Gravity with Strategic Behavior*

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Abstract

The assumptions underlying the estimation of Gravity equations imply that a country's behavior is independent of the actions of others. In practice, a few countries heavily influence global trade. We estimate a network-based Gravity equation, in which every country can impact any trade flow. This approach reduces the role of exporter GDP by two-thirds compared to Panel Data. We construct a new openness index that includes both country-specific and country-pair-specific factors. This index strongly correlates with independent indexes, and suggests that open countries are richer, more likely to converge, and experience less inequality.

Keywords: Gravity Equations, International Trade in Networks, Additive Random Effects, Multiplicative Random Effects, Dynamic Social Networks.

JEL codes: F13, F14, D85, C11, L13.

1 Introduction

The extent to which a country can gain from international trade rests on how open other countries are: imports may increase welfare, but they need exports to finance them. This is why coordinating institutions like the World Trade Organization, or more localized groups such as the European Union, NAFTA, and MERCOSUR, are so successful. This strategic behavior has been largely ignored in the literature estimating Gravity equations. When behavior is strategic, the error terms in the Gravity equation are not independent. Ignoring this produces imprecise estimates, and therefore unreliable predictions of the effects of GDP

*We benefited from conversations with Tevfik Aktekin, Dev Dutta, and Courtney Paulson. We want to thank participants at the UNH Economics Department Brown bag participants, and session participants at the Joint Statistical Meetings in 2022 and 2023 for important feedback.

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and other variables on trade flows. This paper estimates a Gravity equation by explicitly incorporating correlated behavior among countries.

We build on Hoff (2005), who describes an algorithm that can be used to estimate trade relations within a network, where countries are nodes and trade volumes are edges between these nodes. The first element capturing the network structure is the use of country-specific random effects, as opposed to more traditional binary variables. Intuitively, the degree of openness of a country is likely correlated with the degree of openness of its neighbors. Random effects can successfully account for this correlation by assuming country effects are draws of a common distribution, and therefore correlated.

The second element is multiplicative random effects. These capture "third-order dependencies", that is, coordinated behavior between triplets of countries. Examples are when three countries increase trade simultaneously (transitivity). This is typical of countries that share a common currency, like countries in the European Union, since a devaluation is likely to affect all countries similarly. It also accounts for cases where an increase in trade within two countries correlates with a reduction in trade in a third one (balance). An example of this behavior includes sanctions from Europe and the U.S. towards Russia: the sanctions reduced imports of Russian Liquified Natural Gas into Europe, and exports from the U.S. to Europe increased.[1] We argue that these multiplicative random effects have a natural interpretation as bilateral trade barriers.

The last element that denotes a difference between the network analysis and more traditional approaches is that we allow for correlations among different error terms. We assume a rich covariance structure and estimate it along with the rest of the parameters. Note that when the error terms are correlated, Laird and Ware (1982) and Fitzmaurice et al. (2012) show that random effects produce reliable estimates, while fixed effects do not. By modeling country effects as random, we are improving the reliability of our results.

When comparing our estimates to a more standard Panel Data analysis, the largest difference is on the elasticity of trade volumes to exporter GDP. While we find this number to

[1] https://www.reuters.com/business/energy/us-lng-exports-both-lifeline-drain-europe-2023-maguire-2022-12-20/

be around 0.3, a Panel Data approach estimates it close to 1, overestimating its importance by a factor of 3. The importance of importer GDP, on the other hand, is underestimated, but both estimates are quantitatively close to each other. Other measures, such as distance or common language, are within two standard deviations of the network estimates.

We use our estimates of bilateral and country-specific trade barriers to construct a new openness index based on a counterfactual that restores its trade barriers to the mean. Our estimates are causal due to all potential dependencies being incorporated into the model via random effects (McCulloch et al., 2001; Hoff, 2003; Shardell and Ferrucci, 2018), allowing us to trust the results of the counterfactual. In particular, we produce three sub-indices: one for exports, one for imports, and an "overall" measure that adds imports and exports.

We confirm that these indexes are strongly correlated with independently constructed measures of openness. In particular, our index produces a correlation of 0.82 with Duernecker et al. (2022)'s, which expands Arribas et al. (2009)'s index to include a role for the diffusion of ideas via trade. Arribas et al. (2009) produces an index that measures the change in trade volumes should a country remove all trade barriers and home country bias.

We use this index to study the links between openness and other macroeconomic variables. These links have been subject to a great deal of controversy in the literature. They include whether open countries display stronger convergence properties, a potential relation to GDP per capita, and its relation with inequality. Sachs and Warner (1995) argue that open countries are more likely to converge than closed ones, defining openness as satisfying criteria based on trade barriers and other characteristics, such as a socialist versus a capitalist government system. Rodriguez and Rodrik (2000) argue that it is the non-trade characteristics that drive the relationship with convergence. Romer and Frankel (1999) argue that more trade leads to more GDP per capita. The problem is that this is not about openness, but actual trade volumes, which are likely to increase when GDP per capita increases. In terms of inequality, the Stolper-Samuelson theorem proposes that trade has the potential to both increase and reduce inequality. Empirically, Dorn et al. (2022) finds evidence mildly consistent with this theorem. We find evidence of openness being significantly associated to stronger convergence patterns, higher levels of GDP per capita, and lower levels of inequality. The relationship with inequality is stronger for poor countries, providing support, to some extent, to the Stolper-Samuelson theorem.

The notion that trade is strategic is not new. The "Brander-Spencer" model has been widely used in economics, and the premise is that trade policy can be strategic: by fostering exports, a government can redistribute benefits away from a foreign country and into the domestic one based on the assumption that foreigners are influenced by it. Spencer and Brander (2016) define strategic trade policy as "*trade policy that affects the outcome of strategic interactions between firms in an actual or potential international oligopoly*." Several authors have used this framework to show that the foreign reaction to domestic trade policy can be welfare enhancing. These include Brander and Spencer (1985); Bagwell and Staiger (1994) and Eaton and Grossman (1986), among others. Based on these conclusions, Leahy and Neary (2009) highlight the need for coordinating organisms, such as the WTO, to establish rules regarding investment subsidies, given that in an equilibrium where oligopolistic firms compete in international markets, these would be too high.

More recently, the trade war between the U.S. and China that started in 2018 has provided empirical evidence of the effects of trade policy on third countries. Nicita (2019) finds a strong correlation between the drop in imports into the U.S. from China, and increases in exports from third countries into the U.S., such as Taiwan, Mexico, the European Union and Vietnam. Similarly, Fajgelbaum et al. (2023), find evidence of gains in Vietnam, Mexico, Thailand and Korea, among others, from the trade war. Nantembelele et al. (2023) finds gains among several African countries, Mayr-Dorn et al. (2023) finds similar results for Brazil, Choi and Nguyen (2023) for Vietnam, and Alfaro and Chor (2023), for Mexico and Vietnam. These trade diversion effects imply that the error terms in the bilateral Gravity equations are not independent. In fact, recent research focusing on new trade barriers placed by the U.S. shows that other countries retaliate by increasing their own trade barriers (Fajgelbaum et al., 2020), generating a positive correlation between the error terms for the exports from country i to country j and the exports from country j to country i

(unless the change in tariffs is explicitly accounted for).

This article is organized as follows. Section 2 introduces social network structures, and describes the features of the data that we are better capturing via the network framework. Section 3 develops our model and details the estimation strategy. Section 4 describes the data. Section 5 presents the estimates of the Gravity equation under both network analysis and a Panel Data regression. Section 6 develops our openness index and studies how it relates to other independent indexes and macroeconomic variables. Section 7 concludes.

2 Social Network Structures

A social network is a set of players and their ties, where the ties are the researcher's object of interest. In a dynamic social network, these ties change in time. In our case, the players are countries, and the ties are bilateral trade flows. In a graphical representation, each player in the network is represented by a vertex, and two players that are tied are connected by an edge (Wasserman and Faust, 1994). For example, we can define the players as children in the same classroom (vertices), and the ties as their friendship (edges), as in Eke Rubini et al. (2021). The ties can be defined in many forms: in Ji and Jin (2016) and Ji et al. (2022), the network players are statisticians and their tie is co-authorship or citation; in Ng et al. (2021), the network players are a set of Irish politicians, and the ties are their connections on $\mathbb{X}$ (formerly Twitter). While these examples focus on people as players in the network, players can be companies, groups of people, or, as in this paper, countries. For example, in Guo et al. (2022), the networks are formed by cryptocurrencies as players and their return predictability as the ties, or in Giudici and Spelta (2016), international financial flows are modeled as a network where the countries are players, and ties between them represent statistically significant correlations, or, in Wu et al. (2024) the bipartite set of players are stocks and mutual funds and the ties are the interactions between funds and stocks. One reason why networks are used to model relational data is their ability to incorporate complex dependencies in relational data (see Ward and Hoff, 2007; Neville and

Jensen, 2007; Bräuning and Koopman, 2020, among others), such as coordinated ties and third order dependencies.

The main network properties of international trade are the following. First, consider the fact that the degree of openness differs across countries. This can be captured via country-specific intercepts. Fally (2015) proposes to use fixed effects, and this would be the right approach if there was no correlation across countries on the degree of openness. However, it is not likely that these are independent of each other. One reason for this is that it is politically costly to import from a country that will not accept exports in return, so a country with relatively closed neighbors has incentives to remain relatively closed. Random effects are better suited to deal with this situation, since they model country effects as draws from a common distribution, and therefore correlated, with a covariance structure to be estimated. Another advantage of using random effects is that they produce more reliable estimates than fixed effects when the error term is not independent (Laird and Ware, 1982; Fitzmaurice et al., 2012).

The second way in which we incorporate the network structure is via third order dependencies. These include transitive behavior and balance behavior. Transitivity occurs when an increase in trade between countries A and B is typically associated with an increase in trade between A and C, and between B and C. Balancing occurs when an increase in trade between A and B is associated with a reduction in trade between A and C and between B and C. Hoff (2003) shows that third order dependencies can capture this behavior. Moreover, he suggests the use of multiplicative random effects to model these, and incorporates them in the *AMEN* package ("Additive and Multiplicative Random Effects") we use to compute our results.

One last advantage of the algorithm in the *AMEN* package is the dynamic component. The repeated measures feature in the algorithm draws information from observing the same countries trading over time, and uses this information to increase the precision of the model (see Dunson, 2003, for more details).

3 The Model

Consider the following version of the Gravity equation:

$$\log(x_{ijt}) = \alpha_t + \beta_s \ln y_{it} + \beta_r \ln y_{jt} + \beta_o Z_{ijt} + s_i + r_j + \epsilon_{ijt} \tag{1}$$

where x_{ijt} represents imports in country i of goods exported by country j at time t, y_{it} is GDP in country i at time t, and Z_{ijt} are controls specific to countries i and j at time t. The parameters to estimate are $\alpha_{t,t\in\{1,\ldots,T\}}, \beta_s, \beta_r, \beta_o, s_i$, and r_j, where the sample starts in period 1 and ends in period T.

It is noteworthy that we do not follow Santos Silva and Tenreyro (2006), who suggest estimating equation (1) by taking the exponent of both sides of the equation based on two main arguments. The first reason is that taking logs leads to heteroskedasticity, and therefore imprecise estimates when estimated via OLS. The network estimation in this paper does not need homoskedasticity to produce reliable estimates. In other words, our model provides an alternative solution to Santos Silva and Tenreyro (2006)'s. The second reason for taking exponents is to address zeros. The package developed by Hoff (2005) cannot be applied to this alternative functional form. While extending this package to incorporate it would be desirable, it is beyond the scope of this paper. Consequently, we follow the network approach for nonexistent ties (see Hoff, 2005, among others) and replace the log of these observations with 0 (effectively assuming that these countries trade \$1).

A problem arises when zeros result from unreported data. In some cases, only one trading partner reports a bilateral trade flow. For example, Italy might report importing \$10 million worth of goods from Pakistan, while Pakistan may not report any exports to Italy, showing zero trade. In such cases, we use Italy's report. If both countries fail to report, we understand that trade flows are zero. We also eliminate countries that display zero trade flows, and report our findings in Appendix A.

Consider the bilateral term Z_{ijt}. Standard analysis breaks this down into a series of observable characteristics that might affect trade between two countries, such as distance, and binary variables indicating the presence of common borders, common language, and common colonial ties. In addition to these, we include a term to capture non-measurable trade barriers. This can either be a constant term over time, or a stochastic term that fluctuates around a constant mean during the period of analysis.[2] Let Δ_{ijt} be this term. Then $\Delta_{ijt} = \Delta_{ij} + \epsilon_{\Delta,ijt}$, where $\epsilon_{\Delta,ijt} \sim \mathcal{N}(0, \sigma^2_\Delta)$. Thus, the variable Z_{ijt} is

$$Z_{ijt} = \log(d_{ij}) + a_{nij} + a_{lij} + a_{cij} + a_{bij} + \Delta_{ij} + \epsilon_{\Delta ijt} \tag{2}$$

where a_{lij} is equal to 1 if countries i and j share the same language, 0 otherwise, a_{cij} is defined similarly for common colonial ties, and a_{bij} is a binary variable for common borders. The distance between countries is d_{ij}.

Estimating the constant term Δ_{ij} is challenging. It cannot be estimated using binary variables, as samples typically lack sufficient degrees of freedom. In a sample of N countries, there are $N \times (N-1)$ binary terms to estimate. In our case, $N = 186$, which amounts to estimating $34,410$ parameters. Each of these ties is observed T times, where T denotes the number of periods studied. One could increase T to add predictive power to the estimates of these fixed effects, but then the assumption that these do not change over large periods of time becomes questionable.

The approach we follow employs multiplicative random effects, first introduced by Hoff (2005) for the symmetric case (when $x_{ijt} = x_{jit}$), and extended to the non-symmetric case by Hoff (2009). Additionally, the author developed the *AMEN* package in *R*, which can estimate these relationships by modeling trade within a dynamic social network.

[2] It can also incorporate a time trend, as long as this is the same for all country-pairs. This would be absorbed by the time fixed effects.

3.1 Estimation

In this section, we explore more technical aspects of our model and estimation. We organize it in three stages: the treatment of fixed effects,[3] additive random effects, and multiplicative random effects.

Fixed Effects

The fixed effects in equation (1) combined with equation (2) are

$$F_{ijt} = \alpha_t + \beta_s \log y_{it} + \beta_r \log y_{jt} + \beta_d \log d_{ij} + \beta_l a_{lij} + \beta_c a_{cij} + \beta_{tij} a_{tij}$$

Without additive and multiplicative random effects, this equation becomes a standard linear regression with the parameter vector $\beta = \big(\alpha_{t,t\in\{1,\ldots,T\}}, \beta_s, \beta_r, \beta_d, \beta_l, \beta_c, \beta_{tij}\big)$.

Additive Random Effects

The additive random effects include s_i, r_j and ε_{ijt}. The effects s (sender, or exporter) and r (receiver, or importer) take the following structure:

$$\begin{pmatrix} r_i \\ s_i \end{pmatrix} \sim \mathcal{N}_2 \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_r^2 & \sigma_{rs} \\ \sigma_{rs} & \sigma_s^2 \end{pmatrix} \right] \tag{3}$$

where σ_r^2 and σ_s^2 represent the dependence due to same receiver and same sender respectively, and σ_{rs} represents the within country dependence in exports and imports. These constitute the "between unit variance", which is zero under methods that rely on indepen-

[3] We follow the definition of fixed effects in mixed model theory, which differs from that frequently used in economics, where fixed effects refer to parameters associated with observed regression covariates, such as GDP, time or distance. In contrast, random effects are unobserved subject-specific parameters, representing realizations of random variables, such as receiver and sender effects (Demidenko, 2013).

dence of the error term. The error term ε_{ijt} follows the form

$$\begin{pmatrix} \varepsilon_{ijt} \\ \varepsilon_{jit} \end{pmatrix} \sim \mathcal{N}_2 \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\varepsilon^2 & \rho\sigma_\varepsilon \\ \rho\sigma_\varepsilon & \sigma_\varepsilon^2 \end{pmatrix} \right] \tag{4}$$

The term σ_ε^2 represents the variance of ε, and ρ is the correlation between reciprocal error terms, explicitly deviating from the independence assumption commonly used in most Gravity equation-based trade models. Hoff (2021) shows how this structure determines the covariances among different ties, which we summarize in Table 1.

Covariance	Co-Movement Between	Value
$Cov(\varepsilon_{ijt}, \varepsilon_{ikt})$	Exports from country i to all partners	σ_r^2
$Cov(\varepsilon_{ijt}, \varepsilon_{kjt})$	Imports into country j from all partners	σ_s^2
$Cov(\varepsilon_{ijt}, \varepsilon_{jkt})$	Imports and exports in country j	σ_{rs}
$Cov(\varepsilon_{ijt}, \varepsilon_{jit})$	Exports and imports between countries i and j	$2\sigma_{rs} + \rho\sigma_\varepsilon$

Table 1: Co-movement of different error terms.

Additive random effects incorporate the network's dependence structure into our model. The dependence structure can be thought of as describing the ways in which the error terms ε_{ijt} are not independent. Additive random effects capture the following dependence between error terms: *(i)* country i is observed as importer (ε_{ijt} for all j); *(ii)* country i is observed as exporter (ε_{jit} for all j); *(iii)* country i appears either as importer or exporter (ε_{ijt} vs ε_{kit} for all j, k); *(iv)* the reciprocal error terms (ε_{ijt} vs ε_{jit} for all i, j). These are examples of second-order dependencies in networks, and can be obtained from second moments of ε_{ijt}, i.e., $E[\varepsilon_{ijt}^2]$, $E[\varepsilon_{ijt}\varepsilon_{jit}]$, $E[\varepsilon_{ijt}\varepsilon_{ikt}]$, and so on. However, they cannot capture higher-order dependencies such as the dependency between three error terms ε_{ijt}, ε_{jkt}, and ε_{ikt} as this requires third moments of respective error terms, which are equal to zero under additive random effects.

These third moments are usually very active when it comes to trade. In particular, what Viner (1950) defines as trade diversion is a third-order movement. Suppose two countries sign a free trade deal. Trade between those countries is likely to increase, while trade between either of these countries with a third one, left outside the deal, is likely to drop. Incorporating multiplicative random effects to the model allows us to account for higher-order dependencies. We describe these next.

Multiplicative Random Effects

Multiplicative random effects capture patterns exhibited among triplets of countries: the actions of country A might depend on the joint actions of countries B and C (third-order dependencies). They can also be thought of as"representing omitted regression variables or uncovering group structures" (Hoff, 2021) among the countries in the network, such as bilateral trade barriers. Consider the random effects in that result from combining equations (1) and (2):

$$z_{ij} = s_i + r_j + u_i^T v_j + \varepsilon_{ijt} \tag{5}$$

Let $\mathbf{U} = [u_1^T, u_2^T, \ldots, u_N^T]$, $\mathbf{V} = [v_1^T, v_2^T, \ldots, v_N^T]$, $\mathbf{s} = [s_1, s_2, \ldots, s_N], \mathbf{r} = [r_1, r_2, \ldots, r_N]$, and

$$\mathbf{Z} = \begin{bmatrix} 0 & z_{12} & z_{13} & \ldots & z_{1N} \\ z_{21} & 0 & z_{23} & \ldots & z_{2N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ z_{N1} & z_{N2} & z_{N3} & \ldots & 0 \end{bmatrix}$$

Let $\Delta_{ij} = u_i^T v_j$ denote the multiplicative random effect. The vectors $u_i \in \mathcal{R}^k$ and $v_j \in \mathcal{R}^k$ represent random effects, where k is a hyperparameter to be determined by the researcher. As random effects, we assume

$$(u_i, v_i) \sim \mathcal{N}_{2k}(0, \Sigma_{uv}) \tag{6}$$

The covariance matrix Σ_{uv} contains $2k \times 2k$ elements to be estimated. To illustrate, consider $k = 2$. Both u_i and v_i are two-dimensional vectors: $u_i^T = (u_{i1}\ u_{i2})$, $v_i^T = (v_{i1}\ v_{i2})$. Then, the distribution of these effects becomes

$$\begin{pmatrix} u_{i1} \\ v_{i2} \end{pmatrix} \sim \mathcal{N}_4 \left(\begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}, \Sigma_{uv} = \begin{bmatrix} E[u_1 v_1] & E[u_1 v_2] \\ E[u_2 v_1] & E[u_2 v_2] \end{bmatrix} \right) \tag{7}$$

This implies that $u_i, v_i \in \mathcal{R}^k$ and $\mathbf{U}, \mathbf{V}$ are $N \times k$ matrices. We can rewrite equation (5) as $\mathbf{Z} = \mathbf{s1^T} + \mathbf{1r^T} + \mathbf{M} + \mathbf{E}$ and imposing zeros in the diagonal, where $\mathbf{1}$ is a column vector of ones $(N \times 1)$, $\mathbf{E}$ is a $(N \times N)$ matrix of residuals and $\mathbf{M} = \mathbf{UV^T}$ is a $N \times N$ matrix of rank k.

Hoff (2009) suggests using reduced-rank matrices $\mathbf{U}$ and $\mathbf{V}$ (that is, setting $k < N$) to minimize lower-order noise in the data. This, together with distributional assumptions of additive and multiplicative random effects, prevents overfitting the model. The $2k \times 2k$ covariance matrix Σ_{uv} can identify third or higher-order dependencies via third or higher-order moments of random effects.

To select the value of the hyperparameter k, we need to consider that the larger this value, the more accurate the estimation, but also the greater the risk of overfitting the data. We set $k = 4$, as the posterior means show little change beyond this value.

In summary, we estimate the following model:

$$\begin{aligned} \log(x_{ijt}) = \alpha_t + & \beta_s \log y_{it} + \beta_r \log y_{jt} + \beta_d \log(d_{ij}) + \beta_l a_{lij} + \beta_c a_{cij} + \beta_{tij} a_{tij} + \\ & u_i^T v_j + s_i + r_j + \varepsilon_{ijt} \end{aligned} \tag{8}$$

where we impose the structure (4) and (6). The terms $\alpha_t, \beta_s, \beta_r, \beta_d, \beta_l, \beta_c$ and β_b are estimated as fixed effects, while u_i, v_j, s_i and r_j are estimated as random effects.

4 Data

We use annual data on GDP in current dollars, distance between countries in kilometers, trade volumes in current Dollars, and the presence of common borders, common language, and colonial ties, as binary indicators. Our GDP data come from the World Development Indicators. Our distance measures come from the Centre for Prospective Studies and International Information. Data on common language, common borders, and colonial ties come from Fouquin and Hugot (2016). Trade data come from UN COMTRADE. The sample starts in 2000 and ends in 2019 to avoid capturing effects related to COVID-19. Additionally, we choose to start in 2000, rather than including earlier periods, to focus on more recent trade practices. For instance, the rise in China's trade, beginning in 2001 with its accession to the World Trade Organization, introduced many changes in global trade. Including earlier periods would bias our analysis toward outdated trade practices that are no longer valid, calling into question our assumption of stationary bilateral trade barriers,[4] questioning our assumption of stationary bilateral trade barriers. By 2000, the European Union was fully established. We eliminate a few countries based on unavailability of data. We describe this process in Appendix B.

5 Results

We estimate model (8) using the *AMEN* package in R Core Team (2021). The estimation is based on a matrix representation of this model using Gibbs sampling with 500 burn-in periods and, followed by 10,000 iterations of a Markov chain. We set $k = 4$, as estimates do not vary much for other values of k. For exposition, we also include results for $k = 2$ and $k = 0$.

Table 2, column 1, presents our estimates as posterior means, with values in parentheses representing posterior standard deviations. The top panel reports the fixed effects, while the bottom panel provides estimates of random effects. Our estimates align with the existing literature: the greater the GDP of either country, the larger the volume of trade, and the larger the distance, the lower the trade.

Recall that our algorithm proposes a correlation structure among the different error

[4]See Autor et al. (2013) and Pierce and Schott (2016) for evidence of the changes introduced by China's accession to the WTO.

Parameter	Network ($k=4$) (1)	Network ($k=2$) (2)	Network ($k=0$) (3)	Panel Data (4)
Fixed Effects				
$\log gdp_r$	0.716	0.695	0.710	0.622
	(0.017)	(0.017)	(0.014)	(0.038)
$\log gdp_s$	0.315	0.290	0.312	1.074
	(0.017)	(0.017)	(0.015)	(0.018)
$\log distance$	-0.650	-0.776	-1.311	-1.300
	(0.008)	(0.007)	(0.007)	(0.006)
Common Colonial Ties	0.811	1.027	0.933	0.925
	(0.054)	(0.056)	(0.059)	(0.052)
Common Language	1.006	1.113	1.680	1.684
	(0.020)	(0.021)	(0.019)	(0.017)
Common Border	2.445	2.222	2.253	2.274
	(0.041)	(0.044)	(0.045)	(0.041)
Random Effects				
σ_s^2	14.268	11.891	6.745	–
	(2.111)	(1.632)	(0.823)	–
σ_{rs}	26.383	20.234	11.060	–
	(3.751)	(2.883)	(1.400)	–
σ_r^2	51.259	37.031	20.762	–
	(7.172)	(5.362)	(2.574)	–
ρ	0.2674	0.312	0.359	–
	(0.002)	(0.002)	(0.001)	–
σ_ε^2	12.168	13.507	15.371	0.886
	(0.022)	(0.025)	(0.026)	(0.003)

Table 2: Estimation Results. The estimates shown are posterior means, and the numbers between parentheses are posterior standard deviations.

terms. Using Table 1, we derive the different correlations by dividing each covariance by the appropriate variance, which is equal to $\sigma_\varepsilon^2 + \sigma_r^2 + \sigma_s^2$ (see Hoff, 2021, for details). The correlation between exports from country i to all its partners (for a given t) is 0.66. The correlation between all imports into a country is 0.18. The correlation between imports and exports in a country is 0.34. Lastly, the correlation between exports and imports between two countries is 0.69. The positive value of this last correlation implies that we capture evidence of retaliation to some extent, as identified empirically by Fajgelbaum et al. (2020). This happens because our posterior mean for ρ is positive (see Table 1).

Column (2) shows the results when setting $k = 2$, that is, when $u, v \in \mathcal{R}^2$, and column

(3) shows these when there are no third-order dependencies. Comparing columns (1), (2), and (3), we observe that the largest differences come from the estimates of the variables that depend on the country-pair: distance, colonial ties, language, and border. This is due to third-order dependencies directly affecting the country-pair estimates.

5.1 Comparison to Panel Data Estimation

Table 2 shows the results of a more traditional Panel Data estimation in the fourth column. We estimate equation (1), assuming the term ε_{ijt} is a random draw of a Normal distribution and the terms r_i and s_j are fixed effects. More specifically, the model estimated is

$$\log(x_{ijt}) = \alpha_t + \beta_s \log y_{it} + \beta_r \log y_{jt} + \beta_d \log d_{ij} + \beta_l a_{lij} + \beta_c a_{cij} + \beta_{tij} a_{tij} + s_i + r_j + \varepsilon_{ijt} \tag{9}$$

where s_i and r_j are estimated as binary variables and $\varepsilon_{ijt} \sim \mathcal{N}(0, \sigma^2)$. We estimate it using a Bayesian approach with the *R* package *rstanarm* (Goodrich et al., 2024), employing 4 Markov chains and 2,000 iterations. Column (4) in Table 2 shows the results.

Comparing these with those in column (3), which excludes multiplicative random effects to remain as close as possible to the estimates in column (4), we observe a considerable difference between the estimates for GDP, in particular exporter GDP. The Panel Data approach estimates it close to 1, while all network specifications place this estimate well below that, at around 0.3. Thus, the elasticity of trade flows with respect to exporter GDP is about one-third of what the Panel Data approach would suggest. In turn, the Panel Data approach estimates importer GDP to be somewhat less relevant than what the network analysis suggests, although the differences are much smaller than in the case of exporter GDP. The estimates of bilateral variables are close to each other, within two standard deviations.

Recall that the Panel Data regression is, in theory, less reliable than the network approach, since it assumes independence of the error terms when there are strong arguments against this. Another way to argue that the results under a network approach are more reliable comes from the sum of squared errors in each model. For Panel Data, this is 1.06×10^7, while for the network approach without multiplicative random effects, it is 3.14×10^6.

5.2 Multiplicative Random Effects

Figure 1 plots the vectors u and v representing the multiplicative effects when $k = 2$, which allows us to graph them in two dimensions. Red labels represent importers effects (u_i) and blue labels represent exporter effects (v_j). When a country in blue is in the same quadrant as one in red, trade between them is larger than what can be explained with other variables. When they are opposite, trade is lower. When they are adjacent, trade is "in between". The location of these countries is given by the estimate of a two-dimensional vector per country per transaction (importing and exporting). The magnitude of these effects is determined by the absolute value of the estimated coefficients.

Focus on the U.S. (with larger fonts, for easier identification). Both exporting and importing vectors in the U.S. are in the upper-left quadrant, therefore trading more than expected with other countries in that quadrant, and less than expected with countries in the opposite one (the lower-right quadrant). Consider the U.S.'s exporting behavior (in blue). It will export more than what observables would predict to red countries in the upper-left quadrant, such as France, Japan, and Australia. It will export less than the predictions to red countries in the lower-right quadrant, such as Italy, Egypt, and Saudi Arabia. In between are countries in the bottom-left and upper-right quadrants.

In terms of importing, the U.S. imports more than predicted from blue upper-left quadrant countries, such as China, New Zealand, Denmark, and the Netherlands. It imports less than predicted from blue countries in the bottom-right quadrant, such as Russia, Tunisia, and Jordan.

[Figure 1 about here.]

6 Measuring Openness

This section develops a measure of openness for each country, based on a counterfactual that computes the percentage change in trade (imports, exports, or their sum) if all country effects and third order dependencies were to mean-revert. The country that would gain the most is the least open, while the one that would lose the most is the most open.

Our estimates are causal, allowing us to trust the results of the counterfactual. By definition, causal interpretations require: *(i)* independence of observations; and *(ii)* that the expected value of error terms, conditional on independent variables, is zero, i.e., $E[\varepsilon|\mathbf{X}] = 0$. When the dependence structures are correctly specified, observations are independent conditional on the random effects (McCulloch et al., 2001). This assumption would be violated in the presence of omitted variables, but Hoff (2021) argues that multiplicative random effects represent omitted regression variables, making the inference causal.

The results in this section are based on setting $k = 4$, though we observe similar results for other values of k. We consider four measures of trade barriers: sender effects (s_i), receiver effects (r_i), exporter dependencies (v_i) and importer dependencies (u_i). Recall that these variables are drawn from a Normal distribution with mean 0. Thus, the counterfactual developed in this section represents the change in trade volumes if each of these variables were equal to 0.

To compute these measures, we proceed as follows. First, we compute a measure for import openness, one for export openness, and a combined "overall" measure for imports plus exports. Focusing first on export openness, sender random effects s_i directly measure how much additional trade country i generates with every other country relative to the mean, in excess of all control variables, as a percentage. The term $u_j^T v_i$ represents the additional exports from country i to country j, relative to the mean effects, also in percentage terms. We obtain a measure of the aggregate change in exports for country i by summing all the

Overall	Δ_T	Exporter	Δ_x	Importer	Δ_m
THA	0.4231	CHN	-0.3797	THA	-0.0089
CHN	0.6156	JPN	0.0273	GUY	0.0294
USA	0.6519	USA	0.2173	USA	0.4346
JPN	0.6569	KOR	0.4247	NLD	0.4516
KOR	1.1290	THA	0.4320	BLR	0.4701

Table 3: The five most open countries in three categories: as exporter, as importer, and adding imports and exports.

Overall	Δ_T	Exporter	Δ_x	Importer	Δ_m
STP	16.3063	TLS	11.0130	LSO	5.5085
TLS	17.6761	GNB	11.1028	TLS	6.6632
BTN	17.9086	BTN	11.2317	BTN	6.6769
FSM	20.1333	FSM	12.9384	PLW	6.9852
PLW	20.2666	PLW	13.2814	FSM	7.1948

Table 4: The five least open countries in three categories: as exporter, as importer, and adding imports and exports.

exports of country i, calculated as follows:

$$\Delta_{xi} = s_i + \frac{\sum_j (u_j^T v_i) x_{ji}}{\sum_j x_{ji}}$$

Similarly, the measure for imports is

$$\Delta_{mi} = r_i + \frac{\sum_j (u_i^T v_j) x_{ij}}{\sum_j x_{ij}}$$

Finally, the measure for imports plus exports is $\Delta_{Ti} = \Delta_{xi} + \Delta_{mi}$. We use 2015 as the year of the trade flows.

Table 3 shows the top five countries in three categories: most open overall, most open to exports, and most open to imports. The number itself represents how much trade a country would gain if its trade barriers are zero. For example, Thailand, the most open country in the overall category, would increase its trade by 42%. Note that, in principle, this number can be either positive or negative. Even if the elements of the vectors are distributed with mean zero, the mean of their inner product will only be zero when they are uniformly distributed (Hoff, 2003). In fact, the mean of the multiplicative effect is negative, thereby reducing trade on average. Quantitatively, we find very few countries that would reduce trade if their barriers revert to zero, namely China under the exporter index and Thailand under the importer index. Table 4 presents the least open countries. The complete ranking of countries is provided in Appendix C.

In the overall category, the most open countries are Thailand, China, the U.S., Japan and Korea. These countries typically lead openness rankings, supporting our results. The least open countries in the overall category are Sao Tome & Principe, East Timor, Bhutan, Micronesia, and Palau. In particular, if Palau's trade barriers become zero, the increase in trade would be of over 2,000%.

6.1 Openness and Convergence

Having developed a measure of openness, we now examine whether more open countries exhibit a stronger convergence behavior than less open ones. This question has been at the forefront of research in international trade since at least Sachs and Warner (1995). The challenge in answering this question lies in defining openness.

Sachs and Warner (1995) argue that open countries are more likely to converge than closed ones. Wacziarg and Welch (2008) extend the data in time, and find that while the cross-section results are not significant, the evidence shows that when following countries over time, openness increases growth. These papers define a country as open based on five criteria: average tariffs, non-tariff barriers, the political system (socialist vs. capitalist), state monopoly of exports, and black market premium. Rodriguez and Rodrik (2000) show that the main drivers of convergence are the last three, that is, the ones least related to openness to trade, while the first two do not have any incidence on convergence. Dollar (1992) find similar results with a different openness measure, defined based on distortions in the exchange rate and its volatility. Rodriguez and Rodrik argue that it is the volatility that matters for convergence, but this is more a sign of instability than openness. Ben-David (1993) find that European countries began converging only after joining a trade union, although Rodriguez and Rodrik suggest that convergence had started earlier, questioning the link between trade liberalization and convergence.

The standard regression to test for convergence looks for growth rates to be decreasing in an initial level of (log) GDP per capita:

$$g_i = \gamma_0 + \gamma_1 \log(GDPpc_i) + \epsilon_{gi} \tag{10}$$

where g_i is the net growth rate of GDP per capita averaged over a given period of time in country i and $GDPpc_i$ is the GDP per capita at the start of such period. If there is convergence, we would observe $\gamma_1 < 0$.

To test whether openness matters for this relationship, we conduct two exercises.[5] The first one estimates equation (10) independently for 2 subsamples: those above the median, and those below it. The second exercise introduces an interaction term between the openness index and the initial level of GDP per capita:

$$g_i = \gamma_0 + \gamma_1 \log(GDPpc_i) + \gamma_2 I_i + \gamma_3 \log(GDPpc_i) \times I_i + \epsilon_{gi} \tag{11}$$

where I_i is the negative of the counterfactual change in trade should trade barriers in country i mean-revert, and $\epsilon_{gi} \sim N(0, \sigma_g^2)$. In this case, evidence of $\gamma_1 < 0$ indicates convergence, and $\gamma_3 < 0$ would suggest that the more open the country, the stronger the convergence behavior.

Table 5 presents the results of these exercises when using the overall index in the top panel, openness to export in the middle panel, and openness to import in the bottom panel. Our initial GDP per capita is that of the year 2000, and the growth rate is the average of the net annual growth rates between 2000 and 2019.

We find evidence of convergence among the countries in our sample. As shown in column (1) of Table 5, $\gamma_1 = -0.0041$ in equation (10), significant at the 1% level, suggesting that countries that were richer in 2000 grew less than relatively poorer countries. Quantitatively, this implies that a 10% larger GDP per capita in 2000 is associated with a reduction in the

[5] Some countries were eliminated for the exercises in this section. See Appendix D for details.

Coefficient	No Controls	Open countries	Closed countries	Interaction Term
	(1)	(2)	(3)	(4)
Overall Openness				
γ_1	-0.0041	-0.0056	-0.0044	-0.0084
	(0.0012)	(0.0014)	(0.0014)	(0.0020)
γ_2	-	-	-	0.0048
				(0.0020)
γ_3	-	-	-	-0.0004
				(0.0002)
N	181	90	91	181
Openness to Export				
γ_1	-	-0.0059	-0.0044	-0.0095
		(0.0012)	(0.0014)	(0.0019)
γ_2	-	-	-	0.0086
				(0.0027)
γ_3	-	-	-	-0.0008
				(0.0003)
N	-	90	91	181
Openness to Import				
γ_1	-	-0.0059	-0.0038	-0.0050
		(0.0012)	(0.0013)	(0.0019)
γ_2	-	-	-	0.0040
				(0.0060)
γ_3	-	-	-	-0.0002
				(0.0007)
N	-	90	91	181

Table 5: Convergence patterns. The dependent variable is the average annual growth rate of each country between 2000 and 2019. All columns control for GDP per capita in 2000. Columns (1) and (4) include all countries in the sample. Column (2) includes countries with trade costs lower than the median, and column (3) includes countries with trade costs larger than or equal to the median. Column (4) adds as controls the openness index and an interaction term between this and GDP per capita in 2000. The top panel considers trade as the sum of exports plus imports. The middle panel includes only exports, and the bottom panel only imports. Standard deviations in parentheses.

average rate of growth between 2000 and 2019 of 0.04 percentage points.

Columns (2) and (3) suggest that γ_1 is smaller for relatively open countries, indicating accelerated convergence patterns. In particular, in the top panel (overall), relatively open countries experience a 10% increase in initial GDP per capita leads to a drop in the average annual growth rate of 0.06 percentage points. Countries that would trade more if they mean-revert see that the same increase in initial GDP per capita reduces the growth rates by only 0.04 percentage points.

Column (4) shows the results of introducing an interaction term between the initial level of GDP and our openness measure. We estimate $\gamma_3 = -0.0004$, significant at the 1% level, indicating that as countries become more open, convergence patterns strengthen. To illustrate the magnitude of these effects, consider two countries with the same initial GDP per capita: if one is more open by 10%, the more open country can expect a growth rate 0.04 percentage points larger than the other one (assuming convergence for these countries implies positive growth).

6.2 Openness and Wealth

This section explores the correlation between openness and GDP per capita. Romer and Frankel (1999) find empirically that more trade leads to higher levels of GDP per capita. The problem is that this is not about trade *openness*, but about the amount of trade (Rodriguez and Rodrik, 2000).

To answer this question, we compute the correlation between the logarithm of GDP per capita and our measures of openness. This requires selecting a year to use as a dependent variable. We do this for every year in the sample.

Table 8 summarizes our results. The first row shows the average correlation across different years, along with the average of the *p-values*. The second row shows the standard deviations of these measures.[6]

[6] Alternatively, we could average the independent variable across time, as we do in sections 6.3 and 6.4. We choose not to do this with GDP per capita due to its non-stationarity.

Our results show that more open countries are significantly richer. The point estimates range from 0.2 to 0.4, suggesting that a country that is 10% more open than another is between 2% and 4% richer. The $p-values$ suggest that these correlations are significant at the 1% level. These numbers vary very little in time, as the standard deviation shows.

	Overall Openness	$p-value$	*Openness to Export*	$p-value$	*Openness to Import*	$p-value$
Mean	0.3427	2×10^{-6}	0.3790	1.9×10^{-7}	0.2180	0.0032
Std dev.	0.0101	1.8×10^{-6}	0.0120	2.018×10^{-7}	0.0087	0.0012

Table 6: Mean and standard deviation of the correlation between GDP per capita and different measures of openness. The statistics average and compute the standard deviation of the correlation between the index and GDP per capita in year t, for t between the years 2000 and 2019. The mean and standard deviations of the $p-values$ are also computed.

6.3 Openness and Inequality

This section explores the relationship between openness and inequality by focusing on the correlation between our index and the Gini coefficient. A Gini coefficient equal to 0 reflects a distribution where all individuals are homogeneous, that is, no inequality. A Gini coefficient of 1 indicates extreme inequality, where one individual holds all the assets. Thus, the higher the value, the more the inequality. We use the average of this coefficient between 2000 and 2019, as reported by the World Development Indicators.

The Stolper-Samuelson theorem (Stolper and Samuelson, 1941) produces strong predictions about the relationship between openness and inequality. In a world where the inputs of production are skilled and unskilled labor, opening up to trade should increase the relative wage rate of unskilled workers in countries where they are abundant, thus reducing inequality in poor countries. At the same time, this should increase the relative wage of skilled labor in skilled abundant countries, increasing inequality.

Table 7 presents the correlations between our indexes and the Gini coefficient for all countries in its top panel. In all cases, these correlations are very similar. They are negative and significant at the 5% confidence level, suggesting that more open countries tend to be less unequal. However, the coefficients are small, around 0.17, meaning that although this relationship is significant, its quantitative impact is limited.

The middle and bottom panels in Table 7 split the sample of countries into those richer than the median and those equal to or poorer than the median. The reason for doing this is that the Stolper-Samuelson theorem predicts that trade will reduce inequality for poorer countries, but it will increase it for wealthier ones. We find that greater openness is associated with lower inequality levels for both rich and poor countries (though not significantly), which is inconsistent with Stolper-Samuelson. This is expected, as many factors besides trade contribute to inequality. What is interesting is that the correlations are stronger for relatively poor countries, in line with Stolper-Samuelson. The results for poor countries are consistent with Dorn et al. (2022), who find that, among low income countries, more trade is associated with less inequality. Among rich countries, Dorn et al. (2022) find that more trade is associated with more inequality, but, as the authors acknowledge, this result is driven by outliers.

	Overall Openness	*Openness to Export*	*Openness to Import*
All countries			
Correlation	-0.1855	-0.1776	-0.1723
$p - value$	(0.0217)	(0.0281)	(0.0332)
Countries richer than the median			
Correlation	-0.1192	-0.1057	-0.1279
$p - value$	(0.3017)	(0.3602)	(0.2675)
Countries at least as poor as the median			
Correlation	-0.1922	-0.1883	-0.1691
$p - value$	(0.0963)	(0.1033)	(0.1442)

Table 7: Openness and Inequality. Each column presents the correlation between our Indexes and the Gini coefficient. The top panel shows our results for all countries, the middle panel focuses on countries richer than the median, and the bottom one shows countries poorer or equal to the median. p-values in parentheses.

6.4 Our Index vs. Other Measures of Openness

Several indexes of openness have been used in previous studies to assess a country's openness to trade. In this section, we examine the correlation between these indexes and our own measure of openness.

The indexes we consider include the sum of exports and imports over GDP; two averages of tariffs, simple and trade-weighted; three indexes based on tariff revenues: one developed by Jaumotte et al. (2013), the "Trade Freedom" index by the Heritage Foundation, and the index of "Freedom to trade internationally" by the Fraser Institute; and an index that computes the gains in trade volumes relative to a hypothetical economy with no trade barriers, no home bias, and trade volumes leading to diffusion of ideas (Duernecker et al., 2022). Next, we briefly describe these indexes.

- **Imports plus Exports over GDP.** We use data from the World Development Indicators (the sum of exports over GDP and imports over GDP). We compare our index with the averages of this indicator from 2000 to 2019.

- **Average Tariffs (weighted and simple).** We obtain both simple and trade weighted average tariffs from the World Integrated Trade Solution (WITS). We use the averages between 2000 and 2019.

- **Jaumotte et al. (2013)'s Openness Index.** The authors construct an openness index based on an average of the "effective" tariff rate, calculated as the average between the ratio of tariff revenues over imports, and the simple average of all tariff rates. Their data are computed annually and end in 2006. We consider the average for each country between 2000 and 2006. The higher the index, the more open the country.

- **Duernecker et al. (2022)'s Globalization Index.** This index extends the one created by Arribas et al. (2009) by incorporating the transmission of ideas as an additional channel for globalization. Arribas et al. (2009)'s index represents a measure of how far each country is to a hypothetical world with no trade barriers or home bias.

- **Heritage's Trade Freedom Index.** This is computed by the Heritage Foundation as an element in a broader "economic freedom" index. It consists of two elements: a trade-weighted tariff rate, and a quantitative evaluation of non-tariff barriers such as quotas and regulatory restrictions. The higher the index, the more open the country.

- **Fraser's Trade Freedom Index.** The Fraser Institute computes an index of Economic Freedom, and an index of "Freedom to trade internationally" sub-index as one of the 5 sub-indexes that conform the Freedom Index. This includes measures of tariffs, tariff revenues, the standard deviation of tariffs, and non-tariff barriers based on survey data. The higher the index, the more open the country.

It's important to recognize that many of these measures have notable limitations. For example, the ratio of imports and exports to GDP might be low due to a large GDP, meaning that even when the country has no trade barriers, this ratio could still be small. Take the U.S. as an example. In a list of 183 countries with data on imports and exports over GDP in 2019 from the WDI database, the U.S. ranks 181^{st} in terms of openness, surpassing only Cuba and Sudan. Similarly, measures based solely on tariffs overlook non-tariff barriers that reduce trade regardless of their tariffs. These can include governments only sourcing from domestic firms, lower trade due to national defense considerations, quotas, etc. Focusing on the ratio of tariff revenue to imports does not solve this issue. In an extreme case in which a country imports only one product with zero tariffs but does not allow the import of any other goods, this ratio will be zero even if the country is very closed to trade.

Table 8 presents the simple correlation between these indexes and ours across countries. All correlations align with expectations in terms of direction. These correlations are often significant, and in the case of Duernecker et al. (2022), the correlation is quantitatively quite large, with the overall index showing a correlation of 0.83 and the export index 0.86.

Openness Indicator	Overall	Export	Import
$\frac{\text{Imp.+Exp.}}{\text{GDP}}$	0.0626	0.0480	0.0850
	(0.4161)	(0.5329)	(0.2693)
Tariffs (simple avg.)	-0.3829	-0.4108	-0.2446
	(0.0000)	(0.0000)	(0.0014)
Tariffs (weighted avg.)	-0.4942	-0.5229	-0.3325
	(0.0000)	(0.0000)	(0.0000)
Jaumotte et al. (2013)	0.1853	0.1744	0.1760
	(0.0334)	(0.0455)	(0.00436)
Duernecker et al. (2022)	0.8273	0.8568	0.6095
	(0.0000)	(0.0000)	(0.0000)
Heritage Foundation	0.4067	0.4358	0.2658
	(0.0000)	(0.0000)	(0.0005)
Freedom Fraser	0.4977	0.5085	0.3745
	(0.0000)	(0.0000)	(0.0000)

Table 8: Correlations between our openness indexes and third-party openness measures. p-values in parentheses.

7 Conclusion

This paper employs an innovative approach to estimating Gravity equations, allowing for strategic actions across countries. We estimate the Gravity equation within a network, enabling the actions of any country to affect any bilateral trade volume, whether that country is a participant in the transaction or not. A key step is to estimate country effects as random effects, which helps eliminate the biases introduced by the existing correlations among error terms.

We uncover large differences with respect to the Panel Data approach, one of the most commonly used models to study the Gravity Equation. The Panel Data approach severely overestimates the elasticity of trade flows with respect to exporter GDP, finding it three times as large as the estimates under a network approach.

We then use our estimates to create a new index of openness, based on a counterfactual that reverts a country's estimated trade barriers to the mean, and computes the theoretical increase in trade. Countries that would increase trade the least (or reduce it the most) are considered the most open countries. With this new measure of openness, we evaluate the relationship between openness and other macroeconomic indicators that have been subject to much controversy in the literature. Our index avoids the existing criticism to this literature, and finds strong connections between openness and convergence, openness and wealth, and openness and inequality.

The convenience of using off-the-shelf estimation techniques has often led researchers to make independence assumptions that do not align with the data. This implies, among other things, assuming that the error term is independent. Understanding the dependence structure in international trade can provide new insights. These insights can be key for policymakers, who need to understand the consequences of any change in trade barriers: not only for the partner country but for every other country as well.

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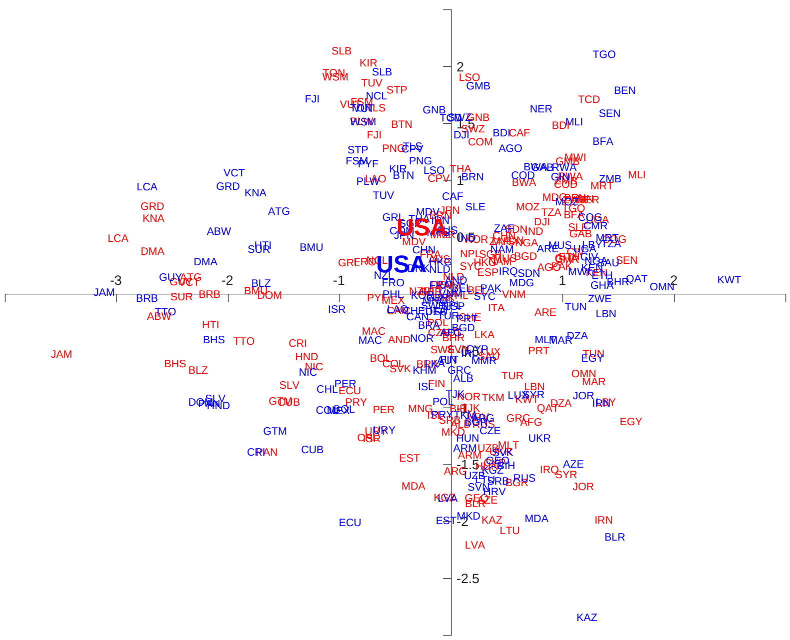

Figure 1: Multiplicative Random Effects. Red labels correspond to importer effects (u_i) and blue labels to exporter effects (v_j). Blue countries partner with red ones. Blue countries in the same quadrant as red ones trade more than what can be expected, while countries in opposite quadrants trade less.

Appendix A Removing Countries with Zero Bilateral Trade Flows

This appendix lists some results when eliminating countries in a way that no bilateral trade flow is zero.

A.1 Data Selection

This section describes the countries removed from our analysis, along with the reasons for doing so.

Lack of data on GDP. The list of countries with no reliable GDP data during the period of our analysis are: AIA, COK, ERI, MSR, SSD, WLF, VEN.

Lack of data on distance. Several countries were not present in the Centre for Prospective Studies and International Information. These include ROU, SRB, COD.

Lack of data on bilateral trade. We found a few countries that did not trade with other ones within our sample. We choose to eliminate these from the sample, which guarantees that we did not work with zero trade flows. These countries include TUN, BOL, CMR, BHR, PRY, UGA, LVA, NPL, SDN, EST, KHM, SLV, CYP, HND, PNG, ISL, TTO, SEN, ZMB, SYR, ZWE, BIH, AFG, LAO, GEO, MLI, PSE, GAB, BWA, BFA, MLT, JAM, ALB, MOZ, HTI, MUS, BEN, MNG, MDG, ARM, BRN, GIN, BHS, NER, COG, NIC, MKD, NAM, MDA, TCD, MWI, RWA, NCL, KGZ, TJK, MRT, BMU, TGO, PYF, CYM, MDV, MNE, FJI, BRB, GUY, SWZ, SLE, SUR, ABW, FRO, AND, DJI, GRL, BDI, BTN, LSO, BLZ, CPV, CAF, LCA, TLS, GMB, ATG, SYC, SLB, GNB, GRD, TCA, COM, KNA, VUT, WSM, VCT, DMA, TON, STP, FSM, PAK, PLW, KIR, TUV, UKR, EGY, ZAF, BGD, TZA, SVK, CUB, DZA, URY, IRQ, YEM, IRN, UZB, TKM, KWT, ISR, NGA, PAN, ECU, AZE, MAC, MMR, DOM, ETH, LBY, AGO, KEN, CRI, GTM, LTU, OMN, QAT, GHA, CIV, KAZ.

A.2 Estimates

Table A.1 shows our estimates when eliminating countries that feature zero trade flows with other countries.

A.3 The Openness Rankings

Table A.2 lists the countries used along with their openness.

Appendix B Criteria for Eliminating Countries

This section describes the countries removed from our analysis, along with the reasons for doing so. We eliminate 42 countries/territories and work with the remaining 186 countries.

Lack of data on GDP. We eliminate nine countries/territories based on unavailable GDP data. These include: AIA, COK, ERI, MSR, WLF, YEM, TCA, CYM, and VEN.

Dissolved Territories and Newly Independent Countries We eliminated two countries due to dissolution (Netherlands Antilles) and independence (Montenegro).

Parameter	Networks ($k=4$) (1)	Networks ($k=2$) (2)	Networks ($k=0$) (3)	Panel Data (4)
Fixed Effects				
$\log gdp_r$	0.637	0.707	0.675	0.775
	(0.009)	(0.010)	(0.012)	(0.039)
$\log gdp_s$	0.371	0.444	0.415	0.505
	(0.010)	(0.011)	(0.012)	(0.036)
$\log distance$	-0.832	-1.367	-1.185	-1.182
	(0.021)	(0.015)	(0.007)	(0.006)
Common Colonial Ties	0.039	0.348	0.370	0.370
	(0.020)	(0.017)	(0.017)	(0.015)
Common Language	0.256	0.122	0.149	0.153
	(0.023)	(0.025)	(0.025)	(0.023)
Common Border	0.461	0.291	0.459	0.461
	(0.025)	(0.026)	(0.030)	(0.025)
Random Effects				
σ_s^2	0.385	0.491	0.520	–
	(0.080)	(0.112)	(0.111)	–
σ_{rs}	0.545	0.672	0.704	–
	(0.13)	(0.175)	(0.368)	–
σ_r^2	1.421	1.651	1.702	–
	(0.285)	(0.348)	(0.368)	–
ρ	0.274	0.340	0.319	–
	(0.006)	(0.006)	(0.005)	–
σ_ε^2	0.464	0.557	0.787	0.886
	(0.003)	(0.004)	(0.005)	(0.003)

Table A.1: Estimation Results when removing trade flows equal to zero. The estimates shown are posterior means, and the numbers between parenthesis are posterior standard deviations.

Lack of data on Distance, Common Borders, Common Language, and Common Colonial Ties. We eliminate two countries based on unavailable distance, common borders, common Language, and/or common colonial ties data. These include: ROU and PSE.

Lack of data on Bilateral Trade. We eliminate a few countries which does not report bilateral trade flow. This process eliminates 9 countries and 31 territories or special entities. These countries are: ATA, ASM, IOT, VGB, CXR, CCK, GNQ, FLK, ATF, GIB, VAT, PRK, LBR, NRU, NIU, MNP, UMI, MHL, SHN, SPM, SMR, SOM, TKL, HMD, CUW, SXM, NFK, PCN, SSD, ESH, SGS, GUM, BVT, BLM, MCO, BES, and MYT.

Country	Δ_T	Δ_x	Δ_m	Country	Δ_T	Δ_x	Δ_m
ARE	1.433	0.630	0.803	ITA	1.377	1.029	0.348
ARG	0.003	0.463	-0.460	JOR	-1.893	-1.980	0.087
AUS	2.275	1.386	0.888	JPN	2.431	1.777	0.654
AUT	-0.348	-0.050	-0.298	KOR	2.415	1.615	0.801
BEL	1.449	0.688	0.761	LBN	-2.862	-2.509	-0.353
BGR	-1.289	-1.183	-0.105	LKA	-1.609	-1.312	-0.297
BLR	-1.027	-0.882	-0.145	LUX	-3.389	-1.841	-1.548
BRA	1.125	0.955	0.171	MAR	-1.693	-1.313	-0.380
CAN	1.252	0.670	0.582	MEX	1.106	0.418	0.688
CHE	0.570	0.583	-0.014	MYS	2.732	1.512	1.220
CHL	1.231	0.920	0.311	NLD	1.778	0.924	0.854
CHN	3.429	2.304	1.125	NOR	-1.081	-0.452	-0.629
COL	-1.232	-0.757	-0.475	NZL	0.777	0.323	0.454
CZE	-0.010	-0.109	0.099	PAK	-1.364	-1.071	-0.293
DEU	2.500	1.644	0.856	PER	-0.012	0.200	-0.212
DNK	-0.508	-0.200	-0.308	PHL	0.332	0.016	0.317
ESP	0.948	0.609	0.339	POL	0.061	-0.022	0.083
FIN	-0.411	-0.103	-0.308	PRT	-0.784	-0.611	-0.173
FRA	1.124	0.827	0.298	RUS	0.622	0.665	-0.043
GBR	1.130	0.666	0.464	SAU	0.704	0.584	0.120
GRC	-1.711	-1.271	-0.440	SGP	3.518	1.858	1.661
HKG	2.772	1.189	1.583	SVN	-1.449	-1.008	-0.441
HRV	-2.787	-2.119	-0.669	SWE	0.254	0.332	-0.078
HUN	-0.063	-0.179	0.116	THA	2.369	1.380	0.988
IDN	1.334	0.957	0.377	TUR	-0.032	-0.101	0.069
IND	1.065	0.602	0.464	USA	3.360	2.070	1.290
IRL	-0.025	0.288	-0.313	VNM	1.174	0.492	0.681

Table A.2: Different openness rankings when eliminating trade flows equal to zero.

Appendix C The Openness Rankings

Tables B.1, B.2 and B.3 list the countries and the value of their overall openness, openness to export and openness to import indexes, respectively. Countries are in descending order of their ranking, so that the top countries are the most open.

Rank	Country	Δ_T	Rank	Country	Δ_T	Rank	Country	Δ_T	Rank	Country	Δ_T
1	THA	0.423	48	IRL	4.553	95	QAT	7.462	142	COG	10.098
2	CHN	0.616	49	EST	4.757	96	FJI	7.481	143	NER	10.151
3	USA	0.652	50	PAK	4.902	97	ETH	7.502	144	GMB	10.333
4	JPN	0.657	51	CRI	4.948	98	NGA	7.556	145	IRQ	10.354
5	KOR	1.129	52	SAU	4.956	99	GRD	7.631	146	PNG	10.360
6	SGP	1.337	53	SVK	5.010	100	ZWE	7.653	147	MNG	10.417
7	NLD	1.571	54	PRT	5.034	101	ISL	7.668	148	BFA	10.511
8	MYS	1.673	55	CIV	5.151	102	MWI	7.700	149	TKM	10.731
9	DEU	1.675	56	ECU	5.199	103	AZE	7.729	150	TON	10.871
10	AUS	1.802	57	PER	5.228	104	BIH	7.748	151	MDV	10.962
11	IND	1.875	58	PAN	5.286	105	PRY	7.806	152	MAC	10.995
12	HKG	2.029	59	GTM	5.350	106	BHR	7.903	153	COD	11.101
13	ITA	2.057	60	CYP	5.421	107	UGA	8.033	154	RWA	11.128
14	BRA	2.212	61	IRN	5.545	108	CMR	8.047	155	ATG	11.138
15	LVA	2.303	62	COL	5.598	109	TTO	8.085	156	TJK	11.192
16	NZL	2.347	63	NOR	5.618	110	MRT	8.146	157	LAO	11.395
17	FRA	2.492	64	EGY	5.655	111	KGZ	8.246	158	BWA	11.427
18	IDN	2.623	65	KAZ	5.676	112	CUB	8.292	159	NCL	11.469
19	ZAF	2.653	66	SVN	5.736	113	BLZ	8.308	160	SLB	11.672
20	LTU	2.775	67	BGD	5.834	114	LBN	8.329	161	KNA	11.678
21	BEL	2.802	68	GEO	5.853	115	SLE	8.429	162	BDI	11.716
22	TUR	2.895	69	KEN	5.929	116	UZB	8.430	163	ABW	11.772
23	ESP	2.938	70	URY	6.007	117	MKD	8.575	164	LCA	11.952
24	SWE	3.009	71	TZA	6.023	118	ARM	8.628	165	BRN	11.987
25	UKR	3.012	72	MLT	6.088	119	ZMB	8.706	166	VUT	12.414
26	GBR	3.162	73	MAR	6.093	120	HTI	8.722	167	WSM	12.765
27	HUN	3.225	74	HRV	6.145	121	DZA	8.730	168	PYF	12.786
28	BLR	3.225	75	OMN	6.336	122	NAM	8.768	169	CAF	12.883
29	DNK	3.226	76	BRB	6.349	123	GIN	8.821	170	KIR	12.986
30	BGR	3.458	77	HND	6.400	124	TGO	8.882	171	CPV	13.304
31	FIN	3.598	78	SEN	6.427	125	KWT	8.888	172	SRB	14.035
32	VNM	3.816	79	DOM	6.469	126	SWZ	9.025	173	TCD	14.086
33	CHL	3.856	80	ISR	6.620	127	MMR	9.035	174	AND	14.095
34	RUS	3.873	81	MDA	6.683	128	DMA	9.087	175	COM	14.131
35	MEX	3.900	82	GHA	6.722	129	LBY	9.146	176	BMU	14.314
36	CZE	3.951	83	JOR	6.781	130	GAB	9.166	177	TUV	14.918
37	POL	3.957	84	MLI	6.797	131	SYC	9.200	178	LSO	15.056
38	PHL	4.000	85	SUR	6.807	132	VCT	9.244	179	FRO	15.148
39	ARE	4.015	86	TUN	6.867	133	BHS	9.326	180	GRL	15.576
40	CHE	4.075	87	SLV	6.875	134	BOL	9.333	181	GNB	16.101
41	LKA	4.091	88	NIC	6.888	135	ALB	9.337	182	STP	16.306
42	CAN	4.095	89	SYR	6.994	136	NPL	9.559	183	TLS	17.676
43	ARG	4.108	90	LUX	7.235	137	SDN	9.666	184	BTN	17.909
44	GUY	4.442	91	KHM	7.368	138	AGO	9.754	185	FSM	20.133
45	JAM	4.452	92	MDG	7.399	139	BEN	9.889	186	PLW	20.267
46	GRC	4.452	93	MOZ	7.426	140	DJI	9.926	–	–	–
47	AUT	4.546	94	MUS	7.453	141	AFG	9.981	–	–	–

Table B.1: The Overall openness rankings.

Rank	Country	Δ_X	Rank	Country	Δ_X	Rank	Country	Δ_X	Rank	Country	Δ_X
1	CHN	-0.380	48	NOR	2.898	95	NIC	5.348	142	COD	5.348
2	JPN	0.027	49	IRN	2.931	96	MMR	5.358	143	IRQ	5.358
3	USA	0.217	50	PRT	3.080	97	SLV	5.412	144	NER	5.412
4	KOR	0.425	51	SAU	3.181	98	NAM	5.450	145	SDN	5.450
5	THA	0.432	52	PER	3.201	99	MLI	5.458	146	TJK	5.458
6	BRA	0.579	53	ISR	3.335	100	MUS	5.459	147	MNG	5.459
7	MYS	0.726	54	ECU	3.364	101	NGA	5.531	148	BWA	5.531
8	DEU	0.808	55	SVK	3.443	102	UGA	5.617	149	BFA	5.617
9	SGP	0.827	56	URY	3.446	103	MDA	5.624	150	AGO	5.624
10	IND	0.849	57	CRI	3.525	104	UZB	5.625	151	BEN	5.625
11	ITA	1.039	58	EGY	3.526	105	CMR	5.687	152	SLB	5.687
12	IDN	1.064	59	GTM	3.572	106	BRB	5.706	153	BRN	5.706
13	AUS	1.076	60	BGD	3.615	107	AZE	5.722	154	DJI	5.722
14	NLD	1.119	61	COL	3.622	108	ETH	5.732	155	GMB	5.732
15	HKG	1.231	62	CIV	3.664	109	BHR	5.817	156	MDV	5.817
16	SWE	1.275	63	JAM	3.709	110	TTO	5.929	157	VCT	5.929
17	NZL	1.328	64	CYP	3.719	111	FJI	5.939	158	RWA	5.939
18	FRA	1.440	65	EST	3.726	112	MOZ	5.964	159	ATG	5.964
19	ARG	1.458	66	PAN	3.838	113	BIH	5.990	160	TON	5.990
20	TUR	1.521	67	OMN	3.933	114	GAB	6.165	161	ABW	6.165
21	DNK	1.597	68	MAR	3.979	115	ZMB	6.185	162	BDI	6.185
22	ZAF	1.661	69	KEN	4.009	116	KWT	6.204	163	VUT	6.204
23	HUN	1.669	70	LUX	4.082	117	BHS	6.242	164	CAF	6.242
24	BEL	1.742	71	MLT	4.110	118	LBN	6.257	165	SRB	6.257
25	LVA	1.758	72	SVN	4.142	119	BLZ	6.312	166	NCL	6.312
26	FIN	1.778	73	KHM	4.286	120	MRT	6.341	167	WSM	6.341
27	GBR	1.826	74	GUY	4.413	121	SLE	6.376	168	KNA	6.376
28	ESP	1.875	75	HRV	4.488	122	HTI	6.420	169	LCA	6.420
29	UKR	1.920	76	KAZ	4.544	123	NPL	6.451	170	AND	6.451
30	LTU	2.015	77	GEO	4.581	124	DZA	6.473	171	TCD	6.473
31	VNM	2.044	78	TZA	4.623	125	LAO	6.586	172	KIR	6.586
32	CHL	2.052	79	QAT	4.632	126	MKD	6.586	173	LSO	6.586
33	RUS	2.103	80	HND	4.680	127	BOL	6.593	174	COM	6.593
34	PHL	2.155	81	TUN	4.681	128	KGZ	6.608	175	CPV	6.608
35	LKA	2.191	82	SYR	4.810	129	PNG	6.725	176	FRO	6.725
36	CHE	2.295	83	JOR	4.866	130	GIN	6.770	177	PYF	6.770
37	BGR	2.351	84	PRY	4.922	131	LBY	6.770	178	BMU	6.770
38	CAN	2.419	85	ISL	4.971	132	GRD	6.806	179	TUV	6.806
39	IRL	2.536	86	CUB	5.005	133	DMA	6.921	180	GRL	6.921
40	AUT	2.601	87	ZWE	5.033	134	ARM	6.987	181	STP	6.987
41	ARE	2.688	88	SEN	5.058	135	AFG	7.001	182	TLS	7.001
42	POL	2.692	89	GHA	5.105	136	ALB	7.002	183	GNB	7.002
43	BLR	2.755	90	DOM	5.107	137	TGO	7.086	184	BTN	7.086
44	MEX	2.810	91	MWI	5.229	138	TKM	7.093	185	FSM	7.093
45	CZE	2.821	92	MDG	5.245	139	COG	7.103	186	PLW	7.103
46	PAK	2.838	93	SWZ	5.303	140	MAC	7.160	–	–	–
47	GRC	2.882	94	SUR	5.331	141	SYC	7.292	–	–	–

Table B.2: The Exporter openness rankings.

Rank	Country	Δ_M	Rank	Country	Δ_M	Rank	Country	Δ_M	Rank	Country	Δ_M
1	THA	-0.009	48	CIV	1.487	95	NGA	2.026	142	IRQ	2.026
2	GUY	0.029	49	NIC	1.540	96	PER	2.027	143	PRY	2.027
3	USA	0.435	50	FJI	1.542	97	GIN	2.052	144	AFG	2.052
4	NLD	0.452	51	HUN	1.556	98	SLE	2.053	145	COG	2.053
5	BLR	0.470	52	IDN	1.560	99	PAK	2.065	146	GAB	2.065
6	SGP	0.510	53	SVK	1.567	100	LBN	2.071	147	BDI	2.071
7	LVA	0.545	54	GRC	1.570	101	BHR	2.086	148	KHM	2.086
8	JPN	0.630	55	SVN	1.595	102	SDN	2.114	149	BHS	2.114
9	BRB	0.642	56	GHA	1.617	103	MAR	2.114	150	NPL	2.114
10	KOR	0.704	57	DNK	1.629	104	EGY	2.129	151	LUX	2.129
11	AUS	0.725	58	BRA	1.633	105	GMB	2.131	152	ISR	2.131
12	JAM	0.743	59	KGZ	1.638	106	MDG	2.154	153	CUB	2.154
13	LTU	0.760	60	ARM	1.641	107	TTO	2.155	154	NAM	2.155
14	HKG	0.798	61	HRV	1.657	108	DMA	2.165	155	ABW	2.165
15	GRD	0.825	62	CAN	1.675	109	SYR	2.184	156	TJK	2.184
16	DEU	0.867	63	CYP	1.703	110	TUN	2.186	157	CPV	2.186
17	VCT	0.927	64	HND	1.720	111	BGD	2.219	158	SLB	2.219
18	MYS	0.947	65	SWE	1.733	112	DZA	2.257	159	PNG	2.257
19	ZAF	0.992	66	BIH	1.758	113	HTI	2.301	160	TKM	2.301
20	CHN	0.995	67	ETH	1.770	114	ALB	2.336	161	KIR	2.336
21	ITA	1.018	68	RUS	1.770	115	CMR	2.361	162	MMR	2.361
22	NZL	1.019	69	VNM	1.772	116	LBY	2.376	163	COD	2.376
23	IND	1.026	70	SAU	1.775	117	OMN	2.403	164	BWA	2.403
24	EST	1.032	71	GTM	1.778	118	UGA	2.416	165	SWZ	2.416
25	FRA	1.051	72	CHE	1.780	119	TON	2.451	166	VUT	2.451
26	MDA	1.060	73	DJI	1.793	120	MWI	2.472	167	WSM	2.472
27	BEL	1.060	74	TGO	1.795	121	ZMB	2.521	168	MAC	2.521
28	ESP	1.063	75	CHL	1.805	122	URY	2.561	169	BRN	2.561
29	MEX	1.090	76	MRT	1.805	123	KNA	2.588	170	BMU	2.588
30	UKR	1.092	77	FIN	1.819	124	IRN	2.614	171	CAF	2.614
31	BGR	1.107	78	AGO	1.833	125	NCL	2.620	172	COM	2.620
32	CZE	1.130	79	ECU	1.835	126	ZWE	2.620	173	TUV	2.620
33	KAZ	1.133	80	PHL	1.846	127	NER	2.643	174	TCD	2.643
34	POL	1.265	81	LKA	1.901	128	ARG	2.650	175	LAO	2.650
35	GEO	1.272	82	SYC	1.908	129	MDV	2.665	176	AND	2.665
36	ARE	1.327	83	JOR	1.915	130	KWT	2.684	177	GNB	2.684
37	GBR	1.336	84	KEN	1.919	131	ISL	2.697	178	GRL	2.697
38	MLI	1.339	85	AUT	1.945	132	BFA	2.715	179	FRO	2.715
39	DOM	1.361	86	BEN	1.950	133	NOR	2.720	180	SRB	2.720
40	SEN	1.369	87	PRT	1.954	134	PYF	2.726	181	STP	2.726
41	TUR	1.374	88	COL	1.976	135	ATG	2.730	182	LSO	2.730
42	TZA	1.400	89	MLT	1.979	136	BOL	2.739	183	TLS	2.739
43	CRI	1.423	90	MKD	1.989	137	MNG	2.764	184	BTN	2.764
44	PAN	1.448	91	MUS	1.994	138	UZB	2.806	185	PLW	2.806
45	MOZ	1.462	92	BLZ	1.996	139	RWA	2.809	186	FSM	2.809
46	SLV	1.463	93	AZE	2.007	140	LCA	2.824	–	–	–
47	SUR	1.476	94	IRL	2.016	141	QAT	2.829	–	–	–

Table B.3: The Importer openness rankings.

Appendix D Selection Criteria for Exercises in Section 6

This section outlines the countries dropped from the analysis in section 6 because of lack of data.

D.1 Openness and Convergence

The following countries do not have data on GDP per capita during the relevant period of analysis: AFG, DJI, FRO, NCL, and STP.

D.2 Openness and Wealth

Table C.1 lists the countries eliminated each year because of lack of data on GDP per capita.

Year	Missing data on GDP p.c. for
2000	AFG, DJI, FRO, NCL, STP
2001	AFG, DJI, FRO, NCL
2002	DJI, FRO, NCL
2003	DJI, FRO, NCL
2004	DJI, FRO, NCL
2005	DJI, FRO, NCL
2006	DJI, FRO, NCL
2007	DJI, FRO, NCL
2008	DJI, NCL
2009	DJI, NCL
2010	DJI, NCL
2011	DJI, NCL
2012	DJI, NCL
2013	NCL
2014	NCL
2015	NCL
2016	NCL
2017	NCL
2018	NCL

Table C.1: Countries excluded from the correlations per year between the openness indexes and GDP per capita due to lack of GDP per capita.

D.3 Openness and Inequality

We exclude the following countries due to lack of Gini data: ABW, AFG, AND, ATG, BHR, BHS, BLZ, BMU, BRB, BRN, CUB, DMA, FRO, GRL, GUY, HKG, KHM, KNA, KWT, LBY, MAC, NCL, NZL, OMN, PLW, PYF, QAT, SAU, SGP, SUR, TKM, TTO, VCT.

D.4 Our Index vs. Other Measures of Openness

Table C.2 shows the countries excluded from the analysis because of lack of index data for each index.

Index	Countries eliminated
$\frac{M+X}{Y}$	–
Tariffs (simple avg.)	AND, ETH, FRO, FSM, GRL, HTI, IRQ, LBY, MKD, NCL, SLE, SRB, SWZ, TUV
Tariffs (weighted avg.)	AND, ETH, FRO, FSM, GRL, HTI, IRQ, LBY, MKD, NCL, SLE, SRB, SWZ, TUV
Jaumotte et al. (2013)	ABW, AFG, AND, ARE, ATG, BHR, BHS, BIH, BLZ, BMU, BRB, BRN, CHE, COM, CPV, CUB, CYP, DJI, DMA, FJI, FRO, FSM, GRD, GRL, GUY, IRQ, ISL, KIR, KNA, LAO, LBY, LCA, LUX, MAC, MDV, MLT, MNG, NCL, PLW, PYF, QAT, SAU, SDN, SLB, SRB, STP, SUR, SYC, TLS, TON, TUV, VCT, VUT, WSM
Duernecker et al. (2022)	AND, COD, FRO, KNA, STP, TLS, VUT
Heritage Foundation	ABW, AND, ATG, BMU, CIV, COG, CPV, FRO, GRD, GRL, KNA, MKD, NCL, PLW, PYF, STP, SWZ, TUV
Freedom Fraser	ABW, AFG, AND, ATG, BMU, CUB, DMA, FRO, FSM, GRD, GRL, KIR, KNA, LCA MAC, MDV, NCL, PLW, PYF, SLB, STP TKM, TON, TUV, UZB, VCT, VUT, WSM

Table C.2: Countries eliminated when computing correlations because of lack of index data.