Quantile Gravity: Economic Integration Agreements, Least Traded Goods, and Least 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 six decades of use, trade economists have focused almost entirely on *conditional mean* estimates of the trade elasticity or of EIA dummy variable effects, recently using three-way fixed effects and using Poisson pseudo maximum likelihood (PPML) to avoid the heteroskedasticity bias from "Jensen's Inequality." However, effects of a trade liberalization likely vary across the distribution of trade flows; for instance, no one has shown systematically – as the extension of the Melitz model in Arkolakis (2010) suggests – that the "growth rate of the volume of trade is larger (from an EIA) the lower the initial sales of goods." Among several potential contributions, we provide first 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. Second, we provide systematic evidence consistent with the Arkolakis (2010) proposition; trade-flow growth effects of any type of EIA are larger at lower (conditional) quantiles, with or without zeros in trade. Third, we show also that the marginal effects of EIAs on trade flows are larger for developing countries' exporters across such quantiles.

Key words: International trade, economic integration agreements, gravity equation, quantile regressions

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"*Comparative statics of trade liberalization predict a large increase in trade for goods with positive* ***but low volumes of previous trade****.*" (Arkolakis (2010), p. 1151; boldface added)

"*From an empirical point of view, we would like to have substantially richer evidence on the magnitude of the trade elasticity based on trade policy variation, and most importantly, on the question of whether the trade elasticity ... is* ***dependent on the particular setting.*** (Goldberg and Pavcnik (2016), p. 31; boldface added)

"*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, cf., 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, cf., United States International Trade Commission

[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). 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, cf. 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).

(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 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, cf., Baier et al. (2018b) and Baier et al. (2019).

However, recent theory and evidence using panel data and conditional mean estimation suggests that EIAs may have *heterogeneous* effects across the distribution of trade, cf., Baier et al. (2015), Egger and Nigai (2015), Baier et al. (2018a) and Baier et al. (2019). Yet, there are few studies that have researched the differential effects of a trade liberalization across the *entire (conditional) distribution* of trade flows of country pairs. One of the first studies to draw attention to these differential effects on the distribution of the trade flows was Kehoe and Ruhl (2003).[3] This paper examined the distribution of trade flows from the formation of NAFTA, organizing trade flows from the "least traded" goods (labeled, in their paper, the extensive margin) to total trade (combining the extensive and intensive margins). The authors found that the largest share of the growth in trade from NAFTA was in the least traded goods, that is, at the lowest trade flows, implying that growth was predominantly at the extensive margin. 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. More recently, Carrere et al. (2020) showed that the positive effect on bilateral

[3] This paper was later published as Kehoe and Ruhl (2013).

trade of a decline in bilateral distance (which reduces bilateral trade costs, like a trade liberalization) also declined monotonically with an increase in the size of the (conditional) trade flows.[4] To our knowledge, this is the first paper to examine the Arkolakis hypothesis systematically using quantile regression.

The potential implications of this study for evaluating the economic welfare gains for EIAs among developing countries are also significant. Many new EIAs are among developing countries. The recently completed African Continental Free Trade Agreement (FTA) spans nearly all of Africa, including 54 of the 55 countries. Yet reliance upon previous conditional mean partial effect estimates of EIAs may underestimate considerably the consequent estimated measures of the economic welfare effects. Baier et al. (2018a) examined the influence of levels of development using conditional mean (OLS and PPML) estimation. While that study could not find significant interaction effects of EIA dummies with exporter and importer per capita incomes – or the differences in per capita incomes – using conditional mean estimation, they did find evidence that the estimated partial effects were significantly *negatively* related to average per capita incomes of country-pairs. However, that study did not provide comparable partial effects for developing versus developed countries. To our knowledge, this is the first paper to examine heterogeneous effects of EIAs across levels of development using quantile regression.

The purpose of this study is to introduce an established econometric approach – *quantile regression* (or QR) – to address these issues. However, to do so, we introduce a novel approach to estimating EIA partial effects with QRs to avoid the well-known "incidental parameters problem" associated with three-way fixed effects and to address zeros. First, as background, QRs can allow estimation of EIA effects across the entire (conditional) distribution of trade flows. Second, QRs are invariant to monotonic transformations, such as logarithmic transformations; consequently, the concern over Jensen's Inequality raised in Santos Silva and Tenreyro (2006) becomes moot. Third, QR estimation is now as easily handled in Stata as PPML. Fourth, in the case with positive trade flows, we use an established alternative procedure (i.e., correlated random effects) to the three-way fixed effects used in the well established Baier and Bergstrand (2007) specification to avoid the incidental parameters problem associated with QR estimation with multiple fixed effects. Fifth, to account for zeros in trade, we introduce a novel (three-step) QR approach (employing Chamberlain-Mundlak correlated random effects in the second and third stages). Among numerous findings in our results, we note now just two. First, our three-step QR approach

[4] Baier et al. (2019) 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, cf., their section 5.2.2 and Table 3, columns (4) and (8).

(accounting for unobserved heterogeneity) yields – at the median conditional quantile of *all* non-negative trade flows – an EIA partial effect of 0.54, which is four to five times the size of typical (conditional mean) PPML partial effects using three-way fixed effects. However, at the 90th conditional quantile, our three-step QR approach yields (after accounting for zeros in the first step) an EIA partial effect of 0.17, which is closer to historical conditional mean estimates of 0.11 using PPML with three-way fixed effects (with or without zeros).

Second, as discussed above, in the canonical Melitz model with exogenous fixed trade costs and constant marginal costs of reaching the "first consumer" in a country, the percentage increase in trade from a trade liberalization across the distribution of bilateral trade flows (and productivities) is constant. However, as Arkolakis (2010) showed, in the presence of increasing marginal market-penetration costs in a market (to reach additional consumers), the percentage increases in trade from a liberalization should decline across quantiles as bilateral trade flows increase in size. Using either positive trade flows alone or our novel three-step QR estimator accounting for zeros, we find strong evidence of declining EIA partial effects with increases in the size of trade flows (more accurately, with increases in either conditional *or* unconditional quantiles). Moreover, in a robustness analysis, we find these results hold up to a logit, Cloglog, or linear probability model in the first stage, across various types of EIAs (such as free trade agreements and deeper agreements), inclusion or exclusion of intra-national trade, to various levels of cutoffs for the "least traded" goods as emphasized in Kehoe and Ruhl (2013), and to 2-digit SITC disaggregated trade flows including interactions of EIA dummies with previous period exporter shares as a percentage of total exports.

Third, a differentiating aspect of our novel (Chamberlain-Mundlak-based) three-stage QR estimator is that – unlike fixed-effects estimators (which suffer from the incidental parameters problem in QRs) – we are able to estimate also across all quantiles the coefficients associated with standard *time-invariant* gravity-equation variables such as bilateral distance, adjacency, common legal origin, etc., which are typically omitted in modern OLS and PPML specifications owing to the presence of time-invariant country-pair fixed effects. Furthermore, using our QR approach, we are able to examine the interactions of EIA dummies with levels of development. Notably, we find systematic evidence of higher partial EIA effects across conditional quantiles for developing countries' trade flows and for trade flows of developing-country exporters. Furthermore, unlike previous studies we show quantitatively the differences between partial effects of developing countries versus developed countries.

Additionally, we conduct two Monte Carlo simulation analyses to evaluate the biases associated with various estimators under alternative error structures. First, using a two-stage approach (which is based upon an extensive-margin decision first, followed by an intensive-margin decision), we examine biases associated with alternative estimation approaches. Among numerous results, we find that PPML with zeros has less bias relative to our three-step QR approach when the conditional variance of the trade flows is a constant or when the conditional variance of the flows is equal to its conditional mean (scaled by the index of dispersion) as in the Poisson distribution, the latter in accord with our expectation. By contrast, if the conditional variance of the flows is equal to the (scaled) *square* of the conditional mean or is a quadratic function of the conditional mean, our three-stage QR approach has less bias. In a sensitivity analysis of these simulation results, our results are robust to adding ones to all trade flow values (not just to zeros), to increasing or decreasing the percentage of zeros by 25 percent, to altering the cutoff value for least-traded goods, and to increasing or decreasing the overdispersion index. Second, the PPML estimation assumes an underlying single data-generating process (DGP); by contrast, the three-stage QR results are premised upon the two-stage DGP discussed just above. Consequently, we also provide a simulation analysis in the spirit of Santos Silva and Tenreyro (2011), which is based upon a one-stage DGP. An interesting outcome from this simulation is that PPML estimates have the least bias when firms are homogeneous (say, in productivities); however, with *heterogeneous firms*, our three-stage QR estimator has lower bias.

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 summarizes aspects of alternative estimation techniques. Section 5 provides econometric specifications, a data description, and a summary of estimates of average (partial) treatment effects of EIAs on bilateral trade flows using conditional mean estimators OLS and PPML (for comparison later to our QR estimates). Section 6 provides empirical results using QR and positive trade flows only, as well as our novel three-step QR approach accounting for zeros. Section 7 provides a robustness analysis. Section 8 examines the Arkolakis proposition using disaggregate trade data and previous period's sales shares. Section 9 demonstrates that developing country exporters have benefited significantly more from EIAs than developed exporters. Section 10 illustrates the relationship between conditional and unconditional quantile predictions. Section 11 provides a Monte Carlo analysis evaluating the biases of alternative estimators under various error structures assuming a two-part DGP. In section 12, we provide Monte Carlo results assuming a one-part DGP. Section 13 concludes.

2 Related Literature

Two influential papers in the mid-2000s questioned the assumption of assuming a log-normal distribution for error terms underlying the standard trade gravity equation's OLS specification and using only positive trade flows. First, Santos Silva and Tenreyro (2006) questioned the long-standing use of OLS to estimate trade gravity equations citing Jensen's Inequality that $E(\ln X|\mathbf{Z}) \neq \ln E(X|\mathbf{Z})$. Much of the subsequent literature inferred inappropriately that an implication of Jensen's Inequality is that the coefficient estimates of log-linear gravity equations using OLS would be biased in the presence of heteroskedasticity. However, as Santos Silva and Tenreyro (2006) correctly pointed out, OLS will still produce consistent estimates of the parameters of $E(\ln X|\mathbf{Z})$ as long as $E(\ln X|\mathbf{Z})$ is a linear function of the regressors; the limitation is that these estimated parameters may not be able to identify correctly the parameters of $E(X|\mathbf{Z})$. Santos Silva and Tenreyro (2006) proposed a Poisson pseudo-maximum likelihood (PPML) estimator using the multiplicative version of the gravity equation in levels to avoid heteroskedasticity bias in parameter estimates of $E(X|\mathbf{Z})$. Moreover, such a specification accommodated zeros in estimation. Using a Monte Carlo analysis, they demonstrated that the biases under PPML are "always small." This led Santos Silva and Tenreyro (2006) to conclude that the "Poisson PML estimator has the essential characteristics needed to make it the new workhorse for the estimation of constant-elasticity models" (p. 649).[5]

A second influential paper was Helpman et al. (2008), which noted the possibility that OLS estimates ignoring zeros led to possible selection bias in coefficient estimates. A second concern was that heterogeneity in firms' productivities could further bias coefficient estimates. Consequently, Helpman et al. (2008) proposed a two-step estimator that first used probit estimation to account for selection into trade, and then OLS on the logs of positive bilateral trade flows in the second stage; the latter stage included controls for potential selection bias and firm-heterogeneity bias.

Hence, since 2010, various papers have emphasized alternative conditional mean estimators, but most have used PPML estimation of the well established Baier and Bergstrand (2007) gravity econometric specification. However, as noted above, most studies using PPML find considerably smaller EIA partial effects on trade than ones estimated using OLS, a result we confirm shortly. As noted earlier, PPML estimates of the average partial effect of an EIA – using positive trade flows or non-negative trade flows – are about 13 percent, which

[5]The literature has alternated between the terms Poisson pseudo-maximum-likelihood (PPML) and Poisson quasi-maximum-likelihood (PQML).

is only *one-quarter* of the average effect estimated historically using OLS.[6]

To differentiate our study from the small number of previous QR trade analyses, we briefly summarize their approaches. In an unpublished paper, Cairns and Ker (2013) used QRs to estimate the variation in income elasticities among six highly disaggregated agricultural products' trade flows, limiting the generality of the findings. Though they included exporter and importer fixed effects, the panel approach adopted was subject to misspecification bias due to not accounting for the time variation in multilateral prices, an issue we will address. Moreover, the paper did not include pair fixed effects to account for endogeneity bias of EIAs, as emphasized in Baier and Bergstrand (2007). As will be addressed shortly, the workhorse (fixed effects) specification for estimating partial effects of EIAs on bilateral trade flows incorporates exporter-year, importer-year, *and* pair fixed effects, cf., Baier and Bergstrand (2007). By contrast, QRs with numerous fixed effects suffer from the "incidental parameters problem"; we will address this issue. Baltagi and Egger (2016) focused only on a cross-section from 2008 to examine heterogeneity across quantiles in the effects of various time-invariant trade-cost proxies such as distance and dummies for adjacency, a common language, and a common colonial history. However, they excluded EIA dummies in their analysis and did not use panel data; hence, their focus was quite different from ours. 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 et al. (2016b) 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 et al. (2016a) 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;

[6] We will present this specification later. Weidner and Zylkin (2021) show that point estimates (partial, or average treatment, effects) using three-way PPML gravity equations are asymptotically consistent for small T. However, for fixed T, point estimates are asymptotically biased as $N \to \infty$ and standard error estimates are biased due to the incidental parameters problem. Their paper provides methods for addressing these shortcomings.

however, this particular paper omits zeros in trade. Finally, Figueiredo et al. (2014) use a three-step panel approach suggested 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. Using sub-samples of the propensity score observations for which the probabilities of zeros are 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.

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.[7] Researchers have long questioned the consistency of results using multiple fixed effects in QR estimation due to the *incidental parameters problem* (IPP), cf., 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 is to combine a first-stage logit (or Cloglog or linear probability) model to predict the probability of observations being zeros – using all three types of fixed effects and any time-varying bilateral variables – to create propensity scores. Using a sub-sample of the observations for which the probabilities of zeros are low, the second step uses a Chamberlain-Mundlak-based correlated-random-effects (CRE) approach to account for unobserved heterogeneity in the estimation of the parameters of interest – notably, EIA partial effects – at various 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

[7] 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, cf., Besstremyannaya and Golovan (2019) and Chen and Huo (2021).

correlated random effects (Mundlak) estimator."

3 Theoretical Context

This section has three parts. First, we review the structural gravity equation theoretical foundations excluding bilateral export fixed costs. This sets the stage for conditional mean estimation of gravity equations based upon a single-stage DGP. Second, we review the structural gravity equation theoretical foundations including bilateral export fixed costs. This sets the stage for conditional mean estimation of gravity equations based upon a two-stage DGP, accounting for zeros in trade in the first stage. Third, we review the structural gravity equation theoretical foundations including bilateral export fixed costs and increasing marginal market-penetration (IMMP) costs. This sets the stage for estimating (three-stage) conditional quantiles of the gravity model, accounting for zeros in trade in the first stage. For brevity, we cite Baier et al. (2018b) extensively for details related to the following discussion.

3.1 Theoretical Gravity Equations *without* Export Fixed Costs

From 1962 until the early 2000s, gravity equations were typically estimated: (1) using log-log specifications in LHS and RHS variables (except for binary variables); (2) using OLS; and (3) ignoring "zeros" in trade flows. Formal theoretical foundations in Anderson (1979), Bergstrand (1985), Bergstrand (1989), and Bergstrand (1990) focused on explaining *positive* trade flows based upon a multiplicative reduced-form function of (levels of) exporter economic size (typically, gross domestic product or GDP), importer economic size, and the price of the bilateral flow relative to a non-linear importer "multilateral" price term.[8] These four papers provided the first formal theoretical economic foundations for estimating bilateral trade-flow gravity equations.

In the early 2000s, several papers provided further theoretical foundations. Baier and Bergstrand (2001) provided further theoretical foundations based upon the Krugman monopolistic competition model to study the growth of world trade. Eaton and Kortum (2002) provided a theoretical foundation based upon a Ricardian model with firms having heterogeneous productivities. Anderson and van Wincoop (2003) developed further the theoretical foundations using an Armington framework with nationally differentiated products to focus on structural gravity. Although all three papers incorporated *ad valorem* variable trade costs (in the form of iceberg costs), none included export fixed costs.[9] In the spirit of Baier

[8]See, for example, Anderson (1979), pp. 114-115, and Bergstrand (1985), p. 477.

[9]The next section deals with the Melitz model with bilateral export fixed costs.

et al. (2018b), all three models just cited can be subsumed in the following structural gravity system of equations:

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

$$\Pi_i = \left[\sum_{j=1}^{N} W_{jt}L_{jt} \left(\frac{\tau_{ij}}{\Phi_{jt}} \right)^{-\epsilon_\tau} \right]^{-1/\epsilon_\tau} \tag{2}$$

$$\Phi_{jt} = \left[\sum_{i=1}^{N} W_{it}L_{it} \left(\frac{\tau_{ij}}{\Pi_i} \right)^{-\epsilon_\tau} \right]^{-1/\epsilon_\tau} \tag{3}$$

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), 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, and ϵ_τ is the *ad valorem* trade-cost "trade elasticity." In the cases of the Anderson-van Wincoop (Armington) and Baier-Bergstrand (Krugman) models, $\epsilon_\tau = \sigma - 1$, 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, $\epsilon_\tau = \theta$, where θ is the (inverse) index of heterogeneity of firms' productivities.[10]

Using PPML, equation (1) potentially can be estimated both in its multiplicative form and allowing zeros in trade flows, assuming implicitly a single-stage DGP. In the case of using exporter-year, importer-year, and country-pair fixed effects (i.e., three-way fixed effects), the conditional mean of the trade elasticity (ϵ_τ) is typically estimated given data on *ad valorem* tariff rates. Also, the conditional mean of the average treatment effect of EIAs is typically estimated replacing $\tau_{ijt}^{-\epsilon_\tau}$ with a time-varying binary variable, EIA_{ijt}, cf., Bergstrand et al. (2015), Baier et al. (2018b), and Baier et al. (2019).

3.2 Theoretical Gravity Equations *with* Export Fixed Costs

Melitz (2003) provided a theoretical foundation for the gravity equation in a setting with Krugman-type monopolistically competitive firms selling slightly differentiated products pro-

[10]This model assumes one factor of production, labor (L), where the wage rate per worker (W) is endogenous and a fourth equation provides its determinants. For brevity, we refer the reader to Baier et al. (2018b) for the relevant specification of the wage-rate equations, noting here that – in each of the three models – W is a negative function of Π, i.e., $W_{jt} = f(\Pi_{jt})$ with $\partial W_{jt}/\partial \Pi_{jt} < 0$.

duced under increasing returns to scale (internal to the firm). One of two distinguishing features of Melitz (2003) was introducing heterogeneity of firms' productivities, providing closed-form solutions by assuming a Pareto distribution for productivities; Eaton and Kortum (2002) introduced firm heterogeneity using instead a Frechet distribution. The second distinguishing feature was the incurring of bilateral export *fixed* costs to enter any market, based upon the expected profitability of sales to another market. The key economic insight is that entrance into any foreign market depends first upon expected variable profits of firm φ in country i exporting to country j exceeding export fixed costs; conditional on such variable profits less export fixed costs being positive, the second-stage, or intensive-margin, decision was to determine the value of this trade flow. Empirically, this suggests a two-stage DGP.

In the context of equations (1)-(3) above and Baier et al. (2018b), we can rewrite the (second-stage) equations as:

$$X_{ijt} = (W_{it}L_{it})(W_{jt}L_{jt})\left(\frac{\tau_{ijt}}{\Pi_{it}\Phi_{jt}}\right)^{-\epsilon_\tau} f_{ijt}^{-\epsilon_f} \tag{4}$$

$$\Pi_i = \left[\sum_{j=1}^{N} W_{jt}L_{jt}\left(\frac{\tau_{ij}}{\Phi_{jt}}\right)^{-\epsilon_\tau} f_{ijt}^{-\epsilon_f}\right]^{-1/\epsilon_\tau} \tag{5}$$

$$\Phi_{jt} = \left[\sum_{i=1}^{N} W_{it}L_{it}\left(\frac{\tau_{ij}}{\Pi_i}\right)^{-\epsilon_\tau} f_{ijt}^{-\epsilon_f}\right]^{-1/\epsilon_\tau} \tag{6}$$

where f_{ijt} represents (bilateral) export fixed costs (conceptually, measured in terms of units of labor) and, in Melitz (2003), $\epsilon_\tau = \theta$, $\epsilon_f = \frac{\theta}{\sigma-1} - 1$, and σ and θ are defined as above. This theoretical foundation undergirded the two-stage estimator in Helpman et al. (2008). That paper assumed a two-stage DGP with the first stage determined by whether variable profits less export fixed costs of some firm φ were non-negative or not; the latter condition was determined by whether the productivity of firm φ was greater (or equal) to the cutoff productivity, φ^*_{ijt}. The second stage of the two-stage DGP – conditional upon positive trade – explained the value of trade.

Finally, 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 the reduction (or increase) in 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.

3.3 Theoretical Gravity Equations with Export Fixed Costs *and* Increasing Marginal Market-Penetration Costs

Motivated by the empirical observation that many more small exporters are present in foreign markets than is consistent with a Pareto distribution, Arkolakis (2010) extended the canonical Melitz model of international trade to allow for increasing marginal market-penetration costs. One implication from his extended Melitz model is that a given trade liberalization should have a *larger* impact on trade in goods with "low volumes of previous [or initial] trade" (p. 1151). To support his case empirically, Arkolakis (2010) reported by deciles (of previously traded goods) the actual ratios of U.S. imports from Mexico in the post-NAFTA period 1998-2000 relative to that in the pre-NAFTA period of 1991-1993. As shown by the *bars* in Figure 1 (which is Figure 13 from Arkolakis (2010)), the larger the volume of trade (along the x-axis) the smaller the percentage *effect* on trade of NAFTA.

The novelty of the Arkolakis model is the introduction of increasing marginal market-penetration (IMMP) costs. As in the Melitz model described above, a firm (or country) enters a foreign market if it is profitable to reach the first consumer; this is the first stage of the DGP. In the second stage of the DGP, the extension of Arkolakis is simply to consider a foreign market that is composed of many consumers, with the firm facing increasing marginal (marketing) costs with "the number of consumers reached" (p. 1152); this is in line with empirical evidence on decreasing returns to advertising spending in markets.

The intuition behind this theoretical conjecture is the following. The typical Melitz model with constant-elasticity-of-substitution (CES) preferences and exogenous (bilateral) variable and fixed trade costs implies a uniform elasticity of substitution between goods; consequently, a given percent tariff reduction implies a uniform percentage increase in bilateral trade. However, in the Arkolakis model with IMMP costs, the number of consumers reached (beyond the first) with each "additional marketing effort" becomes smaller at a geometric rate (i.e., diminishing marginal returns); the marginal cost of serving each additional consumer has increasing "convexity." This implies that the the elasticity of bilateral trade with respect to a given percentage tariff reduction will *decline* with the increase in the size of trade flows.[11]

[11] Recently, Carrere et al. (2020) illustrated a possible "demand-side" rationale for the possible sensitivity of the trade elasticity with respect to (w.r.t.) *ad valorem* variable trade costs. Under the assumption of additively separable preferences, Carrere et al. (2020) show that the trade elasticity w.r.t. *ad valorem* variable trade costs is sensitive to the level of a pair of countries bilateral trade. In Carrere et al. (2020), there was empirical evidence that the bilateral distance elasticities (in absolute terms) were smaller the

In the context of this model, allowing IMMP costs causes the elasticity of trade flows with respect to a fall in tariffs to decrease as initial export sales increase.[12] Specifically, the Arkolakis model motivates the elasticity of trade flows (X_{ijt}) with respect to τ_{ijt}, or ϵ_τ, to be a function of the level of (initial) trade. Hence, ϵ_τ can *vary across quantiles.* In the context of the notation above, we can rewrite equation (4) as:

$$X_{ijt}^q = (W_{it}L_{it})^q (W_{jt}L_{jt})^q \left(\frac{\tau_{ijt}^q}{\Pi_{it}^q \Phi_{jt}^q} \right)^{-\epsilon_\tau^q} f_{ijt}^{-\epsilon_f^q} \tag{7}$$

and rewrite equations (5) and (6) accordingly, where q denotes the conditional quantile. Moreover, we note that the underlying DGP undergirding this framework shares with the preceding section that it is a two-stage process. As in the preceding section, firms first decide whether or not to enter a market, based upon expected variable profits less export fixed costs. In the second stage, firms decide the value of positive trade flows.

Returning to Figure 1, the lines illustrate the alternative theoretical cases. Note that the model with IMMP (i.e., labeled "Endogenous Cost") has a downward sloping relationship relative to the model ignoring IMMP (i.e., labeled "Fixed Cost"). Furthermore, note that the actual ratios (represented by bars) are declining with an increase in decile, but are *not perfectly correlated* with the theoretical ratios (represented by the Endogenous-Cost dots).

4 Alternative Estimation Techniques

This section has two parts. First, we review briefly the OLS and PPML approaches for estimating trade gravity equations. Second, we examine the relative benefits of using a quantile-regression (QR) approach.

4.1 Conditional Mean Estimation Approaches

Head and Mayer (2014) provide one of the few detailed surveys of alternative conditional mean approaches toward estimating gravity equations. Moreover, they provide a Monte Carlo analysis of the alternative approaches that complements the Monte Carlo analysis in Santos Silva and Tenreyro (2006). The penultimate section of Head and Mayer (2014) addresses "Frontiers of Gravity Research." In that section, the first two (of three) topics concern (i) the statistical distribution of "gravity's errors" and (ii) accounting for "zeros" in

larger the bilateral trade flows, as their theory suggested. However, an econometric shortcoming of Carrere et al. (2020) is the absence of zeros and omission of accounting for unobserved heterogeneity.

[12] See Proposition 2 in Arkolakis (2010).

trade flows. To some extent, the present paper picks up where Head and Mayer (2014) left off.

4.1.1 Heteroskedasticity Bias and Log-Linear OLS Specifications

We summarize first the main concerns regarding the statistical distribution of gravity's errors. Equation (8) below provides a standard trade gravity equation estimated historically by ordinary least squares (OLS):

$$\ln X_{ij} = \mathbf{Z}_{ij}^{'}\beta + \ln \eta_{ij} \tag{8}$$

where $\ln X_{ij}$ is an $N(= n^2)$ length vector of trade flows (including, in principle, intra-national trade) among n countries, $\mathbf{Z}_{ij}$ is a $k \times N$ matrix of explanatory variables (which may include logarithms of exporter and importer national incomes, logarithm of bilateral distance, dummy variables, etc.), β is a k-length vector of parameters, and $\ln \eta_{ij}$ is an N-length vector of error terms. Historically, heteroskedasticity of $\ln \eta_{ij}$ was of minor concern as it would just influence the size of the coefficient estimates' standard errors, but would not bias the coefficient estimates. In fact, Santos Silva and Tenreyro (2006) still confirm that OLS will produce consistent estimates of the parameters of $E(\ln X|\mathbf{Z})$, as long as $E(\ln X|\mathbf{Z})$ is a linear function of the regressors.

The issue that Santos Silva and Tenreyro (2006) raised is that OLS estimation of equation (8) will *not* provide consistent estimates of the parameters of $E(X|\mathbf{Z})$. The reason is that, if the variance of η_{ij} is correlated with $\mathbf{Z}_{ij}$, then the log transformation will prevent $\ln \eta_{ij}$ from having a zero conditional expectation. To illustrate, suppose economic theory suggests the relationship $X_{ij} = e^{\mathbf{Z}_{ij}^{'}\beta}$. Because $X_{ij} = e^{\mathbf{Z}_{ij}^{'}\beta}$ holds only on average, then there is an error term (ϵ_{ij}) associated with each observation such that $\epsilon_{ij} = X_{ij} - E(X_{ij}|\mathbf{Z}_{ij})$. Therefore, the stochastic version of the model is:

$$X_{ij} = e^{\mathbf{Z}_{ij}^{'}\beta} + \epsilon_{ij} = e^{\mathbf{Z}_{ij}^{'}\beta}\eta_{ij}. \tag{9}$$

where ϵ_{ij} is an additive error term and η_{ij} is a multiplicative error term such that $\eta_{ij} = 1 + \epsilon_{ij}/\exp(\mathbf{Z}_{ij}^{'}\beta)$ and $E(\eta_{ij}|\mathbf{Z}_{ij}) = 1$. Assuming X_{ij} is positive, the model can be made linear by taking the natural logarithms of both sides to yield equation (8) above. OLS is consistent for β if $\ln \eta_{ij}$ is uncorrelated with $\mathbf{Z}_{ij}$. However, since $\eta_{ij} = 1 + \epsilon_{ij}/\exp(\mathbf{Z}_{ij}^{'}\beta)$, that will be met only under very restrictive assumptions on the distribution of ϵ_{ij}. Hence, OLS on equation (8) will, in general, yield inconsistent estimates of β.[13]

[13] Also, see section 3 of Baier et al. (2018b).

4.1.2 Poisson Pseudo Maximum Likelihood

Santos Silva and Tenreyro (2006) suggest estimating equation (9) using a Poisson pseudo maximum likelihood (PPML) estimator. PPML will generate consistent estimates of β as long as $E(X_{ij}) = e^{\mathbf{Z}'_{ij}\beta}$. One of the advantages of the PPML estimator is that it is valid under "mild" assumptions, as long as the underlying gravity equation is correctly specified. A second advantage is that it gives the same weight to all observations. A third advantage is that PPML does not suffer from the incidental parameters problem in a panel setting with a single fixed effect. Though with three-way fixed effects gravity models, the consistency of the PPML estimator does not follow from the (two-way fixed effects) results in Fernandez-Val and Weidner (2016). However, Weidner and Zylkin (2021) have shown that PPML can provide consistent estimates using three-way fixed effects.

However, a caveat is worth emphasizing. In a Monte Carlo simulation analysis later, we will introduce several error structures, e.g., $Var(X_{ij}|\mathbf{Z}_{ij}) = hE(X_{ij}|\mathbf{Z}_{ij})^{\lambda}$, where h and λ can take on a wide array of values. For instance, under a Poisson distribution $Var(X_{ij}|\mathbf{Z}_{ij}) = E(X_{ij}|\mathbf{Z}_{ij})$. Another PML estimator is the Gamma PML. Under Gamma, $Var(X_{ij}|\mathbf{Z}_{ij}) = hE(X_{ij}|\mathbf{Z}_{ij})^{\lambda}$ where $\lambda = 2$. Note that the assumption under Gamma that $Var(X_{ij}|\mathbf{Z}_{ij})$ is proportional to $[E(X_{ij}|\mathbf{Z}_{ij})]^2$ is similar to that of the log-linear model. Using MaMu tests, researchers have typically found estimates of λ between 1 and 2; hence, one should be wary of assuming with certainty that $\lambda = 1$ *or* that $\lambda = 2$.

4.2 Quantile Regressions

We offer an alternative econometric approach to evaluating the partial treatment effect 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 consistent EIA treatment effects across quantiles, 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.[14] Furthermore, as noted in the introduction, QRs allow us to estimate EIA partial effects *at various quantiles* of the trade-flow distribution, and we provide the first *systematic* empirical examination of the theoretical conjectures of Arkolakis (2010) that trade liberalizations should have declining effects on the percentage increase of trade as the size of flows increase (more accurately, as conditional quantiles increase).

Since many trade researchers may be unfamiliar with QRs, we provide a brief overview

[14] We address the issue of interpreting zeros as censoring or "corners" later.

of the benefits of QRs relative to conditional mean estimators.[15] 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, i.e., $\sum_{ij}|\epsilon_{ij}|$. 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 over 250,000 observations, using unidirectional bilateral trade flows among (potentially) 184 countries with 10 years of data at 5-year intervals. 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.

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

5 Conditional Mean Gravity Estimates

With the exception of the QR trade papers cited in section 2, most gravity-equation estimates have used conditional mean approaches such as OLS and PPML, cf., Head and Mayer (2014) and Baier et al. (2018b). Moreover, most recent studies have followed the three-way fixed effects specifications in Baier and Bergstrand (2007), Baier et al. (2014), Baier et al. (2018a), Baier et al. (2018b), Baier et al. (2019), and Weidner and Zylkin (2021).[16] For trade-policy purposes, conditional mean estimators provide an average treatment – or partial – effect using information from the distributions of bilateral trade flows and the various right-hand-side (RHS) variables. To generate unbiased estimates of these partial effects, one needs a correct specification of the conditional expectation.

For context, the first subsection motivates traditional OLS and PPML conditional mean econometric specifications of the gravity equation for positive trade flows and – for PPML only – for non-negative trade flows, using panel data. The second subsection describes the data set used for our analysis. The third subsection provides a summary of these conditional mean estimates, for which we will provide contrasting estimates using QR methodology later in the paper.

5.1 Conditional Mean Specifications

In reality, the world is not so generous as to provide precise measures of $\Pi_{it}, \Phi_{jt}, \tau_{ijt}$ 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 ($COMCOL_{ij}$).

Head and Mayer (2014) offered a second 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}).[17] Although the Monte Carlo horse

[16] As noted in the introduction, this specification has been used for numerous studies of the effects of Brexit and of free trade agreements.

[17] See Head and Mayer (2014), Section 3.6. Note that this was a different Monte Carlo experiment relative to the one discussed earlier for error distributions, i.e., "Gravity's Errors".

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 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.[18] However, all three of the methods LSDV, DDM, and BVU are effectively "de-meaning" approaches.[19]

We divide the remainder of this section into two parts. The first part addresses OLS and PPML specifications ignoring unobserved heterogeneity. The second part addresses OLS and PPML specifications accounting for unobserved heterogeneity.

5.1.1 Specifications Ignoring Unobserved Heterogeneity

In our empirical work below, it will prove useful to initially provide three specifications for each of OLS and PPML. In this section, we ignore unobserved heterogeneity and so focus on one OLS and one PPML specification. First, we will apply the (unweighted) BV technique of Baier and Bergstrand (2010) – which yielded virtually identical consistent estimates to those of LSDV and DDM with either no censoring or random censoring in Head and Mayer (2014) – using the OLS and PPML estimators. In the traditional BV approach, all bilateral (trade-cost) variables are de-meaned as described below. This particular de-meaning accounts for the influences of the exporter and importer "multilateral price (resistance) terms" at the cross-sectional level, 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).[20] For the BV approach, we consider first a "traditional" BV approach, as suggested in Baier and Bergstrand (2010), ignoring here unobserved heterogeneity. For the OLS regression (with only positive trade flows), this specification (labeled

[18] 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.

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

[20] 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).

"$BVOLS$") takes the following form:

$$\begin{aligned}\ln X_{ijt} = \beta_0 + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} + \beta_3 EIAMR_{ijt} + \beta_4 DISTMR_{ij} \\ +\beta_5 CONTIGMR_{ij} + \beta_6 LANGMR_{ij} + \beta_7 LEGALMR_{ij} + \beta_8 RELIGMR_{ij} \\ +\beta_9 COMCOLMR_{ij} + \sum_{t=1}^{T} \alpha_t YEAR_t + \ln \eta_{ijt}\end{aligned} \tag{10}$$

where $EIAMR_{ijt} = EIA_{ijt} - \frac{1}{N}\sum_{k=1}^{N} EIA_{ikt} - \frac{1}{N}\sum_{l=1}^{N} EIA_{ljt} + \frac{1}{N^2}\sum_{k=1}^{N}\sum_{l=1}^{N} EIA_{klt}$, $DISTMR_{ij} = \ln DIST_{ij} - \frac{1}{N}\sum_{k=1}^{N} \ln DIST_{ik} - \frac{1}{N}\sum_{l=1} \ln DIST_{lj} + \frac{1}{N^2}\sum_{k=1}^{N}\sum_{l=1}^{N} \ln DIST_{kl}$, etc. The specification above includes year dummies ($YEAR_t$) to capture time-varying world GDP and other time-varying world-related factors.

Following Baier et al. (2018b), the analogue PPML specification is:

$$\begin{aligned}X_{ijt} = e^{\beta_0 + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} + \beta_3 EIAMR_{ijt} + \beta_4 DISTMR_{ij} + \beta_5 CONTIGMR_{ij}} \\ \times e^{\beta_6 LANGMR_{ij} + \beta_7 LEGALMR_{ij} + \beta_8 RELIGMR_{ij} + \beta_9 COMCOLMR_{ij} + \sum_{t=1}^{T} \alpha_t YEAR_t} \eta_{ijt}.\end{aligned} \tag{11}$$

5.1.2 Specifications Accounting for Unobserved Heterogeneity

Three-Way Fixed Effects

Although specifications (10) and (11) account for the (unobservable) MR terms from theory, the specifications cannot account for general "unobserved heterogeneity." The second set of specifications uses an exhaustive set of exporter-year, importer-year, and pair fixed effects applying the well established gravity expression for estimating partial EIA effects in Baier and Bergstrand (2007) and Baier et al. (2014). Baier and Bergstrand (2007), or BB, re-evaluated usage of the gravity equation econometrically for estimating partial effects of EIAs on pairs of countries' trade flows using OLS. The first of two main contributions was that self-selection of country-pairs into EIAs likely created a significant endogeneity bias in previous gravity-equation estimates of the (partial) effects of EIAs on trade flows; for instance, the observed variable trade-cost measure may be correlated with unobservable trade costs hidden in the gravity equation's error term. If the determination of EIAs is "slow-moving," gravity equation estimation could use panel techniques and data to avoid endogeneity bias. However, a second important contribution of the BB technique is that – if firms' selection *into exporting* (determined by comparing destination-specific variable profits against destination-specific fixed trade costs) is also "slow-moving" – then the pair fixed effects will also control for selection into positive trade flows (as well as controlling for firm heterogeneity).[21]

Given the problems associated with accounting for endogeneity of EIAs using instrumental variables and cross-section data, BB argued that a better approach to eliminate endogeneity bias of EIAs is to use panel techniques. In the context of the theory and endogenous self-selection of country pairs into EIAs, BB argued that one method to obtain consistent estimates of the partial effect of EIAs is by fixed effects estimation of:

$$\ln X_{ijt} \quad = \quad \gamma_0 + \beta_1 EIA_{ijt} + \varsigma_{it} + \vartheta_{jt} + \varrho_{ij} + \ln \eta_{ijt} \tag{12}$$

where ϱ_{ij} is still the country-pair fixed effect to capture all time-invariant unobservable bilateral factors influencing nominal trade flows and ς_{it} and ϑ_{jt} are exporter-time and importer-time fixed effects to capture, respectively, time-varying exporter and importer GDPs as well as all other time-varying country-specific unobservables in i and j influencing trade, *including* the exporters' and importers' "multilateral price (resistance)" terms. Note also here that one can use EIA_{ijt} or $EIAMR_{ijt}$ in equation (12) because the exporter-year and importer-year fixed effects capture *all* of the "multilateral resistance" elements inside $EIAMR_{ijt}$, suggesting:

$$\ln X_{ijt} \quad = \quad \gamma_0 + \beta_1 EIAMR_{ijt} + \varsigma_{it} + \vartheta_{jt} + \varrho_{ij} + \ln \eta_{ijt}. \tag{13}$$

We estimate both later and confirm this argument empirically. We will also estimate the the specification above using PPML:

$$X_{ijt} = e^{\beta_0 + \beta_1 EIAMR_{ijt} + \varsigma_{it} + \vartheta_{jt} + \varrho_{ij}} \eta_{ijt}. \tag{14}$$

Correlated Random Effects

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

[21] As evidence for the latter, Baier et al. (2014) provided a robustness analysis using a panel adaptation of the Helpman et al. (2008), or HMR, two-stage cross-section technique to account for selection bias into exporting and for firm-heterogeneity bias. Baier et al. (2014) showed that pair fixed effects not only accounted for potential endogeneity bias of EIAs but also for selection-into-exporting bias. With pair fixed effects, the OLS results for positive trade flows in Baier et al. (2014) were virtually identical to their online supplementary results using a two-stage panel HMR approach; pair fixed effects accounted for selection into exporting. Moreover, a panel approach offers an alternative approach to instrumental variables using cross-sectional data (and potentially avoids possible shortcomings of the latter approach). As argued in BB, the problem with using cross-section data and consequently having to employ IV techniques to account for EIA selection bias is the inability practically of satisfying the "exclusion restriction" with confidence. Most variables that influence trade flows also explain selection into EIAs, and it is difficult to find a variable that explains EIAs that does not also explain trade flows.

(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; 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, only recently did Weidner and Zylkin (2021) show the conditions under which PPML with three-way fixed effects will generate unbiased estimates of the partial effects of EIA_{ijt}.

Moreover, although OLS and PPML do not suffer from the incidental parameters problem associated with the large number of pair fixed effects in a large sample with $T < N$, researchers using quantile regressions have yet to establish that QRs with three-way fixed effects can provide unbiased coefficient estimates. QRs suffer from the IPP with a large number of fixed effects. We address this in more detail later.

Accordingly, as discussed in Cameron and Trivedi (2005), Wooldridge (2010) and Baier et al. (2018b), 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 in equations (10) and (11). Since several RHS variables are time-invariant, their time averages are subsumed in the intercept. Consequently, our third (alternative) approach uses *correlated random effects*, or CRE, specifications. Hence, the analogue to equation (10) is:

$$\begin{aligned}\ln X_{ijt} = \beta_0 + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} + \beta_3 EIAMR_{ijt} + \beta_4 DISTMR_{ij} \\ + \beta_5 CONTIGMR_{ij} + \beta_6 LANGMR_{ij} + \beta_7 LEGALMR_{ij} \\ + \beta_8 RELIGMR_{ij} + \beta_9 COMCOLMR_{ij} + \sum_{t=1}^{T} \alpha_t YEAR_t \\ + \beta_{10} \overline{\ln GDP_i} + \beta_{11} \overline{\ln GDP_j} + \beta_{12} \overline{EIAMR_{ij}} + \sum_{t=1}^{T} \gamma_t \overline{YEAR} + \ln \eta_{ijt}\end{aligned} \tag{15}$$

where bars over the variables denote the time-averaged means of the underlying variable.[22]

[22]The variation in the nine $\overline{YEAR}$ variables arises from country pairs entering and leaving the domain of country pairs, i.e., we have an unbalanced panel. In the case of a balanced panel, these variables would be subsumed.

The analogous PPML specification is:

$$X_{ijt} = e^{\beta_0+\beta_1 \ln GDP_{it}+\beta_2 \ln GDP_{jt}+\beta_3 EIAMR_{ijt}+\beta_4 DISTMR_{ij}+\beta_5 CONTIGMR_{ij}} \times e^{\beta_6 LANGMR_{ij}+\beta_7 LEGALMR_{ij}+\beta_8 RELIGMR_{ij}+\beta_9 COMCOLMR_{ij}} \times e^{\sum_{t=1}^{T} \alpha_t YEAR_t+\beta_{10}\overline{\ln GDP_i}+\beta_{11}\overline{\ln GDP_j}+\beta_{12}\overline{EIAMR_{ij}}+\sum_{t=1}^{T} \gamma_t \overline{YEAR}} \eta_{ijt}. \quad (16)$$

5.2 Data

The data on nominal bilateral trade flows comes from the UN Comtrade data base (in thousands of U.S. dollars).[23] 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 et al. (2018a), we use annual trade flows for every 5 years: 1965, 1970, ..., 2010. Hence, in our sample $T = 10$. The potential number of countries in our sample in 2010 is 184; however, the number of countries in a previous year may be smaller because some of these 184 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. Excluding intra-national trade flows (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 1950-2012 (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.

[23] 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.

5.3 Results

Tables 4 summarizes the empirical results associated with the specifications discussed above. Subsequent sections of the paper provide the main empirical QR results and an extensive robustness analysis.

Table 4 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 (10), (15), and (13), respectively, using only positive trade flows.[24] Columns labeled (5)-(7) report the results of PPML specifications (11), (16), and (14), respectively, using only positive trade flows. Columns labeled (8)-(10) report the results of PPML specifications (11), (16), and (14), respectively, using positive trade flows and zeros.[25]

Examining columns (2)-(4) vis-a-vis columns (5)-(7), respectively, yields the first main set of empirical results.[26] As noted earlier, PPML (conditional mean) estimates for EIA effects tend to be significantly smaller than OLS estimates using identical samples; the three OLS estimates for $EIAMR$ are *two to three times* larger than the comparable PPML estimates, when exponentiated. Furthermore, we note that the FE-OLS+ estimate of 0.383 is close to the comparable estimate in Baier and Bergstrand (2007), Table 1, column (1) of 0.460, even though the samples differ. Both the OLS and PPML estimates are similar to those found in the literature for positive flows.

Second, we note that the PPML estimates in columns (8)-(10) using all non-negative trade flows are very similar to the comparable PPML estimates in columns (5)-(7) using only positive trade flows. Such results have been found elsewhere; the inclusion of zeros in PPML estimates using a large sample does not change PPML results materially. By contrast, inclusion of intra-national trade does; we address this later. The contrasting results using OLS and PPML may well then be explained by the heteroskedasticity-bias argument associated with Jensen's Inequality.

Third, all variables' PPML coefficient estimates tend to be systematically smaller than their corresponding OLS coefficient estimates. Notably, the partial effects for common legal origin and common colonial history are all statistically insignificant using PPML but are positive and statistically significant using OLS. For common official religion, the OLS (PPML) estimate is positive (negative) and statistically significant.

Fourth, we note that the CRE results for coefficient estimates for $EIAMR$ are fairly

[24]We chose to report the BV results – BV without CREs and BV with CREs – first, followed by the three-way fixed effects specification.

[25]In Table 4, we use $\ln GDP_{ex}$ for $\ln GDP_i$ and $\ln GDP_{im}$ for $\ln GDP_j$.

[26]Due to our focus in this paper on the structure of error terms and the role of zeros, we omit lagged values of the EIA dummy variable, which would complicate the paper unnecessarily.

close to the full FE specification results. In the OLS specifications, the CRE and FE-OLS+ estimates of 0.430 and 0.383, respectively, only differ by 0.047 and the difference is not statistically significant. For the specifications in columns (6) and (7) of the PPML+ specifications, the CRE and FE $EIAMR$ estimates are 0.130 and 0.121, respectively. With all non-negative observations for PPML, the difference in the $EIAMR$ coefficient estimates is only 0.055, which is not statistically significant. Hence, the CRE approach for controlling for unobserved heterogeneity provides very similar results as three-way FEs.[27]

However, as raised earlier, OLS and PPML provide only *conditional mean* estimates of the partial effects of various bilateral trade-cost variables. By contrast, QR can provide (conditional) partial effects across quantiles – while still accounting for Jensen's Inequality. In the remaining sections of the paper, we examine in detail the QR estimates across quantiles, both for positive flows only as well as for non-negative flows. We also conduct several robustness analyses. The final sections of the paper provide simulation analyses, address the Arkolakis proposition using disaggregate data, and address heterogeneous effects of EIAs for developing countries versus developed countries across quantiles.

6 Quantile Gravity

The first subsection provides standard QR estimates of our BV specification of the gravity equation using only positive trade flows. The second subsection addresses unobserved heterogeneity (ignored in the first set of estimates), using only positive trade flows; we motivate econometrically the rationale for using a standard Chamberlain-Mundlak correlated random effects (CREs) approach to account for unobserved heterogeneity in the context of QRs of a properly-specified gravity equation. The third subsection introduces our novel three-stage QR approach accounting for zeros and unobserved heterogeneity.

6.1 Standard QR Estimation

In section 6.1.1, we address the econometric methodology. In section 6.1.2, we present the results.

6.1.1 Methodology

Recall from section 4.2 that QRs have three major advantages. First, and obvious, QR estimates partial effects at different points in the conditional distribution of the RHS variables. Second, QR estimation is more robust to non-normal errors and outliers, such as

[27] See Baier et al. (2018b) for econometric discussion and similar findings.

large trade flows. Third, QR is invariant to monotonic transformations, such as logarithmic transformations; hence, we can estimate the QR equation in logs but not be subject to Jensen's Inequality. Estimation is easily operationalized using the QRPROCESS command in Stata.[28] For a succinct introduction to QR estimation, see Wooldridge (2010), section 12.10 and (for QRs with panel data) section 12.10.3.

Ignoring for now zeros and any unobserved heterogeneity (except accounting for the MR terms), the QR specification analogous to OLS and PPML specifications (10) and (11), respectively, discussed earlier is:

$$\begin{aligned} Quant_q(\ln X_{ijt}) = \beta_0^q + \beta_1^q \ln GDP_{it} + \beta_2^q \ln GDP_{jt} + \beta_3^q EIAMR_{ijt} \\ + \beta_4^q DISTMR_{ij} + \beta_5^q CONTIGMR_{ij} + \beta_6^q LANGMR_{ij} + \beta_7^q LEGALMR_{ij} \\ + \beta_8^q RELIGMR_{ij} + \beta_9^q COMCOLMR_{ij} + \sum_{t=1}^{T} \alpha_t^q YEAR_t + \eta_{ijt}^q \end{aligned} \tag{17}$$

where $q = 0.10, 0.20, ..., 0.90$.

6.1.2 Results

Table 5 provides our first set of QR empirical results; we label these specifications BVQ. Specification (17) 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 $EIAMR_{ijt}$ (0.372) is more similar to the (conditional mean) FE-OLS+ estimate in column (4) of Table 4 (0.383) than to the PPML estimates in columns (5)-(10). The Q50 estimate of $EIAMR_{ijt}$ at 0.372 lies slightly below the FE-OLS+ estimate of 0.383, but well above the PPML estimates of 0.11-0.12 using FE-PPML.[29]

Second, and consistent with our theoretical conjecture based upon Arkolakis (2010), the partial effects of an EIA are largest at the lowest quantiles – which weigh more heavily the "least traded goods" – and the partial effects (or percentage increases in trade from an EIA) generally decline as conditional quantiles increase.[30]

[28] We utilize the Frisch-Newton interior point method.

[29] At the 40th and 60th quantiles, the coefficient estimates are virtually identical to the FE-OLS+ estimate.

[30] 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 10 that there is a strong 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" (MR) effects, following Baier and Bergstrand (2009b) and Baier and Bergstrand (2010). However, we will show later in a robustness analysis (section 6.5) and Table A9 in Appendix A that the estimated partial effects are nearly identical across quantiles when we include the MR terms *without* constraining their coefficients and any differences

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. This result is also consistent with the IMMP hypothesis in Arkolakis (2010), where one might substitute a *natural* trade-cost reduction for a *policy* trade-cost reduction; however, this interpretation should be approached with caution.[31]

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 zero. Our results for the 90th quantile indicate lower income elasticities.[32]

6.2 Correlated Random Effects Estimation

Section 6.2.1 discusses the methodology for accounting for unobserved heterogeneity. Section 6.2.2 provides the results.

6.2.1 Methodology

As noted, specification (17) does not account for unobserved heterogeneity (except accounting for the MR 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.

are not statistically significant.

[31] We approach cautiously any interpretation of the variance across quantiles in the (largely) *time-invariant* "MR" variables in the context of Arkolakis (2010). The reason is that $EIAMR_{ijt}$ is a time-varying variable, which allows interpreting causality going from $EIAMR_{ijt}$ to (conditional) X_{ijt}, i.e., a trade-policy "shock." By contrast, the substantive part of the variation of the remaining MR variables is cross-sectional, and consequently should not be associated with time-varying trade "shocks" (such as the formation of an EIA).

[32] Table 5 also reports estimates for Q75. While this is not of material importance here with only positive trade flows, Q75 estimates will be important later in the QRs accounting for zeros; under the strong assumption that the position within the conditional and unconditional quantiles can be compared, Q75 will turn out to be the median of positive trade flows in the sample including zeros.

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 $EIAMR$). 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 independent of the covariates, cf., 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:

$$\begin{aligned} Quant_q(\ln X_{ijt}) = \beta_0^q + \beta_1^q \ln GDP_{it} + \beta_2^q \ln GDP_{jt} + \beta_3^q EIAMR_{ijt} \\ +\beta_4^q DISTMR_{ij} + \beta_5^q CONTIGMR_{ij} + \beta_6^q LANGMR_{ij} + \beta_7^q LEGALMR_{ij} \\ +\beta_8^q RELIGMR_{ij} + \beta_9^q COMCOLMR_{ij} + \sum_{t=1}^{T} \alpha_t^q YEAR_t \\ +\beta_{10}^q \overline{\ln GDP}_i + \beta_{11}^q \overline{\ln GDP}_j + \beta_{12}^q \overline{EIAMR}_{ij} + \sum_{t=1}^{T} + \gamma_t^q \overline{YEAR} + \eta_{ijt}^q \end{aligned} \tag{18}$$

where $q = 0.10, 0.20, ..., 0.90$. The bars over variables in equation (18) denote the time-averages of the underlying variables. Note that several MR variables such as $DISTMR_{ij}$ are time-invariant; consequently, their time-averaged means are subsumed in the intercept.

6.2.2 Results

Table 6 provides results of estimating specification (18) for the same ten quantiles as in Table 5 using the same positive trade flows, but now accounting for unobserved heterogeneity using CREs; we label this specification BVQCM.[33] First, we note that, including CREs rather than excluding CREs (as in Table 5), the coefficient estimates for $EIAMR$ are slightly larger for all quantiles, except Q70 and higher quantiles. At the (conditional) median, Q50, of the

[33]The rationale for the inclusion of Q75 will become more apparent in the next section.

positive flows, the $EIAMR$ effect with (without) CREs is 0.495 (0.374). Furthermore, this 0.495 estimate is above the conditional mean OLS coefficient estimate with three-way fixed effects of 0.383.

Second, the Arkolakis proposition of declining growth effects from liberalizations as trade-flows increase remains supported. However, the rate of decline is magnified with CREs. Specifically, at the 10th quantile the $EIAMR$ 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 0.158, which is quite close to the PPML conditional mean estimates. Hence, accounting for unobserved heterogeneity alters the partial effect estimates.

6.3 Quantile Gravity with Zeros

Section 6.3.1 discusses the methodology for accounting for zeros and unobserved heterogeneity. Section 6.3.2 provides the results.

6.3.1 Methodology

We now address the second of the "Frontiers of Gravity Research" raised in Head and Mayer (2014), "Causes and Consequences of Zeros" in trade. The importance of treating zeros is now well established. Zeros may occur in trade for two likely reasons: (1) for economic reasons, it is possible that export fixed costs are sufficiently high to not cover variable profits so that no exporter in some country i is willing to export to country j, or (2) data is missing.[34] Because of the profuse number of zeros in bilateral trade that surface for exporting countries that are economically small, most economists argue that the bulk of zeros is motivated by the first reason. Consequently, there are *different processes* generating the distribution of zeros and the distribution of positive trade flows.[35]

[34] Data could be missing due to countries not reporting or even not recording.

[35] Given either the cutoff-profitability rationale or the missing data rationale, in econometric terms we will interpret the zeros as "censored" observations; consequently, our econometric approach is based upon a censored-QR approach. In related research, econometricians have also viewed the zeros as a "kink" – or "corners" – in a one-part data-generating process (DGP). In our view, motivated by the discussion in section 3 and equation (1), in a one-part DGP a zero trade flow can only be obtained if either one of the country-pair's national outputs/expenditures (or multilateral resistance terms) was zero or bilateral trade costs, τ_{ijt}, were infinity. Since no country in the world has zero national output/expenditures (nor zero multilateral resistance terms), a zero trade flow would require τ_{ijt} to equal infinity, i.e., be "prohibitive." Since there are very few countries with prohibitive tariff rates, this could not explain the vast bulk of zeros in the world's statistical *population* of bilateral trade flows. Consequently, we will use a censored-QR approach in the bulk of this paper; nevertheless, in a simulation analysis much later, we will provide results associated with a one-part DGP with zeros.

Cameron and Trivedi (2005) (pp. 544-546) suggest that generally the participation mechanism and the outcome may be modeled using separate processes. In such a case, they recommend an econometric "two-part model" that first specifies a model for the participation and then specifies in a second step a model for the outcome conditional upon participation being observed. They note that an obvious model for the (first-stage) participation decision is a logit or probit model to predict the likelihood of a positive outcome. Conditioned on this outcome, the second stage determines the level of (positive) activity.

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 a subset of observations where the "true" qth conditional quantile line exceeds the censoring point and then estimating a fixed effects QR on this subset. In the context (and notation) of their paper, the minimization problem for censored QR is:

$$Q_N(\alpha,\beta) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\rho_\tau\left(y_{it}-\alpha_i - x_{it}^{'}\beta\right)\times I\left[\alpha_{i0}+x_{it}^{'}\beta_0 > C_{it}\right]. \tag{19}$$

where y_{it} is the observed outcome variable, x_{it} is a vector of controls, C_{it} is the known censoring point, α_i is the individual effect (fixed effect), and $I[\cdot]$ is an indicator function; this specification is asymptotically equivalent to that of Powell (1986). To obtain the portion in $I[\cdot]$, a binary model is estimated such that:

$$\pi_0 = Pr(\delta_{it}=1|x_{it},\alpha_i,C_{it}) = Pr(u_{it} > -\alpha_{i0} - x_{it}^{T}\beta_0 + C_{it}|x_{it},\alpha_i,C_{it}) \tag{20}$$

and

$$Pr(u_{it} > 0|x_{it},\alpha_i,C_{it}) > 1-q \tag{21}$$

where $\delta_{it}=1$ for uncensored observations and u_{it} 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.

The principle behind the three steps in our paper follows along the intuition in Cameron and Trivedi (2009), which is that the economic process for determination of trade at the extensive margin is different from that at the intensive margin. We create an indicator variable, T_{ijt}, that is the dependent variable used in the first stage, defined as:

$$T_{ijt} = \begin{cases} 1, & \text{if } X_{ijt} \geq 1 \\ 0, & otherwise. \end{cases} \tag{22}$$

In our data set (using actual US dollar flows) the lowest (non-zero) value of X_{ijt} is equal to 1. However, in a robustness analysis later, we will also consider a higher cutoff value (user-defined minimum value, C_{ijt}). In Galvao et al. (2013), the first stage is a binary choice model, such as a logit model. In our context, the first stage is used to determine the probability that at least one producer in country i in period t is entering the foreign market j. In the second stage, Galvao et al. (2013) recommended "applying fixed effects QR" (p. 1077) to subsets of observations. However, our second stage specification needs to account – as earlier for positive trade flows – for unobserved heterogeneity. In our gravity-equation context, three-way fixed effects QR will introduce the IPP. Consequently, we modify the Galvao et al. (2013) approach in the second stage by using instead our Chamberlain-Mundlak-based CRE approach to avoid IPP. As in 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

$$z(\varrho_{ij}, \varsigma_{it}, \vartheta_{jt}, EIA_{ijt}, C_{ijt}) = Pr(T_{ijt} = 1 | \varrho_{ij}, \varsigma_{it}, \vartheta_{jt}, EIA_{ijt}, C_{ijt}) \quad (23)$$

   where z is a propensity score function determining whether T_{ijt} is equal to 1 (if positive trade flow) or equal to 0.[36] Define a subset of observations

$$J_0 = \{(i, j, t : \hat{z}(\varrho_{ij}, \varsigma_{it}, \vartheta_{jt}, EIA_{ijt}, C_{ijt}) > 1 - q + c_N\} \quad (24)$$

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

$$c_N = \min(.05,\ q_{10} \text{ of } \hat{z}) \quad (25)$$

2. Estimate the CRE quantile model in equation (18) for $q = 0.1, ..., 0.9$ 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 the second stage to avoid the IPP.

[36] For robustness, we will also consider later Cloglog and linear probability models with three-way fixed effects for the first stage, as well as a CRE-based first-stage logit; see section 7.3 later. All models are estimated in Stata except for this first stage logit model which is estimated in R using the "feglm" command. This command significantly decreases the time to estimate, especially in the simulations later in section 11 where this first stage is continually repeated. We used the "rcall" Stata program described in Haghish (2021) to allow communication between R and Stata.

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

$$J_1 = \Big\{(i, j, t : \hat{\beta}^0(q)) > \delta_{NT}\Big\} \tag{26}$$

where δ_{NT} is calculated as:

$$\delta_{NT} = 1/3(NT)^{(-1/3)} \tag{27}$$

where N is the number of country-pair observations and T is number of years in the sample. 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).[37]

Intuitively, this procedure (essentially) suggests estimating (in the second and third stages) CRE equation (18) on *subsets* of the full sample where – for various q – the estimated propensity score (that $X_{ijt} \geq 1$), $\hat{z}(\varrho_{ij}, \varsigma_{it}, \vartheta_{jt}, EIA_{ijt}, C_{ijt})$, exceeds 1-$q$. 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.

6.3.2 Results

Table 7 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. Furthermore, we are also interested in the partial EIA effect at the median of all *positive* flows; this is approximately Q75 (see footnote 32). Several results are worth noting. First, as in Table 6 for positive flows with CREs, the partial effects of EIAs also decrease across quantiles, consistent with the Arkolakis proposition and our earlier results.

Second, Table 7 results suggest that omission of accounting for zeros biases the QR estimates upward. To see this, we note that – at the 75th quantile (the median of the positive flows) – the partial effect is 0.251, which is smaller than the partial effect of 0.462 in Table 6 at the 50th quantile (or median) of positive trade flows. Furthermore, at the lowest quantile, Q10, the partial effect is considerably larger than in Tables 5 and 6. However, recall that the sub-samples at low quantiles are smaller, since in these sub-samples it is rarer to have high probabilities of positive trade. Yet, at the 90th quantile (which is approximately the 80th quantile of positive flows) the QR partial EIA effect is 0.220, which is close to (and not statistically different from) the 80th quantile estimate in Table 6 of 0.262.

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

Third, one of the benefits of using the CRE approach in the second (and third) stage is that we can also estimate partial effects *of all other MR variables.* Examining $DISTMR$, we find a one percent fall in distance increases bilateral trade more for the lower conditional quantiles where censoring is more likely to occur. This is consistent with the finding in Carrere et al. (2020). Furthermore, we also find systematic declines in partial effects across quantiles for $CONTIGMR$ and $LEGALMR$; for $DISTMR$, $CONTIGMR$, and $LEGALMR$ there are statistically significant differences between the partial effects for the 10th and 90th quantiles.[38]

Figure 2, Panel A (on the left-hand-side) provides a useful depiction of the $EIAMR_{ijt}$ partial effects at each of ten quantiles, 10-90 (and 75). Note the decline in partial effects as conditional quantiles increase, consistent with Figure 1 from Arkolakis (2010). As in Figure 1 for NAFTA, the actual decline is not monotonic, but it is substantive. Panel B (on the right-hand-side) illustrates the absolute value of the $DISTMR$ partial effects across quantiles; these results are also consistent with the Arkolakis proposition.

7 Robustness Analysis

We conducted numerous robustness analyses along several dimensions. For brevity, we present in the paper a discussion of six of these analyses; in Appendix A we present the results for several others.

Section 7.1 presents one set of robustness results for the sensitivity of the Logit-BVQCM results to an alternative method for handling the approximation for zeros. Section 7.2 illustrates that the Logit-BVQCM results hold up across different types of EIAs, i.e., (shallow) free trade agreements and deeper economic integration agreements. Section 7.3 presents results using instead a linear probability model in the first stage regression. Section 7.4 provides a robustness analysis for inclusion versus exclusion of intra-national trade flows. Section 7.5 allows coefficient estimates of variables' MR terms to be unconstrained. Section 7.6 provides estimates of Logit-BVQCM coefficients to be "adjusted" for dissimilar sample sizes in the second and third stages to be "comparable" in the spirit of Machado et al. (2016).

[38]For $LANGMR$ and $COMCOLMR$, the differences between the 10th and 90th quantiles are not statistically significant.

7.1 QR Robustness 1: Approximations of Zeros

7.1.1 Methodology

As discussed in section 6.3.1, the results of our estimation using the three-stage Logit-BVQCM technique may be sensitive to how we treat "zeros." We rationalized in that section our motivation for 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). 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.[39] Later in section 11 using Monte Carlo simulations, we will address the zeros issue once again.

7.1.2 Results

Appendix A Table A1 provides the results of the robustness analysis of adding ones to all trade flows instead of just the zeros. A comparison of the results in Table 7 (adding 1's to only 0's) and Appendix Table A1 shows that this difference did not materially change the results quantitatively.

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 one 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 Table 8, using a minimum value of USD 10,000 does not have a significant impact upon the results qualitatively or quantitatively. All the partial $EIAMR$ effects remained positive and declined with increases in conditional quantiles. The sole exception occurred at Q10, where the $EIAMR$ partial effect in Table 8 is considerably smaller than that in Table 7.

7.2 QR Robustness 2: Varying Degrees of Economic Integration

7.2.1 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

[39] We also considered using a uniform distribution to generate a random integer between 0.01 and 1; however, the three stage approach could not accommodate this alternative method.

"deeper" trade agreements. Numerous papers have been exploring the trade impact of Deep Trade Agreements (DTAs). The 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 1'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).

7.2.2 Results

In the interest of brevity, we present the results disaggregating EIAs by FTAs and CUCMECUs only for Logit-BVQCM. Table 9 provides the estimates by type of EIA; results for BVQCM (positive trade flows) are in Appendix A Table A2. First, as expected, note that – beginning at Q30 in Table 9 – the effect of CUCMECUs is larger than that for FTAs; for positive flows, the partial effect of CUCMECU is larger than that for FTA for all quantiles. Deeper EIAs have larger partial effects.

Second, for FTAs the results are similar to those for EIAs; at higher quantiles, the partial effects are smaller. For the most part, we also find support for the Arkolakis proposition for deeper agreements; starting at Q30, CUCMECU effects decline with increases in the quantiles. However, we also note a reversal in the trend starting at Q75. For the largest trade flows, CUCMECUs have slightly larger effects, which is likely attributable to the deepness of the European Union countries' integration.

7.3 QR Robustness 3: First-Stage Linear Probability Model

7.3.1 Methodology

Galvao et al. (2013) provides no clear guidance on the choice of estimator for the first stage. Probit with fixed effects is subject to the IPP. Some researchers have argued that logit with fixed effects may suffer from inconsistent estimates. The linear probability model (LPM) is a likely alternative estimator for the first stage determination of the sample of propensity scores for each quantile estimated in the second stage; LPM allows a set of three-way fixed effects in the first-stage only. A natural drawback of the LPM estimator is that the propensity scores can lie outside the range of 0 to 1; also, it is difficult to justify that propensity scores are linear. Hence, there is no ideal first stage estimator. In the interest of a sensitivity analysis, we consider the LPM for the first stage and present the results in the paper.

We also considered a Cloglog first stage estimator and a CRE-based first stage logit estimator (instead of using three-way fixed effects) and present those results in Appendix A.

7.3.2 Results

Table 10 provides the (third-stage) results for Q10-Q90 and Q75 using the LPM in the first stage. There are several findings. First, the QR estimate for the median of positive trade flows (Q75) is 0.426, which is significantly higher than the comparable result in Table 7 using Logit-BVQCM. Second, the estimated $EIAMR$ partial effects decline as conditional quantiles increase, as in previous results. Third, the rate of decline is not as steep as in Table 7, with the $EIAMR$ partial effect at the 10th (90th) quantile estimated at 0.785 (0.336). In general, these results are qualitatively similar to those in Table 7.

As an explanation for the lower (higher) partial effects at the lowest (highest) conditional quantiles for the LPM-BVQCM *relative to* Logit-BVQCM, one must recognize that the sample sizes for the various quantiles in the former are larger; there is a different sample at each quantile using LPM relative to logit. The reason is that the logit model drops observations where the covariates (which include the fixed effects in the first stage) perfectly predict the dependent variable. One example (likely the easiest to identify) are country-pairs that always trade (AT) or never trade (NT) in every year of the sample. Country-pairs that always trade in every year of the sample are likely to have higher trade values than all country-pairs with positive trade in the sample.[40] When we use the LPM model, AT and NT observations are brought back into the estimation and are now included in the second and third stages. In Appendix A Table A3, we detail the types of observations added back into each stage of the estimation across the quantiles. In the AT group which tends to have larger trade-flow values (see Appendix A Figure A1), these trade values are found entering primarily at lower quantiles, tending to reduce $EIAMR$ effects at these quantiles. In the NT group which includes only zero trade values, these observations are found entering at higher quantiles, tending to increase $EIAMR$ effects at these quantiles. Consequently, the

[40] Figure A1 in the appendix shows the density plots for country-pairs that always trade in every year of the sample and all country pairs with positive trade in the sample. We see a larger percentage of higher trade values for the former.

differing characteristics of the two first-stage methods essentially creates a *flatter* LPM-BVQCM "curve" for $EIAMR$ coefficient estimates relative to the Logit-BVQCM "curve" for $EIAMR$ coefficient estimates.[41]

As noted above, we also considered the Cloglog function for the first stage estimator. As shown in Appendix A Table A7, the third stage results were not materially different from those in Table 7. Furthermore, we considered a logit model in the first stage estimator using correlated random effects rather than the three-way fixed effects in the benchmark Logit-BVQCM model. As shown in Appendix A Table A8, the third stage results were not materially different from those in Table 7.

7.4 QR Robustness 4: Intra-national Trade

7.4.1 Methodology

In principle, theoretical foundations for the gravity equation include a nation's trade "with itself." This is often referred to in the gravity-equation literature as "intra-national trade." Hence, in empirical work, several studies have addressed the robustness of results to including intra-national trade flows, which are effectively the output of a nation less its exports; alternatively, this can be termed the domestic expenditure of a country on its domestic output.

As noted in Bergstrand et al. (2015), the empirical dilemma typically faced is that trade flows are measured on a "gross" basis whereas measures of national output – such as Gross Domestic Product (GDP) – are generally measured on a "value-added" basis. In the trade gravity-equation literature, researchers have had to make a difficult choice between three imperfect options. First, some researchers have employed a much smaller database of measures of trade flows and national outputs of *only manufactures* for a small number of countries. For instance, Bergstrand et al. (2015) employed the United Nations UNIDO Industrial Statistics Database as a primary source of national (gross) outputs of manufactures, using the CEPII TradProd Database as a secondary source for manufactures gross outputs. A major drawback is that this allowed trade among only 40 countries and a rest-of-the-world aggregate for only 13 years (1990-2002). Given four-year intervals, the sample size was only 6,724 observations, which is considerably smaller than our sample size of over 120,000 positive trade flows and our complete sample with zeros of nearly 250,000 observations.

[41] Appendix A Tables A4 and A5 provide analogous LPM-BVQCM results using, respectively, the robustness checks of adding one's to all zeros and using a user-defined minimum value of USD 10,000, as addressed earlier for Logit-BVQCM. Appendix A Table A6 provides results using LPM-BVQCM (disaggregated by type of agreement) analogous to the Logit-BVQCM results in Table 9.

Second, the alternative approach, also examined in Bergstrand et al. (2015), was to use *aggregate* trade flows among a much larger number of countries and a much larger number of years, but having to use GDP as a proxy for national output. We note that the World Input-Output Database (WIOD) provides "gross" measures of national output for a small number of countries (40). But as noted importantly in Baier et al. (2019), the correlation coefficient between the measures of intra-national trade for these 40 countries using the WIOD gross output measures and GDP measures was a very high 95.8 percent.

The third alternative approach uses information from input-output tables and potentially provides better measures of domestic and foreign value added if the production network is internationally fragmented, as raised in Timmer et al. (2015).

Interestingly, Campos et al. (2021) recently explored in detail whether the choice of the three techniques matter to structural gravity estimates. They concluded that "the estimates of both the partial effect of trade agreements and the trade elasticity are very close across methods" (p. 7). Consequently, in this study, we use the second approach, constructing intra-national trade by subtracting each country's exports from its GDP. This allowed the use of trade flows among our 184 countries.[42]

7.4.2 Results

Table 11 provides evidence that our results are robust to including intra-national trade. The specifications in columns (2) and (4) in *both* panels include only international trade flows. The specifications in columns (3) and (5) in both panels include international *and* intra-national trade flows. Intra-national trade is, on average, three times international trade. Because intra-national flows are very large relative to typical international trade flows, columns (3) and (5) in both panels include a dummy variable ($INTER \times YearFE$) that accounts for whether the flow is international or intra-national.[43]

Upon closer examination, columns (2) and (3) in Panel A demonstrate using OLS that the additional inclusion of (relatively large) intra-national trade flows increases the EIA partial effect a small amount, most likely due to skewing the trade distribution further to the right (and likely increasing the conditional mean EIA effect). This small increase in partial EIA effects is also found in Panel B using either BVQCM or LPM-BVQCM, for a likely similar reason. By contrast, the PPML estimate of the EIA partial effect is more

[42] For small countries, subtracting each country's aggregate exports from its GDP can occasionally produce negative values, due to the value-added nature of GDP. However, there were only 25 country-year observations that had negative intra-national trade imputations and we truncated these observations at 0. These 25 country-year observations spanned only 10 exporters: the Bahamas, Republic of the Congo, Equatorial Guinea, St. Kitts and Nevis, Liberia, Marshall Islands, Malaysia, Oman, Singapore, and Suriname.

[43] For brevity, we do not report the coefficient estimates for $INTER_{ijt}$.

sensitive to the inclusion of intra-national trade, likely due to PPML's equal weighting of observations in levels.[44]

7.5 QR Robustness 5: Allowing for Unconstrained MR Terms

We mentioned earlier in the paper that we would also provide estimates allowing the coefficient estimates of the "MR" components of the various bilateral trade-cost variables to be left unconstrained. For brevity, we provide a comparable table to Table 7 where the MR components' coefficient estimates are allowed to be unconstrained. However, due to the large number of coefficient estimates, we report in Appendix A Table A9 only the coefficient estimates for $\ln(GDP_{ex})$, $\ln(GDP_{im})$, EIA_{ijt}, etc., as in Table 7. As shown in Appendix A Table A9, the basic results of interest are generally robust to allowing the MR components' coefficient estimates of each bilateral variable to be unconstrained.[45]

7.6 QR Robustness 6: Comparable Partial Effects

In this subsection, we address a concern raised in Machado et al. (2016) regarding mixed distributions and their implications for interpreting the QR partial effects across quantiles. As discussed earlier, we view the data on bilateral trade flows as determined by a two-part DGP process. In this case, we can interpret zeros as censored values. With the results using our three-stage censored QRs, the estimated coefficients are not directly comparable across quantiles because we have different subsamples at each estimation. This is due to the condition that the subsamples only include observations where the propensity scores resulting from the first stage logit are greater than $1 - q + c_N$.

To make the the estimates comparable across quantiles, we calculate the partial or average effect for each subsample by computing the derivative of equation (19) with respect to each regressor. Using this method, for each observation we multiply the propensity score of being in the subsample by the estimated coefficient for each quantile regression. The results are in Table 12. Note that the results are similar to the benchmark results in Table 7 with larger differences at the higher conditional quantiles, where the cutoff for entering the subsample is much lower (i.e., the probability of censoring is lower).

[44] Note that we cannot provide this robustness check for Logit-BVQCM because of the 0-1 constraint on the first-stage logit, as discussed earlier in section 7.3.2.

[45] None of the corresponding coefficient estimates across the two specifications is statistically different.

8 Disaggregated Flows and the Arkolakis (2010) Proposition

Referring back to the introductory quote, central to this paper is providing compelling evidence of the Arkolakis proposition that goods with lower initial sales should have larger effects from an EIA. Up to now, our approach has relied upon quantile regressions. However, the original empirical work in Arkolakis (2010) used 4-digit Standard International Trade Classification (SITC) data.

In this section, we examine in more depth empirically the Arkolakis proposition. First, we employ our novel Logit-BVQCM estimator using 2-digit SITC data.[46] 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 $EIAMR$. Beyond showing the negative influence of the export shares, we will also calculate the marginal effects across quantiles of larger and larger export shares.

8.1 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. Analogous to earlier, for the second and third stages the QR trade model is:

$$\begin{aligned} Quant_q(\ln X_{ijst}) = {} & \beta_0^q + \beta_1^q \ln GDP_{it} + \beta_2^q \ln GDP_{jt} + \beta_3^q EIAMR_{ijt} + \beta_4^q DISTMR_{ij} \\ & + \beta_5^q CONTIGMR_{ij} + \beta_6^q LANGMR_{ij} + \beta_7^q LEGALMR_{ij} + \beta_8^q RELIGMR_{ij} \\ & + \beta_9^q COMCOLMR_{ij} + \sum_{t=1}^{T} \alpha_t^q YEAR_t + \beta_{10}^q \overline{\ln GDP}_i + \beta_{11}^q \overline{\ln GDP}_j \\ & + \beta_{12}^q \overline{EIAMR}_{ij} + \sum_{t=1}^{T} + \gamma_t^q \overline{YEAR} + \sum_{s=1}^{S} \Upsilon_s + \eta_{ijst}^q \end{aligned} \tag{28}$$

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

where subscript s is the SITC product category and Υ_s denotes sector dummies. The three-step QR approach has a first stage logit and is adjusted to consider SITC categories at 2 digit levels:

$$z(\varrho_{ijs}, \varsigma_{ist}, \vartheta_{jst}, EIA_{ijt}, C_{ijst}) = Pr(T_{ijst} = 1 | \varrho_{ijs}, \varsigma_{sit}, \vartheta_{jst}, EIA_{ijt}, C_{ijst}) \tag{29}$$

to calculate the propensity scores. We use these propensity scores to create subsamples that meet criteria such that:

$$J_0 = \{(i, j, s, t : \hat{z}(\varrho_{ijs}, \varsigma_{ist}, \vartheta_{jst}, EIA_{ijt}, C_{ijst}) > 1 - q + c_N\} \tag{30}$$

where subscript s is the SITC sector level.

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 $EIAMR$, $EIAMR_{ijt} * EXSH_{ij,t-5}$. In the context of our Logit-BVQCM specification, we include additionally the time-averaged mean of $EXSH_{ij,t-5}$. This suggests replacing specification (28) with:

$$\begin{aligned} Quant_q(\ln X_{ijst}) = {} & \beta_0^q + \beta_1^q \ln GDP_{it} + \beta_2^q \ln GDP_{jt} + \beta_3^q EIAMR_{ijt} + \beta_4^q DISTMR_{ij} \\ & + \beta_5^q CONTIGMR_{ij} + \beta_6^q LANGMR_{ij} + \beta_7^q LEGALMR_{ij} + \beta_8^q RELIGMR_{ij} \\ & + \beta_9^q COMCOLMR_{ij} + \sum_{t=1}^{T} \alpha_t^q YEAR_t + \beta_{10}^q \overline{\ln GDP}_i + \beta_{11}^q \overline{\ln GDP}_j \\ & + \beta_{12}^q \overline{EIAMR}_{ij} + \sum_{t=1}^{T} + \gamma_t^q \overline{YEAR} + \beta_{13}^q EXSH_{ijs,t-5} + \beta_{14} \overline{EXSH}_{ijs} \\ & + \beta_{15}^q EIAMR_{ijt} * EXSH_{ijs,t-5} + \sum_{s=1}^{S} \Upsilon_s + \eta_{ijst}^q \end{aligned} \tag{31}$$

8.2 Results

The results are presented in Table 13. Consistent with earlier results, we find that the partial effects decline with increases in conditional quantiles. At lower quantiles, the partial effects of $EIAMR_{ijt}$ are lower than in Table 7 and at higher quantiles, the partial effects are higher. However, it is important to note the significant increase in the sizes of the sub-samples that are used. The sub-samples for Table 13 are *20 times* larger than those for our previous estimates using aggregate trade flows.

Importantly, the coefficient estimates for $EIAMR{*}EXSH_{ijs,t-5}$ are negative and statistically significant for most quantiles. This implies 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 (comparable) marginal effects reported in Table 14. As conditional quantiles increase, the (comparable) marginal effects decline. Furthermore, we see going down Table 14 across rows that, as the export share in sector s of country i's exports to country j increases, the marginal effects decline. To our knowledge, this is the first systematic empirical support of the Arkolakis proposition across time, across country-pairs, and across EIAs.

9 Have Developing-Country Exporters Benefited More from EIAs?

Baier et al. (2018a), or BBC, examined the heterogeneous effects of EIAs on country-pairs' trade flows using conditional mean (OLS) estimation including interaction terms. Based upon a 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 the exporter's or importer's per capita GDP, and hence, levels of development. Noting this finding, BBC nevertheless did show that the estimated EIA partial effects were statistically significantly *negatively* related to the country-pairs' (average) per capita GDPs; that is, EIA partial effects were higher for lower per capita income pairs. Moreover, they showed that a 10 percent lower per capita income (for the pair) was associated with a *60 percent* higher EIA partial effect.

In this section, we use the QR methodology of this paper to tackle this issue: Do EIAs actually increase developing-country exports more? For brevity, we extend our benchmark aggregate trade Logit-BVQCM specification in a manner similar to that in the previous section. 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 $EIAMR$ with the log of the exporter's per capita GDP, $EIAMR_{ijt} * \ln PCGDP_{it}$.[47] Accordingly, in this section we estimate:

$$\begin{aligned} Quant_q(\ln X_{ijst}) = {} & \beta_0^q + \beta_1^q \ln GDP_{it} + \beta_2^q \ln GDP_{jt} + \beta_3^q EIAMR_{ijt} + \beta_4^q DISTMR_{ij} \\ & + \beta_5^q CONTIGMR_{ij} + \beta_6^q LANGMR_{ij} + \beta_7^q LEGALMR_{ij} + \beta_8^q RELIGMR_{ij} \\ & + \beta_9^q COMCOLMR_{ij} + \sum_{t=1}^{T} \alpha_t^q YEAR_t + \beta_{10}^q \overline{\ln GDP}_i + \beta_{11}^q \overline{\ln GDP}_j \\ & + \beta_{12}^q \overline{EIAMR}_{ij} + \sum_{t=1}^{T} + \gamma_t^q \overline{YEAR} + \beta_{13}^q \ln PCGDP_{it} + \beta_{14}^q \ln PCGDP_{jt} \\ & + \beta_{15}^q EIAMR_{ijt} * \ln PCGDP_{it} + \beta_{16}^q EIAMR_{ijt} * \ln PCGDP_{jt} \\ & + \beta_{17}^q \overline{\ln PCGDP_i} + \beta_{18}^q \overline{\ln PCGDP}_j + \sum_{s=1}^{S} \Upsilon_s + \eta_{ijst}^q. \end{aligned} \tag{32}$$

Table 15 and the accompanying Figure 5 provide the results. For brevity, we report in Table 15 the marginal effects; the regression results are in Appendix A, Table A10. 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 (comparable) 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 (comparable) 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. Consistent with the results discussed earlier in BBC, we note, for instance, that – at the 10th conditional quantile (first column) and when exponentiated – the marginal EIA effect on trade flows is *84 percent higher* when the exporter's per capita income is at only the 30th percentile relative to being at the 50th percentile (median).

[47] 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.

10 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 7, we have estimates of conditional quantile partial effects for positive trade flows and for non-negative trade flows, respectively. Figure 3 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 64-65 percent. Figure 4 provides the analogous information based upon the Logit-BVQCM results in Table 7 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 37-38 percent.

While this evidence is suggestive, a more rigorous technique is needed to establish unconditional quantile treatment effects. In Appendix B, we use the methodology of Firpo (2007) to provide quantile treatment effects (QTEs). To summarize the two important results, we find first that the QTEs also decline as quantiles increase, similar to our earlier results. We find second that the QTEs are generally of magnitudes quite similar quantitatively to our earlier conditional quantile effects.

11 Monte Carlo Simulations for a Two-Part DGP

In the previous econometric analysis, we have shown that:

(1) For positive trade flows, quantile regressions – with or without accounting for unobserved heterogeneity – provide EIA partial effect estimates at the median quantile that are closer to *historical* three-way FE (conditional mean) OLS estimates than to historical three-way FE (conditional mean) PPML estimates, and are about four to

five times larger than the PPML estimates.

(2) However, at the 90th conditional quantile, QR partial EIA effect estimates are *very close* to PPML estimates.

(3) Accounting for unobserved heterogeneity *and* for zeros using a novel three-step estimator, QR partial EIA effect estimates at the median of positive flows – which is Q75 of all non-negative flows – are about 50 percent smaller than QR partial (median quantile) EIA effect estimates using only positive trade flows.

(4) Across specifications and an extensive empirical robustness analysis, our QR results support the Arkolakis (2010) proposition that the effects of EIAs are larger when initial trade flows tend to be smaller (more specifically, at lower conditional quantiles).

In the spirit of Santos Silva and Tenreyro (2006), Head and Mayer (2014), and Martin and Pham (2020), we conduct a large Monte Carlo simulation analysis of the sensitivity of EIA partial effect estimates across a wide array of "error structures." A novel difference of our simulation study with these three previous simulation studies is that we pay particular attention to the *panel* nature of our data. Most researchers, including the three studies cited above, use a cross-section approach and cross-section data in their simulations. To bear resemblance to the canonical gravity expression for panel data in our econometric work, we introduce the it, jt, and ij dimensions to our analysis and we use the same data as in section 5.2.

In our first simulation analysis, we consider six alternative methods of estimation: OLS (for positive flows only), PPML (positive flows), BVQCM (positive flows), PPML (non-negative flows), Logit-BVQCM (to account for zeros), and LPM-BVQCM (to account for zeros). Also, we will separate results for positive trade flows only (Panel A in subsequent tables) from the results for non-negative trade flows (Panel B results). Noting all of this, we need to recall the discussion in section 3 on alternative "data generating processes" (DGPs). As addressed in section 3, depending upon the underlying theoretical context, one can consider bilateral trade flows as being generated under a single-stage DGP, consistent with the discussion in section 3.1 (gravity without export fixed costs). By contrast, one can also consider bilateral trade flows as being generated under a two-stage DGP, whereby – in the presence of export fixed costs – firms first decide (based upon variable profits relative to export fixed costs) whether or not to enter a market, and then conditional upon entering decide how much to export. In our first set of simulations discussed in this paper, we assume a two-stage DGP similar to that in Head and Mayer (2014) and adapted in Poissonnier (2019). However, because the underlying DGP is a two-stage process, this could affect the measurement of the bias if the (true) underlying DGP is single-stage, such as in Santos Silva and Tenreyro (2011); hence, we caution the reader in this regard. Consequently, in section 12, we will provide simulations under the alternative "null" of a single-stage process.

11.1 Methodology

Our approach for the two-part simulations follows the structural gravity methodology described in Head and Mayer (2014) and adapted in Poissonnier (2019) for panel data. As in Head and Mayer (2014), we start with two RHS variables determining trade flows, a continuous time-invariant variable, $\ln DIST_{ij}$, and a time-varying variable, EIA_{ijt}.[48] In the simulations, the coefficients on $\ln DIST_{ij}$ and EIA_{ijt} are set to -1 and 0.5, respectively, and we use an iterative approach to solve for the multilateral resistance terms Φ_{jt} and Π_{it} using a structural gravity framework as in Poissonnier (2019). Also as in Poissonnier (2019), the convergence criterion is quadratic such that the matrix $\Pi_{it}\Phi^{'}_{jt}$ is continually updated until convergence, which differs from the approach for each multilateral resistance term in Head and Mayer (2014). The data generating process is defined such that variable trade costs (τ_{ijt}) raised to the trade elasticity ($-\theta$) are:

$$\tau_{ijt}^{-\theta} = exp(-\ln DIST_{ij} + 0.5EIA_{ijt}) * \eta_{ijt} \tag{33}$$

where η_{ijt} is defined as in section 4.1.1. We define the variance of η_{ijt} as σ^2_{ijt}. For notational convenience going forward, we define a term μ_{ijt} such that $\mu_{ijt} = exp(-\ln DIST_{ij} + 0.5EIA_{ijt})$. Hence, $\tau_{ijt}^{-\theta} = \mu_{ijt}\eta_{ijt}$, as in Santos Silva and Tenreyro (2006).

To see how estimates from our alternative estimators are sensitive to the structure of gravity's errors, we consider the same four cases for the error structure presented in Santos Silva and Tenreyro (2006). Formally, the four cases we consider are:

1. Case 1: $\sigma^2_{ijt} = h \times \mu_{ijt}^{-2}$; $Var[X_{ijt}|EIA_{ijt}, \ln DIST_{ij}] = h$
2. Case 2: $\sigma^2_{ijt} = h \times \mu_{ijt}^{-1}$; $Var[X_{ijt}|EIA_{ijt}, \ln DIST_{ij}] = h \times \mu_{ijt}$
3. Case 3: $\sigma^2_{ijt} = h$; $Var[X_{ijt}|EIA_{ijt}, \ln DIST_{ij}] = h \times \mu^2_{ijt}$
4. Case 4: $\sigma^2_{ijt} = h \times (\mu_{ijt}^{-1} + \exp(x_{2ijt}))$; $Var[X_{ijt}|EIA_{ijt}, \ln DIST_{ij}] = h \times (\mu_{ijt} + \exp(x_{2ijt})\mu^2_{ijt})$

where the variable x_{2ijt} is a binary variable with mean 0.4.

[48]For the BV equivalent time-invariant and time-varying variables, each are constructed after the simulation data is created for each iteration.

We summarize each of the cases. In Case 1, the variance of ϵ_{ijt} is a constant (h), which implies that the non-linear least squares estimator is optimal; as discussed below, we set $h = 4$ in the benchmark case. Santos Silva and Tenreyro (2006) argue this case is unrealistic for bilateral trade, but – as there – we include it for completeness. In Case 2, the conditional variance of X_{ijt} is equal to its conditional mean, scaled by the index of dispersion h, as in the Poisson distribution. In this case, PPML is the optimal estimator and $\lambda = 1$. In Case 3, $\lambda = 2$, so the conditional variance of X_{ijt} is equal to the square of its conditional mean, scaled by the index of dispersion h, as in the Gamma distribution. In this case, Gamma PML is the optimal estimator. In Case 4, the conditional variance of X_{ijt} is a quadratic function of the mean, but it is not proportional to the square of the mean.

Note that we use the same Constant Variance Mean Ratio (Case 2) and Constant Coefficient of Variation (Case 3) notation that is specified in Head and Mayer (2014). Similar to Head and Mayer (2014), we include an overdisperson parameter, h, that is set initially to 4 as in Head and Mayer (2014). PPML should still remain consistent and efficient. We also provide simulations where h was set to 1 and 10.

The data generating process does not naturally generate zeros. Consequently, we follow Head and Mayer (2014), p. 180, to generate zeros. As in a standard Melitz model, we assume that variable profits of a firm in country i for selling to country j (say, X_{ijt}/α) must exceed export fixed costs f_{ijt} to enter the market, where α is defined as the elasticity of substitution in consumption. Hence, trade can only occur if $X_{ijt} \geq \alpha f_{ijt}$. So we create a threshold (zero profit cutoff) such that trade is positive if:

$$X_{ijt} = \begin{cases} X_{ijt}, & \text{if } X_{ijt} \geq \alpha f_{ijt} \\ 0, & \text{if } X_{ijt} < \alpha f_{ijt} \end{cases} . \tag{34}$$

The mean and variance of the threshold are set to mimic the proportion of zeros observed in the current sample of countries from 1965 to 2010 at 5 year intervals. Total trade cost is defined as:

$$\phi_{ijt} = \tau_{ijt}^{-\theta} f_{it}^{-\left[\frac{\theta}{\alpha-1}-1\right]} \tag{35}$$

Following Head and Mayer (2014), we set $\theta = 5$ and $\theta/(\alpha - 1) = 2.5$ which implies that $\alpha = 3$. Head and Mayer (2014) note that $\theta/(\alpha - 1) = 2.5$ matches the estimates provided by Eaton et al. (2011) of this parameter. Details of the construction of this two-stage DGP are provided in Appendix C.

11.2 Benchmark Simulation Results

For the benchmark simulations, we run all the models using our benchmark treatment of zeros in the data, adding ones to the zeros; our first robustness analysis in the next subsection will address this issue. For all the results, we report the coefficient estimates from 250 iterations of the specifications. For OLS and PPML, we include it, jt, and ij fixed effects. For BVQCM, Logit-BVQCM, and LPM-BVQCM, we include our correlated random effects, as explained earlier. For OLS and PPML specifications, we report the coefficient estimate for EIA_{ijt}, the standard error of the estimate, and the bias (which is two times the deviation of the estimate from 0.5). For BVQCM, Logit-BVQCM, and LPM-BVQCM, we report the coefficient estimate for $EIAMR_{ijt}$, the standard error of the estimate, and the bias.[49]

Table 16 reports the benchmark results. Note that we consider all the estimators used earlier in the empirical analysis. As indicated above, the table (and subsequent tables) are divided into two panels. The top panel uses only positive trade flows. The bottom panel uses all non-negative trade flows. Going down the rows of the top panel in Table 16, the first three estimators are OLS, PPML, and BVQCM, using positive trade flows only for the four different error-structure cases 1-4. In the bottom panel, we examine PPML, Logit-BVQCM, and LPM-BVQCM using positive trade flows and zeros; in a robustness analysis later, we will consider alternative methods for approximating zeros for the second and third stages in Logit-BVQCM and LPM-BVQCM, the percentages of zeros, and alternative indexes of overdispersion. For PPML, we use actual zeros, as standard.

We note several results in Table 16. First, for Case 1 when the conditional variance of X_{ijt} is a constant ($h = 4$) and only positive trade flows are used, PPML has the least bias of the three estimators for the EIA partial effect. For non-negative trade flows, again PPML has the least bias (0.011). The bias of Logit-BVQCM (LPM-BVQCM) is 0.028 (0.039). Second, similar results hold for Case 2, when the conditional variance of X_{ijt} is proportional to the conditional mean. Note that in Case 2, $\lambda = 1$ and the optimal estimator for the Poisson distribution is the PPML. For the case of non-negative trade flows, the relative biases of PPML, Logit-BVQCM, and LPM-BVQCM remain approximately the same as in Case 1.

Several results emerge for Cases 3 and 4. First, in Case 3 (for which Gamma PML is optimal), for positive trade flows PPML has the least bias. However, for non-negative trade flows, Logit-BVQCM has the lowest bias and LPM-BVQCM has the largest bias. For Case

[49] Note that the economic interpretations of these coefficient estimates are the same; from earlier in the paper, results are robust to constraining the MR terms' coefficients or allowing them to be unconstrained.

4, PPML has the largest bias.

11.3 Robustness Analysis

In this section, we discuss five robustness analyses conducted to see the sensitivity of our findings above to several changes.

11.3.1 Adding 1s to All Trade Flows

In empirical section 7, we provided a robustness analysis contrasting our benchmark estimates using the procedure suggested in Cameron and Trivedi (2009), Wooldridge (2010), and Figueiredo et al. (2014) – to add ones only to zeros – with an alternative of adding ones to all trade flows. We implement a similar robustness analysis here in the simulations.

The top panel of Table 17 reports the results for OLS, PPML, and BVQCM using only positive trade flows for this alternative treatment of zeros. Since the top panel uses only positive trade flows, one should not expect any *material* change in the estimates. However, for some (initially) very small trade flows (say, ones) adding a 1 can non-trivially affect the results. This is indeed the case, as expected. A comparison of the estimates from the top panel of Table 17 with the corresponding estimates in Table 16 shows that – for Cases 1 and 2 – the relative biases are approximately the same across the two methods of approximating zeros for OLS and BVQCM; naturally adding ones to all trade flows does impact the PPML estimates slightly, but not materially.

The bottom panel of Table 17 reports that – for Cases 1 and 2 – PPML remains having the smallest bias. However, for Cases 3 and 4, Logit-BVQCM has the smallest bias.

11.3.2 Increase the Number of Observations of Zero by 25 Percent

In this robustness analysis, we increase the number of observations that are zero in every year by 25 percent. The results are provided in Table 18. For brevity, we review only the results for non-negative trade flows in the bottom panel. With a substantive increase in zeros, LPM-BVQCM now has the least bias in all four cases, followed by Logit-BVQCM which has the second lowest level of bias in three of the four cases.

11.3.3 Decrease the Number of Observations of Zero by 25 Percent

Table 19 provides the results of decreasing the number of observations of zero relative to the benchmark. We focus again on the bottom panel, for brevity. With this decrease in the number of trade flows with zeros, PPML has the least bias when using non-negative trade flows in Cases 1 and 2. However, Logit-BVQCM has the least bias in the bottom panel of Table 19 in Cases 3 and 4.

11.3.4 Increase the Cutoff Value for Trade to USD 500,000

In this case, we increase the cutoff value for trade to USD 500,000, similar to the exercise in empirical Section 7. The results are provided in Table 20; we focus on the bottom panel. Increasing the cutoff value for trade relative to the benchmark does not alter materially the biases for the four cases for non-negative trade relative to the benchmark results in Table 16.

11.3.5 Reduce the Overdispersion Index from $h = 4$ to $h = 1$

Table 21 provides the penultimate set of simulation results. In this case, we reduce the index of overdispersion from the value of $h = 4$ as used in the simulations in Head and Mayer (2014) to a lower value of $h = 1$. Focusing again on the bottom panel, the main finding, relative to the benchmark results in Table 16, is that the biases are reduced substantively for all three estimators (PPML, Logit-BVQCM, and LPM-BVQCM) in Cases 3 and 4. For Cases 1 and 2, the biases for all three estimators increase, but there is no change in relative biases (relative to the benchmark Table 16 results).

11.3.6 Increase the Overdispersion Index from $h = 4$ to $h = 10$

Table 22 provides the final set of simulation results in this section. In this case, we increase the index of overdispersion from the value of $h = 4$ as used in our benchmark simulations to a higher value of $h = 10$. Focusing again on the bottom panel, the main finding, relative to the benchmark results in Table 16, is that the biases increase for all three estimators in Cases 3 and 4. For Cases 1 and 2, the biases for all three estimators decrease, with the Logit-BVQCM falling sharply in Case 1. Logit-BVQCM has the least bias in Cases 1, 3, and 4.

In summary, our results indicate that the optimal estimator depends materially on the underlying error structure. In general, we find for the cases of constant variance (Case 1) and a Poisson distribution for errors (Case 2) that the optimal estimator is PPML. However, for Cases 3 and 4, we find significant evidence that Logit-BVQCM or LPM-BVQCM yield less biased estimates.

12 Monte Carlo Simulations 2: One-Part DGP

The simulation results presented in the previous section relied on a structural gravity methodology simulation approach described in Head and Mayer (2014) and adapted in Poissonnier (2019) for panel data and was implicitly a two-stage DGP. The key feature of this approach was the inclusion of fixed trade costs, f_{ijt}, in ϕ_{ijt} (overall trade costs). The simulations closely followed the theoretical gravity specification with export fixed costs developed by Melitz (2003), an extensive margin decision and an intensive margin decision. Given that the PPML estimator is not optimal for a two-stage modeling process, we will present an alternative one-step DGP here for non-negative outcomes.

12.1 Methodology

We now present simulation results that have a one-stage DGP as outlined in Santos Silva and Tenreyro (2011) and Breinlich et al. (2022). Similar to the simulations presented in Santos Silva and Tenreyro (2011), the dependent variable, y_i, has a significant proportion of zero outcomes while its expectation, conditional on its determinants, is expressed as:

$$E(y_i|x_i) = exp(x_i'\beta). \tag{36}$$

We note that this expectation can be represented as a finite mixture of two components: (1) m_i, which is a discrete random variable, and (2) a continuous random variable z_{ik}. In the context of international trade, for convenience let y_i be exports from country i (to some country j) and β a vector of coefficients on x_i. We let m_i denote the number of firms and let z_{ik} denote the exports of a particular firm, where k denotes a firm. Given the discussion, we can express the dependent variable as:

$$y_i = \sum_{k=1}^{m_i} z_{ik} \tag{37}$$

where m_i is a discrete non-negative integer (of possible export firms in country i).

If we assume that z_{ik} and m_i are independent, we can rewrite the expectation as:

$$\begin{aligned} E(y_i|x_i) &= E(m_i|z_{ik})E(z_{ik}|x_i) && (38)\\ &= exp(x_i'\gamma)exp(x_i'\delta) && (39) \end{aligned}$$

so that $\beta = \gamma + \delta$. To simplify the simulation, both Santos Silva and Tenreyro (2011) and

Breinlich et al. (2022) assume $\delta = 0$, which implies that:

$$E(y_i|x_i) = E(m_i|z_{ik}) = exp(x_i'\beta). \tag{40}$$

If z_{ik} is zero for all firms in country i, then the aggregate bilateral trade flow would be zero.

Following Santos Silva and Tenreyro (2011) and Breinlich et al. (2022), we specify that $E(m_i|z_{ik}) = exp(0.4 + \beta z_{ik})$ and $Var(m_i|z_{ik}) = aE(m_i|z_{ik}) + bE(m_i|z_{ik})^2$. Note that Santos Silva and Tenreyro (2011) used varying values of a and b that change the percentage of zeros in the simulated data. Following Breinlich et al. (2022), setting $a = 1$ and $b = 2$ implies that the simulated data will have roughly 50 percent zeros, which is similar to aggregate trade data used in the previous simulations and actual trade data. Both articles note that the Gamma PML is the optimal estimator given the simulation setup, which then should not favor the PPML *or* our three stage approach. We similarly exclude fixed effects, for simplicity. Additionally, we will report the results of the PPML conditional mean while we report $Q_{0.50}, Q_{0.60}, Q_{0.70}, Q_{0.80}, Q_{0.90}$ for our three stage censored quantile model.

We will consider two cases: (1) regressors and parameters are constant across k, and (2) parameters vary across k but each firm faces the same regressors. In Case 1, we consider homogeneous firms. In Case 2, we allow for heterogeneity across firms. In Case 2, we use σ_k to define variation in productivity across firms (i.e., heterogeneous firms):

- Case 1: Homogeneous firms
    - $\beta = -1$ and $z_i \sim \mathcal{N}(0, 1)$
- Case 2: Heterogeneous firms
    - $\beta \sim \mathcal{N}(-1, \sigma_k)$ and $z_i \sim \mathcal{N}(0, 1)$

The simulation will set $n \in \{100,000; 1,000,000\}$ and $k = 1$ (initially).[50] Additionally, we will allow the variation of the firm parameters such that $\sigma_k \in \{0.0, 0.25, 0.50, 0.75, 1.0\}$.

12.2 Results

The results are presented in two parts. The first part is the set of results in Table 23. This table is composed of three panels. Panel A provides the results of estimating the model using PPML. We have two sets of samples: one uses a sample of $n = 100,000$ and the other uses a sample of $n = 1,000,000$. Across rows, we vary the degree of heterogeneity

[50]The setup is analogous to Breinlich et al. (2022) and the choice of k will not be relevant given that our focus is on the aggregate y_i.

among firms (which is also representative of an index of heterogeneity across sectors). With homogeneous firms, PPML has virtually no bias. As we move down rows in Panel A, increasing heterogeneity among firms increases the bias of the PPML conditional mean. The results are virtually identical across columns.

Panel B provides comparable results with $n = 100,000$ using Logit-BVQ. When there is no firm heterogeneity, Logit-BVQ has large bias at Q50, which is at the median of all flows, including zeros as described above. However, near the median of positive flows in the non-negative sample (Q80), Logit-BVQ has the least bias across these quantiles. Moreover, as firm heterogeneity increases as we move down the rows of Panel B, the minimal bias at Q80 persists. Indeed, across every row for Logit-BVQ except for Q50, the bias stays approximately the same as heterogeneity increases. These results are confirmed with the larger sample in Panel C.

Table 24 provides further results from the simulations analogous to those in Breinlich et al. (2022). The top panel presents the results allowing variation in the number of firms (k) in the sample. Clearly, the number of firms does not matter for the results. However, the top panel shows clearly that – with firm homogeneity – PPML has the lowest bias. However, at Q80 (the median of positive flows in the non-negative sample), Logit-BVQ has fairly low bias, certainly relative to that at the median of all non-negative flows.

However, the bottom panel of Table 24 shows that – with firm heterogeneity – PPML, as found earlier, has considerable bias. Yet, Logit-BVQ has much smaller bias, whether at the median of all non-negative flows or at the median of the positive flows.

The bottom line is that – as in the case of the two-part Monte Carlo analysis earlier – which method has the least bias is a function of parameters of the model. Interestingly, under many scenarios, Logit-BVQ has small biases.

13 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, extending the work of Baier et al. (2018a), we found strong evidence that developing country exports benefit more from EIAs than non-developing exporters. Our evidence suggests that developing country exports actually increase more than non-developing countries' exports.

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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14 Figures and Tables

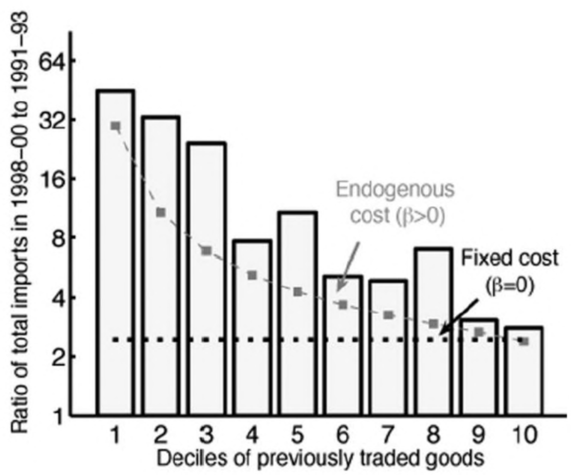

Figure 1: Predicted and actual ratio of U.S. imports from Mexico in 1998-2000 to that in 1991-1993 for each decile of previously traded goods. (Arkolakis, JPE, 2010)

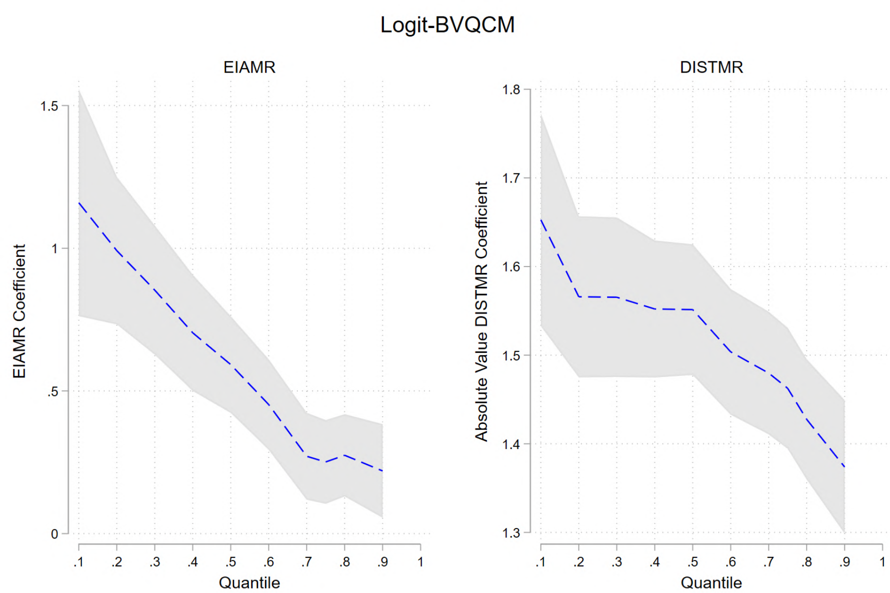

Figure 2: Coefficients on $EIAMR$ (Panel A) and $DISTMR$ (Panel B) from Logit-BVQCM.

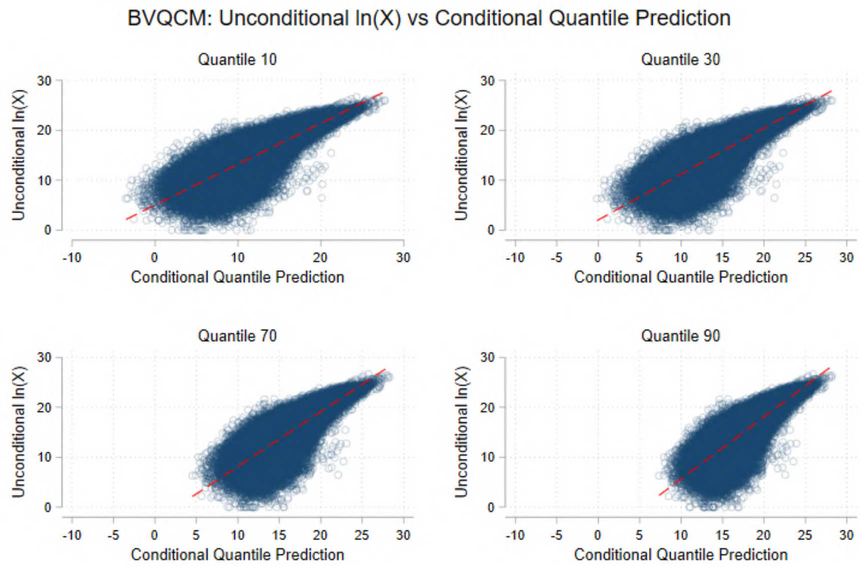

Figure 3: BVQCM

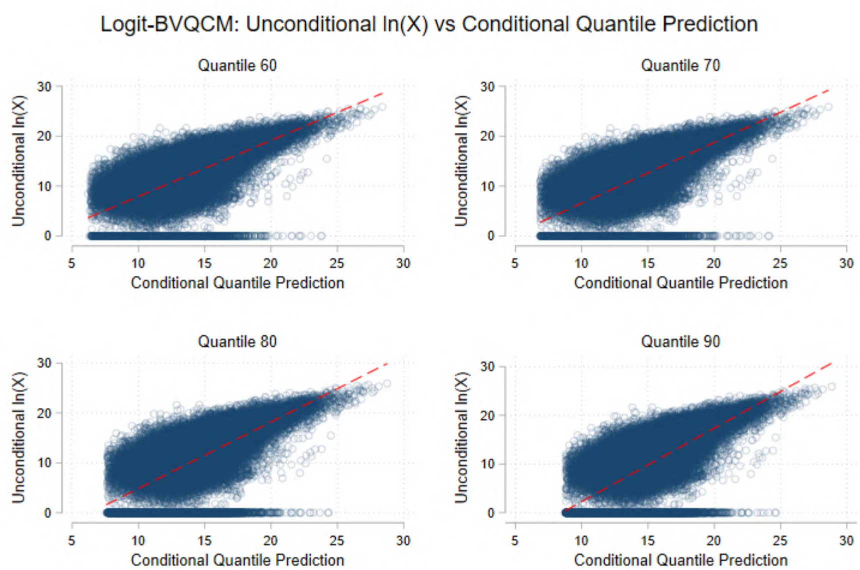

Figure 4: Logit-BVQCM

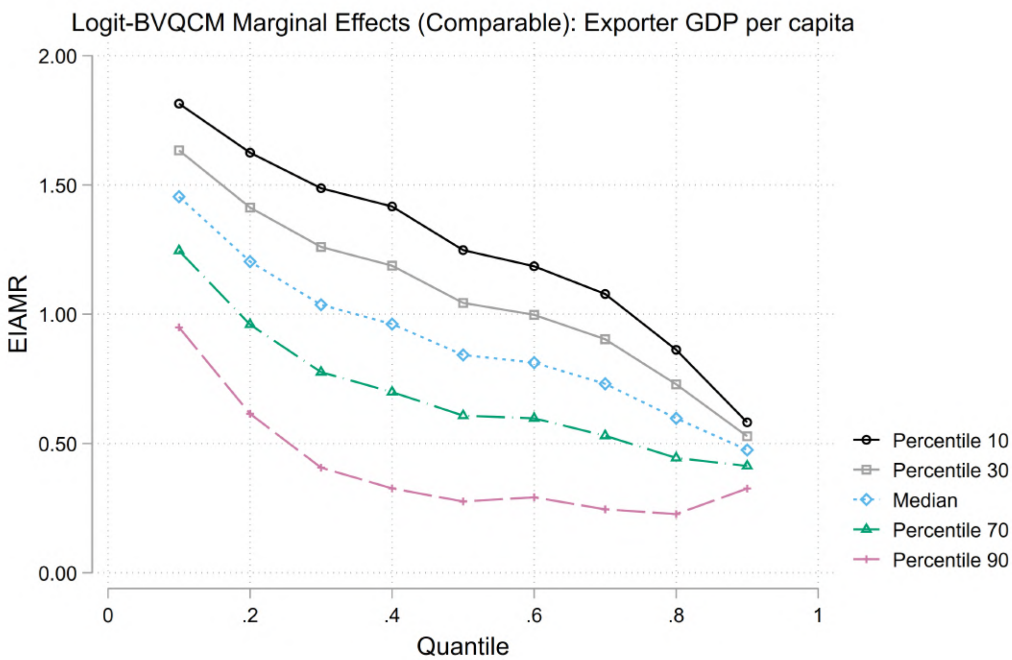

Figure 5: Logit-BVQCM

Note: Percentiles in the legend refer to exporter GDP per capita. "Comparable" refers to the adjustment discussed by Machado et al. (2016) to allow partial effects to be comparable across quantiles.

Table 1: Comparison of Linear Regression and Quantile Regression

Linear Regression	**Quantile Regression**
1. Predicts the conditional mean $E(Y \mid X)$	Predicts conditional quantiles $Q_\tau(Y \mid X)$
2. Often assumes normality	Is distribution agnostic
3. Does not preserve $E(Y \mid X)$ under transformation	Preserves $Q_\tau(Y \mid X)$ 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

Source: Rodriguez and Yao (2017).

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. The median of strictly positive trade values fall between the 74th and 76th percentile. 184 countries are in the sample.

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	-	-

Notes: Total observations are based upon 184 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.

Table 4: 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)	1.113***	0.649***		0.777***	1.025***		0.800***	1.118***	
	(0.005)	(0.022)		(0.015)	(0.085)		(0.015)	(0.084)	
ln(GDPim)	0.950***	0.463***		0.795***	0.903***		0.840***	1.029***	
	(0.006)	(0.024)		(0.019)	(0.058)		(0.018)	(0.048)	
EIAMR	0.529***	0.430***	0.383***	0.213**	0.130*	0.121***	0.242**	0.164**	0.109***
	(0.047)	(0.036)	(0.034)	(0.106)	(0.074)	(0.029)	(0.106)	(0.072)	(0.029)
DISTMR	-1.391***	-1.317***		-0.826***	-0.777***		-0.839***	-0.779***	
	(0.022)	(0.024)		(0.059)	(0.066)		(0.059)	(0.064)	
CONTIGMR	0.458***	0.467***		0.317***	0.347***		0.283***	0.321***	
	(0.089)	(0.088)		(0.090)	(0.094)		(0.090)	(0.094)	
LANGMR	0.460***	0.433***		0.413***	0.386***		0.434***	0.413***	
	(0.050)	(0.049)		(0.112)	(0.110)		(0.114)	(0.110)	
LEGALMR	0.270***	0.253***		0.036	0.050		0.042	0.048	
	(0.034)	(0.033)		(0.094)	(0.093)		(0.094)	(0.093)	
RELIGMR	0.336***	0.298***		-0.240**	-0.246**		-0.253***	-0.266***	
	(0.061)	(0.060)		(0.101)	(0.100)		(0.098)	(0.098)	
COMCOLMR	0.561***	0.461***		-0.439	-0.364		-0.470	-0.355	
	(0.061)	(0.059)		(0.337)	(0.323)		(0.349)	(0.324)	
BV	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Year FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
CRE	No	Yes	No	No	Yes	No	No	Yes	No
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
Adj. R2	0.645	0.656	0.857						
Pseudo R2				0.899	0.901	0.991	0.909	0.911	0.992
Obs	121417	121417	121417	121417	121417	121417	248123	248123	248123

Clustered standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. The + indicates only positive trade values (i.e. $T_{ij} > 0$) were used in the estimation. 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. "Year FE" indicates whether year dummy variables 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 EIAMR yielded identical coefficient estimates. As discussed in the text, the coefficient estimates for EIA in columns (4), (7), and (10) are identical using $EIAMR_{ijt}$ or EIA_{ijt}; the reason is that the exporter-year and importer-year FEs capture all of multilateral resistance elements inside $EIAMR_{ijt}$.

Table 5: BVQ Positive

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q75	(10) Q80	(11) Q90
ln(GDPex)	1.421***	1.329***	1.256***	1.186***	1.121***	1.056***	0.984***	0.943***	0.902***	0.802***
	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
ln(GDPim)	1.086***	1.046***	1.011***	0.981***	0.954***	0.927***	0.898***	0.880***	0.858***	0.820***
	(0.009)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
EIAMR	0.439***	0.423***	0.384***	0.384***	0.372***	0.385***	0.368***	0.362***	0.364***	0.314***
	(0.094)	(0.061)	(0.053)	(0.047)	(0.044)	(0.042)	(0.042)	(0.042)	(0.043)	(0.049)
DISTMR	-1.635***	-1.517***	-1.434***	-1.375***	-1.334***	-1.280***	-1.236***	-1.203***	-1.172***	-1.133***
	(0.039)	(0.029)	(0.027)	(0.025)	(0.024)	(0.024)	(0.024)	(0.023)	(0.022)	(0.024)
CONTIGMR	0.073	0.104	0.187*	0.225**	0.291***	0.295***	0.350***	0.371***	0.398***	0.356***
	(0.127)	(0.115)	(0.112)	(0.107)	(0.103)	(0.100)	(0.103)	(0.099)	(0.098)	(0.099)
LANGMR	0.499***	0.477***	0.475***	0.458***	0.455***	0.469***	0.478***	0.478***	0.458***	0.462***
	(0.078)	(0.062)	(0.057)	(0.054)	(0.052)	(0.053)	(0.053)	(0.053)	(0.054)	(0.058)
LEGALMR	0.188***	0.270***	0.287***	0.304***	0.312***	0.342***	0.357***	0.362***	0.368***	0.333***
	(0.059)	(0.044)	(0.041)	(0.038)	(0.036)	(0.036)	(0.035)	(0.035)	(0.035)	(0.037)
RELIGMR	0.665***	0.550***	0.386***	0.257***	0.174***	0.063	0.029	0.002	-0.009	-0.060
	(0.109)	(0.083)	(0.072)	(0.067)	(0.061)	(0.059)	(0.061)	(0.061)	(0.062)	(0.069)
COMCOLMR	0.618***	0.556***	0.479***	0.458***	0.433***	0.403***	0.384***	0.374***	0.369***	0.390***
	(0.104)	(0.089)	(0.078)	(0.074)	(0.071)	(0.068)	(0.065)	(0.065)	(0.066)	(0.066)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	No	No	No	No	No	No	No	No	No	No
Obs	121417	121417	121417	121417	121417	121417	121417	121417	121417	121417

Clustered standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. 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. "Year FE" indicates whether year dummy variables were included or not; "CRE" indicates whether correlated random effects were used or not.

Table 6: BVQCM Positive

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q75	(10) Q80	(11) Q90
ln(GDPex)	0.777***	0.774***	0.747***	0.711***	0.722***	0.708***	0.690***	0.670***	0.646***	0.577***
	(0.041)	(0.033)	(0.029)	(0.026)	(0.025)	(0.024)	(0.024)	(0.024)	(0.023)	(0.026)
ln(GDPim)	0.521***	0.494***	0.468***	0.460***	0.474***	0.478***	0.490***	0.490***	0.489***	0.524***
	(0.043)	(0.036)	(0.030)	(0.027)	(0.026)	(0.024)	(0.024)	(0.024)	(0.024)	(0.027)
EIAMR	0.498***	0.452***	0.465***	0.472***	0.462***	0.411***	0.358***	0.310***	0.262***	0.158***
	(0.084)	(0.055)	(0.044)	(0.040)	(0.039)	(0.037)	(0.036)	(0.036)	(0.038)	(0.047)
DISTMR	-1.551***	-1.446***	-1.402***	-1.356***	-1.313***	-1.253***	-1.204***	-1.174***	-1.136***	-1.094***
	(0.041)	(0.035)	(0.030)	(0.027)	(0.026)	(0.026)	(0.025)	(0.025)	(0.025)	(0.026)
CONTIGMR	0.147	0.102	0.206*	0.222**	0.303***	0.303***	0.367***	0.404***	0.397***	0.356***
	(0.121)	(0.114)	(0.107)	(0.105)	(0.103)	(0.105)	(0.104)	(0.095)	(0.090)	(0.096)
LANGMR	0.474***	0.458***	0.428***	0.425***	0.423***	0.446***	0.450***	0.445***	0.445***	0.457***
	(0.078)	(0.063)	(0.056)	(0.054)	(0.052)	(0.051)	(0.051)	(0.052)	(0.054)	(0.058)
LEGALMR	0.204***	0.256***	0.266***	0.278***	0.297***	0.322***	0.334***	0.344***	0.348***	0.315***
	(0.059)	(0.046)	(0.039)	(0.037)	(0.036)	(0.035)	(0.034)	(0.034)	(0.035)	(0.035)
RELIGMR	0.562***	0.474***	0.322***	0.229***	0.127**	0.055	-0.033	-0.047	-0.047	-0.036
	(0.105)	(0.084)	(0.071)	(0.065)	(0.060)	(0.059)	(0.059)	(0.059)	(0.061)	(0.070)
COMCOLMR	0.475***	0.385***	0.397***	0.408***	0.400***	0.349***	0.354***	0.336***	0.367***	0.316***
	(0.108)	(0.087)	(0.079)	(0.074)	(0.069)	(0.065)	(0.063)	(0.064)	(0.065)	(0.065)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	121417	121417	121417	121417	121417	121417	121417	121417	121417	121417

Clustered standard errors by country-pair in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. 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. "Year FE" indicates whether year dummy variables were included or not; "CRE" indicates whether correlated random effects were used or not.

Table 7: Logit-BVQCM

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q75	(10) Q80	(11) Q90
ln(GDPex)	1.019***	1.055***	1.091***	1.051***	1.037***	1.009***	0.971***	0.946***	0.918***	0.812***
	(0.078)	(0.061)	(0.055)	(0.047)	(0.042)	(0.039)	(0.037)	(0.035)	(0.035)	(0.038)
ln(GDPim)	0.914***	0.983***	1.017***	0.989***	1.001***	0.968***	0.914***	0.878***	0.874***	0.823***
	(0.074)	(0.055)	(0.051)	(0.043)	(0.038)	(0.037)	(0.036)	(0.036)	(0.036)	(0.039)
EIAMR	1.160***	0.992***	0.853***	0.703***	0.593***	0.452***	0.271***	0.251***	0.275***	0.220***
	(0.203)	(0.132)	(0.115)	(0.104)	(0.086)	(0.081)	(0.078)	(0.075)	(0.073)	(0.084)
DISTMR	-1.653***	-1.566***	-1.565***	-1.552***	-1.551***	-1.504***	-1.480***	-1.463***	-1.428***	-1.374***
	(0.061)	(0.046)	(0.046)	(0.039)	(0.038)	(0.036)	(0.035)	(0.035)	(0.035)	(0.038)
CONTIGMR	0.754***	0.942***	0.849***	0.716***	0.598***	0.638***	0.593***	0.552***	0.554***	0.472***
	(0.234)	(0.191)	(0.164)	(0.147)	(0.149)	(0.153)	(0.141)	(0.135)	(0.131)	(0.129)
LANGMR	0.501***	0.343***	0.388***	0.395***	0.403***	0.461***	0.467***	0.477***	0.488***	0.457***
	(0.133)	(0.101)	(0.094)	(0.088)	(0.085)	(0.082)	(0.078)	(0.078)	(0.079)	(0.080)
LEGALMR	0.328***	0.290***	0.289***	0.283***	0.311***	0.279***	0.275***	0.249***	0.206***	0.164***
	(0.088)	(0.069)	(0.064)	(0.058)	(0.054)	(0.052)	(0.050)	(0.050)	(0.050)	(0.051)
RELIGMR	-0.119	-0.004	0.168	0.169	0.142	0.188**	0.219**	0.208**	0.270***	0.309***
	(0.173)	(0.133)	(0.122)	(0.105)	(0.099)	(0.095)	(0.093)	(0.095)	(0.096)	(0.104)
COMCOLMR	0.578***	0.612***	0.620***	0.690***	0.723***	0.708***	0.668***	0.646***	0.662***	0.610***
	(0.160)	(0.126)	(0.115)	(0.102)	(0.094)	(0.088)	(0.083)	(0.082)	(0.082)	(0.083)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	45721	53410	58986	63751	68164	72317	77088	79697	82460	88975

Clustered standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. The prefix "Logit-" 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. $T_{ij} \geq 0$). 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.

Table 8: Logit-BVQCM (User-defined minimum value of USD 10,000)

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q75	(10) Q80	(11) Q90
ln(GDPex)	0.808***	0.851***	0.959***	0.968***	0.986***	0.977***	0.912***	0.908***	0.868***	0.762***
	(0.066)	(0.053)	(0.047)	(0.041)	(0.038)	(0.037)	(0.034)	(0.034)	(0.034)	(0.036)
ln(GDPim)	0.788***	0.813***	0.849***	0.842***	0.856***	0.867***	0.835***	0.846***	0.816***	0.786***
	(0.062)	(0.052)	(0.043)	(0.037)	(0.036)	(0.036)	(0.034)	(0.034)	(0.034)	(0.038)
EIAMR	0.781***	0.929***	0.885***	0.757***	0.664***	0.555***	0.415***	0.363***	0.278***	0.232***
	(0.139)	(0.124)	(0.089)	(0.084)	(0.081)	(0.072)	(0.069)	(0.067)	(0.065)	(0.076)
DISTMR	-1.273***	-1.293***	-1.313***	-1.292***	-1.297***	-1.308***	-1.278***	-1.266***	-1.239***	-1.203***
	(0.052)	(0.043)	(0.035)	(0.033)	(0.035)	(0.035)	(0.033)	(0.032)	(0.032)	(0.036)
CONTIGMR	0.645***	0.658***	0.623***	0.557***	0.434***	0.398***	0.499***	0.523***	0.536***	0.489***
	(0.205)	(0.178)	(0.135)	(0.125)	(0.133)	(0.138)	(0.136)	(0.128)	(0.121)	(0.118)
LANGMR	0.177*	0.165*	0.239***	0.281***	0.304***	0.348***	0.387***	0.398***	0.398***	0.397***
	(0.099)	(0.089)	(0.080)	(0.075)	(0.077)	(0.076)	(0.074)	(0.076)	(0.077)	(0.081)
LEGALMR	0.289***	0.247***	0.281***	0.287***	0.290***	0.296***	0.269***	0.238***	0.217***	0.191***
	(0.075)	(0.062)	(0.055)	(0.051)	(0.050)	(0.049)	(0.047)	(0.048)	(0.048)	(0.050)
RELIGMR	-0.025	0.031	0.042	-0.012	0.054	0.052	0.060	0.152	0.150*	0.224**
	(0.130)	(0.123)	(0.099)	(0.095)	(0.092)	(0.087)	(0.090)	(0.093)	(0.091)	(0.098)
COMCOLMR	0.372***	0.494***	0.548***	0.570***	0.614***	0.590***	0.581***	0.572***	0.591***	0.524***
	(0.139)	(0.113)	(0.095)	(0.088)	(0.085)	(0.081)	(0.078)	(0.080)	(0.079)	(0.082)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	39966	46728	51774	56121	60258	64541	69174	71755	74599	81087

Clustered standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. The prefix "Logit-" 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. $T_{ij} \geq 0$). The second and third stages are both quantile regressions 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. "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. We create an arbitrary minimum value of USD 10,000 and replace trade values below this cutoff to 1 (i.e. $\ln(X_{ijt}) = 0$ when trade value is 1.)

Table 9: Logit-BVQCM Disaggregated by Type of EIA

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q75	Q80	Q90
ln(GDPex)	1.008***	1.052***	1.084***	1.055***	1.031***	1.005***	0.958***	0.942***	0.913***	0.802***
	(0.079)	(0.061)	(0.055)	(0.047)	(0.042)	(0.039)	(0.037)	(0.035)	(0.035)	(0.038)
ln(GDPim)	0.906***	0.971***	1.015***	0.985***	0.997***	0.957***	0.922***	0.886***	0.884***	0.820***
	(0.073)	(0.055)	(0.051)	(0.044)	(0.038)	(0.037)	(0.036)	(0.036)	(0.036)	(0.039)
FTA-MR	1.230***	0.963***	0.857***	0.748***	0.631***	0.507***	0.362***	0.294***	0.271***	0.096
	(0.197)	(0.129)	(0.112)	(0.099)	(0.086)	(0.081)	(0.078)	(0.077)	(0.074)	(0.080)
CUCMECU-MR	0.828**	0.914***	0.929***	0.756***	0.683***	0.550***	0.518***	0.539***	0.573***	0.682***
	(0.417)	(0.271)	(0.223)	(0.179)	(0.158)	(0.147)	(0.140)	(0.139)	(0.136)	(0.169)
DISTMR	-1.647***	-1.561***	-1.562***	-1.557***	-1.550***	-1.496***	-1.461***	-1.459***	-1.429***	-1.362***
	(0.059)	(0.046)	(0.045)	(0.039)	(0.037)	(0.036)	(0.035)	(0.035)	(0.035)	(0.038)
CONTIGMR	0.886***	0.877***	0.859***	0.689***	0.580***	0.619***	0.665***	0.616***	0.585***	0.501***
	(0.221)	(0.194)	(0.162)	(0.146)	(0.147)	(0.158)	(0.145)	(0.138)	(0.129)	(0.125)
LANGMR	0.491***	0.344***	0.387***	0.395***	0.410***	0.463***	0.483***	0.470***	0.492***	0.463***
	(0.132)	(0.100)	(0.094)	(0.088)	(0.086)	(0.082)	(0.079)	(0.079)	(0.079)	(0.080)
LEGALMR	0.332***	0.296***	0.290***	0.285***	0.303***	0.280***	0.277***	0.247***	0.203***	0.166***
	(0.089)	(0.068)	(0.064)	(0.058)	(0.054)	(0.052)	(0.051)	(0.050)	(0.049)	(0.051)
RELIGMR	-0.120	-0.000	0.150	0.173*	0.147	0.208**	0.233**	0.233**	0.275***	0.334***
	(0.172)	(0.132)	(0.122)	(0.105)	(0.099)	(0.095)	(0.093)	(0.095)	(0.095)	(0.104)
COMCOLMR	0.605***	0.649***	0.629***	0.670***	0.698***	0.693***	0.626***	0.626***	0.641***	0.588***
	(0.161)	(0.129)	(0.115)	(0.102)	(0.094)	(0.089)	(0.083)	(0.083)	(0.082)	(0.083)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	45722	53410	58994	63737	68154	72322	77074	79679	82443	88956

Clustered standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. The prefix "Logit-" 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. $T_{ij} \geq 0$). The second and third stages are both quantile regressions 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. "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. The terms FTA and CUCMECU indicate Free Trade Agreements and deeper trade agreements (including Customs Unions, Common Markets, and Economic Unions), respectively.

Table 10: LPM-BVQCM

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q75	(10) Q80	(11) Q90
ln(GDPex)	0.864***	0.950***	0.941***	0.974***	1.007***	1.002***	0.982***	0.964***	0.936***	0.835***
	(0.060)	(0.037)	(0.032)	(0.029)	(0.028)	(0.026)	(0.025)	(0.025)	(0.025)	(0.025)
ln(GDPim)	0.816***	0.816***	0.854***	0.867***	0.882***	0.860***	0.829***	0.822***	0.814***	0.771***
	(0.066)	(0.039)	(0.032)	(0.028)	(0.027)	(0.026)	(0.026)	(0.027)	(0.027)	(0.029)
EIAMR	0.785***	0.765***	0.766***	0.732***	0.684***	0.618***	0.499***	0.426***	0.359***	0.336***
	(0.077)	(0.050)	(0.043)	(0.042)	(0.041)	(0.041)	(0.042)	(0.042)	(0.043)	(0.050)
DISTMR	-1.188***	-1.228***	-1.259***	-1.308***	-1.340***	-1.369***	-1.383***	-1.383***	-1.394***	-1.378***
	(0.054)	(0.037)	(0.032)	(0.029)	(0.029)	(0.028)	(0.027)	(0.027)	(0.028)	(0.029)
CONTIGMR	-0.203	-0.024	0.107	0.205*	0.302***	0.296***	0.331***	0.414***	0.403***	0.361***
	(0.127)	(0.105)	(0.103)	(0.108)	(0.107)	(0.104)	(0.112)	(0.115)	(0.114)	(0.112)
LANGMR	0.189**	0.217***	0.271***	0.347***	0.457***	0.502***	0.553***	0.581***	0.572***	0.565***
	(0.091)	(0.065)	(0.060)	(0.059)	(0.058)	(0.059)	(0.058)	(0.058)	(0.059)	(0.063)
LEGALMR	0.511***	0.548***	0.487***	0.444***	0.404***	0.414***	0.409***	0.406***	0.371***	0.340***
	(0.067)	(0.048)	(0.042)	(0.039)	(0.039)	(0.040)	(0.039)	(0.039)	(0.039)	(0.041)
RELIGMR	0.340***	0.146*	0.072	0.026	0.020	0.009	0.062	0.094	0.112	0.104
	(0.121)	(0.085)	(0.074)	(0.069)	(0.067)	(0.066)	(0.067)	(0.067)	(0.069)	(0.075)
COMCOLMR	0.140	0.200	0.345***	0.390***	0.398***	0.423***	0.405***	0.405***	0.458***	0.488***
	(0.160)	(0.128)	(0.097)	(0.084)	(0.082)	(0.078)	(0.073)	(0.072)	(0.072)	(0.070)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	48602	74039	91708	105378	116927	127740	140112	147490	155884	176342

Clustered standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. The prefix "LPM-" 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 pair fixed effects using all trade pairs (i.e. $T_{ij} \geq 0$). The second and third stages are both quantile regressions 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. "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.

Table 11: Comparison of EIA Partial Effects With and Without Intra-national Trade

Panel A: OLS (Positive) and PPML (Non-negative)

(1)	(2) OLS+	(3) OLS+ INTRA	(4) PPML	(5) PPML INTRA
EIA	0.383***	0.389***	0.109***	0.277***
	(0.034)	(0.034)	(0.029)	(0.050)
Exporter-Year FE	Yes	Yes	Yes	Yes
Importer-Year FE	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes
INTER x Year FE	No	Yes	No	Yes
Adj. R2	0.851	0.857		
Pseudo R2			0.992	0.998
Obs	117539	118698	248123	249706

Panel B: BVQCM (Positive) and LPM-BVQCM (Non-negative)

(1)	(2) BVQCM+	(3) BVQCM+ INTRA	(4) LPM-BVQCM	(5) LPM-BVQCM INTRA
EIAMR	0.462***	0.485***	0.426***	0.433***
	(0.039)	(0.039)	(0.042)	(0.042)
BV	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes
INTER x Year FE	No	Yes	No	Yes
Obs	121417	122975	147490	149002

Clustered standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. OLS and PPML are average treatment effects. BVQCM is the median estimate of the positive trade flows. The prefix "LPM-" 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 pair fixed effects using all trade pairs (i.e. $T_{ij} \geq 0$). We cannot use logit in the first stage because intra-national trade observations are removed from predicted probabilities. 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. The $INTER \times Year\ FE$ refers to the interaction of an indicator variable, 1 if an observed trade is across an international border (international) and 0 otherwise, and the year dummy variable. LPM-BVQCM and LPM-BVQCM INTRA are estimates at the 75th conditional quantile, which is likely near the median of the positive trade flows in the entire (unconditional) non-negative trade-flow sample; see section 10 later.

Table 12: Logit-BVQCM (Comparable)

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q75	(10) Q80	(11) Q90
ln(GDPex)	1.013***	1.033***	1.048***	0.989***	0.952***	0.902***	0.837***	0.799***	0.757***	0.632***
	(0.078)	(0.060)	(0.053)	(0.044)	(0.039)	(0.035)	(0.032)	(0.030)	(0.029)	(0.030)
ln(GDPim)	0.909***	0.962***	0.977***	0.930***	0.919***	0.865***	0.788***	0.741***	0.721***	0.641***
	(0.074)	(0.054)	(0.049)	(0.041)	(0.035)	(0.033)	(0.031)	(0.031)	(0.030)	(0.030)
EIAMR	1.152***	0.971***	0.820***	0.661***	0.544***	0.404***	0.234***	0.212***	0.227***	0.171***
	(0.202)	(0.129)	(0.111)	(0.098)	(0.079)	(0.072)	(0.067)	(0.063)	(0.061)	(0.065)
DISTMR	-1.642***	-1.533***	-1.504***	-1.460***	-1.424***	-1.344***	-1.276***	-1.235***	-1.178***	-1.070***
	(0.061)	(0.045)	(0.044)	(0.037)	(0.034)	(0.032)	(0.030)	(0.029)	(0.029)	(0.030)
CONTIGMR	0.750***	0.922***	0.816***	0.674***	0.549***	0.570***	0.511***	0.466***	0.458***	0.367***
	(0.233)	(0.187)	(0.158)	(0.138)	(0.137)	(0.137)	(0.121)	(0.114)	(0.108)	(0.100)
LANGMR	0.498***	0.336***	0.373***	0.371***	0.370***	0.412***	0.403***	0.403***	0.403***	0.356***
	(0.132)	(0.098)	(0.090)	(0.083)	(0.078)	(0.073)	(0.067)	(0.066)	(0.065)	(0.063)
LEGALMR	0.326***	0.284***	0.278***	0.266***	0.285***	0.249***	0.238***	0.210***	0.170***	0.128***
	(0.088)	(0.067)	(0.061)	(0.055)	(0.049)	(0.046)	(0.043)	(0.042)	(0.041)	(0.040)
RELIGMR	-0.118	-0.004	0.161	0.159	0.130	0.168**	0.189**	0.175**	0.223***	0.240***
	(0.172)	(0.130)	(0.117)	(0.099)	(0.091)	(0.084)	(0.080)	(0.080)	(0.079)	(0.081)
COMCOLMR	0.575***	0.599***	0.596***	0.650***	0.664***	0.632***	0.576***	0.545***	0.546***	0.475***
	(0.159)	(0.124)	(0.111)	(0.096)	(0.087)	(0.079)	(0.071)	(0.069)	(0.068)	(0.064)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	45721	53410	58986	63751	68164	72317	77088	79697	82460	88975

Clustered standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. The prefix "Logit-" 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. $T_{ij} \geq 0$). 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. "Comparable" refers to the adjustment discussed by Machado et al. (2016) to allow partial effects to be comparable across quantiles.

Table 13: SITC 2 Digit Logit-BVQCM (Comparable) With EXSH_{t-5}

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
ln(GDPex)	0.626***	0.636***	0.648***	0.654***	0.666***	0.664***	0.652***	0.620***	0.553***
	(0.040)	(0.034)	(0.032)	(0.029)	(0.027)	(0.025)	(0.023)	(0.021)	(0.018)
ln(GDPim)	0.707***	0.671***	0.647***	0.623***	0.609***	0.596***	0.564***	0.506***	0.442***
	(0.040)	(0.036)	(0.032)	(0.030)	(0.027)	(0.025)	(0.023)	(0.021)	(0.017)
EIAMR	0.857***	0.792***	0.749***	0.712***	0.694***	0.640***	0.551***	0.484***	0.376***
	(0.067)	(0.056)	(0.051)	(0.047)	(0.043)	(0.040)	(0.036)	(0.032)	(0.027)
DISTMR	-0.907***	-0.928***	-0.926***	-0.922***	-0.900***	-0.866***	-0.814***	-0.734***	-0.599***
	(0.036)	(0.031)	(0.029)	(0.027)	(0.025)	(0.023)	(0.021)	(0.019)	(0.016)
CONTIGMR	0.311***	0.362***	0.360***	0.351***	0.331***	0.307***	0.280***	0.245***	0.222***
	(0.109)	(0.101)	(0.095)	(0.094)	(0.086)	(0.082)	(0.076)	(0.068)	(0.057)
LANGMR	0.278***	0.265***	0.271***	0.258***	0.263***	0.250***	0.242***	0.232***	0.208***
	(0.066)	(0.059)	(0.056)	(0.054)	(0.051)	(0.049)	(0.046)	(0.043)	(0.039)
LEGALMR	0.367***	0.342***	0.336***	0.326***	0.317***	0.307***	0.284***	0.247***	0.203***
	(0.048)	(0.045)	(0.042)	(0.039)	(0.037)	(0.035)	(0.032)	(0.029)	(0.025)
RELIGMR	-0.266***	-0.225***	-0.200***	-0.194***	-0.205***	-0.202***	-0.191***	-0.172***	-0.158***
	(0.086)	(0.075)	(0.070)	(0.065)	(0.062)	(0.058)	(0.054)	(0.049)	(0.046)
COMCOLMR	0.047	0.073	0.101	0.134*	0.157**	0.184***	0.202***	0.210***	0.193***
	(0.095)	(0.084)	(0.077)	(0.071)	(0.067)	(0.062)	(0.058)	(0.050)	(0.043)
EXSH_{t-5}	0.031***	0.034***	0.036***	0.038***	0.040***	0.040***	0.041***	0.042***	0.043***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EIAMR * EXSH_{t-5}	-0.005*	-0.003	-0.002	-0.004**	-0.006***	-0.007***	-0.009***	-0.013***	-0.019***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
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	778998	945562	1082109	1207897	1334939	1472932	1634531	1830913	2083443

Clustered standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. The prefix "Logit-" 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. $T_{ij} \geq 0$). 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. "Comparable" refers to the adjustment discussed by Machado et al. (2016) to allow partial effects to be comparable across quantiles. $EXSH_{t-5}$ 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.

Table 14: Logit-BVQCM Marginal Effects (Comparable): Previous Sales Share

	(1) Q10	(2) Q20	(3) Q30	(4) Q40	(5) Q50	(6) Q60	(7) Q70	(8) Q80	(9) Q90
EIAMR									
Share 0.0%	0.857***	0.792***	0.749***	0.712***	0.694***	0.640***	0.551***	0.484***	0.376***
	(0.067)	(0.056)	(0.051)	(0.047)	(0.043)	(0.040)	(0.036)	(0.032)	(0.027)
Share 0.05%	0.857***	0.792***	0.749***	0.712***	0.694***	0.640***	0.550***	0.483***	0.375***
	(0.067)	(0.056)	(0.051)	(0.046)	(0.043)	(0.040)	(0.036)	(0.032)	(0.027)
Share 0.10%	0.856***	0.792***	0.749***	0.711***	0.694***	0.639***	0.550***	0.483***	0.374***
	(0.067)	(0.056)	(0.051)	(0.046)	(0.043)	(0.040)	(0.036)	(0.032)	(0.027)
Share 0.50%	0.854***	0.790***	0.748***	0.710***	0.691***	0.637***	0.546***	0.477***	0.367***
	(0.067)	(0.056)	(0.050)	(0.046)	(0.043)	(0.040)	(0.036)	(0.032)	(0.027)
Share 1.0%	0.852***	0.789***	0.747***	0.707***	0.688***	0.633***	0.542***	0.471***	0.358***
	(0.067)	(0.056)	(0.050)	(0.046)	(0.043)	(0.040)	(0.036)	(0.032)	(0.027)
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	778998	945562	1082109	1207897	1334939	1472932	1634531	1830913	2083443

Clustered standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. For all trade values, the percentiles of $\ln(X)$ at 50th, 75th, 90th, and 95th correspond to previous export shares at 0%, 0.04%, 0.75%, and 2.47%, respectively.

Table 15: Logit-BVQCM Marginal Effects (Comparable): Exporter GDP per capita

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
EIAMR									
10th Percentile	1.814***	1.625***	1.487***	1.417***	1.248***	1.185***	1.078***	0.862***	0.582***
	(0.331)	(0.213)	(0.233)	(0.207)	(0.197)	(0.186)	(0.155)	(0.125)	(0.137)
30th Percentile	1.634***	1.412***	1.260***	1.188***	1.044***	0.998***	0.903***	0.729***	0.528***
	(0.291)	(0.182)	(0.196)	(0.172)	(0.167)	(0.160)	(0.132)	(0.106)	(0.114)
Median	1.454***	1.203***	1.036***	0.962***	0.842***	0.813***	0.731***	0.597***	0.475***
	(0.265)	(0.164)	(0.171)	(0.147)	(0.145)	(0.142)	(0.117)	(0.095)	(0.099)
70th Percentile	1.245***	0.960***	0.776***	0.699***	0.608***	0.597***	0.530***	0.444***	0.413***
	(0.260)	(0.165)	(0.162)	(0.136)	(0.134)	(0.133)	(0.112)	(0.095)	(0.095)
90th Percentile	0.949***	0.615***	0.407**	0.326**	0.276*	0.292*	0.245*	0.227*	0.326***
	(0.298)	(0.204)	(0.193)	(0.160)	(0.150)	(0.149)	(0.130)	(0.120)	(0.115)
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	45724	53410	58987	63751	68164	72317	77088	82460	88975

Clustered standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. Marginal effects are calculated with importer GDP per capita set at 30th Percentile. The prefix "Logit-" 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. $T_{ij} \geq 0$). 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. "Comparable" refers to the adjustment discussed by Machado et al. (2016) to allow partial effects to be comparable across quantiles.

Table 16: Simulation 1: Benchmark Case of Adding 1s to 0s Only

Panel A:	EIA			
	Case 1	Case 2	Case 3	Case 4
	Trade>0			
(1)	(2)	(3)	(4)	(5)
OLS	0.51603	0.54213	0.59252	0.59110
S.E.	0.00307	0.00616	0.02607	0.02754
Bias	0.03207	0.08426	0.18503	0.18219
PPML	0.50035	0.50140	0.45219	0.44068
S.E.	0.00006	0.00092	0.08009	0.08268
Bias	0.00070	0.00279	0.09561	0.11865
BVQCM	0.45543	0.46700	0.62613	0.63656
S.E.	0.01003	0.01147	0.03561	0.03736
Bias	0.08914	0.06599	0.25225	0.27312
Panel B:	Trade≥0			
(1)	(2)	(3)	(4)	(5)
PPML	0.49450	0.49510	0.44010	0.41946
S.E.	0.00044	0.00100	0.08025	0.08219
Bias	0.01100	0.00979	0.11981	0.16108
Logit-BVQCM	0.51384	0.50760	0.53348	0.53982
S.E.	0.01815	0.02072	0.04696	0.04876
Bias	0.02768	0.01520	0.06695	0.07965
LPM-BVQCM	0.51963	0.51209	0.56937	0.56677
S.E.	0.01096	0.01128	0.03627	0.03805
Bias	0.03927	0.02419	0.13873	0.13355

Robust standard errors are clustered at the country-pair level. The simulations used 250 iterations, Stata 16.1, and R 4.1.0. Adjustment to dependent only occurred when the log of trade values are used. Even in PPML simulations, we add 1 to all actual trade values (including zeros). Bias is percentage difference (in decimal form) from 0.5 (or the EIA effect).

Table 17: Simulation 2: Case of Adding 1s to All Observations

Panel A:	EIA			
	Case 1	Case 2	Case 3	Case 4
	Trade>0			
(1)	(2)	(3)	(4)	(5)
OLS	0.52027	0.54437	0.58295	0.58597
S.E.	0.00288	0.00579	0.02530	0.02661
Bias	0.04054	0.08874	0.16589	0.17193
PPML	0.50086	0.50200	0.44139	0.43341
S.E.	0.00008	0.00092	0.08017	0.08257
Bias	0.00173	0.00400	0.11721	0.13317
BVQCM	0.46573	0.47444	0.63587	0.65536
S.E.	0.00999	0.01141	0.03475	0.03650
Bias	0.06854	0.05113	0.27174	0.31073
Panel B:	Trade≥0			
(1)	(2)	(3)	(4)	(5)
PPML	0.49585	0.49649	0.43787	0.43107
S.E.	0.00038	0.00097	0.07970	0.08163
Bias	0.00830	0.00701	0.12425	0.13786
Logit-BVQCM	0.51325	0.50194	0.51707	0.52015
S.E.	0.01755	0.01981	0.04446	0.04614
Bias	0.02649	0.00389	0.03414	0.04029
LPM-BVQCM	0.52564	0.51408	0.56247	0.56386
S.E.	0.01123	0.01138	0.03533	0.03699
Bias	0.05128	0.02816	0.12494	0.12772

Robust standard errors are clustered at the country-pair level. The simulations used 250 iterations, Stata 16.1, and R 4.1.0. Adjustment to dependent only occurred when the log of trade values are used. In PPML simulations, we use actual trade values (including zeros) and make no adjustment by adding 1 to 0 trade values. Bias is percentage difference (in decimal form) from 0.5 (or the EIA effect).

Table 18: Simulation 3: Case of Increasing Number of Zeros by 25%

Panel A:	EIA			
	Case 1	Case 2	Case 3	Case 4
	Trade>0			
(1)	(2)	(3)	(4)	(5)
OLS	0.50439	0.52764	0.61225	0.61197
S.E.	0.00174	0.00517	0.03014	0.03161
Bias	0.00878	0.05527	0.22449	0.22395
PPML	0.50013	0.50169	0.46506	0.43936
S.E.	0.00004	0.00093	0.08087	0.08339
Bias	0.00026	0.00337	0.06989	0.12127
BVQCM	0.34946	0.37173	0.59222	0.60825
S.E.	0.01105	0.01238	0.03974	0.04159
Bias	0.30109	0.25654	0.18444	0.21650
Panel B:	Trade≥0			
(1)	(2)	(3)	(4)	(5)
PPML	0.47838	0.47893	0.43598	0.41105
S.E.	0.00178	0.00200	0.08045	0.08285
Bias	0.04324	0.04215	0.12804	0.17790
Logit-BVQCM	0.52501	0.51772	0.54427	0.54962
S.E.	0.01540	0.01650	0.04498	0.04687
Bias	0.05001	0.03545	0.08854	0.09923
LPM-BVQCM	0.50867	0.50901	0.54184	0.53736
S.E.	0.01211	0.01233	0.04067	0.04253
Bias	0.01734	0.01802	0.08367	0.07472

Robust standard errors are clustered at the country-pair level. The simulations used 250 iterations, Stata 16.1, and R 4.1.0. Adjustment to dependent only occurred when the log of trade values are used. In PPML simulations, we use actual trade values (including zeros) and make no adjustment by adding 1 to 0 trade values. Bias is percentage difference (in decimal form) from 0.5 (or the EIA effect).

Table 19: Simulation 4: Case of Decreasing Number of Zeros by 25%

Panel A:	EIA			
	Case 1	Case 2	Case 3	Case 4
	Trade>0			
(1)	(2)	(3)	(4)	(5)
OLS	0.51923	0.53381	0.56133	0.56436
S.E.	0.00434	0.00717	0.02413	0.02563
Bias	0.03846	0.06762	0.12265	0.12873
PPML	0.50039	0.50073	0.44339	0.42693
S.E.	0.00006	0.00091	0.07944	0.08173
Bias	0.00079	0.00147	0.11322	0.14614
BVQCM	0.50210	0.49446	0.61029	0.62675
S.E.	0.00997	0.01121	0.03362	0.03555
Bias	0.00420	0.01108	0.22058	0.25349

Panel B:	Trade≥0			
(1)	(2)	(3)	(4)	(5)
PPML	0.49880	0.49913	0.44011	0.42360
S.E.	0.00012	0.00091	0.07941	0.08170
Bias	0.00240	0.00175	0.11978	0.15280
Logit-BVQCM	0.49406	0.51298	0.51469	0.52271
S.E.	0.02381	0.02854	0.05021	0.05239
Bias	0.01188	0.02596	0.02937	0.04542
LPM-BVQCM	0.51294	0.49792	0.55596	0.55630
S.E.	0.01032	0.01110	0.03378	0.03537
Bias	0.02589	0.00415	0.11192	0.11259

Robust standard errors are clustered at the country-pair level. The simulations used 250 iterations, Stata 16.1, and R 4.1.0. Adjustment to dependent only occurred when the log of trade values are used. In PPML simulations, we use actual trade values (including zeros) and make no adjustment by adding 1 to 0 trade values. Bias is percentage difference (in decimal form) from 0.5 (or the EIA effect).

Table 20: Simulation 5: Case with Cutoff Value of $500,000

Panel A:	EIA			
	Case 1	Case 2	Case 3	Case 4
	Trade>0			
(1)	(2)	(3)	(4)	(5)
OLS	0.51664	0.54306	0.59022	0.59230
S.E.	0.00305	0.00615	0.02605	0.02754
Bias	0.03329	0.08611	0.18043	0.18460
PPML	0.50036	0.50150	0.44832	0.43616
S.E.	0.00006	0.00092	0.08029	0.08234
Bias	0.00071	0.00299	0.10336	0.12768
BVQCM	0.45589	0.46914	0.63061	0.65490
S.E.	0.01004	0.01144	0.03558	0.03755
Bias	0.08823	0.06172	0.26122	0.30980
Panel B:	Trade≥0			
(1)	(2)	(3)	(4)	(5)
PPML	0.49451	0.49518	0.43816	0.42596
S.E.	0.00044	0.00100	0.08020	0.08222
Bias	0.01099	0.00963	0.12368	0.14809
Logit-BVQCM	0.51535	0.50632	0.52953	0.53803
S.E.	0.01806	0.02065	0.04692	0.04883
Bias	0.03070	0.01264	0.05906	0.07607
LPM-BVQCM	0.51958	0.51213	0.56424	0.56759
S.E.	0.01097	0.01126	0.03631	0.03825
Bias	0.03915	0.02426	0.12847	0.13518

Robust standard errors are clustered at the country-pair level. The simulations used 250 iterations, Stata 16.1, and R 4.1.0. Adjustment to dependent only occurred when the log of trade values are used. In PPML simulations, we use actual trade values (including zeros) and make no adjustment by adding 1 to 0 trade values. Bias is percentage difference (in decimal form) from 0.5 (or the EIA effect).

Table 21: Simulation 6: Overdispersion Index Reduced from 4 to 1, i.e. $h = 1$

Panel A:	EIA			
	Case 1	Case 2	Case 3	Case 4
	Trade>0			
(1)	(2)	(3)	(4)	(5)
OLS	0.50658	0.51593	0.56088	0.56838
S.E.	0.00190	0.00348	0.01749	0.01909
Bias	0.01317	0.03185	0.12175	0.13675
PPML	0.50011	0.50045	0.47120	0.46437
S.E.	0.00003	0.00046	0.05531	0.05823
Bias	0.00022	0.00091	0.05760	0.07126
BVQCM	0.44480	0.45079	0.52258	0.54311
S.E.	0.00980	0.01041	0.02446	0.02610
Bias	0.11040	0.09842	0.04517	0.08622
Panel B:	Trade≥0			
(1)	(2)	(3)	(4)	(5)
PPML	0.49447	0.49460	0.46349	0.45628
S.E.	0.00044	0.00063	0.05525	0.05816
Bias	0.01107	0.01079	0.07303	0.08743
Logit-BVQCM	0.52338	0.50971	0.51435	0.51921
S.E.	0.01798	0.01837	0.03459	0.03673
Bias	0.04675	0.01942	0.02870	0.03843
LPM-BVQCM	0.52518	0.51804	0.54686	0.54916
S.E.	0.01095	0.01081	0.02469	0.02638
Bias	0.05036	0.03609	0.09372	0.09831

Robust standard errors are clustered at the country-pair level. The simulations used 250 iterations, Stata 16.1, and R 4.1.0. Adjustment to dependent only occurred when the log of trade values are used. In PPML simulations, we use actual trade values (including zeros) and make no adjustment by adding 1 to 0 trade values. Bias is percentage difference (in decimal form) from 0.5 (or the EIA effect).

Table 22: Simulation 7: Overdispersion Index Increased from 4 to 10, i.e. $h = 10$

Panel A:	EIA			
	Case 1	Case 2	Case 3	Case 4
	Trade>0			
(1)	(2)	(3)	(4)	(5)
OLS	0.52607	0.56815	0.59692	0.59985
S.E.	0.00405	0.00855	0.03137	0.03267
Bias	0.05214	0.13629	0.19384	0.19970
PPML	0.50068	0.50271	0.42641	0.39428
S.E.	0.00009	0.00145	0.09416	0.09701
Bias	0.00136	0.00542	0.14717	0.21143
BVQCM	0.46415	0.48191	0.68512	0.70406
S.E.	0.01030	0.01257	0.04276	0.04452
Bias	0.07169	0.03619	0.37025	0.40813
Panel B:	Trade≥0			
(1)	(2)	(3)	(4)	(5)
PPML	0.49446	0.49617	0.41504	0.38267
S.E.	0.00045	0.00148	0.09404	0.09690
Bias	0.01108	0.00766	0.16991	0.23467
Logit-BVQCM	0.50503	0.52002	0.54363	0.54972
S.E.	0.01828	0.02396	0.05388	0.05562
Bias	0.01007	0.04004	0.08726	0.09944
LPM-BVQCM	0.51442	0.51225	0.57529	0.58006
S.E.	0.01095	0.01227	0.04396	0.04574
Bias	0.02885	0.02450	0.15058	0.16013

Robust standard errors are clustered at the country-pair level. The simulations used 250 iterations, Stata 16.1, and R 4.1.0. Adjustment to dependent only occurred when the log of trade values are used. In PPML simulations, we use actual trade values (including zeros) and make no adjustment by adding 1 to 0 trade values. Bias is percentage difference (in decimal form) from 0.5 (or the EIA effect).

Table 23: Simulation for One-Part DGP

Panel A: PPML	$n = 100,000$	$n = 1,000,000$
(1)	(2)	(3)
$\sigma = 0$	-1.000653	-0.9998776
	(0.0114556)	0.0034114
$\sigma = 0.25$	-1.066051	-1.066596
	(0.0205614)	0.0034114
$\sigma = 0.50$	-1.288403	-1.286394
	(0.0577706)	0.0173512
$\sigma = 0.75$	-1.542517	-1.544767
	(0.0599742)	0.0212977
$\sigma = 1.0$	-1.652002	-1.653248
	(0.0553482)	(0.0196304)

Panel B: Logit-QR	$n = 100,000$				
	$Q_{.50}$	$Q_{.60}$	$Q_{.70}$	$Q_{.80}$	$Q_{.90}$
(1)	(2)	(3)	(4)	(5)	(6)
$\sigma = 0$	-1.165343	-1.170695	-1.146849	-1.039147	-0.8966256
	(0.0817294)	(0.0323301)	(0.0166488)	(0.0071459)	(0.0059401)
$\sigma = 0.25$	-1.127125	-1.163318	-1.158612	-1.041043	-0.9031634
	(0.0845641)	(0.0349472)	(0.0189079)	(0.0074888)	(0.0062170)
$\sigma = 0.50$	-1.070306	-1.164445	-1.202391	-1.045299	-0.9171719
	(0.1055132)	(0.0400436)	(0.0185448)	(0.0083877)	(0.0070835)
$\sigma = 0.75$	-0.9884218	-1.178786	-1.24839	-1.045262	-0.9298841
	(0.1303428)	(0.0452036)	(0.0119897)	(0.0087541)	(0.0073268)
$\sigma = 1.0$	-0.7199572	-1.176696	-1.252054	-1.037991	-0.9407848
	(0.2033488)	(0.0494092)	(0.0116664)	(0.0098158)	(0.0081605)

Panel C: Logit-QR	$n = 1,000,000$				
	$Q_{.50}$	$Q_{.60}$	$Q_{.70}$	$Q_{.80}$	$Q_{.90}$
(1)	(2)	(3)	(4)	(5)	(6)
$\sigma = 0$	-1.159581	-1.168899	-1.146424	-1.038993	-0.8965574
	(0.0240261)	(0.0104824)	(0.0057150)	(0.0020882)	(0.0017831)
$\sigma = 0.25$	-1.127429	-1.162825	-1.159378	-1.041256	-0.9033191
	(0.0266184)	(0.0116302)	(0.0059946)	(0.0023218)	(0.0019798)
$\sigma = 0.50$	-1.074606	-1.165059	-1.201262	-1.045021	-0.9165881
	(0.0345299)	(0.0122133)	(0.0065913)	(0.0026530)	(0.0021705)
$\sigma = 0.75$	-0.9814089	-1.176771	-1.249682	-1.044930	-0.929834
	(0.0455976)	(0.0140130)	(0.0034241)	(0.0028412)	(0.0023617)
$\sigma = 1.0$	-0.7284294	-1.175973	-1.251161	-1.037126	-0.9396865
	(0.0607662)	(0.0155981)	(0.0037780)	(0.0031173)	(0.0027543)

The simulations used 500 repetitions, Stata 16.1. The table presents the simulation results of the one-stage DGP as outlined in Santos Silva and Tenreyro (2011) and Breinlich et al. (2022). The variable σ_k is defined as the variation in productivity across firms. Panel A shows the results for the PPML estimator and Panels B and C show results for the Logit-QR at 100,000 and 1,000,000 observations, respectively.

Table 24: Simulation Evidence that k is not relevant

	$\sigma = 0$		
(1)	(2)	(3)	(4)
	PPML	Logit-QR $Q_{.50}$	Logit-QR $Q_{.80}$
$k = 1$	-1.000653	-1.165343	-1.039147
	(0.0114556)	(0.0817294)	(0.0071459)
$k = 10$	-0.9999872	-1.167375)	-1.038725)
	(0.0105943)	(0.0792129)	(0.0069412)
$k = 50$	-0.9992448	-1.161576	-1.038804
	(0.0109702)	(0.0809577)	(0.0070298)

	$\sigma = 0.5$		
(1)	(2)	(3)	(4)
	PPML	Logit-QR $Q_{.50}$	Logit-QR $Q_{.80}$
$k = 1$	-1.288403	-1.070306	-1.045299
	(0.0577706)	(0.1055132)	(0.0083876)
$k = 10$	-1.285168	-1.072648	-1.044448
	(0.0550215)	(0.1077478)	(0.0083467)
$k = 50$	-1.287198	-1.07988	-1.04537
	(0.0590342)	(0.1003397)	(0.0080483)

Resutls for one-stage DGP as outlined in Santos Silva and Tenreyro (2011) and Breinlich et al. (2022). The simulations used 500 repetitions, Stata 16.1. The percentage of zeros of the dependent variable ranges .5029 to .5144 across repetitions. The variables k and σ_k represent the number of firms and the variation in productivity across firms, respectively.

15 Appendix A (Potentially Online)

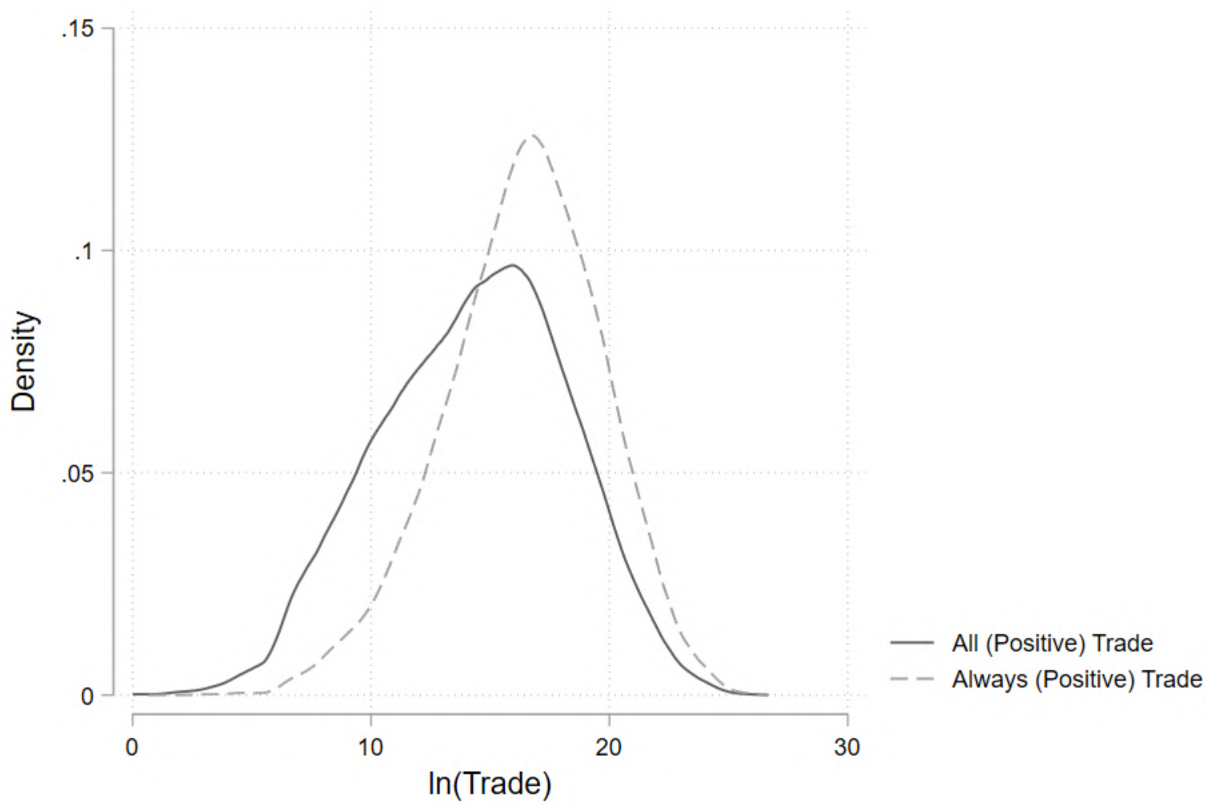

Figure A1: The solid line represents the density of all positive trade values in the sample from 1965-2010. The dotted line represents the density of country-pairs that had positive trade-flow values in every year of the sample.

Table A1: Logit-BVQCM (Adding 1 to All Trade Values)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q75	Q80	Q90
ln(GDPex)	1.019***	1.055***	1.091***	1.052***	1.037***	1.009***	0.971***	0.946***	0.918***	0.812***
	(0.078)	(0.061)	(0.055)	(0.047)	(0.042)	(0.039)	(0.037)	(0.035)	(0.035)	(0.038)
ln(GDPim)	0.914***	0.983***	1.017***	0.990***	1.001***	0.968***	0.914***	0.878***	0.874***	0.823***
	(0.074)	(0.055)	(0.051)	(0.043)	(0.038)	(0.037)	(0.036)	(0.036)	(0.036)	(0.039)
EIAMR	1.159***	0.992***	0.853***	0.701***	0.593***	0.453***	0.270***	0.251***	0.275***	0.220***
	(0.203)	(0.132)	(0.115)	(0.104)	(0.086)	(0.081)	(0.078)	(0.075)	(0.073)	(0.084)
DISTMR	-1.653***	-1.566***	-1.565***	-1.553***	-1.551***	-1.504***	-1.480***	-1.463***	-1.428***	-1.374***
	(0.061)	(0.046)	(0.046)	(0.039)	(0.038)	(0.036)	(0.035)	(0.035)	(0.035)	(0.038)
CONTIGMR	0.755***	0.941***	0.849***	0.717***	0.598***	0.638***	0.591***	0.552***	0.554***	0.472***
	(0.234)	(0.191)	(0.164)	(0.147)	(0.149)	(0.153)	(0.141)	(0.135)	(0.131)	(0.129)
LANGMR	0.501***	0.343***	0.388***	0.395***	0.403***	0.461***	0.467***	0.477***	0.488***	0.457***
	(0.133)	(0.101)	(0.094)	(0.088)	(0.085)	(0.082)	(0.078)	(0.078)	(0.079)	(0.080)
LEGALMR	0.328***	0.290***	0.290***	0.283***	0.311***	0.278***	0.276***	0.248***	0.206***	0.164***
	(0.088)	(0.069)	(0.064)	(0.058)	(0.054)	(0.052)	(0.050)	(0.050)	(0.050)	(0.051)
RELIGMR	-0.119	-0.004	0.168	0.169	0.142	0.186**	0.219**	0.208**	0.270***	0.309***
	(0.173)	(0.133)	(0.122)	(0.105)	(0.099)	(0.095)	(0.093)	(0.095)	(0.096)	(0.104)
COMCOLMR	0.578***	0.612***	0.620***	0.690***	0.723***	0.708***	0.667***	0.646***	0.662***	0.610***
	(0.160)	(0.126)	(0.115)	(0.102)	(0.094)	(0.088)	(0.083)	(0.082)	(0.082)	(0.083)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	45721	53410	58986	63751	68164	72317	77088	79697	82460	88975

Clustered standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. The prefix "Logit-" 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. $T_{ij} \geq 0$). The second and third stages are both quantile regressions 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. "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.

Table A2: BVQCM (Positive) Disaggregated by Type of EIA

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q75	(10) Q80	(11) Q90
ln(GDPex)	0.778***	0.764***	0.748***	0.715***	0.720***	0.703***	0.685***	0.665***	0.646***	0.576***
	(0.041)	(0.033)	(0.029)	(0.026)	(0.025)	(0.024)	(0.024)	(0.023)	(0.023)	(0.026)
ln(GDPim)	0.537***	0.493***	0.485***	0.465***	0.478***	0.479***	0.488***	0.490***	0.489***	0.523***
	(0.043)	(0.036)	(0.030)	(0.027)	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.027)
FTA-MR	0.430***	0.386***	0.400***	0.396***	0.351***	0.321***	0.271***	0.232***	0.201***	0.089*
	(0.085)	(0.056)	(0.045)	(0.041)	(0.038)	(0.036)	(0.036)	(0.036)	(0.036)	(0.046)
CUCMECU-MR	0.805***	0.730***	0.674***	0.698***	0.725***	0.738***	0.637***	0.610***	0.584***	0.385***
	(0.135)	(0.082)	(0.063)	(0.056)	(0.052)	(0.053)	(0.054)	(0.053)	(0.057)	(0.081)
DISTMR	-1.554***	-1.447***	-1.411***	-1.357***	-1.318***	-1.255***	-1.206***	-1.173***	-1.138***	-1.093***
	(0.040)	(0.034)	(0.030)	(0.027)	(0.026)	(0.025)	(0.025)	(0.025)	(0.025)	(0.026)
CONTIGMR	0.271**	0.218*	0.261**	0.289***	0.290***	0.300***	0.376***	0.399***	0.383***	0.381***
	(0.135)	(0.117)	(0.104)	(0.098)	(0.091)	(0.101)	(0.104)	(0.094)	(0.091)	(0.098)
LANGMR	0.441***	0.453***	0.423***	0.428***	0.404***	0.446***	0.448***	0.441***	0.442***	0.458***
	(0.079)	(0.062)	(0.056)	(0.053)	(0.051)	(0.051)	(0.051)	(0.053)	(0.054)	(0.059)
LEGALMR	0.207***	0.240***	0.259***	0.260***	0.296***	0.317***	0.333***	0.346***	0.350***	0.312***
	(0.060)	(0.046)	(0.040)	(0.037)	(0.036)	(0.035)	(0.035)	(0.034)	(0.034)	(0.035)
RELIGMR	0.548***	0.415***	0.292***	0.201***	0.118**	0.036	-0.022	-0.035	-0.045	-0.032
	(0.106)	(0.086)	(0.072)	(0.065)	(0.060)	(0.058)	(0.059)	(0.060)	(0.061)	(0.070)
COMCOLMR	0.511***	0.413***	0.411***	0.440***	0.439***	0.378***	0.367***	0.353***	0.359***	0.305***
	(0.108)	(0.088)	(0.078)	(0.074)	(0.069)	(0.065)	(0.062)	(0.064)	(0.064)	(0.066)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	121417	121417	121417	121417	121417	121417	121417	121417	121417	121417

Clustered standard errors by country-pair in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. 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. "Year FE" indicates whether year dummy variables were included or not; "CRE" indicates whether correlated random effects were used or not. The terms FTA and CUCMECU indicate Free Trade Agreements and deeper trade agreements (including Customs Unions, Common Markets, and Economic Unions), respectively.

Table A3: Comparison of LPM and Logit Observations Included

Quantile	NT Observations	AT Observations
(1)	(2)	(3)
10	0	36,383
20	0	47,619
30	2	50,252
40	47	50,603
50	190	50,658
60	570	50,667
70	1,718	50,668
80	4,129	50,668
90	8,844	50,668

Note: NT and AT represent "never trade" and "always trade" in every year of the sample. Columns (2) and (3) give the count of observations that were included in the LPM estimation but were excluded from the logit estimation due to perfect prediction (identified by pair fixed effects from the first stage).

Table A4: LPM-BVQCM (Adding 1 to All Trade Values)

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q75	(10) Q80	(11) Q90
ln(GDPex)	0.864^{***}	0.949^{***}	0.941^{***}	0.974^{***}	1.007^{***}	1.002^{***}	0.982^{***}	0.964^{***}	0.936^{***}	0.836^{***}
	(0.060)	(0.037)	(0.032)	(0.029)	(0.028)	(0.026)	(0.025)	(0.025)	(0.025)	(0.025)
ln(GDPim)	0.816^{***}	0.816^{***}	0.854^{***}	0.867^{***}	0.882^{***}	0.860^{***}	0.829^{***}	0.822^{***}	0.814^{***}	0.771^{***}
	(0.066)	(0.039)	(0.032)	(0.028)	(0.027)	(0.026)	(0.026)	(0.027)	(0.027)	(0.029)
EIAMR	0.785^{***}	0.766^{***}	0.766^{***}	0.732^{***}	0.684^{***}	0.620^{***}	0.499^{***}	0.426^{***}	0.359^{***}	0.336^{***}
	(0.077)	(0.050)	(0.043)	(0.042)	(0.041)	(0.041)	(0.042)	(0.042)	(0.043)	(0.050)
DISTMR	-1.188^{***}	-1.228^{***}	-1.259^{***}	-1.308^{***}	-1.340^{***}	-1.369^{***}	-1.383^{***}	-1.383^{***}	-1.394^{***}	-1.378^{***}
	(0.054)	(0.037)	(0.032)	(0.029)	(0.029)	(0.028)	(0.027)	(0.027)	(0.028)	(0.029)
CONTIGMR	-0.201	-0.025	0.107	0.204^{*}	0.302^{***}	0.297^{***}	0.331^{***}	0.414^{***}	0.403^{***}	0.361^{***}
	(0.127)	(0.105)	(0.103)	(0.108)	(0.107)	(0.104)	(0.112)	(0.115)	(0.114)	(0.112)
LANGMR	0.189^{**}	0.217^{***}	0.271^{***}	0.347^{***}	0.457^{***}	0.502^{***}	0.553^{***}	0.581^{***}	0.572^{***}	0.565^{***}
	(0.091)	(0.065)	(0.060)	(0.059)	(0.058)	(0.059)	(0.058)	(0.058)	(0.059)	(0.063)
LEGALMR	0.511^{***}	0.548^{***}	0.487^{***}	0.444^{***}	0.404^{***}	0.415^{***}	0.409^{***}	0.406^{***}	0.371^{***}	0.340^{***}
	(0.067)	(0.048)	(0.042)	(0.039)	(0.039)	(0.040)	(0.039)	(0.039)	(0.039)	(0.041)
RELIGMR	0.340^{***}	0.145^{*}	0.072	0.026	0.020	0.009	0.062	0.094	0.112	0.104
	(0.121)	(0.085)	(0.074)	(0.069)	(0.067)	(0.066)	(0.067)	(0.067)	(0.069)	(0.075)
COMCOLMR	0.140	0.201	0.345^{***}	0.390^{***}	0.398^{***}	0.423^{***}	0.405^{***}	0.405^{***}	0.458^{***}	0.488^{***}
	(0.160)	(0.128)	(0.097)	(0.084)	(0.082)	(0.078)	(0.073)	(0.072)	(0.072)	(0.070)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	48602	74039	91708	105378	116927	127740	140112	147490	155884	176342

Clustered standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. The prefix "LPM-" indicates that the three-stage estimation procedure described by Galvao et al. (2013) was implemented to account for censored observations in quantile regressions. The first stage is a linear probability model with exporter-year, importer-year, and pair fixed effects using all trade pair (i.e. $T_{ij} \geq 0$). The second and third stages are both quantile regressions 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. "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. Missing trade values are replaced by 0 and we add 1 to all trade values.

Table A5: LPM-BVQCM (User-defined minimum value of USD 10,000)

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q75	(10) Q80	(11) Q90
ln(GDPex)	0.828***	0.884***	0.877***	0.893***	0.921***	0.928***	0.922***	0.903***	0.896***	0.808***
	(0.051)	(0.036)	(0.030)	(0.027)	(0.026)	(0.025)	(0.023)	(0.024)	(0.024)	(0.025)
ln(GDPim)	0.702***	0.725***	0.738***	0.779***	0.798***	0.808***	0.830***	0.835***	0.824***	0.780***
	(0.054)	(0.035)	(0.030)	(0.026)	(0.026)	(0.025)	(0.025)	(0.025)	(0.026)	(0.028)
EIAMR	0.648***	0.658***	0.691***	0.693***	0.668***	0.607***	0.520***	0.460***	0.391***	0.332***
	(0.066)	(0.043)	(0.039)	(0.037)	(0.038)	(0.038)	(0.039)	(0.039)	(0.040)	(0.047)
DISTMR	-1.139***	-1.133***	-1.150***	-1.171***	-1.186***	-1.212***	-1.224***	-1.244***	-1.252***	-1.282***
	(0.045)	(0.032)	(0.028)	(0.027)	(0.027)	(0.026)	(0.025)	(0.026)	(0.026)	(0.028)
CONTIGMR	-0.019	0.068	0.117	0.176**	0.201**	0.233**	0.319***	0.341***	0.348***	0.347***
	(0.102)	(0.079)	(0.081)	(0.083)	(0.086)	(0.095)	(0.099)	(0.100)	(0.102)	(0.105)
LANGMR	0.088	0.142**	0.170***	0.249***	0.310***	0.417***	0.465***	0.483***	0.502***	0.516***
	(0.078)	(0.060)	(0.057)	(0.053)	(0.054)	(0.054)	(0.054)	(0.055)	(0.057)	(0.061)
LEGALMR	0.506***	0.535***	0.504***	0.462***	0.434***	0.417***	0.416***	0.395***	0.395***	0.351***
	(0.060)	(0.043)	(0.039)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.037)	(0.039)
RELIGMR	0.169	-0.027	-0.056	-0.055	-0.071	-0.090	-0.057	-0.041	-0.022	0.027
	(0.106)	(0.079)	(0.069)	(0.064)	(0.061)	(0.061)	(0.063)	(0.064)	(0.066)	(0.072)
COMCOLMR	0.074	0.220**	0.330***	0.326***	0.366***	0.384***	0.347***	0.370***	0.404***	0.446***
	(0.142)	(0.107)	(0.088)	(0.076)	(0.075)	(0.070)	(0.068)	(0.069)	(0.069)	(0.069)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	41130	62184	77660	90057	100876	111720	124385	132221	141333	163907

Clustered standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. The prefix "LPM-" indicates that the three-stage estimation procedure described by Galvao et al. (2013) was implemented to account for censored observations in quantile regressions. The first stage is a linear probability model with exporter-year, importer-year, and pair fixed effects using all trade pair (i.e. $T_{ij} \geq 0$). The second and third stages are both quantile regressions 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. "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. We create an arbitrary minimum value of USD 10,000 and replace trade values below this cutoff to 1 (i.e. $\ln(X_{ijt}) = 0$ when trade value is 1.)

Table A6: LPM-BVQCM Disaggregated by Type of EIA

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q75	Q80	Q90
ln(GDPex)	0.855***	0.949***	0.939***	0.976***	0.999***	0.995***	0.980***	0.967***	0.940***	0.846***
	(0.060)	(0.038)	(0.032)	(0.029)	(0.028)	(0.026)	(0.025)	(0.025)	(0.025)	(0.025)
ln(GDPim)	0.814***	0.819***	0.848***	0.860***	0.875***	0.857***	0.816***	0.812***	0.797***	0.775***
	(0.064)	(0.039)	(0.032)	(0.028)	(0.027)	(0.026)	(0.026)	(0.027)	(0.027)	(0.029)
FTA-MR	0.722***	0.739***	0.702***	0.625***	0.577***	0.497***	0.374***	0.321***	0.268***	0.236***
	(0.074)	(0.051)	(0.046)	(0.043)	(0.042)	(0.042)	(0.042)	(0.042)	(0.043)	(0.047)
CU-MR	1.119***	0.968***	0.891***	0.778***	0.745***	0.776***	0.727***	0.754***	0.863***	0.935***
	(0.128)	(0.082)	(0.075)	(0.069)	(0.077)	(0.103)	(0.133)	(0.160)	(0.193)	(0.229)
CM-MR	1.081***	1.110***	1.061***	0.981***	0.970***	0.901***	0.771***	0.687***	0.643***	0.550***
	(0.110)	(0.079)	(0.069)	(0.067)	(0.065)	(0.064)	(0.065)	(0.067)	(0.070)	(0.076)
ECU-MR	1.394***	1.281***	1.204***	1.034***	1.033***	0.993***	0.907***	0.961***	0.887***	0.902***
	(0.136)	(0.108)	(0.101)	(0.092)	(0.097)	(0.096)	(0.103)	(0.107)	(0.111)	(0.135)
DISTMR	-1.181***	-1.233***	-1.254***	-1.303***	-1.336***	-1.364***	-1.362***	-1.358***	-1.365***	-1.358***
	(0.053)	(0.037)	(0.031)	(0.029)	(0.028)	(0.027)	(0.027)	(0.027)	(0.028)	(0.028)
CONTIGMR	-0.098	0.004	0.139	0.206*	0.287***	0.322***	0.394***	0.432***	0.429***	0.461***
	(0.129)	(0.105)	(0.103)	(0.106)	(0.107)	(0.110)	(0.105)	(0.105)	(0.107)	(0.111)
LANGMR	0.139	0.197***	0.254***	0.328***	0.420***	0.458***	0.508***	0.529***	0.535***	0.549***
	(0.092)	(0.065)	(0.061)	(0.059)	(0.058)	(0.059)	(0.058)	(0.059)	(0.060)	(0.062)
LEGALMR	0.513***	0.548***	0.483***	0.441***	0.397***	0.408***	0.405***	0.399***	0.363***	0.313***
	(0.067)	(0.048)	(0.043)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.040)
RELIGMR	0.344***	0.135	0.068	0.026	0.028	0.023	0.113*	0.146**	0.178**	0.194***
	(0.119)	(0.086)	(0.075)	(0.069)	(0.068)	(0.066)	(0.067)	(0.068)	(0.070)	(0.074)
COMCOLMR	0.131	0.211*	0.344***	0.410***	0.431***	0.442***	0.400***	0.397***	0.430***	0.426***
	(0.160)	(0.125)	(0.097)	(0.084)	(0.082)	(0.077)	(0.072)	(0.072)	(0.072)	(0.070)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	48554	74049	91721	105379	116916	127750	140093	147492	155879	176335

Clustered standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. The prefix "LPM-" indicates that the three-stage estimation procedure described by Galvao et al. (2013) was implemented to account for censored observations in quantile regressions. The first stage is a linear probability model with exporter-year, importer-year, and pair fixed effects using all trade pair (i.e. $T_{ij} \geq 0$). The second and third stages are both quantile regressions 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. "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. The terms FTA, CU, CM, and ECU indicate Free Trade Agreements, Customs Unions, Common Markets, and Economic Unions, respectively.

Table A7: Cloglog-BVQCM

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q75	(10) Q80	(11) Q90
ln(GDPex)	0.990***	1.037***	1.071***	1.045***	1.041***	1.012***	0.973***	0.953***	0.924***	0.801***
	(0.071)	(0.058)	(0.053)	(0.045)	(0.041)	(0.039)	(0.037)	(0.035)	(0.035)	(0.038)
ln(GDPim)	0.969***	0.968***	0.990***	0.991***	0.991***	0.962***	0.921***	0.880***	0.871***	0.821***
	(0.071)	(0.052)	(0.050)	(0.043)	(0.038)	(0.037)	(0.037)	(0.037)	(0.036)	(0.039)
EIAMR	1.221***	0.967***	0.875***	0.696***	0.578***	0.442***	0.279***	0.243***	0.259***	0.221***
	(0.196)	(0.129)	(0.114)	(0.098)	(0.086)	(0.080)	(0.077)	(0.074)	(0.074)	(0.084)
DISTMR	-1.610***	-1.529***	-1.533***	-1.534***	-1.537***	-1.499***	-1.476***	-1.468***	-1.430***	-1.382***
	(0.057)	(0.044)	(0.044)	(0.038)	(0.037)	(0.036)	(0.035)	(0.035)	(0.035)	(0.039)
CONTIGMR	0.853***	0.968***	0.824***	0.695***	0.586***	0.619***	0.584***	0.535***	0.561***	0.481***
	(0.206)	(0.182)	(0.157)	(0.143)	(0.147)	(0.152)	(0.141)	(0.136)	(0.133)	(0.129)
LANGMR	0.408***	0.284***	0.339***	0.385***	0.384***	0.472***	0.466***	0.473***	0.480***	0.465***
	(0.125)	(0.095)	(0.091)	(0.086)	(0.084)	(0.082)	(0.079)	(0.079)	(0.079)	(0.081)
LEGALMR	0.337***	0.297***	0.295***	0.279***	0.308***	0.272***	0.279***	0.248***	0.213***	0.168***
	(0.082)	(0.065)	(0.062)	(0.057)	(0.053)	(0.052)	(0.050)	(0.050)	(0.050)	(0.052)
RELIGMR	-0.131	0.051	0.157	0.147	0.143	0.152	0.197**	0.190**	0.273***	0.302***
	(0.162)	(0.125)	(0.119)	(0.102)	(0.099)	(0.095)	(0.094)	(0.095)	(0.097)	(0.104)
COMCOLMR	0.639***	0.643***	0.624***	0.676***	0.717***	0.722***	0.670***	0.658***	0.666***	0.610***
	(0.151)	(0.117)	(0.111)	(0.098)	(0.094)	(0.088)	(0.083)	(0.083)	(0.083)	(0.083)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	47846	53532	57767	61783	66081	70436	75584	78327	81530	88866

Clustered standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. The prefix "Cloglog-" 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 with exporter-year, importer-year, and 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 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.

Table A8: Logit(BVCM)-BVQCM

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q75	(10) Q80	(11) Q90
ln(GDPex)	0.952***	0.766***	0.877***	0.920***	0.947***	1.005***	1.030***	1.013***	0.998***	0.889***
	(0.188)	(0.097)	(0.064)	(0.049)	(0.041)	(0.036)	(0.031)	(0.029)	(0.028)	(0.027)
ln(GDPim)	1.551***	1.338***	1.137***	1.059***	1.043***	0.978***	0.899***	0.862***	0.836***	0.820***
	(0.173)	(0.116)	(0.074)	(0.055)	(0.045)	(0.039)	(0.034)	(0.033)	(0.031)	(0.031)
EIAMR	1.311***	1.043***	0.694***	0.637***	0.621***	0.614***	0.534***	0.470***	0.382***	0.317***
	(0.184)	(0.131)	(0.092)	(0.069)	(0.060)	(0.057)	(0.052)	(0.051)	(0.050)	(0.056)
DISTMR	-0.620***	-0.870***	-1.097***	-1.266***	-1.364***	-1.438***	-1.475***	-1.483***	-1.488***	-1.504***
	(0.124)	(0.094)	(0.066)	(0.049)	(0.042)	(0.037)	(0.033)	(0.032)	(0.032)	(0.031)
CONTIGMR	-0.358	-0.365*	-0.327	0.005	0.250*	0.413***	0.452***	0.448***	0.458***	0.521***
	(0.409)	(0.206)	(0.200)	(0.176)	(0.151)	(0.133)	(0.122)	(0.121)	(0.127)	(0.130)
LANGMR	-0.126	0.268*	0.452***	0.550***	0.578***	0.662***	0.689***	0.703***	0.702***	0.649***
	(0.233)	(0.160)	(0.116)	(0.089)	(0.079)	(0.074)	(0.070)	(0.068)	(0.066)	(0.067)
LEGALMR	0.640***	0.531***	0.478***	0.431***	0.374***	0.342***	0.344***	0.351***	0.351***	0.334***
	(0.130)	(0.106)	(0.082)	(0.064)	(0.055)	(0.051)	(0.048)	(0.046)	(0.045)	(0.044)
RELIGMR	0.521*	0.310	0.319**	0.279**	0.271***	0.225**	0.213***	0.220***	0.238***	0.242***
	(0.281)	(0.216)	(0.148)	(0.113)	(0.099)	(0.090)	(0.083)	(0.080)	(0.078)	(0.080)
COMCOLMR	0.367	-0.345	-0.182	-0.035	0.056	0.106	0.220**	0.272***	0.289***	0.480***
	(0.639)	(0.362)	(0.253)	(0.177)	(0.145)	(0.118)	(0.101)	(0.093)	(0.086)	(0.077)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	13546	41369	65212	86623	107807	129315	151591	163161	175435	202987

Clustered standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. 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 where unobserved heterogeneity was accounted for using Chamberlain-Mundlak-based correlated random effects using all trade pairs (i.e. $T_{ij} \geq 0$). The second and third stages are both quantile regressions 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. "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.

Table A9: Logit-BVQCM (Unconstrained MR Terms Coefficients)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q75	Q80	Q90
ln(GDPex)	0.928***	0.977***	1.015***	0.968***	0.926***	0.931***	0.883***	0.850***	0.822***	0.757***
	(0.076)	(0.056)	(0.048)	(0.045)	(0.041)	(0.039)	(0.037)	(0.037)	(0.036)	(0.039)
ln(GDPim)	0.970***	1.050***	1.085***	1.084***	1.048***	1.056***	1.004***	0.989***	0.962***	0.911***
	(0.072)	(0.050)	(0.046)	(0.043)	(0.039)	(0.037)	(0.035)	(0.035)	(0.036)	(0.040)
EIA	0.629***	0.415***	0.278***	0.200**	0.225***	0.207**	0.253***	0.331***	0.325***	0.238***
	(0.163)	(0.116)	(0.100)	(0.092)	(0.083)	(0.080)	(0.079)	(0.079)	(0.077)	(0.089)
ln(DIST)	-1.681***	-1.595***	-1.588***	-1.570***	-1.513***	-1.468***	-1.425***	-1.412***	-1.389***	-1.374***
	(0.054)	(0.044)	(0.042)	(0.036)	(0.034)	(0.034)	(0.035)	(0.036)	(0.036)	(0.037)
CONTIG	0.506**	0.773***	0.781***	0.765***	0.689***	0.619***	0.577***	0.606***	0.527***	0.372***
	(0.237)	(0.190)	(0.171)	(0.138)	(0.124)	(0.126)	(0.136)	(0.132)	(0.123)	(0.122)
LANG	0.564***	0.342***	0.415***	0.412***	0.434***	0.403***	0.441***	0.446***	0.463***	0.442***
	(0.116)	(0.088)	(0.085)	(0.079)	(0.073)	(0.071)	(0.071)	(0.071)	(0.070)	(0.077)
LEGAL	0.393***	0.362***	0.262***	0.243***	0.219***	0.235***	0.221***	0.180***	0.148***	0.132***
	(0.082)	(0.062)	(0.057)	(0.053)	(0.049)	(0.048)	(0.047)	(0.047)	(0.047)	(0.051)
RELIG	-0.132	0.044	0.084	0.160	0.165*	0.195**	0.239***	0.206**	0.196**	0.139
	(0.154)	(0.117)	(0.108)	(0.102)	(0.095)	(0.090)	(0.086)	(0.086)	(0.087)	(0.100)
COMCOL	0.421***	0.501***	0.572***	0.657***	0.692***	0.691***	0.627***	0.651***	0.665***	0.655***
	(0.149)	(0.117)	(0.105)	(0.094)	(0.087)	(0.082)	(0.081)	(0.082)	(0.081)	(0.086)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	45707	53408	58984	63750	68164	72315	77088	79697	82460	88975

Clustered standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. The prefix "Logit-" indicates that the three-stage estimation procedure described by Galvao et al. (2013) was implemented to account for censored observations 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. $T_{ij} \geq 0$). The second and third stages are both quantile regressions 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. "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. "Unconstrained" refers to allowing the coefficient estimates of the “MR” components of the various bilateral trade-cost variables to be left unconstrained.

Table A10: Logit-BVQCM (Comparable): GDP per capitas

(1)	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
ln(GDPex)	0.117	0.463***	0.631***	0.844***	0.899***	0.974***	1.002***	0.972***	0.930***
	(0.198)	(0.150)	(0.124)	(0.101)	(0.094)	(0.085)	(0.077)	(0.074)	(0.076)
ln(GDPim)	0.583***	0.481***	0.653***	0.784***	0.788***	0.784***	0.758***	0.624***	0.650***
	(0.221)	(0.164)	(0.134)	(0.114)	(0.095)	(0.085)	(0.080)	(0.077)	(0.081)
ln(GDPpcex)	0.861***	0.534***	0.338***	0.048	-0.022	-0.145*	-0.198***	-0.251***	-0.307***
	(0.197)	(0.145)	(0.120)	(0.096)	(0.089)	(0.083)	(0.075)	(0.073)	(0.074)
ln(GDPpcim)	0.284	0.448***	0.303**	0.171	0.120	0.060	0.022	0.073	-0.034
	(0.212)	(0.155)	(0.126)	(0.108)	(0.091)	(0.080)	(0.075)	(0.072)	(0.075)
EIAMR	2.535***	2.814***	2.592***	2.799***	2.840***	2.938***	2.903***	2.428***	1.971***
	(0.918)	(0.589)	(0.641)	(0.566)	(0.572)	(0.543)	(0.440)	(0.360)	(0.378)
DISTMR	-1.644***	-1.540***	-1.492***	-1.467***	-1.412***	-1.344***	-1.259***	-1.160***	-1.045***
	(0.059)	(0.046)	(0.042)	(0.038)	(0.035)	(0.032)	(0.030)	(0.028)	(0.029)
CONTIGMR	0.759**	0.989***	0.864***	0.690***	0.572***	0.475***	0.452***	0.492***	0.328***
	(0.299)	(0.181)	(0.164)	(0.136)	(0.130)	(0.128)	(0.125)	(0.105)	(0.095)
LANGMR	0.399***	0.300***	0.324***	0.318***	0.320***	0.375***	0.375***	0.360***	0.375***
	(0.124)	(0.099)	(0.088)	(0.080)	(0.077)	(0.072)	(0.067)	(0.063)	(0.061)
LEGALMR	0.401***	0.321***	0.291***	0.286***	0.267***	0.228***	0.195***	0.169***	0.100**
	(0.087)	(0.068)	(0.060)	(0.053)	(0.049)	(0.046)	(0.043)	(0.040)	(0.040)
RELIGMR	-0.198	-0.059	0.124	0.164*	0.156*	0.159*	0.218***	0.234***	0.284***
	(0.168)	(0.130)	(0.114)	(0.098)	(0.089)	(0.083)	(0.079)	(0.077)	(0.080)
COMCOLMR	0.621***	0.634***	0.667***	0.707***	0.698***	0.663***	0.637***	0.550***	0.480***
	(0.156)	(0.128)	(0.111)	(0.095)	(0.086)	(0.079)	(0.070)	(0.066)	(0.065)
EIAMR∗ln(GDPpcex)	-0.194**	-0.226***	-0.242***	-0.244***	-0.217***	-0.200***	-0.186***	-0.142***	-0.057
	(0.080)	(0.059)	(0.061)	(0.054)	(0.047)	(0.044)	(0.039)	(0.035)	(0.037)
EIAMR∗ln(GDPpcim)	0.052	0.006	0.033	-0.009	-0.064	-0.105*	-0.128***	-0.124***	-0.169***
	(0.089)	(0.067)	(0.065)	(0.053)	(0.053)	(0.053)	(0.045)	(0.041)	(0.038)
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	45724	53410	58987	63751	68164	72317	77088	82460	88975

standard errors by country-pair are in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$. The prefix "Logit-" 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. $T_{ij} \geq 0$). 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. "Comparable" refers to the adjustment discussed by Machado et al. (2016) to allow partial effects to be comparable across quantiles.

16 Appendix B: Quantile Treatment Effects (Potentially Online)

Firpo (2007) developed a method for analysis of the effects of binary regressors on quantiles of the unconditional distribution of the dependent variable. Note that the method is a semiparametric two stage approach where the first stage logit model generates propensity scores and these propensity scores are used to re-weight the QR model suggested in Koenker and Bassett (1978). A key assumption is that the variable of interest is binary and exogenous, which causes complications with our current estimation strategy. First as noted by Baier and Bergstrand (2004), it is quite difficult to predict EIAs between country-pairs due to the complexity of such agreements. Second, our estimation strategy requires the construction of bilateral regressors that have been demeaned (i.e., the BV technique) such that the EIA variable is no longer binary. With these complications in mind, we estimated the model suggested by Firpo (2007) with one slight modification to our specification, namely not demeaning EIA_{ijt}. We use a combination of the BV approximate approach for MR terms and CREs in place of three-way fixed effects in our specification. Since the Firpo (2007) approach requires EIA_{ijt} to be binary, the second stage has re-weighted EIA_{ijt} values without the MR and CRE approximations in the second stage.

The first stage estimation of the Firpo (2007) methodology uses the (logit) EIA_{ijt} specification:

$$\begin{aligned}
EIA_{ijt} = \beta_0 + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} + +\beta_3 DISTMR_{ij} + \beta_4 CONTIGMR_{ij} \\
+\beta_5 LANGMR_{ij} + \beta_6 LEGALMR_{ij} + \beta_7 RELIGMR_{ij} + \beta_8 COMCOLMR_{ij} \\
+ \sum_{t=1}^{T} \alpha_t YEAR_t + \beta_9 \overline{\ln GDP}_i + \beta_{10} \overline{\ln GDP}_j + \sum_{t=1}^{T} + \gamma_t \overline{YEAR} + \eta_{ijt}. \quad (41)
\end{aligned}$$

We know the QTEs for the unconditional outcomes are likely to differ from the benchmark conditional QR partial effect estimates. However, because we do not specify fully the determinants of EIA_{ijt} in this (first stage) logit specification (cf., Baier and Bergstrand (2004)), the second-stage QTE estimates may vary considerably from the benchmark conditional partial effect estimates in Table 6. Below in Table B1, we report the QTEs using only positive flows.

Table B1: Quantile Treatment Effect: Positive Trade

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q75	Q80	Q90
	1.203***	1.170***	1.194***	1.222***	1.141***	0.974***	0.868***	0.853***	0.832***	0.357***
	(0.290)	(0.266)	(0.259)	(0.243)	(0.199)	(0.162)	(0.147)	(0.142)	(0.118)	(0.089)
BV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

17 Appendix C: Monte Carlo Simulations 1, Two-Part DGP (Potentially Online)

This appendix provides a more detailed discussion of the construction of the two-part simulation analysis addressed in section 11 (Monte Carlo Simulations 1: Two-Part DGP). The simulation follows the structural gravity methodology as adapted by Poissonnier (2019) for panel data. The methodology is motivated by a two-stage economic process, as described in section 3. First, a country must have at least one firm in country i whose productivity is sufficiently high that the variable profits from entering the market exceed export fixed costs, f_{ijt}. Trade costs, ϕ_{ijt}, are determined by variable trade costs, τ_{ijt}, and fixed trade costs, f_{ijt}. The expression for trade costs is:

$$\phi_{ijt} = \tau_{ijt}^{-\theta} f_{ijt}^{-\left[\frac{\theta}{\alpha-1}-1\right]} \tag{42}$$

where θ is the trade elasticity in a standard Melitz model and α is the elasticity of substitution.

We let *variable* trade costs be determined by:

$$\tau_{ijt}^{-\theta} = exp(-\ln DIST_{ij} + 0.5EIA_{ijt}) * \eta_{ijt} \tag{43}$$

and assume the variance of η_{ijt} is defined as in Section 11.1 (Cases 1-4). Note the coefficients are set to -1 and 0.5 for $\ln DIST_{ij}$ and EIA_{ijt}, respectively. Several other parameters must also be defined:

- $\theta = 5$
- $\alpha = 1 + \theta/2.5 = 3$
- $h = 4$, heterogeneity parameter

We first set up the initial (naive) gravity specification that ignores f_{ijt}:

$$X_{ijt} = Y_{it}Y_{jt}\frac{\tau_{ijt}^{-\theta}}{\Pi_{it}\Phi_{jt}} = Y_{it}Y_{jt}\frac{exp(-\ln DIST_{ij} + 0.5EIA_{ijt}) * \eta_{ijt}}{\Pi_{it}\Phi_{jt}} \tag{44}$$

where the multilateral resistance terms, Π_{it} and Φ_{jt}, need to be estimated. We follow contraction mapping iterative process for panels in Poissonnier (2019) to estimate the matrix $\hat{\Pi}_{it}\hat{\Phi}'_{jt}$ and iterate until convergence. The simulated trade flow for each bilateral pair is predicted ($\hat{X}_{ijt}$) by structural gravity, equation (44).

The next step is to consider the error variance. We need to have parameter σ as a function of the variance of η. We can rewrite the numerator in the last RHS term in equation (44) as:

$$exp(-\ln DIST_{ij} + 0.5EIA_{ijt} + \eta_{ijt}) = exp(-\ln DIST_{ij} + 0.5EIA_{ijt} + \sigma_{ijt} * u_{ijt}) \quad (45)$$

where u_{ijt} is a standard Normal pseudo-random term and σ_{ijt} is set to satisfy the error variance in Cases 1-4. For example, with Case 2 (Poisson) where $\sigma^2_{ijt} = \mu^{-1}_{ijt} = exp(-\ln DIST_{ij} + 0.5EIA_{ijt})^{-1}$ (and setting $h = 1$):

$$\begin{aligned}
\ln \sigma_{ijt} &= \sqrt{\ln(1 + exp(-\ln DIST_{ij} + 0.5EIA_{ijt})^{-1})} \\
\ln \mu_{ijt} &= -\frac{(\ln \sigma_{ijt})^2}{2} \\
\Rightarrow \eta_{ijt} &= exp(\ln \mu_{ijt} + \sigma_{ijt} * u_{ijt}).
\end{aligned}$$

We can then generate simulated trade values ($\tilde{X}_{ijt}$) including the error term:

$$\tilde{X}_{ijt} = \hat{X}_{ijt} * \eta_{ijt}. \quad (46)$$

However, this measure of trade was built without f_{ijt}. As noted above, trade flows are determined by a two-stage process that includes: (1) variable profits from exporting to a particular destination exceed export fixed cost (f_{ijt}) and (2) determining how much will be exported, conditioned upon exporting. In the construction of f_{ijt}, we use the percentage of zeros in the data for bilateral pairs in each year to find the percentile of $\tilde{X}_t$ that matches the percentage of zeros (where we exclude intra-national trade). At $\tilde{X}_t$ and adding an error term δ:

$$\ln f_{ijt} = \ln \tilde{X}_t - \ln \alpha + \delta_{ijt} \quad (47)$$

where δ_{ijt} is a standard Normal pseudo-random term and α is the elasticity of substitution.

The trade cost must now include f_{ijt} in ϕ_{ijt}:

$$\phi_{ijt} = \tau^{-\theta}_{ijt} f^{-\left[\frac{\theta}{\alpha-1}-1\right]}_{ijt} \quad (48)$$

or

$$\phi_{ijt} = exp\left[-\ln DIST_{ij} + 0.5EIA_{ijt} - \left(\frac{\theta}{\alpha - 1} - 1\right) \ln f_{ijt}\right] \eta_{ijt}. \quad (49)$$

We use the contraction mapping once again to estimate the multilateral resistance terms,

Π_{it} and Φ_{jt}, and simulate trade from the structural gravity equation:

$$\check{X}_{ijt} = Y_{it} Y_{jt} \frac{\hat{\phi}_{ijt}}{\hat{\Pi}_{it} \hat{\Phi}_{jt}} \tag{50}$$

noting that $\check{X}_{ijt} = 0$ if $\check{X}_{ijt} < \alpha * exp(\ln f_{ijt})$.