation of $\ln X_{ijt}$ and the fitted values $Quant_q(\ln X_{ijt})$ are reported as the pseudo R^2.

the exporter's or importer's per capita GDP, and hence, levels of development. However, it is well known that developing countries historically have had much higher levels of tariff and nontariff barriers, compare, International Monetary Fund and World Bank (2001). It is likely that developing countries entering an EIA will have larger reductions in tariff and nontariff barriers than developed countries. This provides a mechanism through which EIAs of developing exporters can have larger trade partial effects than those of developed economies.

In this section, we use the QR methodology of this paper to tackle this issue: Do EIAs actually increase developing countries' exports more than developed countries' exports? For brevity, we use the Logit(BV1FE)-BVQCM specification in a manner similar to that in the previous section.[41] One of the benefits of our BV approach is that we can introduce the logarithms of time-varying exporter and importer per capita GDPs ($\ln PCGDP_{it}$ and $\ln PCGDP_{jt}$, respectively) – variables historically included in gravity-equation specifications (cf., Bergstrand (1989)) but omitted in more recent gravity-equation specifications – and their time-averaged means ($\overline{\ln PCGDP_i}$, $\overline{\ln PCGDP_j}$) due to the CRE approach. Moreover, we include the interaction of $EIABV$ with the log of the exporter's per capita GDP, $EIABV_{ijt} * \ln PCGDP_{it}$.[42] Accordingly, in this section we use the same three-step approach as in previous sections, with the noted modifications. This suggests the (second and) third step QR specification using aggregate trade flows:

$$
\begin{aligned}
Quant_q(\ln X_{ijt}) = {} & \beta_0^q + \beta_1^q \ln GDP_{it}^q + \beta_2^q \ln GDP_{jt}^q \\
& + \beta_3^q EIABV_{ijt}^q + \beta_4^q DISTBV_{ij}^q \\
& + \beta_5^q CONTIGBV_{ij}^q + \beta_6^q LANGBV_{ij}^q \\
& + \beta_7^q LEGALBV_{ij}^q + \beta_8^q RELIGBV_{ij}^q \\
& + \beta_9^q COMCOLBV_{ij}^q + \sum_{t=1}^{T} \alpha_t^q YEAR_t \\
& + \beta_{10}^q \overline{\ln GDP_i}^q + \beta_{11}^q \overline{\ln GDP_j}^q \\
& + \beta_{12}^q \overline{EIABV}_{ij}^q + \beta_{13}^q \ln PCGDP_{it}^q \\
& + \beta_{14}^q \ln PCGDP_{jt}^q + \beta_{15}^q (EIABV_{ijt} * \ln PCGDP_{it})^q \\
& + \beta_{16}^q (EIABV_{ijt} * \ln PCGDP_{jt})^q \\
& + \beta_{17}^q \overline{\ln PCGDP_i}^q + \beta_{18}^q \overline{\ln PCGDP_j}^q + \eta_{ijt}^q \qquad (15)
\end{aligned}
$$

Table 11 and the accompanying Figure 4 provide the results. For brevity, we report in Table 11 the marginal effects; these are shown also in Figure 4. The format of the table is analogous to previous tables; we report (third-stage) marginal effects across quantiles (across columns). The distinguishing feature of this table is that we report the EIA marginal effects by various percentiles of the distribution of exporter per capita GDPs. The poorest (richest) exporters – trading at a particular quantile – are in the 10th (90th) percentile. First, we note that – as before – as quantiles increase the marginal effects decline. Second, this decline with rising quantiles holds at all percentiles of exporter per capita income. Third, and most importantly, as exporter per capita GDP increases – going down the rows – the EIA marginal effects decline, with the exception of Q10 (where, as we have noted, we have less confidence in the results). Consistent with the results discussed earlier in BBC, we note,

TABLE 11 | Logit(BV1FE)-BVQCM marginal effects: Exporter GDP per capita.

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
EIABV									
10th Percentile	1.666*	1.072***	1.226***	1.137***	1.040***	0.899***	0.804***	0.641***	0.385***
	(0.966)	(0.351)	(0.262)	(0.228)	(0.182)	(0.160)	(0.139)	(0.117)	(0.102)
30th Percentile	1.909**	1.044***	1.110***	1.027***	0.899***	0.756***	0.645***	0.510***	0.315***
	(0.800)	(0.291)	(0.213)	(0.182)	(0.144)	(0.128)	(0.110)	(0.092)	(0.079)
Median	2.097***	1.014***	0.996***	0.919***	0.761***	0.614***	0.489***	0.382***	0.246***
	(0.567)	(0.241)	(0.173)	(0.142)	(0.113)	(0.101)	(0.086)	(0.072)	(0.061)
70th Percentile	2.253***	0.977***	0.864***	0.793***	0.600***	0.451***	0.308***	0.233***	0.166***
	(0.466)	(0.203)	(0.147)	(0.113)	(0.092)	(0.083)	(0.071)	(0.059)	(0.051)
90th Percentile	2.413***	0.925***	0.675***	0.613***	0.371***	0.217**	0.050	0.021	0.053
	(0.442)	(0.205)	(0.165)	(0.128)	(0.106)	(0.098)	(0.083)	(0.073)	(0.067)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	19667	33691	45453	55925	65532	76537	87456	100863	116903

Note: Clustered standard errors by country-pair are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The coefficients reported are the average marginal effects. The prefix "Logit(BV1FE)-" indicates that the three-stage estimation procedure described by Galvao et al. (2013) was implemented to account for zeros in quantile regressions. The first stage is a logit model with pair fixed effects using all trade pairs (i.e., $T_{ij} \geq 0$) and note that using pair fixed effects removes intra-national trade and any observations perfectly predicted by the pair fixed effects. The second and third stages are both quantile regressions using Frisch-Newton interior point method at each decile. BV indicates that the "Bonus Vetus" methodology described in Baier and Bergstrand (2009a) and Baier and Bergstrand (2010) was used."Year FE" indicates whether year dummy variables were included or not in the second and third stages; "CRE" indicates whether correlated random effects were used or not in the second and third stages.

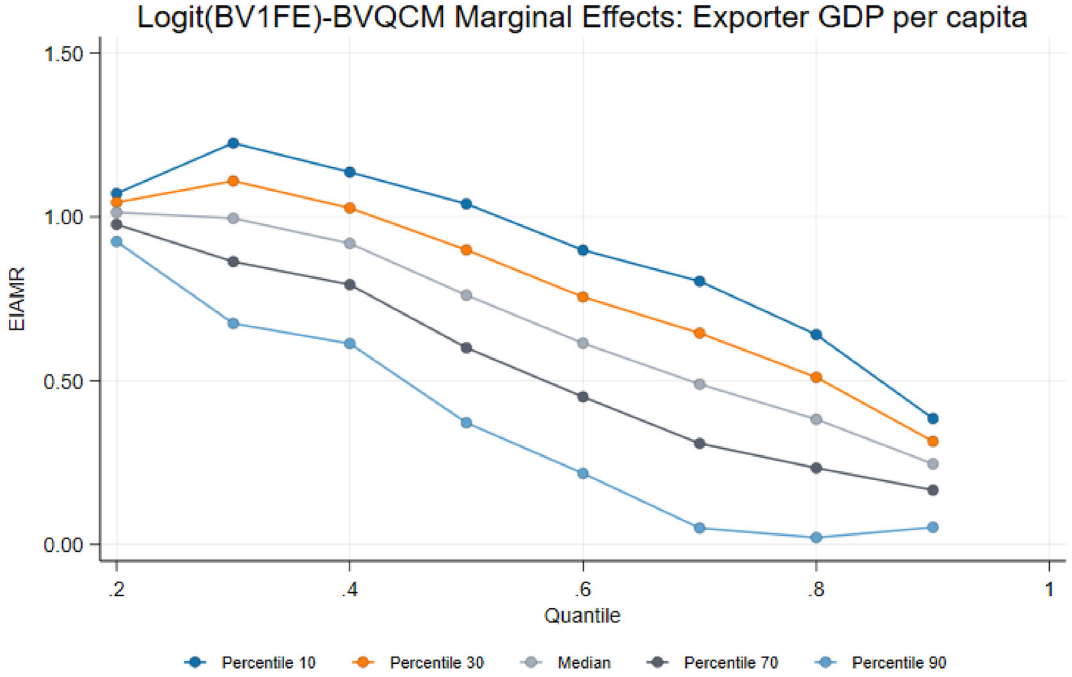

FIGURE 4 | Logit(BV1FE)-BVQCM. [Colour figure can be viewed at wileyonlinelibrary.com] *Note.* Percentiles in the legend refer to exporter GDP per capita.

for instance, that – at the 20th conditional quantile (second column) and when exponentiated – the marginal EIA effect on trade flows is *26 percent higher* when the exporter's per capita income is at only the 10th percentile relative to being at the 90th percentile. Finally, when we use Logit(3FE) in the first stage of the estimation, the results for Q10 are similar to those for the other conditional quantiles; these results are provided in Table 12 and displayed in Figure 5.

TABLE 12 | Logit(3FE)-BVQCM marginal effects: Exporter GDP per capita.

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
EIABV									
10th Percentile	2.186***	1.599***	1.419***	1.258***	1.190***	1.021***	0.911***	0.716***	0.369***
	(0.328)	(0.218)	(0.218)	(0.214)	(0.174)	(0.163)	(0.144)	(0.129)	(0.139)
30th Percentile	1.912***	1.392***	1.210***	1.077***	0.994***	0.839***	0.732***	0.572***	0.314***
	(0.266)	(0.178)	(0.173)	(0.168)	(0.137)	(0.129)	(0.113)	(0.100)	(0.108)
Median	1.642***	1.188***	1.003***	0.898***	0.802***	0.660***	0.555***	0.431***	0.260***
	(0.225)	(0.149)	(0.137)	(0.129)	(0.107)	(0.101)	(0.089)	(0.076)	(0.083)
70th Percentile	1.329***	0.952***	0.764***	0.691***	0.578***	0.453***	0.350***	0.266***	0.197***
	(0.215)	(0.140)	(0.117)	(0.103)	(0.087)	(0.083)	(0.073)	(0.064)	(0.068)
90th Percentile	0.882***	0.615***	0.422***	0.396***	0.258**	0.156	0.057	0.032	0.108
	(0.278)	(0.174)	(0.146)	(0.123)	(0.106)	(0.098)	(0.090)	(0.085)	(0.089)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	48792	55411	60544	64932	69183	73290	77924	83166	89412

Note: Clustered standard errors by country-pair are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Marginal effects are calculated with importer GDP per capita set at 30th Percentile. The prefix "Logit(3FE)-" indicates that the three-stage estimation procedure described by Galvao et al. (2013) was implemented to account for zeros in quantile regressions. The first stage is a logit model with exporter-year, importer-year, and pair fixed effects using all trade pairs (i.e., $T_{ij} \geq 0$) and note that using pair fixed effects removes intra-national trade. Additionally, any observations perfectly predicted by the exporter-year, importer-year, and pair fixed effects are also removed. The second and third stages are both quantile regressions using Frisch-Newton interior point method at each decile. BV indicates that the "Bonus Vetus" methodology described in Baier and Bergstrand (2009a) and Baier and Bergstrand (2010) was used."Year FE" indicates whether year dummy variables were included or not in the second and third stages; "CRE" indicates whether correlated random effects were used or not in the second and third stages.

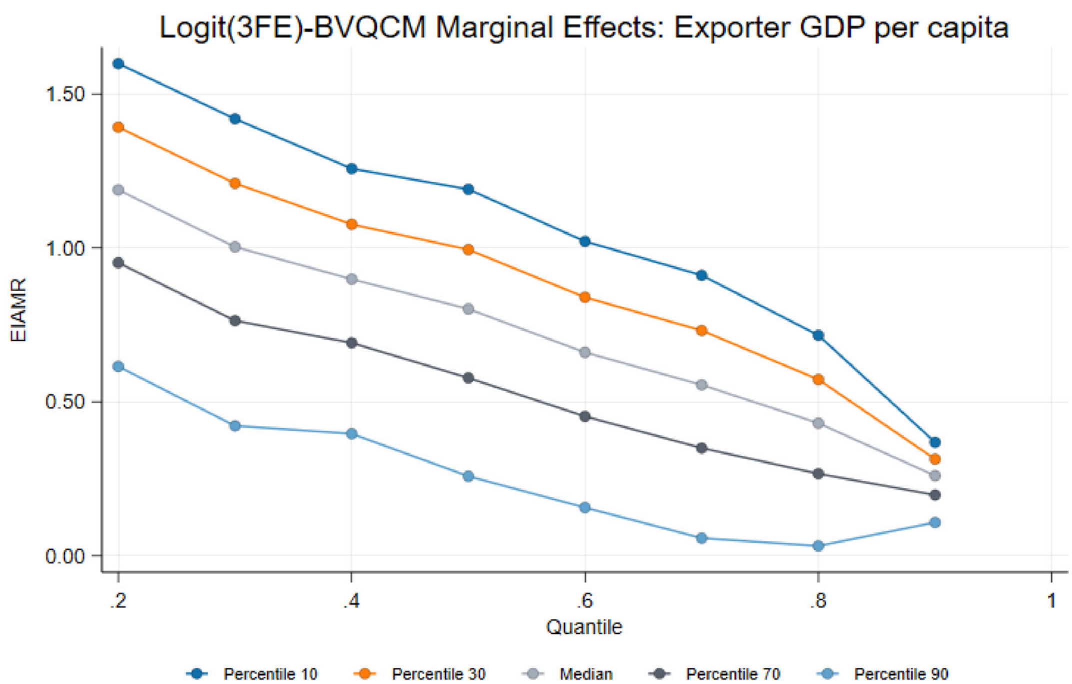

FIGURE 5 | Logit(3FE)-BVQCM. [Colour figure can be viewed at wileyonlinelibrary.com] *Note.* Percentiles in the legend refer to exporter GDP per capita.

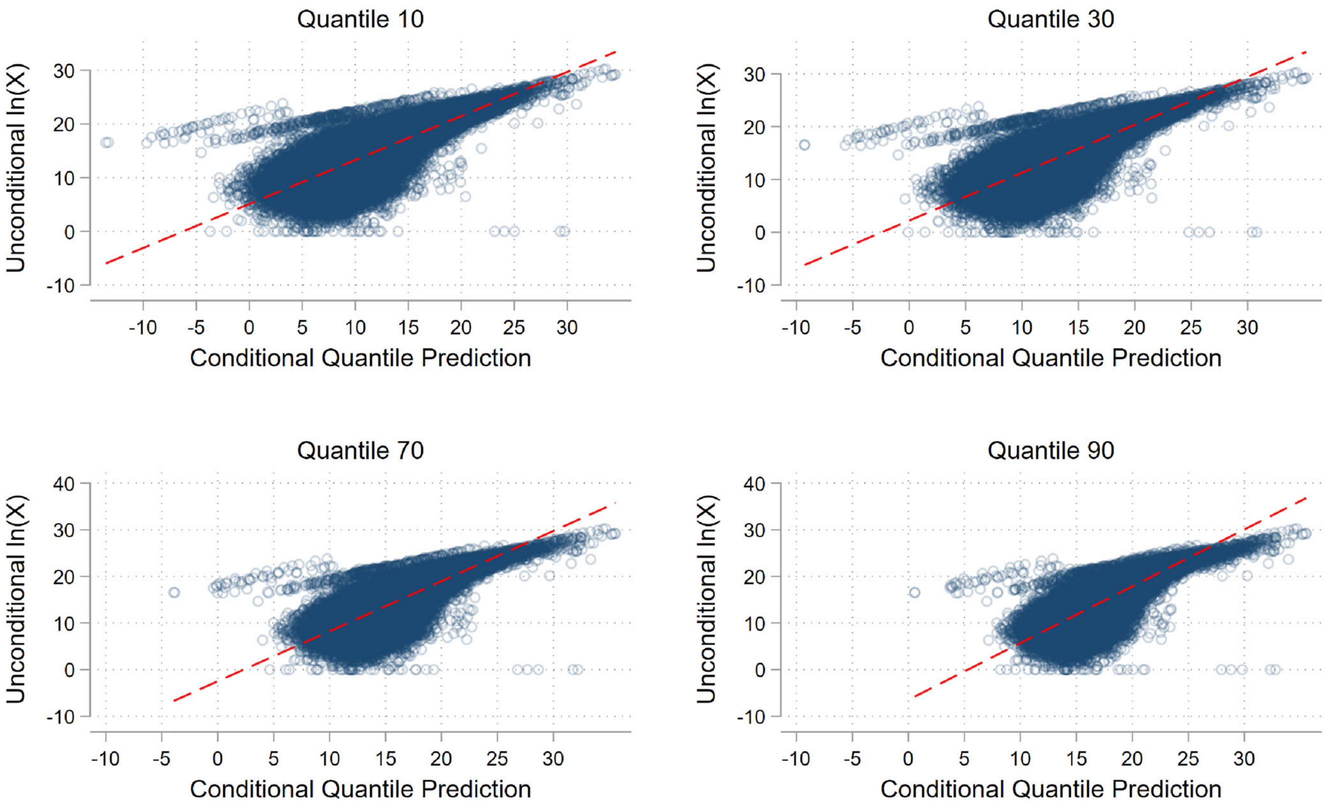

FIGURE 6 | BVQCM. [Colour figure can be viewed at wileyonlinelibrary.com]

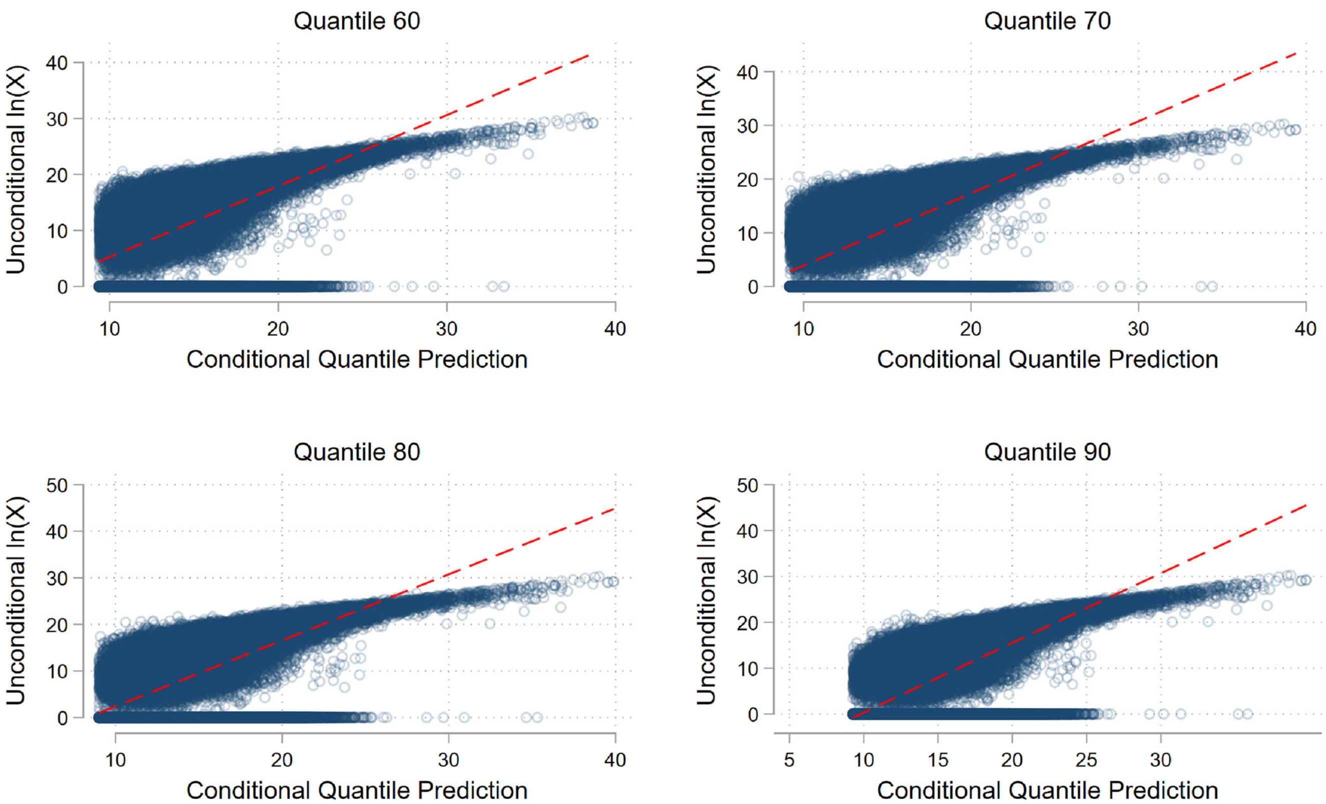

FIGURE 7 | Logit(BVCM)-BVQCM. [Colour figure can be viewed at wileyonlinelibrary.com]

8 | Unconditional vs. Conditional Quantiles

In this section, we discuss briefly the correlation between the conditional and unconditional dependent variables. A typical approach (cf., Machado et al. (2016)) uses the squared correlation of these two variables as a pseudo R^2, or a goodness of fit measure, of their estimations. Although not definitive, we find a clear positive correlation between the conditional quantile fitted values and the unconditional trade values.

For brevity, we discuss suggestive evidence of a positive relationship between conditional quantile predictions of the log of trade flows and the unconditional values of the log of trade flows. Recall from Tables 6 and 8, we have estimates of conditional quantile partial effects for positive trade flows and for non-negative trade flows, respectively. Figure 6 provides, for positive flows, a scatterplot as well as the fitted regression line between the unconditional values of the log of trade on the vertical axis and the conditional quantile predictions for four alternative quantiles (0.1, 0.3, 0.7, and 0.9). The scatterplots and fitted regression lines show a strong positive correlation between these values; the pseudo R^2 values for various quantiles are 63-65 percent. Figure 7 provides the analogous information based upon the Logit(BVCM)-BVQCM results for all non-negative trade flows. In this case, we examine the relationship between the unconditional logs of trade flows and their corresponding conditional quantile predictions for the quantiles of positive flows (0.6, 0.7 0.8, and 0.9). Again, the scatterplots and fitted regression lines show strong positive relationships; the pseudo R^2 values for various quantiles are 30–43 percent.[43]

9 | Conclusions

The purpose of this paper was to provide an alternative *conditional quantile* method for estimating the effects of economic integration agreements on trade flows – and, in principle, also for estimating trade elasticities – to the well established *conditional mean* estimators ordinary least squares (OLS) and Poisson pseudo maximum likelihood (PPML). We focused on quantile regressions (QRs), which have played only a limited role to date in evaluating one of two parameters that are *central* to quantifying the economic welfare gains or losses from trade-policy liberalizations.

First, QRs offer an alternative way to PPML to circumvent the Jensen's Inequality issue associated with OLS. The zeros issue is addressed using a novel extension of the Galvao et al. (2013) three-step estimator to account for zeros in trade and using Chamberlain-Mundlak-based correlated random effects to address unobserved heterogeneity, avoiding the incidental parameters problem associated with three-way fixed effects in the context of QRs.

Second, we found in general that the partial effect of an EIA at the median of positive trade flows using our three-step QR approach was fairly close to historical OLS conditional mean effects. Yet, we also found that at the highest conditional quantiles – where trade flows are likely the largest – our QR EIA partial effects were close to historical PPML conditional mean estimates.

Third, QR allowed us to examine empirically the theoretical proposition in Arkolakis (2010) and Kehoe and Ruhl (2013) that the effects of an economic integration agreement tend to be largest where initial trade volumes are *low* or, more accurately, at low conditional quantiles. While those earlier studies focused upon a few selected EIAs for selected time periods, we provided systematic evidence confirming Arkolakis' theoretical proposition over nearly the universe of EIAs and trade flows in the world spanning 50 years.

Fourth, we found strong evidence that developing country exporters benefit more from EIAs than non-developing country exporters. Our evidence suggests that developing countries' exports actually increase more than developed countries' exports in response to a trade liberalization.

Our study suggests a promising methodology for future analyses of the trade-flow and economic-welfare effects of trade-policy changes *across the distribution* of all trade flows.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

[1] The gravity equation has been the "workhorse" for explaining empirically determinants of international trade flows for over 60 years. Neglected early on for its absence of theoretical foundations, the trade gravity equation became more accepted with formal theoretical foundations in Anderson (1979), Helpman and Krugman (1985), Bergstrand (1985), Bergstrand (1989), and Bergstrand (1990). The trade gravity equation's embrace by the trade literature was solidified in influential papers such as Baier and Bergstrand (2001), Eaton and Kortum (2002), Anderson and van Wincoop (2003), Redding (2011), Arkolakis et al. (2012), Head and Mayer (2014), and Costinot and Rodriguez-Clare (2014). For an excellent recent discussion of the influence of the gravity equation, see Carrere et al. (2020); that paper also examines gravity equation relationships using quantile regression. While for implementation in this study we will focus on EIA (dummy variable) partial effect estimates, the methodology in this paper can be used also for estimating partial effects of *ad valorem* tariff rates or transport-cost factors. The use of EIA dummy variables captures

difficult-to-measure policy-related fixed trade costs alongside tariff rates, compare, United States International Trade Commission (2016).

[2] See HM Treasury (2016), Brakman et al. (2018), Dhingra et al. (2017), Felbermayr et al. (2017), Gudgin et al. (2017), and Oberhofer and Pfaffermayr (2021).

[3] We discuss other related papers in the next section.

[4] Although we discuss Arkolakis (2010)'s proposition later – that increasing marginal market-penetration costs reduce the effects of trade liberalization for firms with larger initial sales – there is a clear connection with Chen and Novy (2022). While Chen and Novy (2022) focus on import shares and Arkolakis (2010) on entry costs, both papers conclude that larger initial trade flows reduce the marginal effects of trade liberalization measures such as economic integration agreements (EIAs).

[5] We will compare predictions from the conditional distribution to those of the unconditional distribution later.

[6] It is important to note at the outset that the heterogeneous effects found at different points along the conditional distribution do not *definitively* imply that the EIA effects vary at these different points. Although the quantile model at each point is understood to be a local measure and is assumed to be robust to outliers and heteroskedasticity, a failure of these assumptions will lead to heterogeneous point estimates even when the EIA effects are homogeneous across the conditional distribution.

[7] To claim a causal interpretation of the estimates at each quantile, we must assume that $Q_\epsilon(\tau|X) = 0$ holds at each τ, which is analogous to the strict exogeneity assumption in OLS regression (Wooldridge 2010). As with most empirical research, since we cannot know with absolute certainty whether strict exogeneity holds or if the empirical model is correctly specified, we consider the estimates at each point along the conditional distribution to be approximations of the true quantile at τ. Wooldridge (2010) notes that common dependent variables such as wealth and income – and we argue the same for trade flows – have heteroskedastic errors and likely violate the independence assumption. He further explains that a monotonic transformation, such as a logarithmic transformation, of the dependent variable is more likely to satisfy the independence assumption.

[8] As will be discussed shortly, Figueiredo et al. (2014) and Figueiredo and Lima (2020) used a three-step panel approach originally suggested by Chernozhukov and Hong (2002), and adapted by Galvao et al. (2013), but included linear three-way fixed effects, which may suffer from IPP.

[9] The comprehensive discussion of the treatment of quantiles in the presence of zero trade flows is treated in Section 5.1. The essence of the approach is a two-stage procedure for "censored" quantile regression (noting that a third stage is used to simply guarantee efficiency). Zero trade flows play a role in the first stage. We use a binary estimation model (logit, linear probability, etc.) to "select" an "informative" subset of observations for the second stage. Specifically, we select some (and not necessarily the largest) subset of observations where the "true" qth conditional quantile line exceeds the censoring point. In the second step, we use this informative set of observations to estimate the conditional quantile functions.

[10] Baier et al. (2019) also provided some evidence (using conditional mean estimates) supporting Kehoe and Ruhl (2013) and Arkolakis (2010) that the smaller the extensive margin of trade (in the previous period) the larger the EIA partial effect, compare, their Section 5.2.2 and Table 3, columns (4) and (8).

[11] In the context of trade gravity equations, exporter per capita GDPs played a more prominent role prior to the New Quantitative Trade Models that largely exclude the variable. However, Bergstrand (1989) and Bergstrand (1990) provided a theoretical foundation for including exporter per capita GDP in a trade gravity equation.

[12] See International Monetary Fund and World Bank (2001).

[13] Also, one of the motivations for this exercise is that – due to the properties of the "Bonus Vetus" technique – there is a potential plethora of *country-specific* variables for which one could show that EIA effects differ by country variable (i.e., exporter per capita GDP is just one).

[14] Chen and Novy (2022) estimate trade cost heterogeneity using an interaction term between currency union binary variable and the logarithmic predicted import shares in a PPML model. Note that the authors must use the model estimates and assume values for the log predicted import shares to evaluate the heterogeneity across the conditional distribution. Models that rely on conditional mean estimates and interactions to show trade cost heterogeneity must make further assumptions about the interacted term to evaluate the partial effects of the variable of interest.

[15] Melitz and Redding (2015) provide a Melitz (2003)-based theoretical framework, but assuming *truncated* Pareto productivities, that motivates varying trade elasticities. Brooks and Pujolas (2019) introduce a general preference structure (additively separable utility) alongside a general technology (constant returns to scale) and intermediate goods that can be aggregated into final goods. Their Proposition 3 shows that the trade elasticity is variable owing to: (i) variable sectoral elasticities, (ii) varying curvature of the utility function, and/or (iii) variable compositions of expenditures by country pairs given a change in trade costs.

[16] Note that Figueiredo et al. (2014) used a conditional logit (*xtlogit* in Stata) to account for the large number of country-pair fixed effects and estimate the first stage propensity. Although the conditional logit accounts the country-pair fixed effects, it does not specifically provide estimates of the fixed effects and the calculated propensity scores assume that the fixed effects are equal to zero. This implies that the estimates of the fixed effects were not considered when calculating the propensity scores.

[17] In Figueiredo et al. (2014), the authors actually have two components to the second stage. First, they estimate an OLS specification with three-way fixed effects. Then, to avoid the *explicit* inclusion of the large number of pair fixed effects, they use the Canay (2011) procedure; this procedure de-means the LHS variable for the second stage to avoid including the pair fixed effects in the second step. However, a limitation of the Canay procedure is that it imposes a common pair fixed effect across *all* quantiles. Moreover, this procedure's validity has been questioned as it ignores asymptotic bias of estimates, compare, Besstremyannaya and Golovan (2019) and Chen and Huo (2021).

[18] We will discuss c_N later but just note now it is a small constant to exclude cases near the boundary.

[19] Heterogeneity in the trade effects of EIAs has also been examined empirically using expectile regression, compare, Bergstrand et al. (2024). Although quantile regressions can be interpreted as a generalization of median regression, expectile regressions can be interpreted as a generalization of mean regression. Based on the underlying conditional mean PPML method, asymmetric PPML allows estimating partial effects along the entire conditional distribution of trade flows while still accommodating standard three-way fixed effects and interpreting zeros as corners. Bergstrand et al. (2024), however, focuses on the role of larger effects at lower expectiles in terms of extensive margin expansions.

[20] This model assumes one factor of production, labor (L), where the wage rate per worker (W) is endogenous and a separate equation provides its determinants, alongside equations determining Π_{it} and Φ_{jt}. For brevity, we refer the reader to Baier, Kerr, and Yotov (2018) for the relevant specification of the wage-rate, Π_{it} and Φ_{jt} equations, noting here that W is a negative function of Π, that is, $W_{jt} = f(\Pi_{jt})$ with $\partial W_{jt}/\partial \Pi_{jt} < 0$.

[21] Baier and Bergstrand (2009b) introduced (nonparametric) matching econometrics to the analysis of EIAs.

[22] See Head and Mayer (2014), Section 3.6.

[23] It should be noted though that, after various percentages of the smallest trade flows were censored, the tetrad method of Head et al. (2010) had the least inconsistent estimates.

[24] See Table 3.3 in Head and Mayer (2014).

[25] As discussed in Baier and Bergstrand (2010), unweighted BV (or BVU) yields consistent estimates for estimation (as coefficient estimates are associated with deviations of variables from their means), whereas GDP-share-weighted BV (or BVW) best addresses comparative statics (for small changes). The principle behind the BV approach is that a first-order Taylor-series expansion of Equation (1) above generates an equation that is a linear function of observables described shortly. However, every Taylor-series expansion needs to be "centered" around a value. In Baier and Bergstrand (2009a), the expansion was centered around symmetric trade costs (t), yielding RHS variables that were GDP-share weighted (BVW). However, Baier and Bergstrand (2010), Section 4, show that a centering around symmetric trade costs *and* symmetric country sizes yields RHS variables that use simple weights (BVU). The latter leads to consistent coefficient estimates, as shown in Bergstrand et al. (2013) and Head and Mayer (2014).

[26] The data was downloaded from CEPII (http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=8) October 2021. The CEPII data set has an indicator for whether a country exists in year t and keep only country pairs where both countries existed.

[27] We can show that our results are robust to using annual data.

[28] Later in this paper, we will examine empirically in more detail the Arkolakis proposition using both disaggregated data as well as previous periods' export shares. Moreover, we will show later in Section 8 that there is a strong positive correlation between the logs of the unconditional trade flows and the conditional trade-flow predictions. Also, we use the term "partial" effect of an EIA even though – as constructed based upon theory – we are also controlling for exporter and importer "multilateral resistance" effects, following Baier and Bergstrand (2009b) and Baier and Bergstrand (2010) (MR in original papers, BV in the current paper).

[29] For $DISTBV$, we are referring to the absolute values of the partial effects.

[30] Galvao et al. (2013)'s empirical approach followed Tang et al. (2012) to use an "informative subset" for censored quantile estimation that did not rely on trimming and smoothing procedures discussed in Chernozhukov and Hong (2002), which can complicate the estimation.

[31] GLL suggest a parametric estimation of the propensity score. This could be a logit, probit, complementary log-log (Cloglog), or linear probability model (LPM).

[32] For robustness, we will also consider later a first stage linear probability and Cloglog models as well as logit and linear probability models with one- and three-way fixed effects for the first stage; see Sections 5.3.6 and 5.3.7 later. All models are estimated in Stata except for this first stage logit model (with and without fixed effects) which is estimated in R using the "feglm" command. This command significantly decreases the time to estimate, especially in the simulations later in the appendix where this first stage is continually repeated. We used the "rcall" Stata program described in Haghish (2021) to allow communication between R and Stata.

[33] This condition is similar to Chernozhukov and Hong (2002) and Tang et al. (2012).

[34] In the third stage, we cluster standard errors by country pairs.

[35] Note that our method is distinguished from the two-stage method in Helpman et al. (2008), or HMR. The HMR method is essentially a instrumental variable method to deal with omitted variable bias due to selection or observing only positive trade flows in the gravity model. Essentially, their first stage is used to estimate the inverse Mills ratio to account for selection bias. Our first stage, on the other hand, creates a sub-sample that meets the requirement that the propensity score is larger than $1 - q$, or a subset where the "true" qth conditional quantile line exceeds the censoring point. Noted in Galvao et al. (2013), focusing on a subset of observations that meets this criterion at each quantile will give the censored QR estimator at that quantile. Also, subsets meeting the criteria will include *both censored and uncensored observations* from the full sample.

[36] We calculate the marginal effect of $EIABV$ as:

$$\mathrm{ME}_{\mathrm{EIABV}} = \frac{\partial}{\partial EIABV} \max(0, \hat{Q}_{\tau}\left(\ln\left(X_{ijt}\right) | RHS_{ijt}, \overline{\omega}\right) \cdot Pr\left(\lambda_{ijt} = 1 | RHS_{ijt}, \overline{\omega}, C_{ijt}\right))$$

where $\mathrm{ME}_{\mathrm{EIABV}}$ is the marginal (partial) effect of EIABV, $\hat{Q}\tau\left(\ln(X_{ijt})|\mathrm{RHS}_{ijt}, \overline{\omega}\right)$ is the estimated conditional quantile function of $\ln(X_{ijt})$ at quantile τ given RHS_{ijt} and $\overline{\omega}$, and $\Pr\left(\lambda_{ijt} = 1|\mathrm{RHS}_{ijt}, \overline{\omega}, C_{ijt}\right)$ is the estimated propensity score from the first-stage logit model.

[37] We also considered using a uniform distribution to generate a random integer between 0.01 and 1; however, the first stage could not identify non-trading partners, which would require further assumptions.

[38] The estimation was performed using the *feglm* command in the R *fixest* package.

[39] At 2-digit SITC level, this leads to millions of observations, making QR estimation difficult. 4-digit SITC data would be practically infeasible.

[40] We use the methods described in Machado et al. (2016) to create comparable average marginal (partial) effects across quantiles at specified export shares. We will use the term marginal effects instead of average marginal effects, for brevity.

[41] Consequently, recall from earlier that, with fixed effects in the first step, intra-national trade flows are perfectly predicted and hence omitted in the second and third stage estimations.

[42] We have also experimented with alternative specifications to account for developing-developed countries, but for brevity only report this specification's results. The results are similar using alternative specifications.

[43] Firpo (2007) developed a method for estimation of the partial effects of regressors on quantiles of the *unconditional* distribution of the dependent variable. In the Online Supplement, we use this method to generate estimates of these "quantile treatment effects."

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1.** Supporting Information.

Appendix A

Appendix A reports results for various models. Specifically, Subsection A summarizes the estimates of average (partial) effects of EIAs on bilateral trade flows using conditional mean estimators OLS and PPML. Although not directly comparable to our QR estimates, a reference to estimates using OLS and PPML using the BV and CRE approaches might be useful. In Subsection A, the full results of the abbreviated Table 8 are presented in Tables A2–A10.

Conditional Mean Specifications

As discussed in Cameron and Trivedi (2005), Wooldridge (2010) and Baier, Kerr, and Yotov (2018), an alternative approach to three-way fixed effects to generate unbiased estimates of the EIA partial effect using OLS and PPML is to incorporate the *time averages* of all the RHS variables. The analogue to Equation (5) is:

$$\begin{aligned}\ln X_{ijt} = {} & \beta_0 + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} + \beta_3 EIABV_{ijt} + \beta_4 DISTBV_{ij} \\ & + \beta_5 CONTIGBV_{ij} + \beta_6 LANGBV_{ij} + \beta_7 LEGALBV_{ij} \\ & + \beta_9 COMCOLBV_{ij} + \sum_{t=1}^{T} \alpha_t INTER_{ij} \times YEAR_t \\ & + \beta_{10}\overline{\ln GDP_i} + \beta_{11}\overline{\ln GDP_j} + \beta_{12}\overline{EIABV_{ij}} + \ln \eta_{ijt} \qquad \text{(A1)}\end{aligned}$$

where bars over the variables denote the time-averaged means of the underlying variable. The analogous PPML specification is:

$$X_{ijt} = e^{\beta_0+\beta_1 \ln GDP_{it}+\beta_2 \ln GDP_{jt}+\beta_3 EIABV_{ijt}+\beta_4 DISTBV_{ij}+\beta_5 CONTIGBV_{ij}} \times e^{\beta_6 LANGBV_{ij}+\beta_7 LEGALBV_{ij}+\beta_8 RELIGBV_{ij}+\beta_9 COMCOLBV_{ij}} \times e^{\sum_{t=1}^{T}\alpha_t INTER_{ij}\times YEAR_t+\beta_{10}\overline{\ln GDP_i}+\beta_{11}\overline{\ln GDP_j}+\beta_{12}\overline{EIABV_{ij}}} \eta_{ijt} \quad \text{(A2)}$$

Table A1 summarizes the empirical results associated with the specifications discussed above. Table A1 is organized according to ten columns, with the first column providing identification of the right-hand-side (RHS) variables. Columns labeled (2–4) report the results of OLS specifications analogous to (A1) for BV without CRE, BV and CRE, and three-way fixed effects, respectfully. Columns labeled (5–7) report the results of PPML specifications analogous to (A2) with the same ordering as columns (2–4) for only positive trade flows, then similar for columns labeled (8–10) for non-negative trade flows.

Robustness Analysis

In Sub-section 5.3, we reported EIAs partial effects for various robustness analysis. The full tables are reported in this sub-section.

TABLE A1 | Methods comparison.

(1)	(2) BVOLS+	(3) BVOLS+	(4) FE-OLS+	(5) BVPPML+	(6) BVPPML+	(7) FE-PPML+	(8) BVPPML	(9) BVPPML	(10) FE-PPML
ln(GDPex)	1.076***	1.068***		0.577***	0.642***		0.564***	0.586***	
	(0.006)	(0.029)		(0.015)	(0.063)		(0.016)	(0.063)	
ln(GDPim)	0.919***	1.069***		0.575***	0.486***		0.595***	0.497***	
	(0.006)	(0.029)		(0.016)	(0.076)		(0.017)	(0.061)	
EIABV	0.699***	0.537***	0.385***	0.514***	0.490***	0.288***	0.450***	0.321***	0.277***
	(0.057)	(0.040)	(0.034)	(0.094)	(0.106)	(0.045)	(0.088)	(0.083)	(0.050)
DISTBV	−1.310***	−1.283***		−0.158***	−0.173***		−0.190***	−0.220***	
	(0.029)	(0.032)		(0.054)	(0.061)		(0.062)	(0.072)	
CONTIGBV	0.436***	0.402***		1.331***	1.340***		1.539***	1.507***	
	(0.094)	(0.095)		(0.173)	(0.181)		(0.186)	(0.209)	
LANGBV	0.463***	0.461***		0.244**	0.244**		0.217**	0.264**	
	(0.051)	(0.051)		(0.100)	(0.107)		(0.099)	(0.118)	
LEGALBV	0.265***	0.266***		−0.121	−0.127		−0.182**	−0.217**	
	(0.034)	(0.034)		(0.081)	(0.081)		(0.086)	(0.085)	
RELIGBV	0.315***	0.304***		−0.454**	−0.476**		−0.272	−0.244	
	(0.064)	(0.063)		(0.210)	(0.223)		(0.243)	(0.260)	
COMCOLBV	0.492***	0.471***		0.422	0.427		0.990***	1.003**	
	(0.063)	(0.064)		(0.268)	(0.292)		(0.368)	(0.395)	
Exp-Yr FE	No	No	Yes	No	No	Yes	No	No	Yes
Imp-Yr FE	No	No	Yes	No	No	Yes	No	No	Yes
Pair FE	No	No	Yes	No	No	Yes	No	No	Yes
BV	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
INTER × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	No	Yes	No	No	Yes	No	No	Yes	No
Adj. R2	0.635	0.635	0.862						
Pseudo R2				0.969	0.969	0.998	0.975	0.975	0.998
Obs	122999	122999	122999	122999	122999	122999	249705	249705	249705

Note: Clustered standard errors by country-pair are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The + indicates only positive trade values (i.e., $T_{ij} > 0$) were used in the estimation and includes intra-national trade. The BV abbreviation indicates "Bonus Vetus" methodology described in Baier and Bergstrand (2009a) and Baier and Bergstrand (2010). OLS and PPML are abbreviations for ordinary least squares and Poisson pseudo maximum likelihood, respectively. "FE" denotes the three-way (full) fixed effects specification. "INTER × Year FE" indicates the interaction of a dummy variable that is 1 if international trade and 0 otherwise, and a year dummy variable were included or not; "CRE" indicates whether correlated random effects were used or not. Note that singletons and separated observations were kept in columns 4, 7, and 10, but only the standard errors change marginally and coefficients are not affected. The "FE" specifications using EIA rather than EIABV yielded identical coefficient estimates. As discussed in the text, the coefficient estimates for EIA in columns (4), (7), and (10) are identical using $EIABV_{ijt}$ or EIA_{ijt}; the reason is that the exporter-year and importer-year FEs capture all of multilateral resistance elements inside $EIABV_{ijt}$.

TABLE A2 | Cloglog(BVCM)-BVQCM.

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
ln(GDPex)	0.859***	1.029***	1.017***	1.012***	0.950***	0.916***	0.864***	0.760***	0.607***
	(0.128)	(0.068)	(0.047)	(0.038)	(0.029)	(0.024)	(0.020)	(0.016)	(0.014)
ln(GDPim)	1.629***	1.336***	1.197***	1.054***	0.938***	0.838***	0.758***	0.674***	0.584***
	(0.152)	(0.087)	(0.053)	(0.040)	(0.030)	(0.026)	(0.022)	(0.018)	(0.016)
EIABV	1.622***	1.062***	0.742***	0.648***	0.567***	0.512***	0.374***	0.197***	0.141***
	(0.249)	(0.108)	(0.072)	(0.054)	(0.045)	(0.041)	(0.035)	(0.030)	(0.032)
DISTBV	−0.790***	−1.010***	−1.066***	−1.127***	−1.113***	−1.075***	−1.020***	−0.960***	−0.881***
	(0.140)	(0.081)	(0.050)	(0.038)	(0.030)	(0.026)	(0.022)	(0.019)	(0.017)
CONTIGBV	−0.227	−0.126	0.111	0.236*	0.451***	0.572***	0.602***	0.680***	0.643***
	(0.273)	(0.178)	(0.142)	(0.123)	(0.109)	(0.096)	(0.090)	(0.090)	(0.080)
LANGBV	0.196	0.205	0.206**	0.292***	0.341***	0.408***	0.451***	0.429***	0.379***
	(0.243)	(0.140)	(0.094)	(0.072)	(0.060)	(0.055)	(0.047)	(0.041)	(0.038)
LEGALBV	0.549***	0.448***	0.418***	0.366***	0.297***	0.262***	0.223***	0.197***	0.156***
	(0.165)	(0.094)	(0.067)	(0.051)	(0.041)	(0.037)	(0.032)	(0.028)	(0.025)
RELIGBV	0.144	0.351*	0.271**	0.248***	0.239***	0.220***	0.234***	0.266***	0.264***
	(0.424)	(0.200)	(0.120)	(0.090)	(0.075)	(0.065)	(0.055)	(0.048)	(0.045)
COMCOLBV	1.620***	0.944***	0.687***	0.471***	0.405***	0.289***	0.262***	0.275***	0.337***
	(0.485)	(0.278)	(0.179)	(0.130)	(0.099)	(0.080)	(0.065)	(0.052)	(0.043)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
INTER × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.135	0.197	0.204	0.223	0.252	0.293	0.339	0.398	0.459
Obs	20134	39028	57159	76498	97985	123196	152118	185143	220960

Note: Clustered standard errors by country-pair are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The prefix "Cloglog(BVCM)-" indicates that the three-stage estimation procedure described by Galvao et al. (2013) was implemented to account for zeros in quantile regressions. The first stage is a complementary log-log model that uses "Bonus Vetus" (BV) methodology described in Baier and Bergstrand (2009a) and Baier and Bergstrand (2010) and correlated random effects (CM) using all trade pairs (i.e., $T_{ij} \geq 0$). The second and third stages are both quantile regressions using Frisch-Newton interior point method at each decile. "BV" and "CRE" indicate that "Bonus Vetus" and correlated random effects were used or not in the second and third stages. "INTER × Year FE" indicates the interaction of a dummy variable that is 1 if international trade and 0 otherwise, and a year dummy variable were included or not in all three stages. Following Machado et al. (2016), the squared correlation of ln X_{ijt} and the fitted values $Quant_q(\ln X_{ijt})$ are reported as the pseudo R^2.

TABLE A3 | LPM(BVCM)-BVQCM.

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
ln(GDPex)	0.717***	0.968***	0.967***	0.974***	0.923***	0.888***	0.850***	0.755***	0.617***
	(0.179)	(0.067)	(0.046)	(0.036)	(0.028)	(0.024)	(0.020)	(0.016)	(0.014)
ln(GDPim)	2.362***	1.386***	1.192***	1.065***	0.955***	0.830***	0.768***	0.685***	0.597***
	(0.396)	(0.091)	(0.051)	(0.039)	(0.030)	(0.025)	(0.022)	(0.018)	(0.016)
EIABV	1.931***	0.941***	0.680***	0.516***	0.469***	0.398***	0.282***	0.164***	0.138***
	(0.551)	(0.106)	(0.070)	(0.052)	(0.045)	(0.040)	(0.035)	(0.030)	(0.032)
DISTBV	−0.589***	−0.920***	−1.000***	−1.080***	−1.094***	−1.072***	−1.028***	−0.974***	−0.885***
	(0.182)	(0.077)	(0.050)	(0.037)	(0.029)	(0.025)	(0.022)	(0.019)	(0.017)
CONTIGBV	−0.418	−0.104	0.120	0.183	0.384***	0.491***	0.564***	0.642***	0.646***
	(0.408)	(0.172)	(0.140)	(0.125)	(0.110)	(0.095)	(0.090)	(0.091)	(0.080)
LANGBV	0.420	0.138	0.137	0.333***	0.364***	0.436***	0.458***	0.438***	0.379***
	(0.379)	(0.141)	(0.094)	(0.070)	(0.059)	(0.053)	(0.047)	(0.041)	(0.038)
LEGALBV	0.545	0.503***	0.452***	0.332***	0.271***	0.220***	0.205***	0.190***	0.161***
	(0.380)	(0.092)	(0.065)	(0.050)	(0.041)	(0.036)	(0.032)	(0.028)	(0.025)
RELIGBV	0.037	0.301	0.234**	0.291***	0.287***	0.265***	0.275***	0.275***	0.263***
	(0.578)	(0.196)	(0.117)	(0.090)	(0.075)	(0.064)	(0.055)	(0.048)	(0.045)
COMCOLBV	1.725**	0.882***	0.640***	0.438***	0.304***	0.275***	0.251***	0.292***	0.341***
	(0.716)	(0.268)	(0.178)	(0.126)	(0.098)	(0.079)	(0.064)	(0.051)	(0.043)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
INTER × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.128	0.194	0.203	0.232	0.273	0.317	0.365	0.417	0.455
Obs	21313	37018	58970	86203	113354	139885	167535	196636	219481

Note: Clustered standard errors by country-pair are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The prefix "LPM(BVCM)-" indicates that the three-stage estimation procedure described by Galvao et al. (2013) was implemented to account for zeros in quantile regressions. The first stage is a linear probability model that uses "Bonus Vetus" (BV) methodology described in Baier and Bergstrand (2009a) and Baier and Bergstrand (2010) and correlated random effects (CM) using all trade pairs (i.e., $T_{ij} \geq 0$). The second and third stages are both quantile regressions using Frisch-Newton interior point method at each decile. "BV" and "CRE" indicate that "Bonus Vetus" and correlated random effects were used or not in the second and third stages. "INTER × Year FE" indicates the interaction of a dummy variable that is 1 if international trade and 0 otherwise, and a year dummy variable were included or not in all three stages. Following Machado et al. (2016), the squared correlation of ln X_{ijt} and the fitted values $Quant_q(\ln X_{ijt})$ are reported as the pseudo R^2.

TABLE A4 | Logit(BVCM)-BVQCM: Adding 1 to all trade values.

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
ln(GDPex)	0.775***	1.014***	1.013***	1.005***	0.955***	0.931***	0.886***	0.789***	0.638***
	(0.175)	(0.074)	(0.049)	(0.038)	(0.030)	(0.025)	(0.021)	(0.017)	(0.015)
ln(GDPim)	2.506***	1.551***	1.203***	1.081***	0.975***	0.861***	0.792***	0.703***	0.623***
	(0.391)	(0.099)	(0.057)	(0.042)	(0.032)	(0.027)	(0.022)	(0.019)	(0.016)
EIABV	2.286	1.034***	0.728***	0.565***	0.544***	0.482***	0.391***	0.231***	0.164***
	(1.497)	(0.131)	(0.080)	(0.057)	(0.047)	(0.042)	(0.036)	(0.031)	(0.031)
DISTBV	−0.577**	−0.874***	−1.084***	−1.164***	−1.155***	−1.115***	−1.049***	−0.982***	−0.888***
	(0.245)	(0.089)	(0.057)	(0.040)	(0.031)	(0.027)	(0.023)	(0.020)	(0.017)
CONTIGBV	−0.843	−0.228	0.042	0.216	0.410***	0.539***	0.623***	0.701***	0.687***
	(1.290)	(0.207)	(0.163)	(0.133)	(0.113)	(0.098)	(0.093)	(0.093)	(0.081)
LANGBV	0.270	0.278*	0.296***	0.377***	0.373***	0.438***	0.460***	0.435***	0.384***
	(0.570)	(0.164)	(0.106)	(0.075)	(0.062)	(0.056)	(0.049)	(0.043)	(0.039)
LEGALBV	0.582	0.458***	0.387***	0.319***	0.287***	0.252***	0.225***	0.220***	0.181***
	(0.923)	(0.107)	(0.074)	(0.054)	(0.043)	(0.038)	(0.033)	(0.029)	(0.025)
RELIGBV	0.023	0.446**	0.364***	0.353***	0.294***	0.242***	0.233***	0.252***	0.245***
	(0.601)	(0.214)	(0.132)	(0.097)	(0.078)	(0.067)	(0.057)	(0.050)	(0.046)
COMCOLBV	2.009	0.842***	0.701***	0.491***	0.379***	0.322***	0.277***	0.282***	0.333***
	(1.522)	(0.286)	(0.193)	(0.134)	(0.102)	(0.082)	(0.067)	(0.054)	(0.044)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
INTER × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.096	0.201	0.211	0.232	0.262	0.298	0.337	0.382	0.432
Obs	22739	47303	69033	89031	108901	130925	153708	178253	206294

Note: Clustered standard errors by country-pair are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The prefix "Logit(BVCM)-" indicates that the three-stage estimation procedure described by Galvao et al. (2013) was implemented to account for zeros in quantile regressions. The first stage is a logit model that uses "Bonus Vetus" (BV) methodology described in Baier and Bergstrand (2009a) and Baier and Bergstrand (2010) and correlated random effects (CM) using all trade pairs (i.e., $T_{ij} \geq 0$). The second and third stages are both quantile regressions using Frisch-Newton interior point method at each decile. "BV" and "CRE" indicate that "Bonus Vetus" and correlated random effects were used or not in the second and third stages. "INTER × Year FE" indicates the interaction of a dummy variable that is 1 if international trade and 0 otherwise, and a year dummy variable were included or not in all three stages. Following Machado et al. (2016), the squared correlation of $\ln X_{ijt}$ and the fitted values $Quant_q(\ln X_{ijt})$ are reported as the pseudo R^2. We add one to all trade flows to accommodate zeros.

TABLE A5 | Logit(BVCM)-BVQCM: User defined minimum \$10,000.

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
ln(GDPex)	0.653***	1.004***	0.979***	0.972***	0.928***	0.880***	0.841***	0.743***	0.601***
	(0.203)	(0.078)	(0.048)	(0.036)	(0.028)	(0.024)	(0.020)	(0.016)	(0.014)
ln(GDPim)	2.982***	1.474***	1.211***	1.048***	0.937***	0.849***	0.759***	0.675***	0.589***
	(0.620)	(0.104)	(0.056)	(0.040)	(0.030)	(0.026)	(0.021)	(0.018)	(0.015)
EIABV	2.268***	0.992***	0.660***	0.552***	0.520***	0.477***	0.384***	0.256***	0.171***
	(0.574)	(0.138)	(0.075)	(0.053)	(0.043)	(0.040)	(0.034)	(0.029)	(0.028)
DISTBV	−0.536***	−0.869***	−1.022***	−1.082***	−1.059***	−1.017***	−0.955***	−0.880***	−0.801***
	(0.193)	(0.093)	(0.055)	(0.039)	(0.029)	(0.026)	(0.022)	(0.019)	(0.016)
CONTIGBV	−0.908	−0.164	0.046	0.243**	0.424***	0.560***	0.600***	0.686***	0.671***
	(0.662)	(0.226)	(0.148)	(0.120)	(0.104)	(0.093)	(0.085)	(0.084)	(0.074)
LANGBV	0.147	0.184	0.197*	0.262***	0.307***	0.357***	0.401***	0.391***	0.356***
	(0.401)	(0.174)	(0.102)	(0.074)	(0.060)	(0.054)	(0.047)	(0.041)	(0.037)
LEGALBV	0.479	0.453***	0.421***	0.339***	0.301***	0.271***	0.223***	0.217***	0.174***
	(0.321)	(0.115)	(0.072)	(0.052)	(0.041)	(0.037)	(0.032)	(0.027)	(0.024)
RELIGBV	0.216	0.386*	0.326***	0.282***	0.231***	0.185***	0.182***	0.196***	0.203***
	(0.651)	(0.231)	(0.126)	(0.093)	(0.074)	(0.065)	(0.055)	(0.047)	(0.043)
COMCOLBV	2.631***	1.149***	0.809***	0.517***	0.410***	0.289***	0.277***	0.259***	0.272***
	(0.870)	(0.309)	(0.195)	(0.134)	(0.097)	(0.080)	(0.064)	(0.052)	(0.042)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
INTER × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.102	0.190	0.194	0.213	0.238	0.271	0.310	0.355	0.411
Obs	23502	44377	62840	80134	97223	115679	136192	159122	187499

Note: Clustered standard errors by country-pair are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The prefix "Logit(BVCM)-" indicates that the three-stage estimation procedure described by Galvao et al. (2013) was implemented to account for zeros in quantile regressions. The first stage is a logit model that uses "Bonus Vetus" (BV) methodology described in Baier and Bergstrand (2009a) and Baier and Bergstrand (2010) and correlated random effects (CM) using all trade pairs (i.e., $T_{ij} \geq 0$). The second and third stages are both quantile regressions using Frisch-Newton interior point method at each decile. "BV" and "CRE" indicate that "Bonus Vetus" and correlated random effects were used or not in the second and third stages. "INTER × Year FE" indicates the interaction of a dummy variable that is 1 if international trade and 0 otherwise, and a year dummy variable were included or not in all three stages. Following Machado et al. (2016), the squared correlation of $\ln X_{ijt}$ and the fitted values $Quant_q(\ln X_{ijt})$ are reported as the pseudo R^2. We replace all trade values less than \$10,000 to one to allow for approximations of zeros.

TABLE A6 | Logit(BVCM)-BVQCM: FTA vs. Deep agreements.

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
ln(GDPex)	0.743***	1.033***	1.016***	0.997***	0.954***	0.928***	0.882***	0.788***	0.637***
	(0.157)	(0.073)	(0.049)	(0.037)	(0.030)	(0.025)	(0.021)	(0.017)	(0.015)
ln(GDPim)	2.501***	1.549***	1.206***	1.083***	0.980***	0.863***	0.793***	0.704***	0.625***
	(0.459)	(0.099)	(0.055)	(0.041)	(0.032)	(0.027)	(0.022)	(0.019)	(0.016)
FTABV	2.115***	1.008***	0.709***	0.535***	0.482***	0.391***	0.274***	0.151***	0.116***
	(0.819)	(0.128)	(0.078)	(0.056)	(0.047)	(0.042)	(0.036)	(0.031)	(0.030)
CUCMECUBV	2.902***	1.143***	0.707***	0.563***	0.619***	0.559***	0.495***	0.426***	0.437***
	(1.064)	(0.196)	(0.120)	(0.087)	(0.071)	(0.061)	(0.052)	(0.048)	(0.065)
DISTBV	−0.595***	−0.918***	−1.117***	−1.178***	−1.161***	−1.113***	−1.057***	−0.985***	−0.886***
	(0.190)	(0.088)	(0.056)	(0.038)	(0.030)	(0.026)	(0.022)	(0.020)	(0.017)
CONTIGBV	−0.963*	−0.177	0.149	0.322**	0.473***	0.548***	0.584***	0.678***	0.690***
	(0.568)	(0.223)	(0.161)	(0.126)	(0.103)	(0.091)	(0.088)	(0.091)	(0.080)
LANGBV	0.320	0.195	0.292***	0.368***	0.371***	0.419***	0.443***	0.433***	0.385***
	(0.356)	(0.172)	(0.108)	(0.074)	(0.061)	(0.055)	(0.048)	(0.042)	(0.039)
LEGALBV	0.504*	0.446***	0.369***	0.310***	0.276***	0.242***	0.223***	0.215***	0.181***
	(0.273)	(0.109)	(0.074)	(0.053)	(0.043)	(0.038)	(0.033)	(0.029)	(0.025)
RELIGBV	0.117	0.370*	0.259*	0.282***	0.255***	0.236***	0.240***	0.238***	0.245***
	(0.589)	(0.224)	(0.140)	(0.099)	(0.078)	(0.067)	(0.057)	(0.049)	(0.046)
COMCOLBV	2.004**	0.866***	0.708***	0.543***	0.428***	0.367***	0.316***	0.310***	0.328***
	(0.938)	(0.286)	(0.191)	(0.133)	(0.100)	(0.081)	(0.067)	(0.053)	(0.044)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
INTER × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.096	0.202	0.212	0.234	0.263	0.299	0.337	0.382	0.432
Obs	22702	47314	69055	89096	108988	130985	153726	178234	206240

Note: Clustered standard errors by country-pair are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The prefix "Logit(BVCM)-" indicates that the three-stage estimation procedure described by Galvao et al. (2013) was implemented to account for zeros in quantile regressions. The first stage is a logit model that uses "Bonus Vetus" (BV) methodology described in Baier and Bergstrand (2009a) and Baier and Bergstrand (2010) and correlated random effects (CM) using all trade pairs (i.e., $T_{ij} \geq 0$). The second and third stages are both quantile regressions using Frisch-Newton interior point method at each decile. "BV" and "CRE" indicate that "Bonus Vetus" and correlated random effects were used or not in the second and third stages. "INTER × Year FE" indicates the interaction of a dummy variable that is 1 if international trade and 0 otherwise, and a year dummy variable were included or not in all three stages. Following Machado et al. (2016), the squared correlation of $\ln X_{ijt}$ and the fitted values $Quant_q(\ln X_{ijt})$ are reported as the pseudo R^2. The terms FTA and CUCMECU indicate Free Trade Agreements and deeper trade agreements (including Customs Unions, Common Markets, and Economic Unions), respectively.

TABLE A7 | Logit(BV1FE)-BVQCM.

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
ln(GDPex)	1.167***	1.403***	1.150***	1.006***	0.983***	1.026***	0.890***	0.758***	0.598***
	(0.246)	(0.114)	(0.077)	(0.054)	(0.044)	(0.036)	(0.030)	(0.025)	(0.022)
ln(GDPim)	1.049***	0.941***	1.151***	1.090***	1.019***	1.038***	0.933***	0.802***	0.659***
	(0.216)	(0.104)	(0.065)	(0.048)	(0.040)	(0.035)	(0.029)	(0.025)	(0.021)
EIABV	2.072***	0.917***	0.813***	0.705***	0.536***	0.354***	0.236***	0.156***	0.108**
	(0.323)	(0.192)	(0.158)	(0.117)	(0.089)	(0.077)	(0.066)	(0.056)	(0.051)
DISTBV	−1.166***	−1.335***	−1.301***	−1.246***	−1.187***	−1.122***	−1.045***	−0.947***	−0.809***
	(0.157)	(0.074)	(0.054)	(0.042)	(0.035)	(0.032)	(0.027)	(0.024)	(0.022)
CONTIGBV	0.374	0.462	0.643***	0.691***	0.517***	0.496***	0.400***	0.334***	0.264***
	(0.458)	(0.329)	(0.235)	(0.176)	(0.144)	(0.131)	(0.113)	(0.093)	(0.081)
LANGBV	0.897***	0.144	0.191	0.184**	0.188**	0.240***	0.320***	0.314***	0.275***
	(0.293)	(0.153)	(0.116)	(0.089)	(0.078)	(0.070)	(0.062)	(0.054)	(0.049)
LEGALBV	0.233	0.274**	0.346***	0.332***	0.286***	0.255***	0.196***	0.178***	0.128***
	(0.218)	(0.107)	(0.075)	(0.061)	(0.050)	(0.044)	(0.039)	(0.035)	(0.031)
RELIGBV	−0.383	0.101	0.122	0.177	0.185**	0.159*	0.166**	0.178***	0.176***
	(0.415)	(0.224)	(0.149)	(0.115)	(0.093)	(0.083)	(0.072)	(0.066)	(0.060)
COMCOLBV	0.350	0.389*	0.370**	0.413***	0.515***	0.477***	0.445***	0.396***	0.353***
	(0.492)	(0.209)	(0.161)	(0.120)	(0.093)	(0.079)	(0.067)	(0.058)	(0.051)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.290	0.250	0.225	0.195	0.184	0.170	0.172	0.179	0.192
Obs	18863	33044	45076	55675	65352	76591	87473	100466	117041

Note: Clustered standard errors by country-pair are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The prefix "Logit(BV1FE)-" indicates that the three-stage estimation procedure described by Galvao et al. (2013) was implemented to account for zeros in quantile regressions. The first stage is a logit model with country-pair fixed effects, "Bonus Vetus" (BV) methodology described in Baier and Bergstrand (2009a) and Baier and Bergstrand (2010), and correlated random effects (CM) using all trade pairs (i.e., $T_{ij} \geq 0$). The second and third stages are both quantile regressions using Frisch-Newton interior point method at each decile. "BV" and "CRE" indicate that "Bonus Vetus" and correlated random effects were used or not in the second and third stages. "INTER × Year FE" indicates the interaction of a dummy variable that is 1 if international trade and 0 otherwise, and a year dummy variable were included or not in all three stages. Following Machado et al. (2016), the squared correlation of $\ln X_{ijt}$ and the fitted values $Quant_q(\ln X_{ijt})$ are reported as the pseudo R^2.

TABLE A8 | Logit(3FE)-BVQCM.

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
ln(GDPex)	1.101***	1.159***	1.130***	1.068***	1.015***	0.969***	0.919***	0.844***	0.714***
	(0.079)	(0.057)	(0.051)	(0.043)	(0.037)	(0.033)	(0.030)	(0.028)	(0.029)
ln(GDPim)	1.145***	1.111***	1.093***	1.039***	1.005***	0.955***	0.905***	0.844***	0.750***
	(0.068)	(0.052)	(0.045)	(0.039)	(0.033)	(0.030)	(0.028)	(0.027)	(0.028)
EIABV	1.241***	0.891***	0.774***	0.672***	0.547***	0.387***	0.226***	0.180***	0.166**
	(0.193)	(0.138)	(0.113)	(0.100)	(0.080)	(0.072)	(0.068)	(0.062)	(0.066)
DISTBV	−1.667***	−1.558***	−1.510***	−1.469***	−1.418***	−1.346***	−1.272***	−1.175***	−1.054***
	(0.063)	(0.044)	(0.044)	(0.038)	(0.035)	(0.032)	(0.030)	(0.029)	(0.030)
CONTIGBV	0.647**	0.908***	0.826***	0.684***	0.583***	0.556***	0.494***	0.428***	0.371***
	(0.270)	(0.179)	(0.161)	(0.144)	(0.137)	(0.137)	(0.120)	(0.106)	(0.106)
LANGBV	0.499***	0.377***	0.377***	0.360***	0.344***	0.385***	0.405***	0.397***	0.361***
	(0.129)	(0.102)	(0.090)	(0.084)	(0.079)	(0.073)	(0.067)	(0.064)	(0.064)
LEGALBV	0.299***	0.274***	0.268***	0.284***	0.284***	0.252***	0.234***	0.172***	0.130***
	(0.086)	(0.069)	(0.061)	(0.055)	(0.049)	(0.046)	(0.043)	(0.041)	(0.040)
RELIGBV	−0.110	0.082	0.197*	0.160	0.162*	0.201**	0.228***	0.255***	0.269***
	(0.172)	(0.131)	(0.118)	(0.101)	(0.090)	(0.084)	(0.081)	(0.080)	(0.080)
COMCOLBV	0.641***	0.567***	0.608***	0.673***	0.698***	0.648***	0.567***	0.552***	0.485***
	(0.160)	(0.129)	(0.110)	(0.096)	(0.087)	(0.079)	(0.072)	(0.068)	(0.065)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.449	0.419	0.398	0.383	0.374	0.370	0.371	0.374	0.381
Obs	48784	55408	60531	64936	69199	73286	77920	83170	89433

Note: Clustered standard errors by country-pair are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The prefix "Logit(3FE)-" indicates that the three-stage estimation procedure described by Galvao et al. (2013) was implemented to account for zeros in quantile regressions. The first stage is a logit model with exporter-year, importer-year, and country-pair fixed effects using all trade pairs (i.e., $T_{ij} \geq 0$). The second and third stages are both quantile regressions using Frisch-Newton interior point method at each decile. "BV" and "CRE" indicate that "Bonus Vetus" and correlated random effects were used or not in the second and third stages. "INTER × Year FE" indicates the interaction of a dummy variable that is 1 if international trade and 0 otherwise, and a year dummy variable were included or not in all three stages. Following Machado et al. (2016), the squared correlation of $\ln X_{ijt}$ and the fitted values $Quant_q(\ln X_{ijt})$ are reported as the pseudo R^2.

TABLE A9 | LPM(BV1FE)-BVQCM.

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
ln(GDPex)	1.048***	1.101***	1.043***	1.023***	1.000***	0.922***	0.858***	0.762***	0.642***
	(0.055)	(0.036)	(0.031)	(0.027)	(0.024)	(0.021)	(0.019)	(0.017)	(0.015)
ln(GDPim)	0.954***	0.906***	0.923***	0.979***	0.963***	0.873***	0.781***	0.703***	0.614***
	(0.057)	(0.037)	(0.031)	(0.027)	(0.024)	(0.022)	(0.020)	(0.018)	(0.016)
EIABV	0.797***	0.715***	0.647***	0.597***	0.493***	0.452***	0.353***	0.239***	0.180***
	(0.083)	(0.054)	(0.045)	(0.041)	(0.038)	(0.035)	(0.033)	(0.030)	(0.031)
DISTBV	−1.157***	−1.181***	−1.192***	−1.171***	−1.127***	−1.084***	−1.039***	−0.969***	−0.895***
	(0.062)	(0.038)	(0.032)	(0.027)	(0.024)	(0.022)	(0.021)	(0.019)	(0.018)
CONTIGBV	−0.077	0.156	0.306***	0.315***	0.390***	0.468***	0.547***	0.669***	0.646***
	(0.130)	(0.105)	(0.102)	(0.098)	(0.093)	(0.089)	(0.089)	(0.089)	(0.083)
LANGBV	0.068	0.133*	0.158**	0.236***	0.300***	0.353***	0.399***	0.385***	0.362***
	(0.097)	(0.070)	(0.062)	(0.057)	(0.052)	(0.048)	(0.044)	(0.041)	(0.039)
LEGALBV	0.457***	0.428***	0.451***	0.401***	0.347***	0.300***	0.260***	0.247***	0.194***
	(0.073)	(0.052)	(0.043)	(0.038)	(0.035)	(0.032)	(0.030)	(0.027)	(0.025)
RELIGBV	0.391***	0.351***	0.204***	0.213***	0.188***	0.174***	0.183***	0.211***	0.220***
	(0.135)	(0.094)	(0.077)	(0.067)	(0.060)	(0.054)	(0.051)	(0.047)	(0.046)
COMCOLBV	0.452**	0.551***	0.452***	0.453***	0.406***	0.409***	0.391***	0.385***	0.387***
	(0.180)	(0.127)	(0.100)	(0.079)	(0.071)	(0.064)	(0.056)	(0.050)	(0.044)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.614	0.537	0.467	0.405	0.374	0.365	0.372	0.397	0.429
Obs	49918	70234	86398	101086	118166	135300	155913	178037	201148

Note: Clustered standard errors by country-pair are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The prefix "LPM(BV1FE)-" indicates that the three-stage estimation procedure described by Galvao et al. (2013) was implemented to account for zeros in quantile regressions. The first stage is a linear probability model with country-pair fixed effects, "Bonus Vetus" (BV) methodology described in Baier and Bergstrand (2009a) and Baier and Bergstrand (2010), and correlated random effects (CM) using all trade pairs (i.e., $T_{ij} \geq 0$). The second and third stages are both quantile regressions using Frisch-Newton interior point method at each decile. "BV" and "CRE" indicate that "Bonus Vetus" and correlated random effects were used or not in the second and third stages. "INTER × Year FE" indicates the interaction of a dummy variable that is 1 if international trade and 0 otherwise, and a year dummy variable were included or not in all three stages. Following Machado et al. (2016), the squared correlation of ln X_{ijt} and the fitted values $Quant_q(\ln X_{ijt})$ are reported as the pseudo R^2.

TABLE A10 | LPM(3FE)-BVQCM.

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
ln(GDPex)	1.105***	1.058***	1.008***	1.008***	0.975***	0.949***	0.907***	0.824***	0.697***
	(0.046)	(0.033)	(0.028)	(0.026)	(0.023)	(0.021)	(0.019)	(0.017)	(0.016)
ln(GDPim)	1.046***	0.982***	0.927***	0.897***	0.874***	0.842***	0.795***	0.745***	0.661***
	(0.047)	(0.032)	(0.027)	(0.025)	(0.022)	(0.021)	(0.020)	(0.019)	(0.018)
EIABV	0.784***	0.763***	0.716***	0.649***	0.566***	0.486***	0.359***	0.234***	0.207***
	(0.072)	(0.051)	(0.043)	(0.038)	(0.036)	(0.035)	(0.033)	(0.032)	(0.034)
DISTBV	−1.251***	−1.225***	−1.240***	−1.243***	−1.228***	−1.201***	−1.151***	−1.069***	−0.963***
	(0.048)	(0.035)	(0.029)	(0.025)	(0.024)	(0.023)	(0.021)	(0.020)	(0.019)
CONTIGBV	−0.055	0.147	0.308***	0.406***	0.443***	0.531***	0.623***	0.691***	0.659***
	(0.122)	(0.099)	(0.098)	(0.098)	(0.091)	(0.099)	(0.097)	(0.094)	(0.087)
LANGBV	0.099	0.191***	0.255***	0.317***	0.375***	0.426***	0.440***	0.426***	0.391***
	(0.083)	(0.063)	(0.058)	(0.054)	(0.051)	(0.050)	(0.046)	(0.043)	(0.042)
LEGALBV	0.571***	0.470***	0.411***	0.361***	0.334***	0.313***	0.299***	0.253***	0.207***
	(0.062)	(0.046)	(0.040)	(0.036)	(0.034)	(0.033)	(0.031)	(0.029)	(0.027)
RELIGBV	0.255**	0.228***	0.158**	0.119*	0.142**	0.146***	0.198***	0.234***	0.229***
	(0.121)	(0.085)	(0.070)	(0.063)	(0.058)	(0.055)	(0.053)	(0.051)	(0.050)
COMCOLBV	0.351**	0.447***	0.466***	0.494***	0.489***	0.458***	0.442***	0.445***	0.412***
	(0.139)	(0.104)	(0.084)	(0.073)	(0.068)	(0.064)	(0.057)	(0.052)	(0.047)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.646	0.611	0.572	0.533	0.512	0.506	0.503	0.486	0.467
Obs	63609	84619	100090	112601	123648	135149	148957	167113	189001

Note: Clustered standard errors by country-pair are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The prefix "LPM(3FE)-" indicates that the three-stage estimation procedure described by Galvao et al. (2013) was implemented to account for zeros in quantile regressions. The first stage is a linear probability model with exporter-year, importer-year, and country-pair fixed effects using all trade pairs (i.e., $T_{ij} \geq 0$). The second and third stages are both quantile regressions using Frisch-Newton interior point method at each decile. "BV" and "CRE" indicate that "Bonus Vetus" and correlated random effects were used or not in the second and third stages. "INTER × Year FE" indicates the interaction of a dummy variable that is 1 if international trade and 0 otherwise, and a year dummy variable were included or not in all three stages. Following Machado et al. (2016), the squared correlation of $\ln X_{ijt}$ and the fitted values $Quant_q(\ln X_{ijt})$ are reported as the pseudo R^2.