The Geography of Gravity*

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Abstract

Although geography has been considered an important factor in international trade spatial heterogeneity has not been fully investigated in the regression of standard gravity models. This paper contributes to the literature by investigating how gravity works geographically in bilateral trades. First, geographically weighted regression of the gravity model reveals spatial variations of estimated parameters. Second, the regional or continental dummies in the standard gravity model appear to not fully capture these geographical characteristics. Third, the location used in the regression, whether exporter's or importer's, remarkably influences the coefficient values of exporter's and importer's variables such as GDP.

Keywords: Gravity model; geographically weighted regression; spatial heterogeneity
JEL classification: F10; F14

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1 Introduction

Pioneered by Tinbergen (1962), the gravity equation in bilateral trade flows has been empirically used in the international trade literature. Its basic idea is as follows: (i) bilateral trade increases proportionately with the economic size of the destination and the origin economies and (ii) more distant countries suffer from more transport costs. Existing literature generally finds that average GDP and distance elasticities are close to positive unity and negative unity, respectively under ordinary least squares (OLS)-based regression.[1] In this paper, we investigate the role of geography by extending the standard gravity model.

International trade may vary geographically. First, the economic size of a certain country increases its exports to or imports from a certain partner country. However, the spatial proliferation resulting from the economic size has not been investigated in the literature. For example, one may wonder to which extent the gravity of the US GDP geographically reaches. Second, while trade decreases with increasing physical distance, the impact of bilateral distance may not be homogenous among country pairs, depending on the geography. For instance, natural environments such as mountains, deserts, and rivers and many geographical factors could be obstacles to incur trade costs. Similarly, land or ice barriers could result in indirect routes for countries adjacent to the sea. However, it would be difficult to introduce all such geographical factors in one gravity model.

To capture the spatial aspect of the gravity, regional or continent dummy has been used in the literature. Frankel (1997) includes regional dummies such as Western Europe, East Asia, and APEC in the estimation model. Disdier and Head (2008) introduce a dummy "single continent" to capture land versus ocean differences. Hillberry and Hummels (2008) show that the macro-level home bias in trade flows is largely driven by geographic aggregation. Hillberry and Hummels (2008) find that the aggregate trade–distance relationship in intra-US trade over short distance is driven entirely by the fact that most establishments ship only to geographically proximate customers, rather than shipping to many customers in values that decrease with distance.

In this paper, we investigate the effect of geography on gravity models and empirically assess the role of spatial heterogeneity. Existing OLS-based regression analyses can only produce global parameter estimates rather than local parameter estimates. The geographically weighted regression (GWR) approach has several merits. First, in contrast to the global estimates such as OLS, we can detect how the coefficients for each independent variable are regionally dispersed under GWR regression. In other words, we can estimate each region's own regression. Second, it can substantially reduce spatial error correlation when there is country heterogeneity in the GWR coefficients. Third, GWR does not need geographical variables in the regression including regional dummies such as Africa, America, Asia, and Europe. Fourth, since each regression location has its own constant term, it largely accounts for region-fixed effects. Fifth, we incorporate SST's idea into the gravity equation and estimate the model without log-linearization.

In the benchmark case, we use exporter's latitude and longitude as geographical information to estimate GWR. This is because the empirical literature interprets trade flows

[1]For example, Disdier and Head (2008) and Head and Mayer (2014) perform meta analysis by collecting a large set of estimates in the literature and find that the elasticity of trade with respect to distance is -0.95 since 1990.

from country i to j as exports from country i to j, depending on the theoretically derived gravity equation in the literature including Anderson and Wincoop (2003) and Eaton and Kortum (2002). However, at least in the estimation model, trade flows from country i to j can also be interpreted as imports of country j from i. Furthermore, when exporters and importers are both plural, whether the location of estimation is i or j becomes important. Our prior is that if we interpret trade flows from i to j as exports of country i to other j countries, the characteristics of exporter i may influence the results, and vice versa. Hence, in the benchmark case, we use exporter i's location in the estimation following the interpretation of existing literature and as a robustness check, we also use importer j's location to investigate the effect of locations.

Our main findings are as follows. First, we find that local variations exist originating from the geographical heterogeneity. GWR analysis shows that the distribution of for each variable differs one another. This implies that the global estimates cannot capture local variations. For example, being a landlocked country in Europe (Austria) is different from being a landlocked country in Central Asia (Mongolia) or Sahara (Chad). Second, GWR analysis reveals how the estimated parameters for each exporter's location are locally distributed. We find that the estimates are clustered among selected economic masses. For example, while countries adjacent to the US share similar coefficient values with the US, European countries also obtain their own results. Third, the regional or continental dummy in the standard gravity model may not fully capture the geographical characteristics. In other words, there exist various patterns within a region or a continent.

As a robustness check, we re-estimate the GWR model by using the information of importer's location because the geography may have different meanings to the exporter and importer countries with different locations. We find that the degree of dispersion in the estimated coefficient values depends crucially on at which location we estimate the model. In particular, the variables of exporter's and importer's own variables including GDP, GDP per capita, landlock, and remoteness are considerably influenced by the estimation location.

When we use exporter's location, we have more dispersed coefficient values of exporter's variables than those of importer's variables. In contrast, in the importer location case, we obtain more dispersed coefficient values of importer's variables than those of exporter's variables. This is because the estimation based on the importer's location includes more information of the importer, and hence the estimated results of importer's variables are more dispersed reflecting the idiosyncratic characteristics of importers. On the other hand, the coefficients of exporter's variables are less dispersed reflecting that the estimation based on the importer's location includes less information of the exporters.

Furthermore, Santos Silva and Tenreyro (henceforth, SST, 2006) argue that the logarithmic transformation of the standard gravity model is not relevant to estimate elasticities because the multiplicative trade models with multiplicative errors do not satisfy the assumption of the homoscedasticity of the error term.[2] As an alternative, SST propose the estimation without taking logs by using the Poisson pseudo maximu likelihood (PPML) estimator.

To handle this problem, we perform the geographically weighted Poisson regression (GWPR) modelling technique proposed by Nakaya et al. (2005).[3] We generally sup-

[2]In this case, there is an inconsistency problem of the OLS estimator due to the dependency between the error term of the transformed log-linear model and the regressors.

[3]Nakaya et al. (2005) analyze disease patterns resulting from spatially non-stationary processes.

plement SST's global results. For example, the absolute values of the coefficients on exporter's and importer's GDPs and distance are much smaller in many regions even under our local Poisson regression.

The rest of the paper is organized as follows. Sections 2 and 3 describe the estimation methodology and explain the data, respectively. Section 4 presents the main results under GWR. Section 5 shows the results based on the importer's location. Section 6 presents the results under Anderson and van Wincoop (2003) specification. Section 7 compares the GWR results with those of GWPR. Section 8 concludes.

2 Estimation methodology

In this section, we explain our estimation methodology.

The simplest form of a gravity model for trade is provided by

$$T_{ij} = A_0 Y_i^{\alpha_1} Y_j^{\alpha_2} D_{ij}^{\alpha_3} u_{ij}, \tag{1}$$

where T_{ij}, Y_i, Y_j and D_{ij} denote trade flows from country i to j, GDPs of countries i and j, and the distance between countries i and j, respectively. A_0, α_1, α_2, and α_3 are unknown parameters to be estimated. u_{ij} is an error term.

In logged forms, the equation becomes

$$t_{ij} = \alpha_0 + \alpha_1 y_i + \alpha_2 y_j + \alpha_3 d_{ij} + \eta_{ij}, \tag{2}$$

where $t_{ij} \equiv \ln T_{ij}$, $\alpha_0 \equiv A_0$, $y_i \equiv \ln Y_i$, $y_j \equiv \ln Y_j$, $D_{ij} \equiv \ln D_{ij}$, and $\ln \eta_{ij} \equiv u_{ij}$. This type of an ordinary linear regression (OLR) model estimates α by using the OLS method and the estimator can be written as

$$\hat{\alpha} = (y'y)^{-1} y't. \tag{3}$$

SST advocate the PPML approach because the OLR model can be biased in the presense of heteroskedasiticity. Hence, the model without log-linearization becomes the Poisson regression model as follows

$$T_{ij} = \exp(\alpha_0 + \alpha_1 y_i + \alpha_2 y_j + \alpha_3 d_{ij}) + \varepsilon_{ij}, \tag{4}$$

where $T_{ij} \geq 0$ and $E[\varepsilon_{ij} | y_i, y_j, d_{ij}] = 0$, while η_{ij} in Equation (2) may not be statistically independent of the regressors.

We estimate the GWR and GWPR models by extending the above-mentioned OLR and PPML models. As discussed by Yoo (2012), GWR allows the coefficients of explanatory variables to differ by locality by giving relatively more weight to geographically close observations. OLR assumes that the coefficients of the independent variables are constant within a region, thereby omitting fine-grained spatial information of observations by estimating an average effect. It can be verified that the average value does provide a meaningful summary if there is little variation within the defined space. However, given spatially differentiated economic activities, the global statistic may not accurately reflect local conditions. GWR accounts for spatial heterogeneity in responses to variables by estimating separate regressions for each location. GWR primarily uses geographically close observations to estimates local coefficients. The weight represents the adjacency effects for neighboring locations within a specified distance. Following the assumption that more proximate locations are more alike, the weights decay with distance. In other words, the estimated coefficient of α_1, say, at Britain may differ from that at Japan because the surrounding observations and weights are different.

The GWR gravity model is specified as

$$t_{ij} = \alpha_{0,i} + \alpha_{1,i} y_i + \alpha_{2,i} y_j + \alpha_{3,i} d_{ij} + \eta_{ij}, \tag{5}$$

Note that in contrast to the OLS gravity model, our GWR gravity model estimates one regression for each location.

To estimate each parameter at the ith location, we conduct a weighted regression where each observation is given a weight w_j The parameters in the GWR model in Equation (5) can be calibrated using the weighted least squares approach.

$$\hat{\alpha}_i = (y' W_i y)^{-1} y' W_i t \quad \forall i = 1, \cdots, N \tag{6}$$

where the weighting matrix W_i is the N by N matrix whose off-diagonal elements are zero and whose diagonal elements are the weights of each observation. Note that w_i is a decreasing function of distance between the two points.

There are two classic ways to determine the weight of each observation. A fixed kernel uses a given bandwidth, which does not vary with data density. Thus, the number of observations used in estimation differs according to data density. More observations are used in the area with denser observations than in the area with sparser observations. An adaptive kernel uses a fixed number of observations. Thus, the bandwidth differs according to data density, and larger bandwidth is used in the area where observations are sparse than in the area where observations are dense. One of the classic options of geographical kernel type for GWR is adaptive bi-square kernel.

$$w_i = \begin{cases} (1 - d_{ij}^2/\theta_{i(k)}^2)^2, & if \quad d_{ij} < \theta_{i(k)} \\ 0, & otherwise \end{cases} \tag{7}$$

where $\theta_{i(k)}$ is an adaptive bandwidth size defined as the k th nearest neighbor distance. The bi-square kernel has a clear-cut range where kernel weighting is non-zero. Empirically, the optimal bandwidth is determined by minimizing $AICc$ or cross validation.[4]

SST argue that log-linearization of the empirical model in the presense of heteroskedasticity leads to inconsisitent estimates. Therefore, we estimate the GWPR gravity model specified as

$$T_{ij} = \exp(\alpha_{0,i} + \alpha_{1,i} y_i + \alpha_{2,i} y_j + \alpha_{3,i} d_{ij}) + \varepsilon_{ij}, \tag{8}$$

where T_{ij} is a level variable as in SST. In this case, GWR uses the Poisson regression model instead of OLS when running a separate regression for each location.

In the GWPR estimation, the bandwidth is around 2700 out of 9613 export flows. This implies that nearby 2700 get positive weight when we calculate local coefficients of each location.

[4] Akaike information criterion-corrected (AICc) is a measure of the relative quality of statistical models for a given set of data. Cross vaildation $= \sum_{i=1}^{N} (y_i - \hat{y}_{\neq i})^2$ where $\hat{y}_{\neq i}$ is the fitted value of y_i with the observations for point i omitted from the calibration process.

3 Data

Data are taken from SST, which covers 136 countries in 1990. Hence, 18,360 observations of bilateral export flows are obtained with 136×135 country pairs. When we exclude zero bilateral trade, 9,613 country pairs have positive export flows.[5] Using SST data, we can compare our local estimation results with global estimates of SST. The spatial distributions of GDP data are graphically displayed on the world map in Fig. 1.[6] We have relatively high levels of GDPs for each continent: the US in North America, Brazil in South America, developed countries in Western Europe, Japan in East Asia, and Australia in the Southeast Asia. According to the gravity model, large trade can be explained by these large economy masses. Our methodological merit is to geographically investigate the extent of gravity that each mass has spatially. In contrast to the other continents, there exists no country with a large economic size in Africa. In the estimation, we also investigate how the African countries are affected by big massess in other continents.

Insert Fig. 1 here.

4 Empirical results

In this section, we explain the main results. After showing the global estimates under OLS and PPML, we show the histograms of local esitmates based on the values and display them on the world map.

4.1 OLS and PPML results

We begin by showing the OLS and PPML results. Using ArcGIS 10.1 software, we reproduce the OLS estimates. The results for traditional OLS and PPML are presented in Tables 1 and 2, respectively.[7] Tables 1 and 2 also present the minimum and maximum values via GWR and GWPR, respectively.

Insert Tables 1 and 2 here.

Fig. 2 geographically displays the residuals of OLS. We observe that the residuals are not distributed over the world map unlike the implicit assumption of the OLS model. Some groups of OLS residuals are clustering regionally, which implies that the effects of independent variables are not geographically constant.

Insert Fig. 2 here.

[5] We also perform estimation including trade data with literally zero. However, we find that the estimated values are too and in some cases the signs are opposite for these pairs of countries. As discussed in the previous literature, there exist many problems with zero trade in the perspective of estimation and quality of data. For example, zeros can just be missig observations. Hence, in this paper, we only show the results with positive trade flows.

[6] For further details, see SST.

[7] PPML results are taken from SST.

4.2 GWR results

4.2.1 Histograms of local estimates

In this subsection, we compare our local results with global estimates for each variable. Fig. 3 displays the histograms of estimated local coefficients, where we categorize countries by equally dividing the entire range of coefficients into eight subranges. The red bars include the global estimates and at a glance, we can notice that all global estimates are located in one of eight subgroups of local estimates: the global estimates for all coefficients locate within the third-eighth to the sixth-eighth subranges.

We can also observe that the distribution for each variable differs one another and the shape is much different from normal or uniform distributions. This implies that local variations exist due to geography. One exception is importer's remoteness variable: the global estimate is -0.199 locating in the fourth-eighth subrange and 58 local estimates are clustering in the same subrange. Furthermore, 30 and 20 local estiamtes are neighboring to the global estimate, locating in the third-eighth and fifth-eighth subranges, respectively. In many other cases, however, bimodal or multimodal distributions are observed, which implies that the global estimates can capture the average impacts of each variable but cannot trace the spatial heterogeneity of this locally distributed estimates.

In the existing structural gravity literature including Eaton and Kortum (2002) and Anderson and van Wincoop (2003), the predicted value of economic sizes of exporting and importing countries are theoretically unity, and OLS estimates in the empirical literature are generally close to this value. The globally estimated coefficient on aggregate GDP of exporting countries is 0.942 and the corresponding local estimates range from 0.820 to 1.114. We find that the estimated GDP elasticities in some countries are even larger than unity. In the sixth-eighth to top-eighth ranges, for example, 32 out of 136 total estimates are higher than unity, ranging from 1.004 to 1.114. Regarding importer's GDP, the coeffients of importer's GDP range from 0.723 to 0.957, while the corresponding global estimate is 0.802. We find that 86 local estimates in the fourth-eighth to the top-eighth ranges, are larger than the global estimate.

Turning to the distance variable, its negative effect on trade flows is globally estimated as much as -1.163. Existing literature including Disdier and Head (2008) highlighted the so-called time-dependent 'distance puzzle', which indicates that the estimated negative effect of distance on trade flows has increased over the several decades. In this paper, the distance elasticities of trade are space-dependent scattering among countries, ranging from -1.958 and -0.707. It appears that the spatial variations of the deterrent effect of the distance are huge: 19 local estimates within the bottom-eighth subrange, from -1.958 to -1.802, are more than twice compared to 8 estimates in the top-eight subrange, from -0.863 to -0.707.

The negative coefficients on the land-locked dummies are interpreted as an indicator of accessibility to ocean transportation. In the case of importer's land-locked dummy, the global estimate is -0.662 and all local coefficients are negative ranging from -0.999 to -0.491. In Table 1, on the other hand, the global estimate of exporter's land-locked dummy is not statistically significant. One of the reasons could be that some local estimates are positive: 25 countries in the seventh-eighth subrange and 9 countries in the top-eighth subrange have positive estimates.

However, in some cases, the signs of the estimated coefficients turn out to be opposite to those predicted in the literature. One example is GDP per capita. As countries develep, they tend to liberalize their economy and hence trade more. Furthermore, more developed countries would have more advanced transportation infrastructures. Hence, the sign of exporter's GDP per capita is expected to be positive and the global estimate is 0.192 consistant with the literature. If we observe the results locally, however, we find that the signs of cofficients of exporter's GDP per capita are negative in eight locations. We also observe a similar pattern in the coefficients of importer's GDP per capita with 23 negative signs. Further, the signs of a border dummy turns out to be negative in 30 locations, while existing literature expects a positive sign because adjacent countries seem to trade more. For some local estimates, we also observe opposite signs for the coefficients of colonial tie, free trade agreements (FTAs) dummies, and the openness variable. In the next subsection, we discuss which countries face opposite signs.

The hypothesis regarding the remoteness variable is that larger distances to all other countries might increase bilateral trade flows between two trading partners. Global estimates are positive both on exporter's and importer's remoteness. However, our estimates on exporter's remoteness are considerably dispersed ranging from -8.202 to 4.780, which is the largest local variation among the estimated coefficients. 25 estimates enter the top-eighth group ranging from 3.158 to 4.780, while 9 estimates are in the bottom-eighth and second-eighth groups ranging from -8.202 to -4.959.

Insert Fig. 3 here.

4.2.2 Geographical distribution

Fig. 4 geographically shows the GWR results on the world map. For visibility, we display the estimates by equally dividing into four subranges. The region with red, orange, light green, and green colors indicates the bottom-fourth to the top-fourth subranges, respectively. Our main finding under GWR is that the values of estimated coefficients are spatially clustering region by region within the same subrange, which is not captured by global estimates such as OLS linear regressions.

Further, we assert that a simply regional classification in the global gravity model may not fully reflect the actual geographical patterns. Existing literature such as Frankel (1997) includes regional dummies such as Western Europe and East Asia in the estimation model. Disdier and Head (2008) introduce a dummy "single continent" to capture land versus ocean differences. Our results supplement their econometric classification introducing more flexibility into the regression model. For example, countries in the American continent, whether North America or South America, generally have the same results regarding distance, importer's GDP per capita, border, language, exporter's and importer's remoteness, and colonial tie. In the case of distance, all American countries fall into the third-fourth group ranging from -1.313 to -1.038, and in the case of border dummy, they belong to the top-fourth subrange from 0.517 to 0.886.

However, their specification of regional or continent dummy is crude and exogenously given. Our estimation strategy can overcome this problem endogenously finding out to which extent the estimates are clustering. In the case of exporter's GDP, only Canada and the US enter into the same subrange, while in the case of importer's GDP, countries in North America, Central America, and the northern part of South America share the same subrange of estimates.[8] For the openness variable, all four subranges exist throughout the

[8]Central America covers Costa Rica, El Salvador, Mexico, and Panama and the northern part of

whole American continent. Hence, the American continent or North America and South America dummies in the global gravity model may not be a good indicator to group the countries with the same pattern.

Moving onto Africa, we observe more complicated patterns within a given continent. Countries in the African continent do not share the same coefficients in all cases. In the case of exporter's GDP, distance, exporter's GDP percapita, exporter's remoteness, FTA, and openness, the coefficients in African countries are scattered from the bottom- to top-fourth groups, implying that a single African dummy cannot capture all these geographical characteristics. In particular, North African countries such as Algeria, Morocco, and Tunisia closely follow the patterns of European countries, indicating the economic gravity of Europe reaches to North Africa. However, in other regions of Africa, we observe various patterns of the coefficient variables. In the cases of exporter's GDP per capita and FTA, the coefficients are clustering in North Africa and South Africa, respectively. In some cases such as exporter's and importer's GDPs per capita, languge, and openness, the estimated coefficients are grouped into western and eastern parts of the African continent.

In the case of Asia, countries in East Asia and Southeast Asia share the same range of coefficient values almost in all cases. However, South Asia and West Asia reveal their own patterns. Similarly, we observe different patterns of estimates in the European region. Therefore, it is not useful to introduce a single dummy of Africa and Asia in the global gravity model because there is no single pattern to divide the charateristics.

Looking at exporter's GDP, some local estimates are lower than the global estimates, 0.942, in the broad regions in the pacific rim and surrouding the South Atlantic Ocean, ranging from 0.820 to 0.883, whereas other regions such as Europe, North Africa, and countries surrounding the Indian ocean share high estimates. Some examples of bottom fourth subrange are Argentina, Brazil, and Mexico in Central and South America, Angola and Cameroon in Africa, and Japan and Korea in East Asia. The similar phenomenon is observed among the regions on the pacific rim for the importer's GDP variable. East Asian region is ranked in the bottom fourth subranges, ranging from 0.723 to 0.770. In other words, compared to other regions, the economic size of these Asian countries plays a minor role when they export goods to other countries.

Further, the estimated elasticity of distance is not locally constant but geographically heterogenous. We find that local distance coefficients are divergent ranging from -1.958 to -0.707.[9] The negative effect of distance is strongly observable in countries located in Africa and the Middle East. It is noticeable that the physical distance has the least effect on the European region.

The literature interpret the positive sign of the globally estimated coefficients of GDP per capita as follows: richer countries do trade more than the poor ones. The graphs shows that this should not necessarily be the case. The estimates of exporter's GDP per capita in the bottom fourth region overlap with those of exporter's GDP in many cases. Further, the signs of many coefficients in the Africa region located in the bottom region turn out to be negative.[10] European countries except Iceland, Portugal, and Spain, and East Asian countries are generally in the highest subrange.

South America includes Colombia, Ecuador, Suriname, and Venezuela.

[9]The corresponding global estimate is -1.163.

[10]The examples include Comoros, Madagascar, Malawi, Mauritius, South Africa, Zambia, and Zimbabwe.

Insert Fig. 4 here.

5 Comparision between origin and destination locations

In this section, we estimate the GWR model based on the importer's location. In the empirical literature on gravity models, trade flows from country i to j are interpreted as exports from country i to j, following the microfoundations in the theoretical literature, including Anderson and Wincoop (2003) and Eaton and Kortum (2002), where exports from country i to j are dependent variables in their structural gravity models. However, the empirical gravity model is indifferent to whether the dependent variable is exports from i to j or imports from i to j. In another strand of literature, Anderson and Yotov (2010) calculated the incidence of bilateral trade costs, which are the proportions of trade costs paid by sellers and buyers. Hence, even with uniform trade costs, if the exporter's incidence is large, the supply to the rest of the world could become small, and larger importer's incidence may lower the importer's demand. Furthermore, for country i's incidence as an exporter and an importer can be different because the trading partners are not symmetric. For example, Japan's large exporting destinations are the US, China, and Korea but one of the main importing origins are oil producing countries. Therefore, to capture the asymmetric charateristics as exporters and importers, we estimate the GWR model with the same dependent and independent variables with only one exception: the geographical information of the importer rather than the exporter is imposed to the model.

Fig. 5 displays the histograms of estimated coefficients under the importer's locations. In the benchmark model, we use exporter's location, which is country A in Fig. 5, and hence the GWR model includes trade flows 1, 2, 3, and 6 in estimating local coefficients. In this regression, exports of country A including 1 and 3 are highly weighted than exports of country B including 2 and 6. However, this regression excludes country C's exports because country C is outside the bandwidth of the exporter A's location. If we consider Germany as one example of country A, neiboring countries such as France and the UK become country B and countries located far from Germany become country C. In this case, all exports from Germany to the rest of the world as weighted most in the local estimation and those from other countries, locating inside the bandwidth, to the rest of the world are included but less weighted. However, exports from countries C, say China, Japan and Korea, are excluded in this local estimation. Consequently, our benchmark estimation could capture the exporter's incidence in specific region, Europe in our example.

On the other hand, if we use country A's location as an importer's geographical information, the GWR model includes trade flows 1, 2, 4, and 5. In this case, country A's imports including 2 and 4 are highly weighted, while country B's imports including 1 and 5 are less weighted. Furthermore, country C's imports including 3 and 6 are not included. Returning back to the upper example, the imports of Germany from the rest of the world are mostly weighted and those of adjecent countries are less weighted but those outside the bandwidth are not included in the local estimation. Hence, even if we use Germany's geographical information, our estimated result could capture the importer's incidence.

If we estimate the model based on exporter's location, the characteristics of country A are the most important source in explaining the coefficient of exporter's GDP. In Fig. 5, Country A's exports, 1 and 3, are highly weighted than country B's exports, 2 and 6. This makes each coefficient of exporter's GDP be more dependent on the exporter in the corresponding location. In the case of the coefficient of importer's GDP, the order of importance changes. Country participates in two trade flows as an importer: 3 high weight) and 6 (low weight). Country B participates in trade flow 1 (high weight) as an importer. Country A participates in trade flow 2 (low weight) as an importer. The impact from country A is lessened, and hence, the variation is lowered.

If we estimate the model based on the importer's location, country A's characteristics are the most important in explaining the coefficient of importer's GDP. In Fig. 5, country A's imports, 2 and 4, are highly weighted than country B's imports, 1 and 5. This makes each coefficient of importer's GDP more dependent on the importer in the corresponding location. In the case of the coefficient of exporter's GDP, the order of importance changes. Country C participates in two trade flows as an exporter: 4 (high weight) and 5 (low weight). Country B participates in trade flow 2 (high weight) as an exporter. Country A participates in trade flow 1 (low weight) as an exporter.

Insert Fig. 5 here.

Fig. 6 displays the histograms of results under the importer's location information. In contrast to the exporter-location case, we have more dispersed coefficient values of importer's variables than those of exporter's variables. For examples, the coefficient values of importer's GDP estimated under importer's location range from 0.535 to 1.133, while those of exporter's GDP range from 0.928 to 1.025. The coefficient values of importer's GDP per capita range from -0.314 to 0.363, while those of exporter's GDP per capita range from -0.009 to 0.471. If the importer is landlocked, we observe a wider range from -1.395 to 0.295, while the estimates of exporter's dummy ise in a narrower band ranging from -0.555 to 0.145. The estimated coefficients of importer's remoteness range from -2.852 to 3.570, while those of exporter's remoteness range from -0.548 to 1.879.

Furthermore, compared to the benchmark case under exporter's location, the ranges of coefficient values of importer's variables become wider. For example, the coefficient values of the importer's GDP estimated under importer's location range from 0.535 to 1.133, while those under exporter's location range from 0.723 to 0.957. The coefficient value of importer's GDP per capita ranges from -0.314 to 0.363, while that under exporter's location ranges from -0.125 to 0.269. If the importer is landlocked, the coefficient is more diversified, ranging from -1.395 to 0.295, while that under exporter's location ranges from -0.999 to -0.491. The estimated coefficients of importer's remoteness range from -2.852 to 3.570, while those under exporter's location range from -1.388 to 1.114.

The ranges of exporter's variables are narrowed compared to the benchmark case. The coefficient values of exporter's GDP estimated under the importer's location range from 0.664 to 0.835, while those of exporter's GDP range from 0.582 to 1.163. The coefficient value of exporter's GDP per capita ranges from 0.011 to 0.387, while that of exporter's location ranges from -0.381 to 0.493. If the exporter is landlocked, the coefficient is more narrowed ranging from -0.955 to 0.045, while that of exporter's location ranges from -2.439 to -0.278. The estimated coefficients of exporter's remoteness range from -1.514 to 1.061, while those under exporter's location range from -6.336 to 7.664.

Fig. 7 geographically displays the GWR results based on the importer's location. Interestingly, whether we estimate the model under exporter's location or under importer's location, we find that in general countries are ranked in the same subranges in common variables such as distance, border, language, colonial tie, and FTA. For the distance variable, for example, countries in Africa and Middle East are in the lowest subrange. In other words, the negative effect of physical distance is prevalent both when they export and import.

However, there exists some heterogeneity on the size of the effects of these variables. For the border dummy, European countries are in the bottom fourth subrange in both cases but 30 estimates are negative under exporter's location while 73 estimates are negative under importer's location. For the colonial-tie dummy, only four countries in Africa, Cameron, Equatorial Guinea, and Gabon have negative signs in the benchmark case. Under importer's location, 22 countries are found to have negative signs. Among them East Asian counties are notable. For the FTA dummy, in contrast, 32 estimates are negative in the benchmark case. In particular, we observe this negative effect in Europe, Northern part of Africa, and Middle East. Under importer's location, we find a similar pattern in the same region but the negative estimates are found only in four countries.

Insert Figs. 6 and 7 here.

6 Anderson-van Wincoop gravity equation

Anderson and van Wincoop (2003) argue that multilateral resistance terms should be included when we estimate the gravity equation. Fixed effects have been used to capture the effect of multilateral terms in the recent gravity equation including Redding and Venables (2000) and Feenstra (2002). In this section, hence, we run GWR using fixed effects to take account of the multilateral resistance terms.

As discussed by SST, the distance elasticity -1.347 is substantially larger than that with with no fixed effects. The effects on sharing a common border, languange, and colonial ties become limited as much as 0.174, 0.406, 0.310, respectively, while the corresponding results under OLS without considering the fixed effects become 0.314, 0.678, and 0.491. Only the effect on common colonial ties become larger from 0.397 to 0.666.

When we use fixed effects in the specification of our GWR model, we find that the effect on common colonial ties becomes generally larger with the range [0.204 1.107] compared to those with no fixed effect, [-0.100 0.760]. For common language dummy, the effect becomes limited with the range [0.029 0.847], while the range in the benchmark is [0.111 1.294]. For the distance dummy and FTA dummy, our estimates becomes narrowed with the ranges [-1.701 -0.948] and [-0.175], repectively, while the ranges with no fixed effects are [-1.958 -0.707] and [-0.376 2.916], respectively. On the other hand, for the common border dummy, the range becomes widened: from [-0.278 0.886] to [-0.777 0.913].

Countries in Europe and North Africa enjoy the favorable effects on colonial ties with the lowest harmful effect on distance. However, these countries have the lowest subranges for border and FTA dummy variables. Our interpretation is that these countries trade with non-neighboring countries rather than neighboring countries. This suggests that in Europe where developed countries are compactly located, sharing a border is not a decisive factor of trade. For example, France and Austria whose coefficeints are both negative can trade easily without sharing a border.

In contrast, countries in other regions of Africa experience the most negative effect on distance and common colonical ties, while sharing a common border seem to have a largest positive effect in the east and south regions. Sharing a common border has the most favorable effect in the American continent, while sharing a common language seems to play a negligible role in explaining trade flows. We also find that countries in this region get the positive effect on FTA and common colonial ties. Among common variables, the FTA dummy appears to play the most important role in East Asia and Southeast Asia, while the language dummy, border dummy, and the colonial tie are less important.

Insert Fig. 8 here.

7 Comparison with GWPR

In this section, we show the GWR results and compare them with the GWPR results. By doing this, we investigate whether the difference between OLS and PPML found in SST still holds under the local regression. Fig. 9 displays the GWPR results based on exporter's location. We explain only the results based on exporter's location because we obtain a similar pattern under importer's location.

SST find that the coefficients on GDP under Poisson regression are not close to unity and smaller than those under OLS. We support their finding in our location regression. The estimated coefficients of exporter's GDP in GWR are generally high ranging from 0.820 to 1.114, while those under GWPR are in the range from 0.582 to 1.163. As shown in Fig. 9, the coefficients for over 80 countries are located below the bottom value, 0.820, under GWPR. We also find a similar result for importer's GDP variable.

SST also find that the deterrent effect of physical distance on trade flows is much larger under OLS. We support their finding: the coefficients based on GWR range from -1.958 to -0.707, whereas the Poisson estimates range from -1.399 to -0.202. Furthermore, 52 coefficients cluster around the PPML estimate at the range from -0.805 to -0.607. In contrast, we find that in most regions, the coefficients are lower than negative unity under GWR.

The global Poisson estimate of colonial ties is found to be not significantly different from zero, while OLS estimates are. Our GWR estimates also generate a siginificantly positive role in almost all countries, ranging from -0.100 to 0.760, while our GWPR estimates reveal that the coefficients of almost half of the sample countries are negative. SST also find that FTAs play a much smaller role with much lower PPML estimates than OLS estimates, and the openness dummy in OLS regression is negative while Poisson estimates are not significantly different from zero. In our GWR model, the estimates of FTAs and openness range from -0.376 to 2.926 and -0.474 to 0.617, respectively, while in GWPR model, they range from -0.733 to 1.319 and -1.152 to 1.295, respectively. Hence, our results reconcile with those of SST.

However, in contrast to SST, we find that a common-border effect does not disappear but instead increases in our GWPR model. Although GWR estimates are in a narrower range from -0.278 to 0.886, many countries have a positive sign.

Insert Fig. 9 here.

7.1 Comparison of global and local poisson estimates

SST find that the coefficients on exporter's and importer's GDPs are not close to unity under Poisson estimation. Our GWPR estimates complement their finding: the estimated GDP elasticities in most countries are much smaller than unity. For example, the PPML estimates of exporter's GDP is 0.721 and we find that the GWPR estimates in 29 countries are less than the PPML estimate. In the sixth-eighth to top-eighth ranges, only 16 out of 136 country estimates are close to or higher than unity, ranging from 0.947 to 1.163. Regarding importer's GDP, in the second-eighth to fourth-eighth ranges, 85 estimates cluster around the PPML estimate, 0.732, ranging from 0.701 to 0.785. In the top-eighth range, only 4 coefficient values range from 0.869 to 0.893, which is still much lower than unity.

SST find that the deterrent effect of physical distance on trade flows is much smaller under Poisson estimation. We support their finding: more than 90 coefficients under GWPR range from -0.803 to -0.212. However, we also find that the estimates in 48 countries exceed negative unity.

From Fig. 10, only the coefficients of Border, Landlock(ex), Language, and Colonial-ties have bimodal distributions. These bimodal distributions suggest that local variations exist due to geography. For example, the impact of being a landlocked country in Europe (Austria) can be different from that of Central Asia (Mongolia). However, the global estimates can capture the average impacts of bimodal distribution.

In contrast to SST, who find that sharing a border does not influence trade flows, a common-border effect does not disappear but increases in our GWPR model. Our GWPR estimates with the range from -0.359 to 2.056 and 41 estiamtes cluster around the global estimate in the second-eighth range. However, 113 coefficients are positive and 87 coefficients are larger than unity. 19 coefficients are clustered from 1.755 to 2.056.

In the existing literature, the negative coefficients on the land-locked dummies are interpreted as an indication of cheaper costs of ocean transportation. While our Poisson estimates reveal that negative coefficients on exporter's land locked dummy prevail in most regions, their distribution does not seem to be monotonic. 68 estimates cluster in the sixth and seventh ranges among -0.744 and -0.066, while 22 estimates are in the bottom sixth range from -2.439 to -2.100. In the case of importer's land-locked dummy, all coefficients are negative and 77 coefficients cluster in the fifth and sixth ranges from -0.603 to -0.381.

The hypothesis regarding remoteness is that larger distances to all other countries might increase bilateral trade flows between two trading partners. Global Poisson estimates by SST are positive both on exporter's and importer's remoteness. However, our estimates on exporter's remoteness are considerably dispersed ranging from -6.336 to 7.664, which is the largest local variation among the estimated coefficients. 5 estimates enter the top-eighth group ranging from 5.914 to 7.664, while 6 estimates are in the bottom-eighth group ranging from -6.336 to -4.586.

SST find that Poisson estimates of colonial ties are not significantly different from zero. Our GWPR estimates reveal that the coefficients of almost half the number of sample countries are negative while the others are positive. 50 coefficients cluster in the sixth-eighth range of 0.165 and 0.365, while 22, 4 and 25 coefficients are in the bottom-, second-, and third-eighth ranges from -0.840 to -0.639, from -0.639 to -0.438, and from -0.438 to -0.237, respectively. In other words, the dispersion of the estimated values from zero possibly explains why the global PPML estimate is not significantly different from zero.

SST find that Poisson estimates on common language are significant. Our GWPR estimates shows that coefficients have a bimodal distribution. While coefficients are clustered most in the fourth-eighth range from 0.344 to 0.599, 23 coefficients are clustered in the top-eighth group ranging from 1.364 to 1.617.

SST assert that free trade agreements (FTAs) play a much smaller role finding much lower PPML estimates than OLS estimates. They also find that Poisson estimates on the openess dummy are not significantly different from zero. In our GWPR model, the FTA coefficients range from -0.792 to 1.219 and among them 55 coefficients are within the range of 0.216 and 0.468. On the other hand, we observe an important role of FTAs in 15 coefficients in the seventh- and top-eighth groups ranging from 0.720 to 1.219, while we also observe deterrent effects of FTAs in over 38 countries. The openness dummy coefficients are scattered around zero, ranging from -1.068 to 1.504. As in the colonial-tie dummy case, this might be the reason why PPML is not significant from zero. Hence, our result supplements SST's finding.

Insert Fig. 10 here.

8 Conclusion

In this paper, we perform local regression geographically extending global regression in the existing literature. In particular, we apply GWR approach to investigate the role of geography in the trade gravity equation.

We contribute to the trade literature by showing new findings as follows. First, our local regression reveals that the estimated parameters are locally clustered among selected economic masses. Second, the regional or continental dummy in the standard gravity model may not fully capture the geographical characteristics. Third, the degree of dispersion in the estimated coefficient values depends crucially on the location at which we estimate the model. In particular, we find that exporter's and importer's variables such as GDP are considerably influenced by the estimation location.

There is a strand of literature that investigates the effect of distance on trade pattern thoughout time. For example, Disdier and Head (2008) find that the estimated nagative impact of distance on trade increased around the middle of the twentieth century and remained high since then. Carrere, Melo, and Wilson (2013) find that low-income countries exhibit a significant rising distance effect on their trade, while the distance puzzle for trade within richer countries disappers. While the estimation in this paper is based on cross-sectional data, future research should include panel investigation to capture the distance puzzle.

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Table 1. The global and GWR gravity equation

Estimator:	OLS	GWR			
Location:		Exporter		Importer	
		min	*max*	*min*	*max*
Log GDP (ex)	0.942**	0.820	1.114	0.928	1.025
Log GDP (im)	0.802**	0.723	0.957	0.535	1.133
Log GDP per capita (ex)	0.192**	-0.076	0.523	-0.009	0.471
Log GDP per capita (im)	0.091**	-0.125	0.269	-0.314	0.363
Landlock dummy (ex)	-0.060	-1.453	0.415	-0.555	0.145
Landlock dummy (im)	-0.662**	-0.999	-0.491	-1.395	-0.295
Remoteness (ex)	0.471**	-8.202	4.780	-0.548	1.879
Remoteness (im)	-0.199**	-1.388	1.114	-2.852	3.570
Log distance	-1.163**	-1.958	-0.707	-2.107	-0.941
Contiguity dummy	0.294**	-0.278	0.886	-0.846	1.373
Common-language dummy	0.680**	0.111	1.294	0.017	1.033
Colonial-tie dummy	0.378**	-0.100	0.760	-0.108	0.866
FTA dummy	0.771**	-0.376	2.916	-0.042	3.006
Openness	-0.045**	-0.474	0.617	-0.579	0.427

Note: ex and im denote exporter and importer, respectively. *min* and *max* represent the lowest and highest estimated values, respectively. Number of observations are 9613 in all cases. The bandwidth in estimation is 2659 in GWR based on exporter's location, and 2721 in GWR based on importer's location, respectively.

Table 2. The global and GWPR gravity equation

Estimator:	PPML	GWPR			
Location:		Exporter		Importer	
		min	*max*	*min*	*max*
Log GDP (ex)	0.721**	0.582	1.163	0.664	0.835
Log GDP (im)	0.732**	0.673	0.893	0.516	0.857
Log GDP per capita (ex)	0.154**	-0.381	0.493	0.011	0.387
Log GDP per capita (im)	0.133**	-0.128	0.357	-0.199	0.423
Landlock dummy (ex)	−0.873**	-2.439	0.278	-0.955	0.045
Landlock dummy (im)	−0.704**	-1.047	-0.159	-2.011	0.355
Remoteness (ex)	0.647**	-6.336	7.664	-1.514	1.061
Remoteness (im)	0.549**	-2.419	1.676	-2.790	2.929
Log distance	−0.776**	-1.399	-0.212	-1.658	-0.327
Contiguity dummy	0.202	-0.359	2.056	-0.339	1.858
Common-language dummy	0.752	-0.421	1.617	-0.004	1.389
Colonial-tie dummy	0.019**	-0.840	0.771	-1.011	0.619
FTA dummy	0.179**	-0.792	1.219	-0.173	2.117
Openness	−0.139	-1.068	1.504	-0.712	0.679

Note: ex and im denote exporter and importer, respectively. *min* and *max* represent the lowest and highest estimated values, respectively. Number of observations are 9613 in all cases. The bandwidth in estimation is 2628 in GWPR based on exporter's location, 2721 in GWPR based on importer's location, respectively.

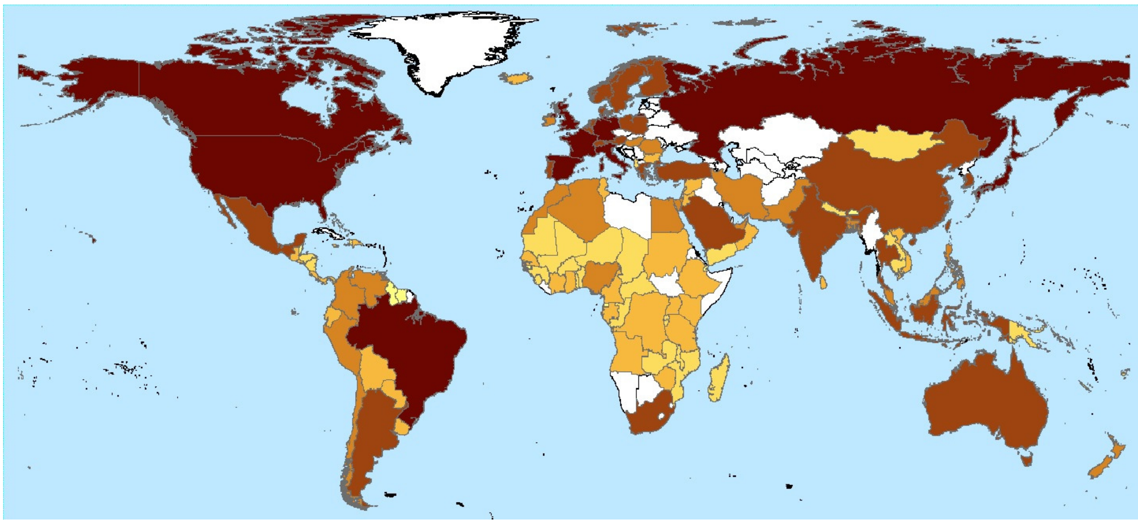

Fig. 1. GDP Data

Note: Darkness of brown colors indicates the GDP level. Nonsample countries are shown in white.

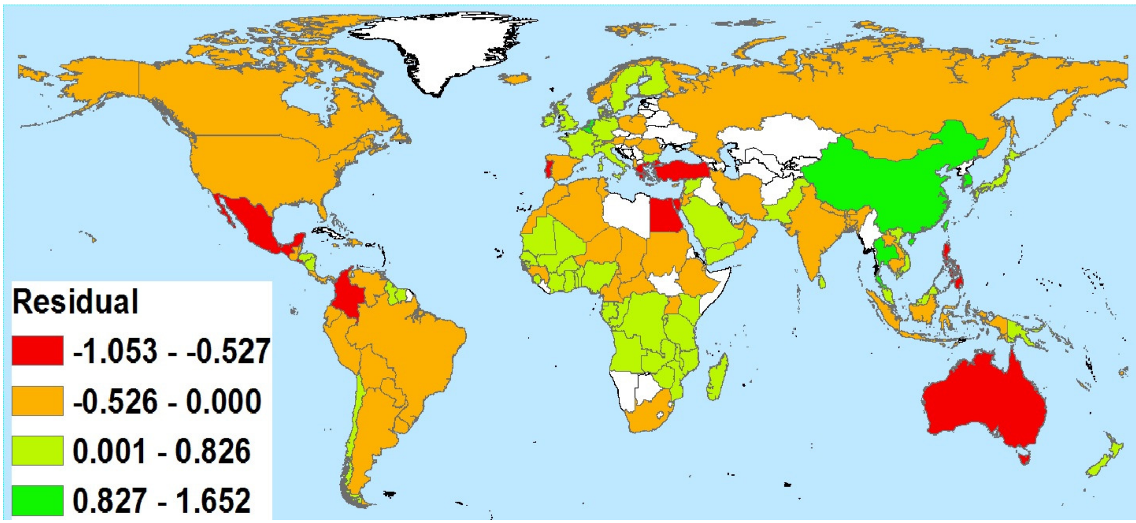

Fig. 2. Residuals of baseline OLS regression

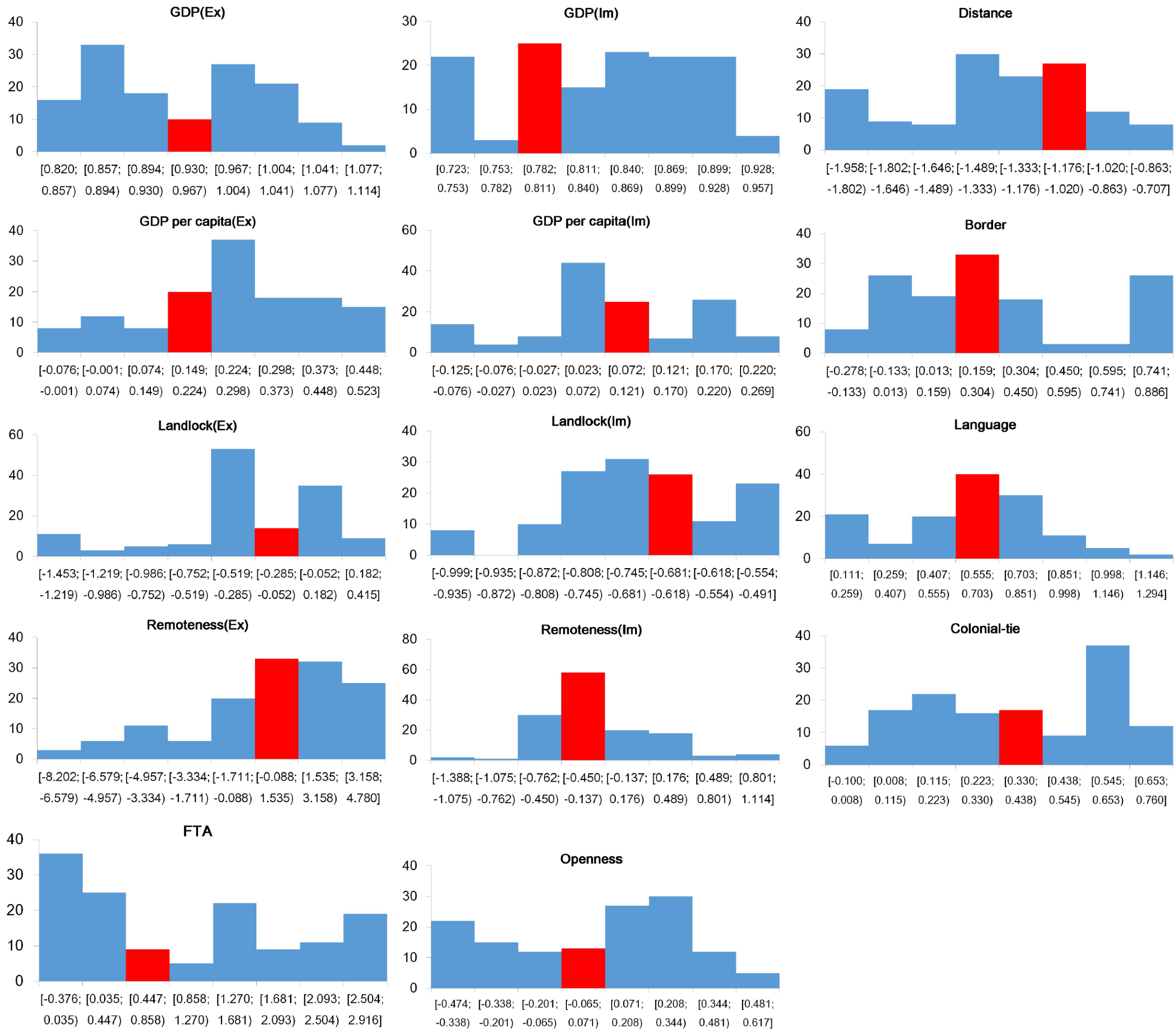

Fig. 3. Histogram of coefficients estimated under exporter's locations
Note: Ex and Im denote exporter and importer, respectively.

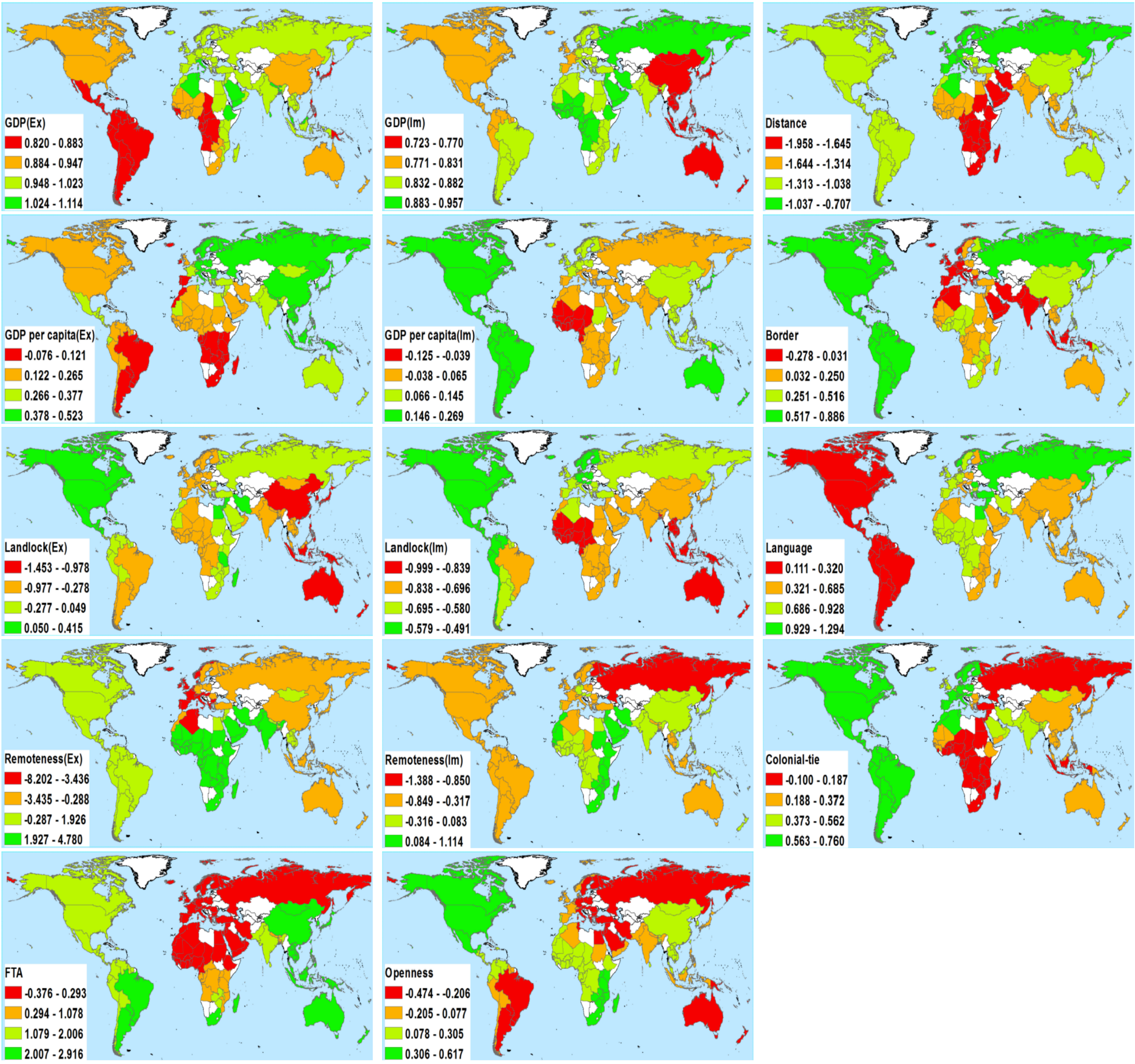

Fig. 4. GWR results based on exporter's locations
Note: Ex and Im denote exporter and importer, respectively.

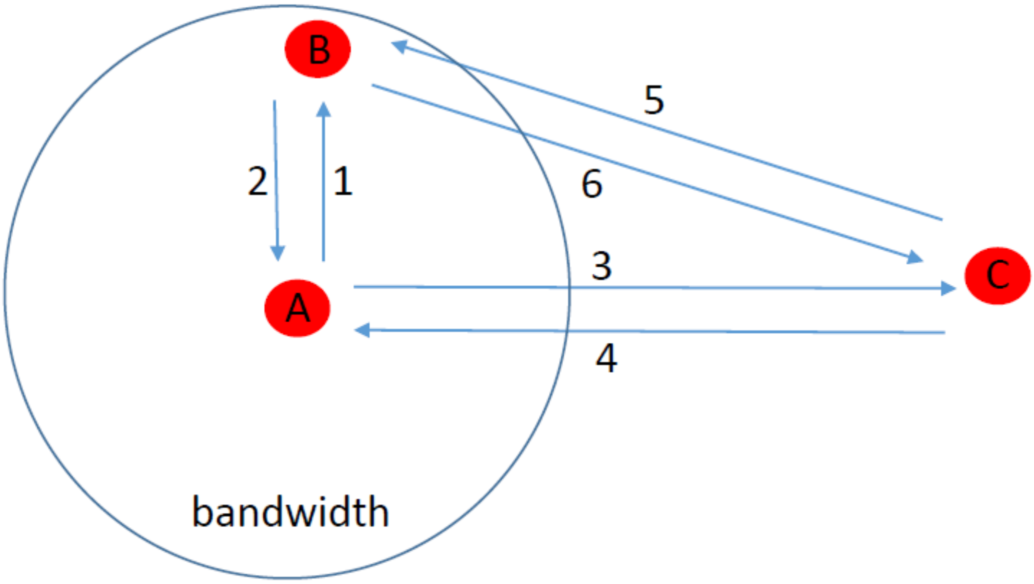

Fig. 5. Exporter versus importer locations

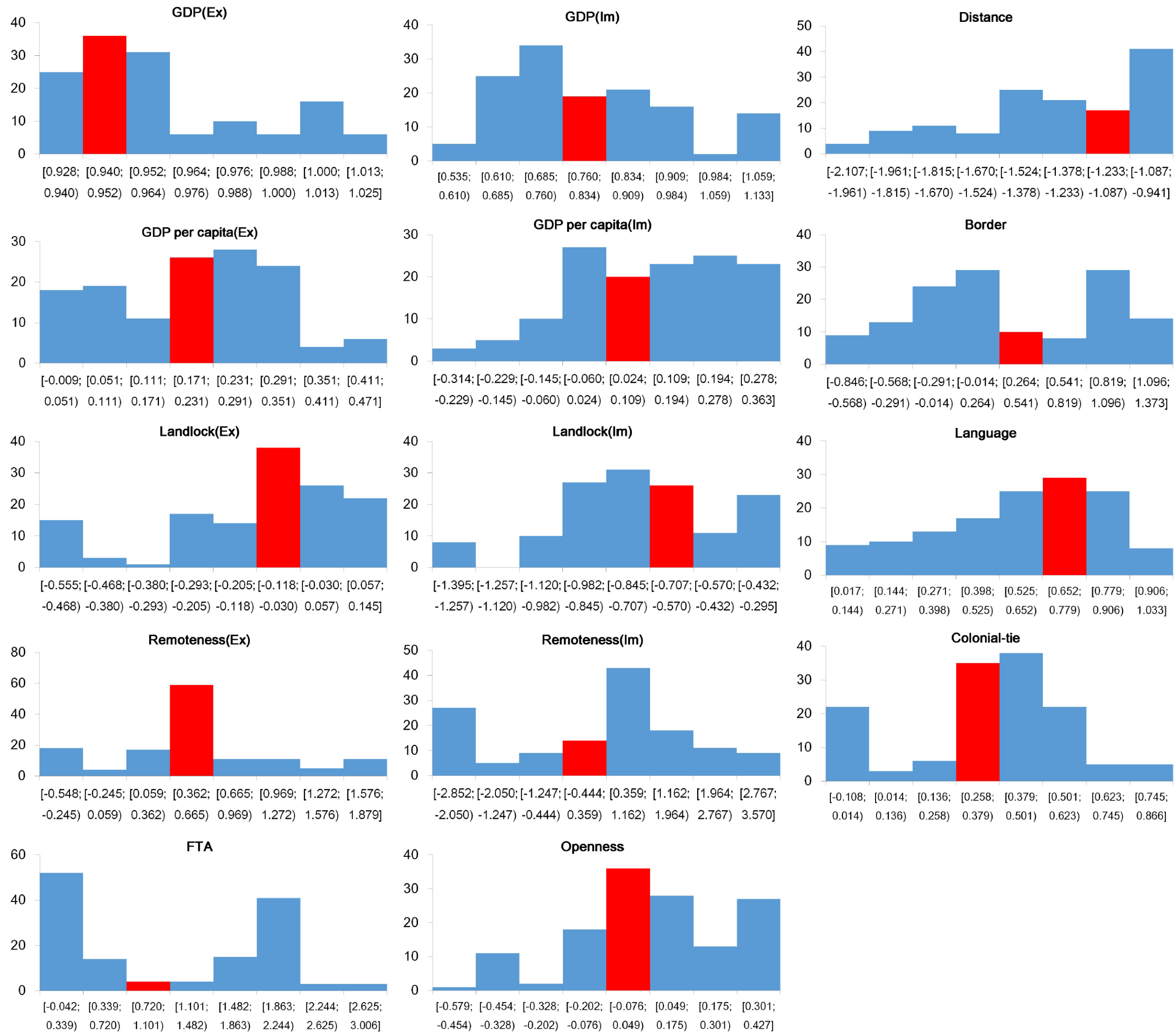

Fig. 6. Histogram of coefficients estimated under importer's locations
Note: Ex and Im denote exporter and importer, respectively.

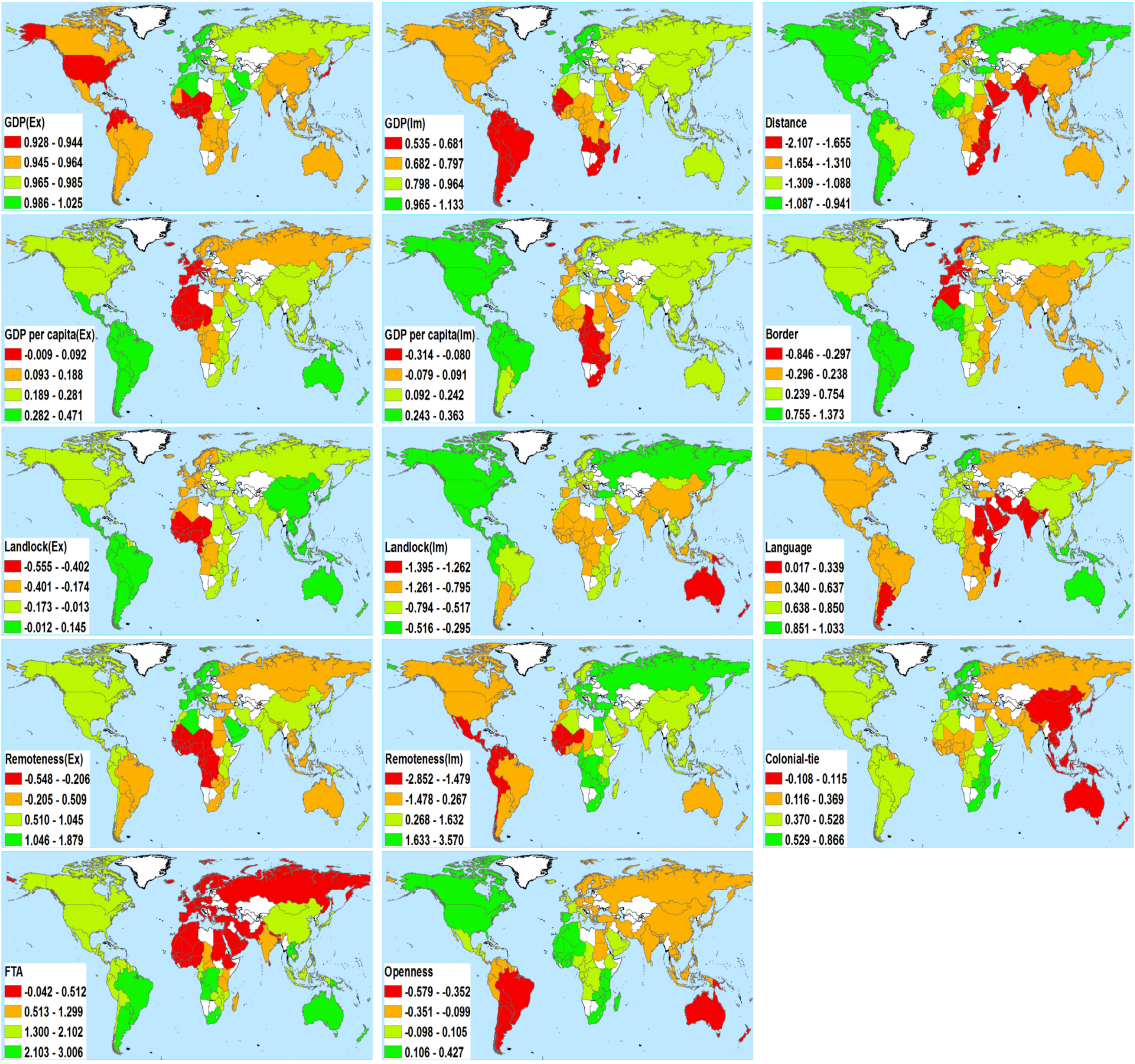

Fig. 7. GWR results based on importer's locations

Note: Ex and Im denote exporter and importer, respectively.

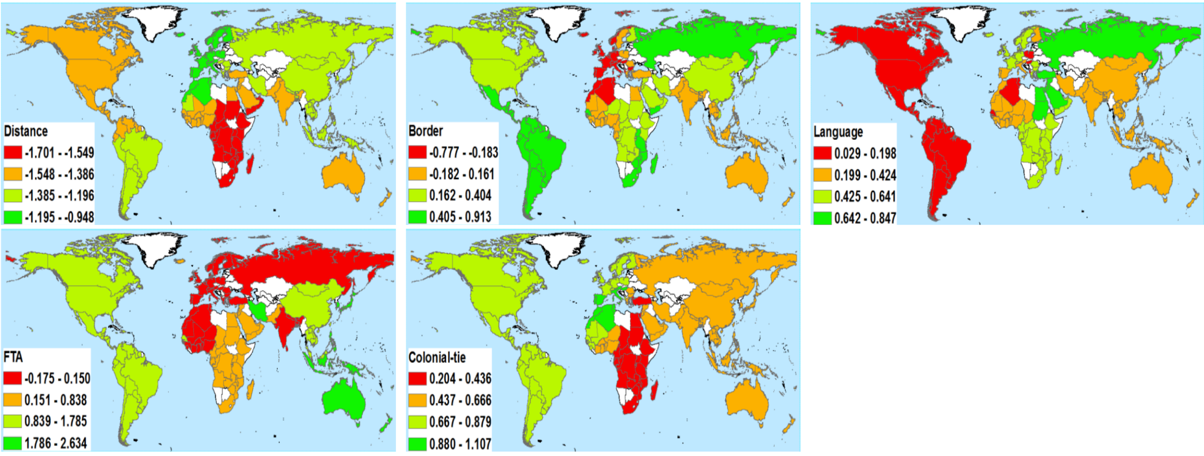

Fig. 8. Anderson-van Wincoop gravity equation

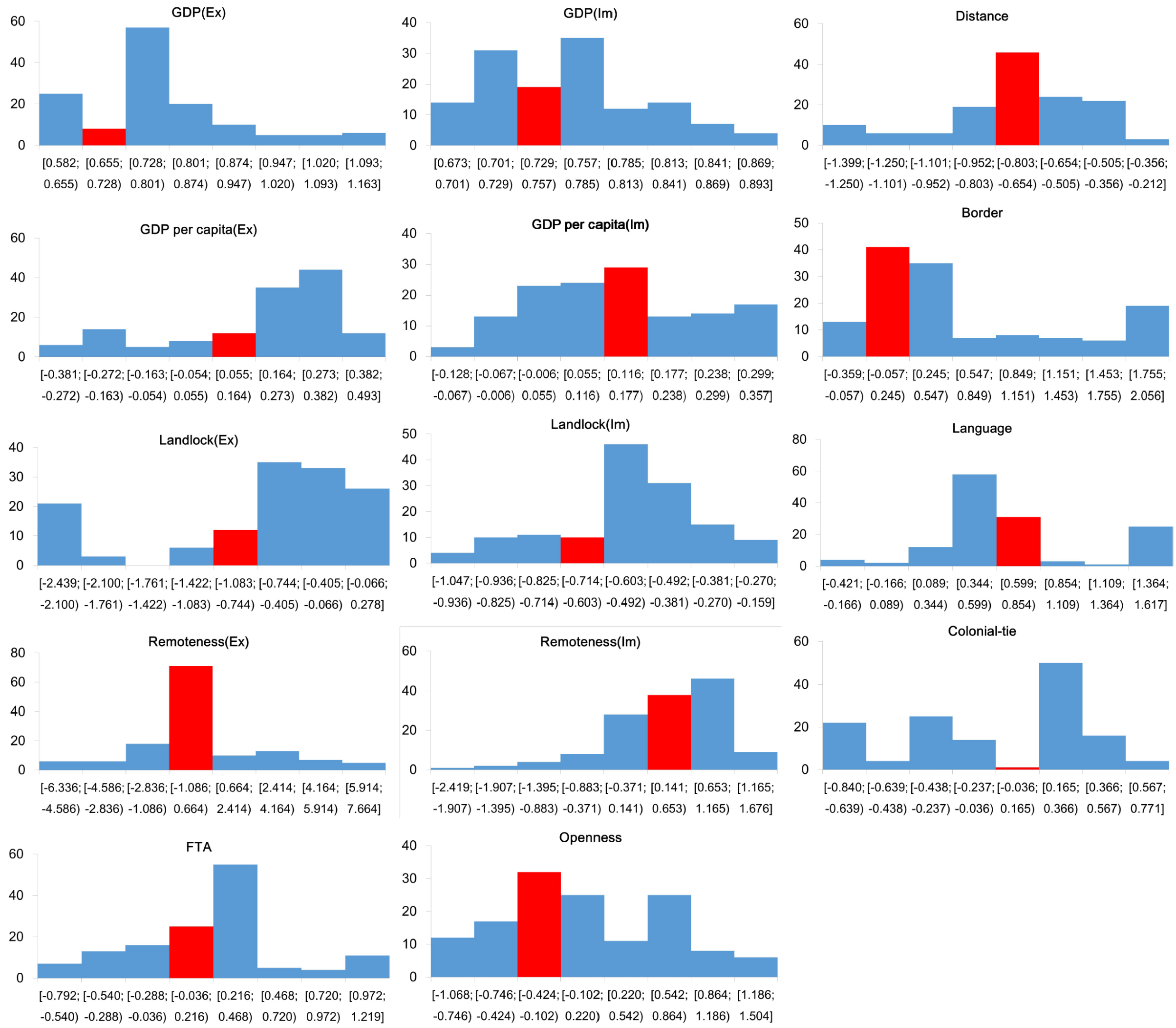

Fig. 9. Histogram of GWPR coefficients estimated under exporter's locations
Note: Ex and Im denote exporter and importer, respectively.

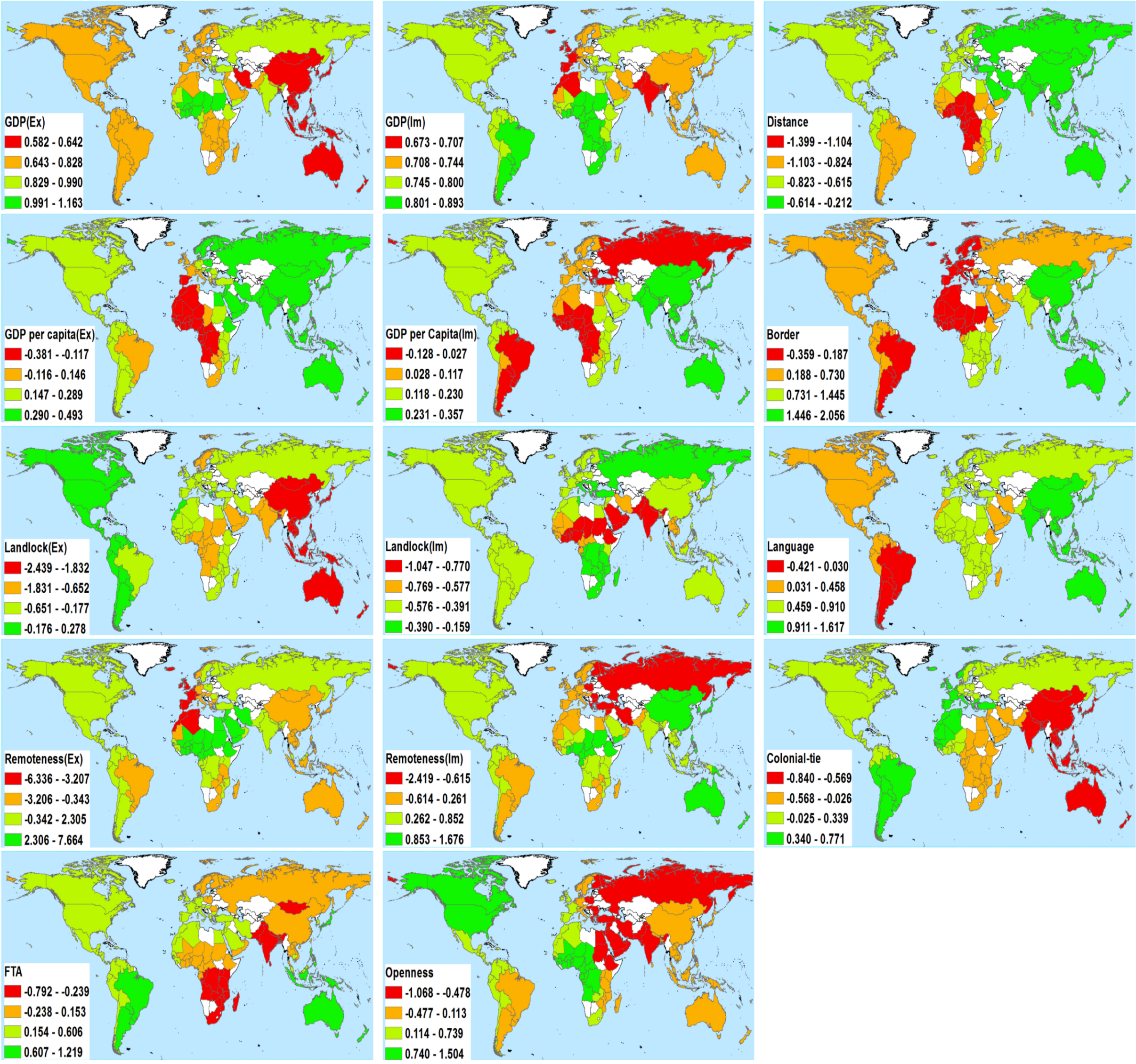

Fig. 10. GWPR results based on exporter locations
Note: Ex and Im denote exporter and importer, respectively.

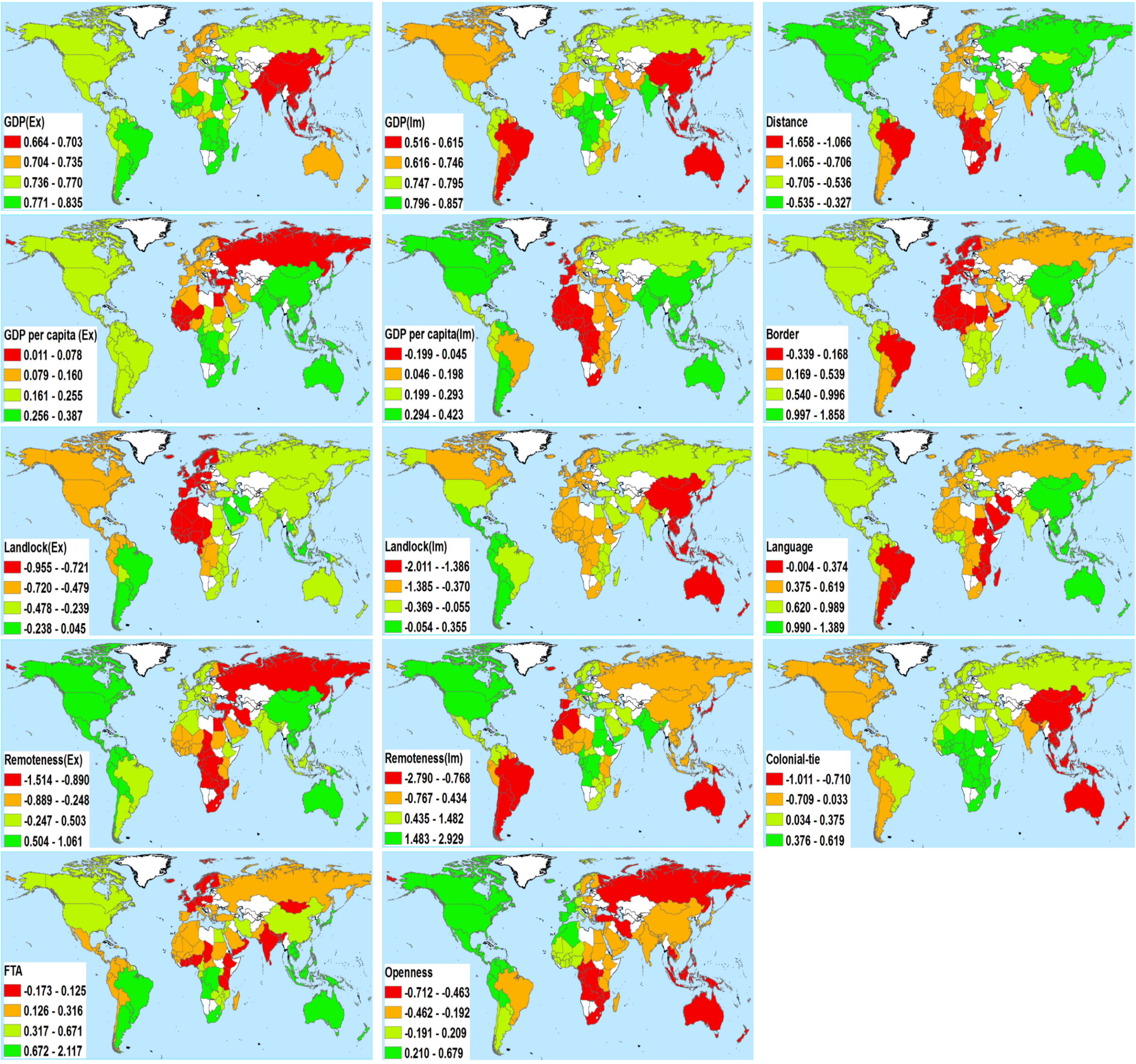

Fig. 12. GWPR results based on importer's locations

Note: Ex and Im denote exporter and importer, respectively.