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Effects of COVID-19 on Trade Flows in the Presence of Ethnic Dissimilarity

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Abstract

This paper explores the impacts of COVID-19 on the bilateral trade flows in the presence of ethnic distances. I use the distance-adjusted ethno linguistic fractionalization index (DELF) to measure ethnic proximity and the monthly trade data developed by the International Monetary Fund (IMF). I find that within a country pair with larger ethnic distances, an increase in COVID-19 cases in the exporter negatively affects export volume significantly. Considering other things remain the same, I find that a ten percent increase in COVID-19 cases in the exporting country is linked to a 0.0376 percent greater decline in export volume when the ethnic composites of the two countries are completely heterogeneous than when they are entirely homogeneous. If so, governments should consider strategies to promote trade, lower transaction costs, and trade barriers between nations with greater ethnic differences. Failure to fully realize recovery potential will probably result in an inefficient recovery process and an unequal distribution of resources. The result provides insight into the post-pandemic period for policy making. It is reasonable to predict that a larger ethnic distance within a country pair will also impact trade volume in the recovery period if it is causing a more significant decline in trade in response to COVID-19 cases in the exporter.

Keywords: Bilateral Trade, COVID-19, Distance-Adjusted Ethno-Linguistic Fractionalization Index (DELF), Ethnic Dissimilarity, Gravity Equation, International Trade.

Introduction

The world has suffered from unparalleled disruptions since the outbreak of COVID-19: the up surging death toll, the stagnated economies, the revamping populism, the frozen supply chains, etc. According to the United Nations Conference on Trade and Development (UNCTAD) (1), the world trade openness index decreased by 8.5% in 2020. Notably, the index reflects a 17.8% decline for least developed countries (LDCs), and the trade-to-GDP ratio in developing economies, excluding China, plummeted by 10.3%. Although the trade to GDP ratio in developed regions (M49) also experienced a dramatic decline by 8.6%, the rate is much lower compared to the less developed economies, which usually correspond to ethnically marginalized countries with a colonization history. The pandemic cannot discriminate, whereas policies, specifically trade policies in this context, can. The existing literature has already revealed a negative impact of ethnic and cultural distance between countries on the bilateral trade volume during normal times (i.e., without the turbulence of the pandemic) within certain regions, such as the European Union and West Africa (2,3). Additionally, there has been a plethora of literature proving statistically the negative impact of COVID-19 on bilateral trade both within specific regions and around the globe (4-6). The literature has also found that other factors, such as regional trade agreements, can effectively add more resilience to bilateral trade during the pandemic (4, 7). The diaspora keeps in touch with their homeland through money transfers or potential return, but most importantly, by involvement in corporate, political, and scientific networks. These networks have the capacity to produce money and trade flows, technological transfers, and the spread of institutional and social norms that support growth (8). It uses the country's Diaspora rate and size (people and area) to explain per capita income, like the international trade model put forth in previous research (9). Numerous recent studies on trade and migration openness have made extensive use of this model (10-14). It is claimed that claims, "we are all nationalists now" (15). Even before the pandemic, it was not hard to see a trajectory of

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nationalism, such as the MAGA (Make America Great Again) hat of former US President Donald J. Trump, the Vote Leave campaign for Brexit, the US-China trade war, and so much more (16). As COVID-19 became increasingly uncontrollable, more isolating actions like the closure of borders and trade protectionism were taken over the course by governments worldwide. At the same time, some studies suggest that consumer ethnocentrism could be a factor that impacts people's decisions between purchasing local products and purchasing foreign imported products (17). For example, some consumers reduce their purchases of imported goods because they believe that buying imported products will harm their economy and lead to higher unemployment rates (18). Since the outbreak of coronavirus, a huge decline in trade volume has been observed. As shown in past studies (1, 19, 20), the World Trade Organization (WTO) forecasts in October 2020 a 9.2% decline in the world merchandise trade volume for 2020. Meanwhile, according to a survey, one-third of global consumers now worry that products shipped from abroad may bring safety risks, with 47% indicating that they are reluctant to buy products from the US and China (21).

The effect of the current pandemic on global trade was analyzed, suggesting a negative effect of COVID-19 on international trade relations by applying the gravity model (22). A common approach to analyze bilateral trade is applying the gravity equation, for which a theoretical foundation has been set by applying the Constant Elasticity of Substitution (CES) (23). Moreover, much research has been done to solve potential estimation challenges, i.e., endogeneity. For example, it is suggested to use directional fixed effects, which are importer and exporter fixed effects, in cross-section estimations to compute multilateral resistances (24). The problems of zero trade flows and heteroscedasticity can be solved by using Poisson Pseudo Maximum Likelihood (PPML) (25). Reverse causality was treated effectively by country-pair fixed effects, given the difficulty of finding an appropriate instrument for the instrumental variable approach (26, 27).

In addition to the structural gravity model, there have been studies discussing the effect of ethnicity on cross-border trade which recommends that a joint ethnicity may lessen the transaction costs related to agricultural trade using data from cross-border trade between Niger and Nigeria (3). Also, cultural proximity, reflected by the bilateral score data of the Eurovision Song Contest (ESC), positively affects trade volumes (2). Nevertheless, both papers are limited to a certain region, with more focused on cross-border trade between Niger and Nigeria (3) and, on bilateral trade of European country pairs (2). The conclusion can likely be generalized to international bilateral trade. Still, it would not be surprising if the results are related to or even caused by regional characteristics, given that it only considers three ethnic groups, Hausa, Zarma, and Kanuri (3), and ESC, a dataset unique for Europe, is applied (2). Thus, an analysis of the effect of ethnic proximity on bilateral trade in an international setting is important. I include in our dataset 50 major exporters and 50 importers around the globe to achieve this goal. I chose the 50 exporting countries and 50 importing countries based on the World Trade Statistical Review 2020. They are the top 50 exporters and importers in global merchandise trade. The countries included are also listed in the appendix in Table A1.

In terms of ethnic fractionalization and economic growth, it has been shown that larger ethnic fractionalization exerts a negative effect on economic development, especially for countries in Africa (28); the approach is updated by using the new ELF data and concludes that a completely homogeneous country expects an approximately 2% higher growth rate as opposed to a completely heterogeneous country (29); the finding is confirmed and an exception is added in case of rich countries (29). Ethnic diversity within a country could also have an effect on trade. As for the impact of ethnic diversity within a country on trade, the former could significantly affect the categories of goods that the country tends to produce (30). More specifically, countries with relatively heterogeneous populations tend to export goods produced by technology that is more sustainable for employees. Furthermore, ethnic and cultural diversity within a country pair exerts an influence on trade as well. Two channels are proposed: reduced transaction costs and preferences, through which higher cultural proximity between two countries could increase trade (31). A positive effect of cultural proximity between countries on trade in differentiated goods has been revealed by

using the ESC as a proxy of cultural distance within country pairs (2), and a similar result has been observed by employing a variable of bilateral opinion (32).

Equally important is the strand of literature on the effect of COVID-19 on trade volume. Using the monthly trade of the European Union member states, it is shown that a decline in trade induced by COVID-19 and significantly negative trade effects related to COVID-19 cases per capita in both the destination and origin countries (5). Using monthly data while involving a different scope of countries and time periods it is found that a greater negative impact of COVID-19 on bilateral trade for countries within the same regional trade agreements before the pandemic, and the highest negative impact for exports between high-income countries (4).

To examine the effect of COVID-19 in the presence of ethnic heterogeneity between countries on bilateral trade in a larger scope requires an effective measurement of the key independent variable, ethnic distance. A suitable measure of cultural affinity between countries within a single country or within a country pair is proposed, which is the DELF index (33). When the population is considered completely homogeneous, the index equals 0; when the population is completely heterogeneous, the index equals 1 (33). The paper also produces the regression (2) and shows a valid and significant effect of DELF on trade (33). However, the interaction effect of DELF and infectious diseases on bilateral trade are not analyzed here (33), which I incorporate into my study. This paper shows the impact of COVID-19 cases in the presence of cultural affinity (measured by DELF index) on bilateral trade.

The specific objective of the study is to estimate the effects of COVID-19 on bilateral trade volume in the presence of ethno-linguistic distance by applying the gravity model and primarily the Poisson Pseudo-Maximum Likelihood (PPML) estimator. I set up the regression model to examine whether there is a causal interaction effect of the "ethnic distance between two countries" and COVID-19 cases of each country on the country pair's bilateral trade volume on an international scale. The interaction term is composed of the product of the logarithm of the number of active COVID-19 cases and the ethnic composite of DELF. I use the monthly trade data of 206 countries as the origin countries exporting to 207 destination countries over the course of January 2020 to December 2020. The IMF DOTS dataset does not include the data for Taiwan as an exporting country.

The remainder of this paper is structured as follows. Section 2 provides the theoretical framework, which mainly elaborates on the derivation of the regression model based on the gravity equation, data sources, a data description, and the empirical model and estimation method. Section 3 offers the regression results. Section 4 shows the discussion that entails the interpretation of the results, referencing other research. Finally, Section 5 concludes and gives directions for future research.

Methodology

Theoretical Framework

I apply the structural gravity model to analyze the effect of ethnic proximity between two countries on bilateral trade, starting with the structural gravity system derived from the CES approach (23). The maximization problem is solved with the CES utility function of consumers in regions $\boldsymbol{j}$, $\left(\sum_i \boldsymbol{\beta_i}^{\frac{1-\sigma}{\sigma}} \boldsymbol{c_{ij}}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$, subject to the budget constraint $\sum_i \boldsymbol{p_{ij}c_{ij}} = \sum_i \boldsymbol{p_i t_{ij} c_{ij}} = \boldsymbol{y_j}$, where $\boldsymbol{c_{ij}}$ is the consumption by region $\boldsymbol{j}$ consumers of goods from region $\boldsymbol{i}$, σ is the elasticity of substitution between all goods, β_i is a positive distribution parameter, and $\boldsymbol{y_j}$ is the nominal income of region $\boldsymbol{j}$'s residents (16). It employs a trade cost factor $\boldsymbol{t_{ij}}$ to represent the trade barrier between the two countries (16). Therefore, the price of region $\boldsymbol{i}$ goods for region $\boldsymbol{i}$ consumers is set as $\boldsymbol{p_i}$ whereas that for region $\boldsymbol{j}$ consumers is $\boldsymbol{p_{ij}}$. The trade volume from $\boldsymbol{i}$ to $\boldsymbol{j}$ is $\boldsymbol{x_{ij}} = \boldsymbol{p_{ij}c_{ij}}$, which renders the total income of region $\boldsymbol{i}$, $\boldsymbol{y_i}$, equal to $\sum_j \boldsymbol{x_{ij}}$. The optimization problem gives $\boldsymbol{x_{ij}} = \left(\frac{\beta_i p_i t_{ij}}{P_j}\right)^{(1-\sigma)} \boldsymbol{y_j}$, where $\boldsymbol{P_j}$, referred to as multilateral resistance, stands for $\left[\sum_i \left(\boldsymbol{\beta_i p_i t_{ij}}\right)^{(1-\sigma)}\right]^{\frac{1}{1-\sigma}}$.Therefore, $\boldsymbol{y_i} = (\boldsymbol{\beta_i p_i})^{1-\sigma} \sum_j \left(\frac{t_{ij}}{P_j}\right)^{1-\sigma} \boldsymbol{y_j}$. The paper defines the world nominal income as $\boldsymbol{y^W} \equiv \sum_j \boldsymbol{y_j}$ and income share as $\theta_j \equiv \frac{y_j}{y^W}$, which yields $\boldsymbol{x_{ij}} = \frac{y_i y_j}{y^W}\left(\frac{t_{ij}}{P_i P_j}\right)^{1-\sigma}$, where $\boldsymbol{P_i} \equiv [\sum_j \left(\frac{t_{ij}}{P_j}\right)^{1-\sigma} \boldsymbol{\theta_j}]^{\frac{1}{1-\sigma}}$,

representing the outward multilateral resistance, and $\boldsymbol{P_j \equiv [\sum_i \left(\frac{t_{ij}}{P_i}\right)^{1-\sigma} \theta_i]^{\frac{1}{1-\sigma}}}$, representing the inward multilateral resistance.

If I log-linearize the system, I get the prototype of the regression model as below,

$$\boldsymbol{lnx_{ij} = lny_i + lny_j - ln\ lny^W + (1-\sigma)lnt_{ij} - (1-\sigma)lnP_j - (1-\sigma)lnP_i + \varepsilon_{ij,t}} \quad [1]$$

I decompose equation 1 into three main components: national income, trade costs, and multilateral resistance. While iterative custom nonlinear least squares programming is used to account for the multilateral resistances (23), other works suggest that applying directional fixed effects can also solve the problem with more efficiency (34). Therefore, the basic OLS model without considering multilateral resistance terms can be written as,

where $\boldsymbol{DIST}$ stands for distance, $\boldsymbol{CNTG}$ for continuity of borders, $\boldsymbol{LANG}$ for language, and $\boldsymbol{Y}$ for national output. Accordingly, the OLS model controlling for multilateral resistance terms is,

$$\boldsymbol{lnX_{ij} = \beta_0 + \beta_1\ ln\ ln\ DIST_{ij} + \beta_2 CNTG_{ij} + \beta_3 LANG_{ij} + \cdots + \beta_4 lnY_i + \beta_5 lnY_j + \varepsilon_{ij,t}} \quad [2]$$

$$\boldsymbol{lnX_{ij} = \beta_1\ ln\ ln\ DIST_{ij} + \beta_2 CNTG_{ij} + \beta_3 LANG_{ij} + \cdots + \beta_4 lnY_i + \beta_5 lnY_j + \pi_i + \rho_j + \varepsilon_{ij,t}} \quad [3]$$

where π_i denotes the exporter-time fixed effects that will account for the outward multilateral resistances, and ρ_j denotes the importer-time fixed effects that will account for the inward multilateral resistances.

In addition, there are potentially significant biases due to heteroskedasticity and zero values of the dependent variable (25). The authors attribute the biases to the neglect of the impact of Jansen's inequality, $\boldsymbol{E(lny) \neq lnE(y)}$, and suggest that the PPML model can solve both problems (18). Therefore, I employ the PPML model with fixed effects to avoid the potential bias. The corresponding basic model is in the form of the following equation,

$$\boldsymbol{X_{ij,t} = exp\ [\beta_1\ ln\ ln\ DIST_{ij} + \beta_2 CNTG_{ij} + \beta_3 LANG_{ij} + \pi_{i,t}, + \rho_{i,t} + \cdots] \times \varepsilon_{ij,t}} \quad [4]$$

For both the OLS and PPML models, I further modify them in the empirical models and estimation methods section to fit the context of bilateral trade, ethnicity, and COVID-19.

Ethnic Dissimilarity Index

The degree to which two ethnic groups are unequally dispersed across geographic regions is measured statistically by the ethnic dissimilarity index. It shows what proportion of one group would need to move in order to have an equitable distribution that mirrors the distribution of the other group. Greater segregation and unevenness are suggested by a higher score, whilst more even distribution is indicated by a lower index. The dissimilarity index falls between 0 and 1. When there is no dissimilarity, as indicated by a score of 0, both groups are dispersed equally throughout the regions. Complete segregation, in which one group is fully concentrated in one region and the other group is fully concentrated in another, is indicated by a score of 1. The index is computed by adding up the absolute variations in each group's percentage in each area, and then dividing the total by two. The dissimilarity index value is larger, for instance, if the population of a group in a certain location is disproportionately higher or lower than the total population. When examining residential segregation, the dissimilarity index is frequently employed to gauge how concentrated various racial or ethnic groups are in various locations. It can also be used to evaluate segregation in healthcare systems or comprehend the unequal distribution of various demographic traits, among other situations. The study of multi-group segregation is made possible by the index's ability to be generalized to more than two groups simultaneously.

Data Description and Analysis

I used eight datasets in the study. The first dataset is the data series for the dependent variable, bilateral imports, from the Direction of Trade Statistics (DoTS) developed by the IMF (35). It records bilateral merchandise trade in USD between IMF trading entities. Since COVID-19

started mainly after January 2020 globally, I apply export data from February 2020 to August 2020 (36). I include data from the IMF for 50 large exporters (Table A2 in the Appendix) and 50 destination countries (Table A3 in the Appendix). The datasets for each country's GDP and population are also gathered from IMF. The dataset for the currency of each country comes from Iban country currency codes (37). Free Trade Agreement (FTA) information comes from (19), FTA in force, and I only include FTA activated before 2020 (38). The dataset for whether the country is landlocked, area information, whether two countries share a common official language, the weighted distance between the two countries, and whether the two countries are contiguous are provided by Centre d'Études Prospectives et d'Informations Internationales (CEPII) Database (39), with its variables explained in past research (40).

The DELF database is found in DELF country pair data, and I apply the DELF for religion and the DELF for ethnicity (33). The DELF between Taiwan and the Chinese mainland and between Hong Kong and the Chinese mainland are unavailable, so I assume their religious and ethnic composites are the same as the Chinese mainland.

The index is derived from "a mutual similarity matrix", with its elements denoted by $\boldsymbol{s_{ab}}$ which signifies the similarity value between two individuals $\boldsymbol{i}$ and $\boldsymbol{j}$ for $\boldsymbol{a, b} \in \{\boldsymbol{1}, \dots, \boldsymbol{N}\}$ within a society with $\boldsymbol{N}$ individuals (33). Therefore $\boldsymbol{s_{ab}}$ satisfies the following conditions and characteristics.

$\boldsymbol{1 \geq s_{ab} \geq 0}$

$\boldsymbol{s_{ab} = 0, when\ a \neq b}$

$\boldsymbol{s_{ab} = 1, when\ a = b}$

Here, a similarity value of one indicates perfect similarity, whereas that of zero indicates complete dissimilarity. Since it is almost impossible to collect individual statistics in this regard, the population is divided into $\boldsymbol{K}$ different groups, and the similarity value is calculated between groups (33). The authors denote the population within each group as $\boldsymbol{m_k}$ for all $\boldsymbol{k} \in \{\boldsymbol{1}, \dots, \boldsymbol{K}\}$ and thus relative group size as $\boldsymbol{g_k = \frac{m_k}{N_k}}$. DELF is derived as below accordingly.

$$\boldsymbol{DELF = 1 - \frac{1}{N_k N_l} \sum_{k=1}^{K} \sum_{l=1}^{L} m_k m_l s_{kl} = 1 - \sum_{k=1}^{K} \sum_{l=1}^{L} \frac{m_k}{N_k} \frac{m_l}{N_l} s_{kl} = 1 - \sum_{k=1}^{K} \sum_{l=1}^{L} g_k g_l s_{kl}}$$

The remaining problem is the measure to calculate $\boldsymbol{s_{kl}}$, the similarity value between the two groups *k* and *l*. The ethnic-racial distance is derived by using fragmentation based on genealogical relatedness (33). The author employs an ethnic-racial taxonomy (41), where each group is "assigned a six-character code based on differences in race, skin pigmentation, and ethnic origin." Due to data unavailability, apart from the method (41) used to derive ethnic-racial distance, it develops the index for religion from "a pure categorical assessment" (33).

The dataset for COVID-19 cases for each country is gathered from the Global Map of Johns Hopkins Coronavirus Resource Center in 2020 (42), and I use monthly active cases. According to Johns Hopkins CRC, active cases = total cases - total recovered - total deaths. I use the case number collected on the last day of each month. The data for Taiwan and Hong Kong is collected from past research (43). The descriptive statistics are as provided in Table 1.

Table 1: Descriptive Statistics

Variable	Observation	Mean	Standard Deviation	Min	Max
Export	17444	4.756e+08	1.828e+09	0	4.485e+10
GDP of exporting countries	17500	29158.521	21713.44	1876.525	81867.462
GDP of importing countries	17500	27916.163	21942.441	1876.525	81867.462
Population of exporting countries	17500	109.818	271.094	2.802	1404.331
Population of importing countries	17500	111.717	270.248	5.009	1404.331

Landlocked	17500	.22	.442	0	1
Island	17500	.32	.518	0	1
Area of exporting countries	17500	1753264.9	3450791.8	646	17075400
Area of importing countries	17500	1684970.5	3446605.6	646	17075400
Distance	17500	6746.251	4481.356	9.56	19369.966
Currency	17500	.066	.249	0	1
FTA	17500	.39	.488	0	1
Language	17500	.08	.271	0	1
Continuity of Border	17500	.042	.201	0	1
DELF_religion	17500	.562	.43	.001	1
DELF_ethno	17500	.788	.288	.009	1
COVID cases in exporting countries	17500	61270.829	289063.52	0	3656478
COVID cases in importing countries	17500	62089.311	289103.21	0	3656478

According to Table 1, I have 18 variables, among which twelve are continuous variables (Export, Area Exporter, GDP Exporter, Area Importer, GDP Importer, Distance, Population Exporter, Population Importer, DELF_religion, DELF_ethno, COVID Exporter, and COVID Importer), and the others are dummy variables (Landlocked, Island, Currency, FTA, Language, and Continuity of border). The mean, standard deviation, minimum value and maximum value of each of the variables are given in Table 1. DELF_ethno, which means complete homogeneity when the value is 0 and complete heterogeneity when the value is 1, has a mean of 0.788 and a standard deviation of 0.288, suggesting a relatively small ethnic similarity among the countries but a large range of countries with different degrees of ethnic similarity selected.

Empirical Models and Estimation Methods

For estimating the effect of the ethnic distance between two countries on bilateral trade in response to COVID-19 cases, I use the interaction term made of the ethnic composite of DELF and the COVID-19 cases in each country within the country pair as the variable of interest, allowing for other determinants of trade as the control variables. I propose the model in simple OLS form for clarity and revise it for other analysis methods, including OLS with fixed effects and PPML with and without fixed effects. I choose the covariate variables (44), which are theoretically coherent with the model that I derive in section 2, because they are all potential determinants of national income and trade costs.

$$ln\ \boldsymbol{ln}\left(\boldsymbol{X_{ijt}}\right) = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\ \boldsymbol{ln\ ln}\left(\boldsymbol{Y_{it}}\right) + \boldsymbol{\beta_2}\ \boldsymbol{ln\ ln}\left(\boldsymbol{Y_{jt}}\right) + \boldsymbol{\beta_3}\ \boldsymbol{ln\ ln}\left(\boldsymbol{Pop_{it}}\right) + \boldsymbol{\beta_4}\ \boldsymbol{ln\ ln}\left(\boldsymbol{Pop_{jt}}\right) + \boldsymbol{\beta_5 Landl_{ijt}} + \boldsymbol{\beta_6 Island_{ijt}} + \boldsymbol{\beta_7}\ \boldsymbol{ln\ ln}\left(\boldsymbol{Area_{it}Area_{jt}}\right) + \boldsymbol{\beta_8 Dist_{ij}} + \boldsymbol{\beta_8 CU_{ij}} + \boldsymbol{\beta_9 FTA_{ij}} + \boldsymbol{\beta_{10} Lang_{ij}} + \boldsymbol{\beta_{11} Cont_{ij}} + \boldsymbol{\beta_{12} DELF\_religion_{ij}} + \boldsymbol{\beta_{13} DELF\_ethno_{ij}} + \boldsymbol{\beta_{14}}\ \boldsymbol{ln\ ln}\left(\boldsymbol{COVID_{it}}\right) + \boldsymbol{\beta_{15}}\ \boldsymbol{ln\ ln}\left(\boldsymbol{COVID_{jt}}\right) + \boldsymbol{\alpha_1}\left(\boldsymbol{DELF\_ethno_{ijt}ln}\left(\boldsymbol{COVID_{it}}\right)\right) + \boldsymbol{\alpha_2}\left(\boldsymbol{DELF\_ethno_{ijt}ln}\left(\boldsymbol{COVID_{jt}}\right)\right) + \boldsymbol{\varepsilon_{ijt}}$$

[5]

where $\boldsymbol{i}$ means the exporter, $\boldsymbol{j}$ refers to the importer, t refers to time subscript and the variables are defined as: $\boldsymbol{X_{ij}}$ denotes monthly real exports from $\boldsymbol{i}$ to $\boldsymbol{j}$ in dollars, $\boldsymbol{Y}$ is real GDP per capita in dollars for the trading countries, $\boldsymbol{Pop}$ is the population for the trading countries, $\boldsymbol{Landl_{ij}}$ denotes the country is landlocked in the country-pair (0,1), $\boldsymbol{Island_{ij}}$ shows whether the country is an island nation in the pair (0,1), $\boldsymbol{Area}$ is the area of each trading partner in square kilometers, $\boldsymbol{Dist_{ij}}$ represents the distance between country $\boldsymbol{i}$ and $\boldsymbol{j}$, calculated from respective longitude and latitude, $\boldsymbol{CU_{ij}}$ is a dummy variable which is unity if $\boldsymbol{i}$ and $\boldsymbol{j}$ use the same currency, $\boldsymbol{FTA_{ij}}$ is a dummy variable which is unity if $\boldsymbol{i}$ and $\boldsymbol{j}$ both belong to the same regional trade agreement, $\boldsymbol{Lang_{ij}}$ is a dummy variable which equals one if $\boldsymbol{i}$ and $\boldsymbol{j}$ have a common official language, $\boldsymbol{Cont_{ij}}$ is a dummy

variable which equals one if i and j share the common border, $DELF\_religion_{ij}$ means the religion composite DELF between country i and j, $DELF\_ethno_{ij}$ means the ethnic composite DELF between country i and j, COVID encompasses the number of active COVID-19 cases for the trading countries, β is a vector of nuisance coefficients, and ε_{ij} represents the omitted other influences on exports. The coefficients of interest are α's in the model, and α_1 and α_2 denote the interaction effect of an additional percentage of COVID-19 cases of country i and country j respectively and the ethnic composite of DELF on exports.

Results

The regression results are provided in Table 2. Column [1] shows the OLS regression results without fixed effects; column [2] represents the OLS regression results with fixed effects controlling for multilateral resistance; column [3] reflects the PPML regression results without fixed effects; column [4] displays the PPML regression results with fixed effects controlling for multilateral resistance. The results in Table 2 with and without fixed effects are extremely different. Given the essentiality of fixed effects in our panel data and their function to control for multilateral resistance, I believe that the results with fixed effects are more reasonable theoretically. From an empirical perspective, the estimates in the models with fixed effects in Table 2 indicate that the gravity model, in general, fits the context well as the directions and sizes of most of the coefficients are consistent with the empirical results in the existing literature using the gravity models (2, 25, 33, 44).

Table 2: Regression Results Using OLS Without Fixed Effects, OLS with Fixed Effects, and PPML with Fixed Effects (FE) and PPML Without Fixed Effects During COVID-19

	[1]	[2]	[3]	[4]
VARIABLES	**OLS without FE**	**OLS with FE**	**PPML without FE**	**PPML with FE**
Landlocked	-0.0222	-3.395***	-0.00277	-0.0780***
	(0.0390)	(0.341)	(0.00236)	(0.0263)
Island	-0.333***	0.408**	-0.0167***	0.255***
	(0.0336)	(0.162)	(0.00171)	(0.0326)
lnArea_EI	-0.243***	0.0538***	-0.0134***	0.0177***
	(0.00841)	(0.0203)	(0.000503)	(0.00241)
lnDistance	-0.593***	-1.191***	-0.0338***	-0.0640***
	(0.0267)	(0.0629)	(0.00147)	(0.00357)
Currency	-0.00622	-0.0789	-0.00462*	-0.00702
	(0.0748)	(0.121)	(0.00243)	(0.00707)
FTA	0.470***	0.266**	0.0278***	0.0171***
	(0.0350)	(0.105)	(0.00191)	(0.00604)
Language	0.302***	0.265**	0.0160***	0.0141*
	(0.0575)	(0.129)	(0.00320)	(0.00730)
Continuous	0.899***	0.472***	0.0380***	0.0178**
	(0.0862)	(0.160)	(0.00393)	(0.00909)
DELF_religion	-0.450***	-0.750***	-0.0266***	-0.0477***
	(0.0488)	(0.162)	(0.00286)	(0.00995)
DELF_ethno	-1.534***	0.836***	-0.0805***	0.0503***
	(0.222)	(0.312)	(0.0109)	(0.0182)
lnCOVID_Exporter	-0.137***	0.304***	-0.00726***	0.0446***
	(0.0201)	(0.0346)	(0.000752)	(0.00439)
lnCOVID_Importer	0.00511	-0.0922***	0.000141	0.00703***
	(0.0194)	(0.0325)	(0.000750)	(0.00265)
Interaction_Exporter	0.0731***	-0.0577**	0.00383***	-0.00376**
	(0.0229)	(0.0275)	(0.000956)	(0.00157)
Interaction_Importer	0.0101	0.0149	0.000782	0.00166
	(0.0221)	(0.0345)	(0.000964)	(0.00195)

lnGDP_Exporter	1.292***		0.0702***	
	(0.0208)		(0.00142)	
lnGDP_Importer	1.017***		0.0553***	
	(0.0195)		(0.00105)	
lnPop_Exporter	1.478***		0.0803***	
	(0.0176)		(0.00117)	
lnPop_Importer	1.274***		0.0694***	
	(0.0183)		(0.00102)	
Constant	-1.473***	26.72***	1.841***	2.312***
	(0.425)	(0.956)	(0.0253)	(0.151)
Observations	13,575	13,575	13,575	13,575
R-squared	0.560	0.776	0.541	0.751

Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Column [4] shows that the coefficient of $\boldsymbol{Interaction\_Exporter}$ ($= \boldsymbol{DELF\_ethno} \times \boldsymbol{COVID\_Exporter}$), -0.00376, shows that a ten-percent increase in the number of COVID-19 cases in the exporter causes 0.0376-percent more decline in export volume when the ethnic composites of the two countries are completely heterogeneous than when the ethnic composites of the two countries are completely homogeneous, controlling for all the other variables. The coefficient of the $\boldsymbol{ln(Dist)}$, -0.0640, considering other variables remained the same, one-percent increase in the physical distance between the trade partners is associated with a decrease of 0.064 percent in export. The coefficient of $\boldsymbol{landl}$, -0.0780, indicates that landlocked countries tend to have 0.078 percent fewer exports than countries along the coastlines, ceteris paribus. The coefficient of $\boldsymbol{FTA}$, 0.0171, represents those countries in the same free trade agreement, given all other conditions are the same, are more likely to have 0.0171 percent more in exports. The coefficient of $\boldsymbol{DELF\_ethno}$, 0.00503, shows that a 0.1-unit increase in $\boldsymbol{DELF\_ethno}$ is associated with a 0.00503-percent increase in export volume, ceteris paribus. The robustness results are given in the Table A4, Table A5, and Table A6 in the Appendix.

Discussion

The rise in the number of COVID-19 cases in the exporter causes a decline in export volume when the ethnic composites of the two countries are entirely diverse, compared to when the ethnic composites of the two countries are entirely similar, keeping all other variables constant. There is an inverse relationship between physical distance among the trade partners and the export volume, which suggests that more geographically distant countries tend to trade less than geographically closer countries. This result is supported by past studies (2, 25, 33, 44). Landlocked countries tend to have fewer exports than countries along the coastlines due to more transportation costs, lengthier transit times, and the need to depend on bordering countries for access to international trade routes, which is similar to the results found in past researches (33, 44). Countries involved in an identical free trade agreement are more likely to have more exports (25, 33, 44).

Governments can lessen trade frictions based on ethnicity during emergencies by emphasizing measures that promote equity, transparency, and inclusivity. Along with addressing historical injustices, they can guarantee fair access to resources and encourage fair trading practices. No matter the ethnic composition of the participating countries, the government can negotiate trade agreements that give priority to fair and equitable terms for all of them. It can also guarantee that all ethnic groups have equal access to domestic and international markets and trade opportunities. It is also possible to provide transparent and easily accessible information about trade policies and regulations, which will ensure that all stakeholders, including various ethnic groups, are aware of the rules of the game. Furthermore, resources can be distributed fairly, guaranteeing that all ethnic groups have access to the infrastructure, technology, and financial support required to engage in trade. Concerns can also be addressed, and agreement on trade policy can be reached by open communication and engagement with other ethnic groups. Governments might also set up procedures for gathering opinions from

various ethnic groups regarding the effects of trade policies, and then utilize this data to hone and enhance those policies. The following are other measures that governments can take: putting in place affirmative action programs that give historically underprivileged ethnic groups tailored assistance to help them get over obstacles to trade and economic involvement; tackling historical discrimination and inequality with focused interventions, like financial aid, job training, or access to education and skill-building programs; encouraging social inclusion and integration of various ethnic groups, which creates a feeling of community and encourages cooperation and collaboration in trade and economic activities; encouraging supply chain diversification to lessen dependence on particular areas or ethnic groups, which increases the system's resilience to shocks; putting money into dependable infrastructure and logistics to guarantee safe and effective trade flows, irrespective of ethnic origin; enacting regulatory flexibility to adjust to shifting conditions and ease trade in times of crisis while maintaining fairness and transparency; bolstering international organizations and multilateral cooperation to handle global crises and guarantee inclusive and equitable trade policies; offering technical assistance to developing nations to help them develop their capacity and engage in international trade; and striving to create global standards for trade and economic cooperation that support just and equitable outcomes for all. By putting these measures into practice, countries may build a more robust and inclusive trade system that helps all ethnic groups during times of international emergency.

Conclusion

This paper explores that there is a statistically significant indication of the negative effects of COVID-19 cases on trade in the exporting country in the presence of larger ethnic dissimilarity between the trading partners. I find that a ten-percent increase in the number of COVID-19 cases in the exporting country is associated with a 0.0376-percent more decline in export volume when the ethnic composites of the two countries are completely heterogeneous than when the ethnic composites of the two countries are completely homogeneous, ceteris paribus. If so, governments ought to consider strategies to promote commerce, lower transaction costs, and lower trade barriers between nations with greater ethnic distances. The analyses of this study can be helpful for policy making, especially during the post-pandemic period.

Along with the strength of this paper, simultaneously, there are scopes for researchers to improve and to further relevant ideas in the future. For instance, the variance of the estimates could get smaller if I consider a larger sample; due to limited data availability, I have only used the data for bilateral trade for seven months while consecutive periods do not allow for adjustment in trade flows (24); researchers could also attempt to examine whether the effect that I discuss in this paper is caused by an inevitable increase in transaction cost or by ineffective nationalist policies; in addition, the reasons behind the significantly positive effect of the ethnic distance number of COVID-19 cases in both the importers and the exporters can be interesting to look into. Moreover, future studies might employ instrumental variables, a difference-in-differences (DiD) framework, or another potent causal method. In addition, the DELF index could be replaced with stringency indices or indices such as the Oxford COVID-19 Government Response Tracker to account for heterogeneity.

Abbreviations

CEPII: Centre d'Études Prospectives et d'Informations Internationales, CES: Constant Elasticity of Substitution, DELF: Distance-adjusted Ethnolinguistic Fractionalization, DoTS: Direction of Trade Statistics, ESC: Eurovision Song Contest, FTA: Free Trade Agreement, IMF: International Monetary Fund, LDC: Least Developed Countries, MAGA: Make America Great Again, PPML: Poisson Pseudo-Maximum Likelihood, UNCTAD: United Nations Conference on Trade and Development.

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Author Contributions

Nazmul Islam: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Supervision, Writing – original draft, review and editing.

Conflict of Interest

The authors have no conflicts of interest.

Ethics Approval

Not Applicable.

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Appendix

Table A1: Similarity Classification Based on Ethnic-Racial Groups (25)

E-L-Code	Description	Similarity level	Number of distinct groups	s_{kl}^{E}
A	Race	1	5	.01
AU	Geographical race	2	13	.21
AUG	Major culture area	3	18	.59
AUG-03	Local race	4	72	.88
AUG-03-b	Ethno-racial family	5	393	1.0

Table A2: List of Exporters

China	Russian Federation	Brazil	Romania
United States	Singapore	Czech Republic	Finland
Germany	Spain	Turkey	Qatar
Netherlands	Chinese Taipei	Austria	Philippines
Japan	India	Ireland	Chile
France	Switzerland	Indonesia	Portugal
Korea, Republic of	United Arab Emirates	Sweden	Argentina
Hong Kong, China	Australia	Hungary	Kuwait, the State of
Italy	Saudi Arabia, Kingdom of	Denmark	Nigeria
United Kingdom	Viet Nam	Norway	Israel
Mexico	Poland	South Africa	Kazakhstan
Canada	Thailand	Slovak Republic	
Belgium	Malaysia	Iraq	

Table A3: List of Importers

United States	Belgium	Austria	Portugal
China	Spain	Brazil	Norway
Germany	Singapore	Czech Republic	Israel
Japan	Chinese Taipei	Indonesia	Finland
United Kingdom	Switzerland	Sweden	Egypt
France	Poland	Saudi Arabia, Kingdom of	Chile
Netherlands	United Arab Emirates	Hungary	Greece
Hongkong, China	Russian Federation	Philippines	Ukraine
Korea, Republic of	Viet Nam	South Africa	Bangladesh
India	Thailand	Ireland	Iraq
Italy	Australia	Denmark	Colombia
Mexico	Turkey	Romania	
Canada	Malaysia	Slovak Republic	

Table A4: Robustness Test Results Using PPML with Fixed Effects

VARIABLES	(1) lnExport	(2) lnExport	(3) lnExport	(4) lnExport	(5) lnExport
DELF_ethno	0.0503***	0.0503***	0.0503***	0.0503***	-0.0750***
	(0.0182)	(0.0182)	(0.0182)	(0.0182)	(0.0190)
lnCOVID_Exporter	0.0446***	0.0323***	0.0289***	0.0231***	0.00176
	(0.00439)	(0.00274)	(0.00379)	(0.00265)	(0.00333)
lnCOVID_Importer	0.00703***	0.00921***	-0.00448**	-8.14e-05	-0.0100***
	(0.00265)	(0.00282)	(0.00207)	(0.00206)	(0.00229)
Interaction_Exporter	-0.00376**	-0.00376**	-0.00376**	-0.00376**	-0.000988
	(0.00157)	(0.00157)	(0.00157)	(0.00157)	(0.00183)
Interaction_Importer	0.00166	0.00166	0.00166	0.00166	0.00409*
	(0.00195)	(0.00195)	(0.00195)	(0.00195)	(0.00212)
Landlocked	-0.0780***		-0.119***	0.120***	0.0562*
	(0.0263)		(0.0187)	(0.0328)	(0.0302)
Island	0.255***	0.256***		0.227***	0.194***
	(0.0326)	(0.0328)		(0.0302)	(0.0311)
lnArea_EI	0.0177***	0.0139***	-0.00270*		0.000825
	(0.00241)	(0.00199)	(0.00140)		(0.00150)
lnDistance	-0.0640***	-0.0640***	-0.0640***	-0.0640***	
	(0.00357)	(0.00357)	(0.00357)	(0.00357)	
Currency	-0.00702	-0.00702	-0.00702	-0.00702	0.0168**
	(0.00707)	(0.00707)	(0.00707)	(0.00707)	(0.00730)
FTA	0.0171***	0.0171***	0.0171***	0.0171***	0.0403***
	(0.00604)	(0.00604)	(0.00604)	(0.00604)	(0.00596)
Language	0.0141*	0.0141*	0.0141*	0.0141*	0.0232***
	(0.00730)	(0.00730)	(0.00730)	(0.00730)	(0.00770)
Continuous	0.0178**	0.0178**	0.0178**	0.0178**	0.0754***
	(0.00909)	(0.00909)	(0.00909)	(0.00909)	(0.00975)
DELF_religion	-0.0477***	-0.0477***	-0.0477***	-0.0477***	-0.0637***
	(0.00995)	(0.00995)	(0.00995)	(0.00995)	(0.0103)
Constant	2.312***	2.456***	3.347***	2.819***	2.688***
	(0.151)	(0.131)	(0.0550)	(0.0715)	(0.0611)
Observations	13,575	13,575	13,575	13,575	13,575
R-squared	0.751	0.751	0.751	0.751	0.719

Table A4: Robustness Test Results Using PPML with Fixed Effects. (Continued)

VARIABLES	(6) lnExport	(7) lnExport	(8) lnExport	(9) lnExport	(10) lnExport
DELF_ethno	0.0491***	0.0531***	0.0473***	0.0559***	0.0285*
	(0.0182)	(0.0183)	(0.0182)	(0.0184)	(0.0170)
lnCOVID_Exporter	0.00156	0.0267***	0.0209***	0.0335***	0.0371***
	(0.00323)	(0.00386)	(0.00326)	(0.00508)	(0.00300)
lnCOVID_Importer	-0.00466**	-0.00318	-0.00150	0.00266	-0.00247
	(0.00214)	(0.00208)	(0.00222)	(0.00231)	(0.00190)
Interaction_Exporter	-0.00366**	-0.00392**	-0.00367**	-0.00391**	-0.00374**

	(0.00157)	(0.00159)	(0.00157)	(0.00157)	(0.00153)
Interaction_Importer	0.00173	0.00135	0.00186	0.00137	0.00179
	(0.00195)	(0.00195)	(0.00194)	(0.00197)	(0.00189)
Landlocked	0.0478	-0.128***	-0.187***	-0.0190	0.0436
	(0.0293)	(0.0206)	(0.0221)	(0.0319)	(0.0315)
Island	0.223***	0.0157	0.0271**	0.329***	0.233***
	(0.0305)	(0.00986)	(0.0105)	(0.0362)	(0.0336)
lnArea_EI	-0.00321**	-0.00249	-0.00435**	0.0383***	0.0198***
	(0.00143)	(0.00155)	(0.00179)	(0.00381)	(0.00193)
lnDistance	-0.0635***	-0.0673***	-0.0646***	-0.0669***	-0.0668***
	(0.00349)	(0.00323)	(0.00359)	(0.00335)	(0.00348)
Currency		-0.00489	-0.00719	-0.00704	-0.00602
		(0.00708)	(0.00706)	(0.00702)	(0.00718)
FTA	0.0168***		0.0169***	0.0167***	0.0185***
	(0.00604)		(0.00606)	(0.00604)	(0.00607)
Language	0.0142*	0.0137*		0.0171**	0.0159**
	(0.00731)	(0.00733)		(0.00709)	(0.00733)
Continuous	0.0178*	0.0166*	0.0219**		0.0188**
	(0.00912)	(0.00893)	(0.00881)		(0.00929)
DELF_religion	-0.0476***	-0.0489***	-0.0484***	-0.0480***	
	(0.00995)	(0.00999)	(0.00992)	(0.0100)	
Constant	3.167***	3.382***	3.404***	1.835***	2.475***
	(0.0665)	(0.0621)	(0.0634)	(0.166)	(0.112)
Observations	13,575	13,575	13,575	13,575	13,575
R-squared	0.750	0.749	0.750	0.750	0.748

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Robustness Test Results Using PPML with Fixed Effects. (Continued)

	(11)	(12)	(13)	(14)	(15)
VARIABLES	**lnExport**	**lnExport**	**lnExport**	**lnExport**	**lnExport**
DELF_ethno	-0.149***	-0.149***	-0.149***	-0.149***	0.0325*
	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0169)
lnCOVID_Exporter	0.0157***	0.0223***	-0.00641*	0.0289***	0.0285***
	(0.00434)	(0.00384)	(0.00341)	(0.00222)	(0.00210)
lnCOVID_Importer	-0.00104	-0.00104	0.00310	-0.00569***	-0.0109***
	(0.00212)	(0.00212)	(0.00195)	(0.00189)	(0.00186)
Interaction_Exporter	-0.000991	-0.000991	-0.000991	-0.000991	-0.00392**
	(0.00189)	(0.00189)	(0.00189)	(0.00189)	(0.00157)
Interaction_Importer	0.00315	0.00315	0.00315	0.00315	0.00141
	(0.00208)	(0.00208)	(0.00208)	(0.00208)	(0.00188)
Landlocked		-0.0453*	0.0579**	0.134***	0.122***
		(0.0241)	(0.0286)	(0.0356)	(0.0340)
Island			0.236***	0.187***	0.199***
			(0.0329)	(0.0266)	(0.0261)
lnArea_EI				0.0340***	0.0450***
				(0.00428)	(0.00415)
lnDistance					-0.0747***
					(0.00287)

Currency					
FTA					
Language					
Continuous					
DELF_religion					
Constant	2.784***	2.784***	2.696***	1.625***	1.900***
	(0.0576)	(0.0576)	(0.0473)	(0.169)	(0.166)
Observations	13,575	13,575	13,575	13,575	13,575
R-squared	0.687	0.687	0.687	0.687	0.746

Table A4: Robustness Test Results Using PPML with Fixed Effects. (Continued)

	(16)	(17)	(18)	(19)
VARIABLES	**lnExport**	**lnExport**	**lnExport**	**lnExport**
DELF_ethno	0.0332*	0.0312*	0.0342**	0.0285*
	(0.0170)	(0.0170)	(0.0171)	(0.0170)
lnCOVID_Exporter	0.0224***	0.0234***	0.0187***	0.0371***
	(0.00180)	(0.00185)	(0.00266)	(0.00300)
lnCOVID_Importer	-0.0104***	-0.00988***	0.00791***	-0.00247
	(0.00186)	(0.00187)	(0.00216)	(0.00190)
Interaction_Exporter	-0.00398**	-0.00382**	-0.00390**	-0.00374**
	(0.00157)	(0.00155)	(0.00154)	(0.00153)
Interaction_Importer	0.00137	0.00167	0.00149	0.00179
	(0.00189)	(0.00189)	(0.00191)	(0.00189)
Landlocked	0.118***	0.126***	-0.147***	0.0436
	(0.0337)	(0.0340)	(0.0146)	(0.0315)
Island	0.203***	0.211***	-0.0428***	0.233***
	(0.0264)	(0.0266)	(0.0113)	(0.0336)
lnArea_EI	0.0447***	0.0448***	-0.00309	0.0198***
	(0.00412)	(0.00413)	(0.00213)	(0.00193)
lnDistance	-0.0750***	-0.0717***	-0.0698***	-0.0668***
	(0.00298)	(0.00335)	(0.00335)	(0.00348)
Currency	-0.00395	-0.00621	-0.00601	-0.00602
	(0.00709)	(0.00707)	(0.00711)	(0.00718)
FTA		0.0177***	0.0181***	0.0185***
		(0.00611)	(0.00608)	(0.00607)
Language			0.0191***	0.0159**
			(0.00714)	(0.00733)
Continuous				0.0188**
				(0.00929)
DELF_religion				
Constant	1.969***	1.913***	3.443***	2.475***
	(0.160)	(0.162)	(0.0426)	(0.112)
Observations	13,575	13,575	13,575	13,575

R-squared	0.746	0.747	0.748	0.748

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A5: Regression Results of PPML Regressions of All Countries and Major Continents

VARIABLES	(1) All Countries	(2) Europe	(3) Asia	(4) Americas	(5) Africa
lnDistance	-0.764***	-0.912***	-0.426***	-1.279***	-0.660***
	(0.0108)	(0.0202)	(0.0161)	(0.0375)	(0.0653)
Currency Union (CU)	0.545***	2.009***	-0.434***	0.495***	0.528***
	(0.0476)	(0.113)	(0.0957)	(0.0685)	(0.0641)
FTA	0.113***	0.509***	0.0871**	-1.180***	0.493***
	(0.0332)	(0.0669)	(0.0389)	(0.109)	(0.127)
Contiguous	0.441***	0.230***	0.329***	0.331***	0.696***
	(0.0224)	(0.0230)	(0.0331)	(0.0515)	(0.0763)
DELF	-0.114	-0.755***	-1.299***	0.583**	-1.437***
	(0.106)	(0.276)	(0.240)	(0.270)	(0.425)
lnCOVID Export	-0.0294***	0.0799***	-0.152***	0.000666	0.147***
	(0.0103)	(0.0223)	(0.0176)	(0.0205)	(0.0427)
lnCOVID Import	-0.0275***	-0.0904***	0.0847***	-0.0266	-0.0459
	(0.0100)	(0.0250)	(0.0167)	(0.0210)	(0.0297)
lnCOVID Export#c.DELF	-0.00781	-0.167***	0.137***	0.00733	-0.215***
	(0.0112)	(0.0418)	(0.0205)	(0.0350)	(0.0479)
lnCOVID Import#c.DELF	0.0223**	0.210***	-0.130***	0.0140	0.180***
	(0.0113)	(0.0430)	(0.0180)	(0.0342)	(0.0484)
Constant	17.11***	19.31***	16.42***	27.68***	19.25***
	(0.264)	(0.285)	(0.349)	(0.360)	(0.634)
Observations	174,678	12,795	15,280	9,075	13,117

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A6: Empirical Results of Generalized Linear Model (GLM) (with a Gamma-Distributed Dependent Variable) Regressions of All Countries and Major Continents

VARIABLES	(1) All Countries	(2) Europe	(3) Asia	(4) Americas	(5) Africa
lnDistance	-1.164***	-1.742***	-1.009***	-1.367***	-1.423***
	(0.0103)	(0.0296)	(0.0286)	(0.0393)	(0.0574)
Currency Union (CU)	0.723***	-0.327**	-0.463***	0.892***	0.647***
	(0.0378)	(0.128)	(0.0991)	(0.0766)	(0.0622)
FTA	0.218***	0.258***	0.858***	-0.0835	0.669***
	(0.0196)	(0.0675)	(0.0429)	(0.213)	(0.106)
Contiguous	0.828***	0.137***	0.910***	0.180***	1.171***
	(0.0334)	(0.0406)	(0.0536)	(0.0655)	(0.0755)
DELF	-1.597***	-1.196***	-0.571**	-5.120***	-0.549
	(0.106)	(0.360)	(0.230)	(0.348)	(0.340)
lnCOVID Export	0.0215**	0.00166	-0.0468*	0.104***	0.167***
	(0.0103)	(0.0238)	(0.0242)	(0.0334)	(0.0386)
lnCOVID Import	-0.0963***	-0.0239	0.0131	-0.218***	-0.133***

	(0.0106)	(0.0252)	(0.0240)	(0.0325)	(0.0448)
lnCOVID Export#DELF	-0.0317***	-0.0163	0.0161	-0.245***	-0.212***
	(0.0101)	(0.0381)	(0.0262)	(0.0438)	(0.0401)
lnCOVID Import#DELF	0.112***	0.0650*	-0.0183	0.437***	0.211***
	(0.00997)	(0.0359)	(0.0241)	(0.0455)	(0.0445)
Constant	21.31***	24.69***	19.81***	30.50***	22.68***
	(0.191)	(0.314)	(0.309)	(0.511)	(0.504)
Observations	174,678	12,795	15,280	9,075	13,117

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1