Country Image and International Trade*

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Abstract

We study the impact of country image on international trade flows. We find that a one percentage point increase in the positive response ratio—the proportion of people in the importing country who view the exporting country positively—is associated with at least a one percent increase in the aggregate trade flow. By disaggregating trade flows by the type of goods, we also find that both homogeneous and differentiated goods are positively affected by better country image and that the impact of country image tends to be larger when more substitutes are available in the international market.

1 Introduction

Country image, or the way in which a country is viewed by others, varies over time. For example, when France and Germany opposed the US-led Iraq War in early 2003, the trans-Atlantic relationship severely worsened. Miller (2003) reported that between February and April in 2003 French exports to the US dropped by 17 percent and American tourism tumbled by a quarter. In several parts of Germany, bars and restaurants refused to serve Coca-Cola, Budweiser beer, Marlboro cigarettes, and other renowned American brands (The Economist, 2003).

International politics plays an important role in the formation of country image, but other factors also matter. For example, a series of product scandals in China in recent years—such as the 2007 pet food recalls and the 2008 Chinese milk scandal where pet food and infant formula were contaminated with Melamine—have scared consumers across the world and damaged the country image of China. In Japan, consumers reacted particularly strongly to the 2008 incident of insecticide-contaminated dumplings from China. In a poll conducted right after the incident, 76 percent of Japanese said that they would not use Chinese food again (Agence France Presse, 2008).

These anecdotes indicate that country image may affect the flow of international trade. It is plausible that consumers obtain utility [disutility] from consuming the products of a country they view positively [negatively], which in turn may encourage [discourage] the imports from that country. Alternatively, country image may also affect the transaction cost of marketing a good in a foreign country. An exporter may find it more difficult to engage and establish a local distribution channel for its goods in an importing country where its country image is marred. However, some of the goods traded internationally, e.g., oil and precious metals, are produced in a limited set of countries. For these goods, consumers or importers may find it difficult to avoid imports from a country they view negatively. This suggests that the impact of country image is likely to vary across different types of goods.

Built on Anderson and van Wincoop (2003), we derive a gravity equation disaggregated by the type of goods. We then derive estimation equations for both aggregate and disaggregate trade flows in a manner consistent with the theory. We find that country image significantly affects international trade flows both economically and statistically. A one percentage point increase in the positive response ratio, or the proportion of people in the importing country who view the exporting country positively, is associated with at least a one percent increase in the aggregate bilateral trade flow. We also find that country image positively affects both homogeneous and differentiated goods. However, the magnitude of impact tends to be larger in a sector where substitutes are more widely available in the international market.

This paper is organized as follows: In Section 2, we review the related literature and highlight our contributions. In Section 3, we discuss the theoretical model and econometric specifications. In Section 4, we describe the data. Section 5 presents the estimation results and Section 6 concludes.

2 Review of Related Literature

This study is related to three strands of literature. First, it is related to the boycott literature because boycott tends to take place when country image severely worsens. For example, Michaels and Zhi (2010) argue that the worsening US-French relationship during the Iraq War led to a reduction of bilateral trade by about 9 percent. Chavis and Leslie (2009) look at the impact of the US boycott of French wine and find that the boycott resulted in 26 percent lower weekly sales at its peak and 13 percent lower sales over the six months of boycott.

Some boycott studies, however, find no significant effects. For example, Ashenfelter et al.

(2007) find that the US boycott of French wine had no effect once the cyclical peak at holiday time and secular decline in the sales of French wine in the US are taken into account. Similarly, Teoh et al. (1999) find that the boycott of South Africa's apartheid regime had little valuation effect on the financial sector.

Covering all industries in all the major economies, we extend the boycott literature by studying the impact of country image in a general context. We find that the impact is both economically and statistically significant. This indicates that, even in the absence of visible events such as boycotts, country image affects the real economy.

Second, this study is also related to the literature on the role of social capital and networks in international trade, because country image is likely to be related to the social capital and networks among the trading partners. For example, Rauch and Trindade (2002) find that the presence of ethnic Chinese networks increases bilateral trade flows of differentiated goods among Southeast Asian countries by nearly 60 percent. Rauch (2001) provides a survey on the role and importance of social networks in international trade.

Guiso et al. (2009) find that differences in the bilateral trust level among European countries have economically important effects on bilateral trade, foreign direct investment, and foreign portfolio investment. Their study suggests that perceptions rooted in culture are important determinants of economic exchange. Similarly, using the share of those in each EU15 member country who support the accession of each central and eastern European country to the EU, Disdier and Mayer (2007) find that bilateral affinity has a positive effect on trade flows.

This study is similar to Guiso et al. (2009) and Disdier and Mayer (2007) in the broad sense that we also study the effects of social capital on trade. However, our study utilizes country image, a measure not based on a specific event such as the EU accession. Instead of focusing on Europe, we include a wide range of countries in our analysis. Our results show that the importance of public opinion is fairly general.

In addition, this study extends Disdier and Mayer (2007) and Guiso et al. (2009) in two aspects: In one aspect, we examine both aggregate and disaggregate trade flows in a way consistent with the theoretical model. In the other aspect, we allow for the possibility of reverse causality. Reverse causality is potentially important because the increased level of trade flow could alter the country image and other indicators of public opinion. For example, if the imports from a particular country are considered useful and of good quality, the image of that country may improve as a result of increased trade flow. On the other hand, when an increased level of trade flow leads to trade frictions, the country image may worsen as a result. These types of reverse causalities in the present context cannot be satisfactorily dealt with by time-invariant instrumental variables (IVs), as done in Guiso et al. (2009). With a panel dataset, we address this issue by time-varying IVs. We also carry out panel Granger-causality tests to verify the absence of reverse causality.

Third, this study is also related to the marketing literature on country of origin and foreign products. A large number of studies have consistently found that the country of origin influences the consumers' perception of the product involved (See, for example, Bilkey and Nes (1982)). Consumers may attach symbolic and emotional values to the country of origin of a product and hold social and personal norms related to the country of origin (Obermiller and Spangenberg, 1989; Verlegh and Steenkamp, 1999). As a result, consumers may avoid buying products from a country regardless of their quality evaluation.

For example, Klein et al. (1998) find that Chinese consumers in general view Japanese goods positively regardless of their levels of animosity towards Japan, but those with stronger animosity towards Japan tend to avoid buying Japanese products. Similarly, Nijssen and Douglas (2004) find that Dutch consumers with stronger animosity towards Germany tend to be more reluctant to buy German products. These studies show that the war animosity, or the animosity due to past military aggression, is more important than the economic animosity, which may arise from the inflow of foreign products. These findings are consistent with the results of our study: as will be shown, the impact of country image comes mainly from the cross-sectional variations, which may have reflected the history of war and diplomatic tensions across countries.

3 Gravity Model

Overview of the Gravity Model

To estimate the impact of country image on international trade flows, we adopt the gravity model. The use of the gravity model for international trade started in the 1960s with Tinbergen (1962) and Pöyhönen (1963). Since then, the gravity model has been routinely used in the international trade literature to study the effects of various factors on trade flows, including the impact of international trade agreements (Rose, 2004; Chang and Lee, 2011), currency unions (Rose, 2000; Glick and Rose, 2002), border effects (McCallum, 1995; Anderson and van Wincoop, 2003), trust (Guiso et al., 2009), and likelihood of war (Martin et al., 2008).

The development of economic theory that justifies the gravity model lagged behind the early success of its empirical applications. Anderson (1979) is the first to provide a rigorous microeconomic foundation for the gravity equation under the constant elasticity of substitution (CES) preferences. Various theoretical justifications have been made since then, including Bergstrand (1985, 1989, 1990), Deardorff (1998), and Anderson and van Wincoop (2003). In this paper, we consider a straightforward extension of Anderson and van Wincoop (2003) by allowing for heterogeneous impacts across different types of goods. In our application, we first categorize goods into homogeneous and differentiated goods following Rauch (1999). We then disaggregate goods at the level of six-digit Harmonized System (HS) product codes.

When deriving an estimable equation, Anderson and van Wincoop (2003) impose a symmetric structure of trade resistance. A logical consequence of the symmetry assumption is that the value of bilateral exports is equal to the value of bilateral imports in each country with each trading partner. This appears to be a problematic assumption in this study, because our dataset includes country pairs with large bilateral trade imbalances such as the China-US and Japan-US pairings. Furthermore, the symmetry assumption is inappropriate in our application because a worsening of the exporting country's image in the importing country does not necessarily coincide with a worsening of the importing country's image in the exporting country. Therefore, we derive the empirical gravity equations without the symmetry assumption.

Derivation of the Gravity Equation

Assume that there are N countries and K types of goods in the economy. We denote the exporting country by i and importing country by j, where $i, j \in \{1, \ldots, N\}$. We use the subscript $k \in \{1, \ldots, K\}$ to denote the type of the good.

Let $c_{ij\tau k}$ be the quantity of the type-k goods exported from country i and consumed by country j's consumers in year τ. We assume that consumers have Cobb-Douglas preferences for different types of goods exported from a given country i, which are represented by parameter $\alpha_{ik}(> 0)$ with $\sum_k \alpha_{ik} = 1$ for all i.

Next, denote the producer price in the exporting country by $p_{i\tau k}$ and the corresponding consumer price in the importing country by $p^c_{ij\tau k}$. We assume that these prices are related by $p^c_{ij\tau k} = t_{ij\tau k} p_{i\tau k}$, where $t_{ij\tau k}$ is the bilateral trade resistance term for the trade flow of type-k goods from country i to country j in year τ.

As with Anderson and van Wincoop (2003), we make the Armington assumption and consider a system of CES preferences with respect to the goods produced by different countries of origin. Thus, consumers in country j solve the following maximization problem:

$$\max \left[\sum_i \beta_{ij}^{\frac{1-\sigma}{\sigma}} \left[\prod_k c_{ij\tau k}^{\alpha_{ik}} \right]^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \quad \text{s.t.} \quad y_{j\tau} = \sum_i \sum_k p^c_{ij\tau k} c_{ij\tau k}, \tag{1}$$

where β_{ij} is the taste parameter, $\sigma(> 1)$ the elasticity of substitution across sources of imports, and $y_{j\tau}$ the national income in country j in year τ. Because our model is closed in each year, we fix the time at year τ and drop the subscript τ for the time being to simplify the presentation.

Denote the aggregate trade resistance for the trade flow from country i to country j by $T_{ij} \equiv \prod_k [t_{ijk}]^{\alpha_{ik}}$ and the combined taste-trade-resistance term by $\omega_{ij} \equiv \beta_{ij} T_{ij}$. Solving eq. (1), we have:[1]

$$c_{ijk} = \frac{\alpha_{ik} y_j}{p^c_{ijk}} \cdot \left[\frac{\omega_{ij} P_i}{\Pi^0_j} \right]^{1-\sigma}, \quad \text{where} \quad P_i \equiv \prod_k [p_{ik} \alpha_{ik}^{-1}]^{\alpha_{ik}} \quad \text{and} \quad \Pi^0_j \equiv \left[\Sigma_i [\omega_{ij} P_i]^{1-\sigma} \right]^{\frac{1}{1-\sigma}}. \tag{2}$$

P_i is a producer price index for exports from country i and Π^0_j is the 'inward' multilateral resistance for importing country j, which can be considered a consumer price index for its

[1] Derivation is provided in Appendix A.1.

imports.

Let the world income be $y_w \equiv \sum_j y_j$, the income share of country j be $s_j \equiv y_j/y_w$, and the value of type-k goods imported from country i evaluated at the consumer price be $C_{ijk} \equiv p^c_{ijk} c_{ijk}$. Using the market-clearing condition, $y_i = \sum_j \sum_k C_{ijk}$, we have the following equations:[2]

$$\Pi^0_j = \left[\sum_i s_i \left[\frac{\omega_{ij}}{\Pi^1_i} \right]^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \text{ with } \Pi^1_i \equiv \left[\sum_j s_j \left[\frac{\omega_{ij}}{\Pi^0_j} \right]^{1-\sigma} \right]^{\frac{1}{1-\sigma}}, \text{ and} \tag{3}$$

$$z^c_{ijk} \equiv \frac{C_{ijk}}{y_i y_j} = \frac{\alpha_{ik}}{y_w} \cdot \left[\frac{\omega_{ij}}{\Pi^0_j \Pi^1_i} \right]^{1-\sigma}, \tag{4}$$

where z^c_{ijk} is the trade flow normalized for the size of the two trading countries and Π^1_i is the 'outward' multilateral resistance for exporting country i, which can be considered a consumer price index for its exports. Eq. (4) is the gravity equation disaggregated by the type of goods. By setting $K = 1$ (and thus $\alpha_{i1} = 1$), assuming taste homogeneity (i.e., $\beta_{ij} = \beta_i$ for all j) and symmetric bilateral trade barriers (i.e., $t_{ij1} = t_{ji1}$), and rearranging the terms, eq. (4) reduces to the gravity equation eq. (13) in Anderson and van Wincoop (2003).

Econometric Specification

As noted earlier, Anderson and van Wincoop (2003) assume that the bilateral trade resistance is symmetric (i.e., $T_{ij} = T_{ji}$ for all i and j). They make this assumption in view of the fact that the trade flow satisfying eq. (4) can be explained by a set of alternative trade resistance terms $\tilde{T}_{ij} \equiv \lambda_i \theta_j T_{ij}$ and price indices $\tilde{P}_i \equiv P_i/\lambda_i$ with exporter- and importer-specific positive scalars λ_i and θ_j.[3] As a result, one cannot empirically distinguish (T_{ij}, P_i) and $(\tilde{T}_{ij}, \tilde{P}_i)$.

However, this observation does not imply that asymmetric inference is not possible. The scaling factors can be absorbed by introducing exporter- and importer-specific fixed effects, and so long as there are variations in T_{ij} after the control, we can still identify the effect of factors that affect trade flows asymmetrically (See also Baier and Bergstrand (2009)).

Anderson and van Wincoop (2003) suggest two approaches to estimate eq. (4) under the

[2]Derivation is provided in Appendix A.2.

[3]Correspondingly, let $\tilde{\omega}_{ij} \equiv \lambda_i \theta_j \omega_{ij}$ and define $\tilde{\Pi}^0_j$ and $\tilde{\Pi}^1_i$ as Π^0_j and Π^1_i with ω_{ij} and P_i replaced by $\tilde{\omega}_{ij}$ and $\tilde{P}_i$ in their definitions, respectively. Then, we can rewrite eq. (4) as $z^c_{ijk} = \frac{\alpha_{ik}}{y_w} \cdot \left[\frac{\tilde{\omega}_{ij}}{\tilde{\Pi}^0_j \tilde{\Pi}^1_i} \right]^{1-\sigma}$.

symmetry assumption, which implies $\Pi_i^0 = \Pi_i^1$ for all i. One approach is to estimate this by a non-linear least squares (NLS) regression. The NLS approach requires solving the equilibrium MR term Π^0, which in turn requires the observations of the determinants of bilateral trade resistance for *all* countries. This is problematic because we do not have country image data for a large number of country pairs (i, j). Therefore, we do not adopt the NLS approach.

The other approach Anderson and van Wincoop (2003) suggest is to model the multilateral resistance $\Pi^0(= \Pi^1)$ as fixed effects. We adopt a similar approach, but because we do not assume symmetry, we distinguish between the importer- and exporter-specific fixed effects for each country. This two-way fixed-effects estimation is attractive because we do not need the information about the third-party countries not included in the data.

Although a change in country image could conceptually affect the taste parameter β_{ij} as well as the bilateral trade resistance T_{ij}, eq. (4) clearly shows that we cannot distinguish their changes separately in trade flows, because they affect z_{ijk}^c jointly through the combined taste-trade-resistance term ω_{ij}. To operationalize the estimation and simplify the exposition, we hereafter maintain the following taste-homogeneity assumption: $\beta_{ij} = \beta_i$ for all j (see also Anderson and van Wincoop (2003)). By making this assumption, we operationally ascribe the effects of country image (and other covariates) to the change in the bilateral trade resistance.[4] In the aggregate analysis, this taste-homogeneity assumption is innocuous, because we could always reinterpret the effect estimate obtained under the assumption as the combined effect of tastes and trade resistance when the assumption is relaxed. In the disaggregate analysis, however, this equivalence does not hold in some estimation equations, where the effect estimate identified can only be interpreted as the the effect of covariates on trade resistance per se.

To derive an estimation equation for eq. (4), we bring back the time subscript τ into the equations. We hypothesize that the trade resistance term can be modelled in the following manner:

$$t_{ij\tau k} = \exp\left[-\sum_l \gamma_{kl}^0 x_{ij\tau}^l - \eta_{i\tau}^0 - \delta_{j\tau}^0\right], \tag{5}$$

where $x_{ij\tau}^l$ is the l-th covariate that may affect the trade resistance for the trade flow with $l \in \{1, \ldots, L\}$. The fixed-effects terms $\eta_{i\tau}^0$ and $\delta_{j\tau}^0$ are specific to the exporter and the importer

[4] With the assumption $\beta_{ij} = \beta_i$, the common factor β_i in ω_{ij} and Π_i^1 cancels out in eq. (4), leaving $\omega_{ij} = T_{ij}$.

in each year, respectively. We estimate the parameter γ^0_{kl} or its transformation. In this formulation, the bilateral resistance is determined by the country-specific factors in importing and exporting countries as well as the bilateral characteristics $x^l_{ij\tau}$, all of which may vary over time.

Plugging eq. (5) into the gravity equation eq. (4), taking a logarithm, and adding an error term $\epsilon_{ij\tau k}$ and time subscripts, we have the following estimation equation:[5]

$$\ln z^c_{ij\tau k} = \sum_l \sum_{k'} \gamma_{k'l}\alpha_{ik'}x^l_{ij\tau} + a_{ik} + \eta_{i\tau} + \delta_{j\tau} + \epsilon_{ij\tau k}, \tag{6}$$

where $a_{ik} \equiv \ln \alpha_{ik}$, $\eta_{i\tau} \equiv -\ln y_{w\tau} + [\sigma - 1][\eta^0_{i\tau} + \ln \Pi^1_{i\tau} - \ln \beta_i]$, $\delta_{j\tau} \equiv [\sigma - 1][\delta^0_{j\tau} + \ln \Pi^0_{j\tau}]$, and $\gamma_{kl} \equiv [\sigma - 1]\gamma^0_{kl}$. It is straightforward to verify that eq. (6) remains valid if we relax the taste-homogeneity assumption and replace the LHS of eq. (5) by $\beta_{ij\tau}t_{ij\tau k}$. Thus, the parameters can be interpreted generally to incorporate both the effect on taste and on trade resistance, as argued earlier.

Eq. (6) shows that asymmetric inference is indeed possible, because any scaling factors, λ_i and θ_j, will be completely absorbed by the exporter- and importer-specific dummy variables. As long as $x^l_{ij\tau}$ varies over ij asymmetrically, the parameter γ can be identified.

To derive the aggregate estimation equation, we assume that $\gamma_{kl} \equiv \gamma_l$ holds for all k. Under this assumption, we can take a summation of eq. (4) over k to arrive at the following equation:[6]

$$\ln z^c_{ij\tau} = \sum_l \gamma_l x^l_{ij\tau} + \eta_{i\tau} + \delta_{j\tau} + \epsilon_{ij\tau}. \tag{7}$$

We estimate eq. (7) by a two-way fixed-effects regression. Notice that this estimation equation is different from Anderson and van Wincoop (2003), because the exporter fixed effect η is allowed to be different from the importer fixed effect δ for each country. As a result, we have a total of $2N - 1$ dummy variables in a cross-section regression (instead of $N - 1$ as in Anderson and van Wincoop (2003)).[7]

[5] To simplify the presentation, we use ϵ as the non-systematic part of the dependent variable. Therefore, ϵ in each estimation equation does not necessarily have the same definition.

[6] There are two other ways to derive eq. (7): First, simply letting $K = 1$ and dropping subscripts k, we have eq. (7). Second, if we let $\alpha_{ik} = \alpha_k$ for all i and $\gamma_l \equiv \sum_k \alpha_k \gamma_{kl}$, we again have eq. (7).

[7] Because the number of importing countries differs from that of exporting countries and because they vary over years in our data, we adjust the number of dummy variables appropriately in the actual estimation.

We also verify our aggregate estimates with the first-order log-linear approximation to Π_j^0 and Π_i^1 proposed by Baier and Bergstrand (2009), which also allows for asymmetric trade resistance. To accommodate the panel data structure, we add a year-specific fixed-effect term. Therefore, the approximated estimation equation has the following form:[8]

$$\ln z_{ij\tau}^c = \sum_l \gamma_l \tilde{x}_{ij\tau}^l + \iota_\tau + \epsilon_{ij\tau}, \tag{8}$$

where $\tilde{x}_{ij\tau}^l \equiv x_{ij\tau}^l - \sum_{i'} s_{i'\tau} x_{i'j\tau}^l - \sum_{j'} s_{j'\tau} x_{ij'\tau}^l$ is the l-th covariate adjusted for the multilateral resistance and $\iota_\tau \equiv -\ln y_{w\tau} + \sum_l \gamma_l \sum_i \sum_j s_{i\tau} s_{j\tau} x_{ij\tau}^l + 2[\sigma - 1] \ln \Pi_{1\tau}^0$ is modelled as a year-specific fixed effect. The adjustment term, $\sum_{j'} s_{j'\tau} x_{ij'\tau}^l$, measures the average trade resistance (in terms of x^l) for country i's exports weighted by the income shares of all its trading partners. The adjustment term for the importing country, $\sum_{i'} s_{i'\tau} x_{i'j\tau}^l$, has an analogous interpretation. Because we do not have observations for all countries, we use the sample average weighted by the sample income shares.

The log-linear approximation in eq. (8) is particularly useful when the model is extended to the context of dynamic panel estimation discussed in the Technical Appendix. This is because the number of regressors in eq. (8) is much smaller than that in eq. (7), which in turn allows us to avoid having too many moment conditions or arbitrarily dropping some moment conditions.

Estimating the disaggregated gravity equation eq. (6) is not as straightforward as estimating the aggregate gravity equations (7) and (8), because eq. (6) is a non-linear equation in α_{ik} ($a_{ik} \equiv \ln \alpha_{ik}$). If we treat $\eta_{i\tau}$ and $\delta_{j\tau}$ as fixed effects, the number of parameters to be estimated becomes too large for estimation methods that involve numerical maximization such as non-linear least squares and maximum likelihood estimation. Therefore, we adopt the Iterated Linear Least Squares (ILLS) estimator proposed by Blundell and Robin (1999), which exploits the conditional linearity of the estimation equation. In our application, when we have a "guess" of α_{ik}, we can treat $\alpha_{ik} x_{ij\tau}^l$ as regressors and run a two-way fixed-effects least-squares regression. This in turn allows us to find a new estimate of a_{ik}, which allows us to "update" the value of α_{ik}. The iteration continues until convergence is attained.[9]

[8]The derivation is given in Appendix A.3.

[9]The asymptotics adopted by Blundell and Robin (1999) do not apply to our data, because the number of regressors increases as N or T increases. However, the estimator can be justified as a first-order approximation near the true parameter value. We provide the derivation of the ILLS estimator based on this approach and

A few observations are worthwhile to note regarding the estimation of eq. (6). First, note that γ's have to be estimated jointly across sectors, as the trade flow in one sector depends on the trade resistance of all sectors. This is in contrast with the typical practice of estimating the gravity equation separately for each sector. Second, note that the identification of γ_{kl} is possible due to the variation introduced by the interaction between the covariates $x_{ij\tau}$ and the parameters α_{ik}, and not due to the variation over k within $ij\tau$ combinations, as the systematic part of that variation would be completely absorbed by a_{ik}.

We can avoid the difficulty associated with the non-linear estimation of eq. (6) by directly estimating γ^0. This can be achieved by exploiting the difference between the normalized trade flows evaluated at the producer price ($z^p_{ij\tau k} \equiv z^c_{ij\tau k}/t_{ij\tau k}$) and the consumer price ($z^c_{ij\tau k}$). Taking their log difference gives us the following estimation equation:

$$(-\ln t_{ij\tau k} =) \ln z^p_{ij\tau k} - \ln z^c_{ij\tau k} = \sum_l \gamma^0_{kl} x^l_{ij\tau} + \eta^0_{i\tau} + \delta^0_{j\tau} + \epsilon_{ij\tau k}, \tag{9}$$

where the dependent variable reflects the gap between the producer and consumer prices and measures the 'lack of trade resistance.' It is clear that by using estimation equation (9), we can only identify the effect of covariates on bilateral trade resistance, unlike estimation equation (6), whose parameter estimates can potentially be reinterpreted to incorporate effects on tastes as well. In any case, eq. (9) holds irrespective of the taste-homogeneity assumption.

Finally, we can also derive the following estimation equation by substituting eq. (6) in eq. (9):

$$\ln z^p_{ij\tau k} = \sum_l \gamma^0_{kl} x^l_{ij\tau} + a_{ik} + \psi_{ij\tau} + \epsilon_{ij\tau k}, \tag{10}$$

where $\psi_{ij\tau} \equiv \sum_l \sum_{k'} \gamma_{k'l} \alpha_{ik'} x^l_{ij\tau} + \eta_{i\tau} + \delta_{j\tau} + \eta^0_{i\tau} + \delta^0_{j\tau}$. The taste-homogeneity assumption again is not necessary in deriving this estimation equation, as the fixed effect term $\psi_{ij\tau}$ will absorb any variation in $\beta_{ij\tau}$. This estimation equation can be estimated with two-way fixed effects, where the first set of fixed effects is determined by the combination of the exporting country and the type of goods, and the second set by the combination of the exporting country, importing country, and year. Similar to eq. (9), this estimation equation identifies only the effect of covariates on bilateral trade resistance. On the other hand, because this estimation

present the expressions for the point estimate and variance matrix in Appendix A.4.

relies only on z^p, and because various errors are absorbed by $\psi_{ij\tau}$, we expect this specification to be more robust than eq. (9). The shortcoming of the specification, however, is that, using the first type as the reference type, we can only identify the relative impact $\gamma^0_{kl} - \gamma^0_{1l}$ but not the absolute impact. We discuss additional issues regarding the estimation of eqs. (6), (9), and (10) in Section 5.

4 Data

We use the United Nations Commodity Trade Statistics Database (UN COMTRADE) for disaggregated trade flows. It records trade flows at the level of six-digit Harmonized System (HS) product codes. We take the data for aggregate trade flows from the Direction of Trade (DOTS) statistics maintained by the International Monetary Fund. The DOTS dataset is useful for aggregate analysis because it fills in missing data for some country pairs and years with estimates. The trade flows are all expressed in current US dollars. For y_i, we use the Gross Domestic Product also in current US dollars taken from the World Development Indicators. Following the empirical gravity literature, we have compiled a typical list of proxies for trade resistance. These include physical and genetic distance between trading partners, their colonial and language ties, and their status in regional or multilateral trade agreements.

To measure country image, we use the BBC World Opinion Poll (WOP) data for years 2005-2011. The data contain the positive [negative] response ratio $PS_{ij\tau}$ [$NG_{ij\tau}$], which represents the proportion of respondents in country j who said at the beginning of year τ that country i has a mainly positive [negative] influence in the world. For most records (country-pair-years), we also have the neutral response ratio $NU_{ij\tau}$ and the proportion $NA_{ij\tau}$ of respondents who gave no answer or said "don't know".[10] We define the valid response ratio $RS_{ij\tau}$ as the sum of the positive, negative, and neutral response ratios.[11]

As shown in the Data Appendix, the set of evaluating and evaluated countries in the original WOP data varies substantially over years. We restrict our analysis to a subsample of countries that appear most frequently to have a stable set of countries. Having a stable set of countries in the sample helps us to avoid attributing the effects of sampling variations to the covariates

[10]Neutral responses include "neither" and "depends".

[11]Therefore, $RS_{ij\tau} \equiv PS_{ij\tau} + NG_{ij\tau} + NU_{ij\tau} = 1 - NA_{ij\tau}$.

Table 1: The number of evaluating and evaluated countries and their GDP and population shares in the restricted sample.

Year	Evaluated Country			Evaluating Country		
	# Country	% GDP	% Pop	# Country	% GDP	% Pop
2005	6	46.4	29.4	10	66.2	52.5
2006	9	57.7	49.2	10	57.0	51.4
2007	10	56.8	49.2	9	56.5	50.2
2008	12	62.1	55.1	11	63.7	52.0
2009	13	66.1	55.4	9	62.2	48.9
2010	13	66.1	55.3	11	65.2	54.1
2011	13	—	—	11	—	—

in the estimation of eq. (8), because the multilateral resistance terms are approximated by the corresponding sample averages. The restricted sample consists of the following 13 countries: Brazil, Canada, China, France, Germany, India, Iran, Israel, Japan, Pakistan, Russia, the United Kingdom, and the United States.[12] Table 1 shows that the GDP shares for the evaluated and evaluating countries in the Gross World Product (GWP) are reasonably stable in the restricted sample. Because only 0.5 percent of records in the restricted sample have zero trade flows in the DOTS dataset, we ignore the complications due to zero trade flows. Further details of the data used in this study are given in the Data Appendix.

Figure 1 provides an overview of the evaluation of countries in the restricted sample. The left-hand-side [right-hand-side] of the figure reports the average positive response ratio $\overline{PS}_{i \cdot \tau}$ [$\overline{NG}_{i \cdot \tau}$], where the averages are taken over the evaluating countries j without weights. Notice that the right axis is in the reverse order to facilitate comparisons. The figure shows that countries like Canada and Germany have a consistently good country image (i.e., the fraction of people who view these countries positively [negatively] is larger [smaller] than other countries) over the observation period. On the other hand, some other countries, such as Iran and Pakistan, have a consistently poor country image.

While the ranking of countries in terms of $\overline{PS}_{i \cdot \tau}$ and $\overline{NG}_{i \cdot \tau}$ are quite stable over time, there are two notable exceptions, which may be related to the issues discussed in the introduction. First, the country image of the United States significantly improved since 2007. This coincides

[12] These countries appear at least 130 times as an evaluating or evaluated country. While North Korea also satisfies this criterion, we exclude it from our main analysis because we do not have reliable GDP figures and other key statistics for this country. No other country excluded from the restricted sample satisfies this criterion.

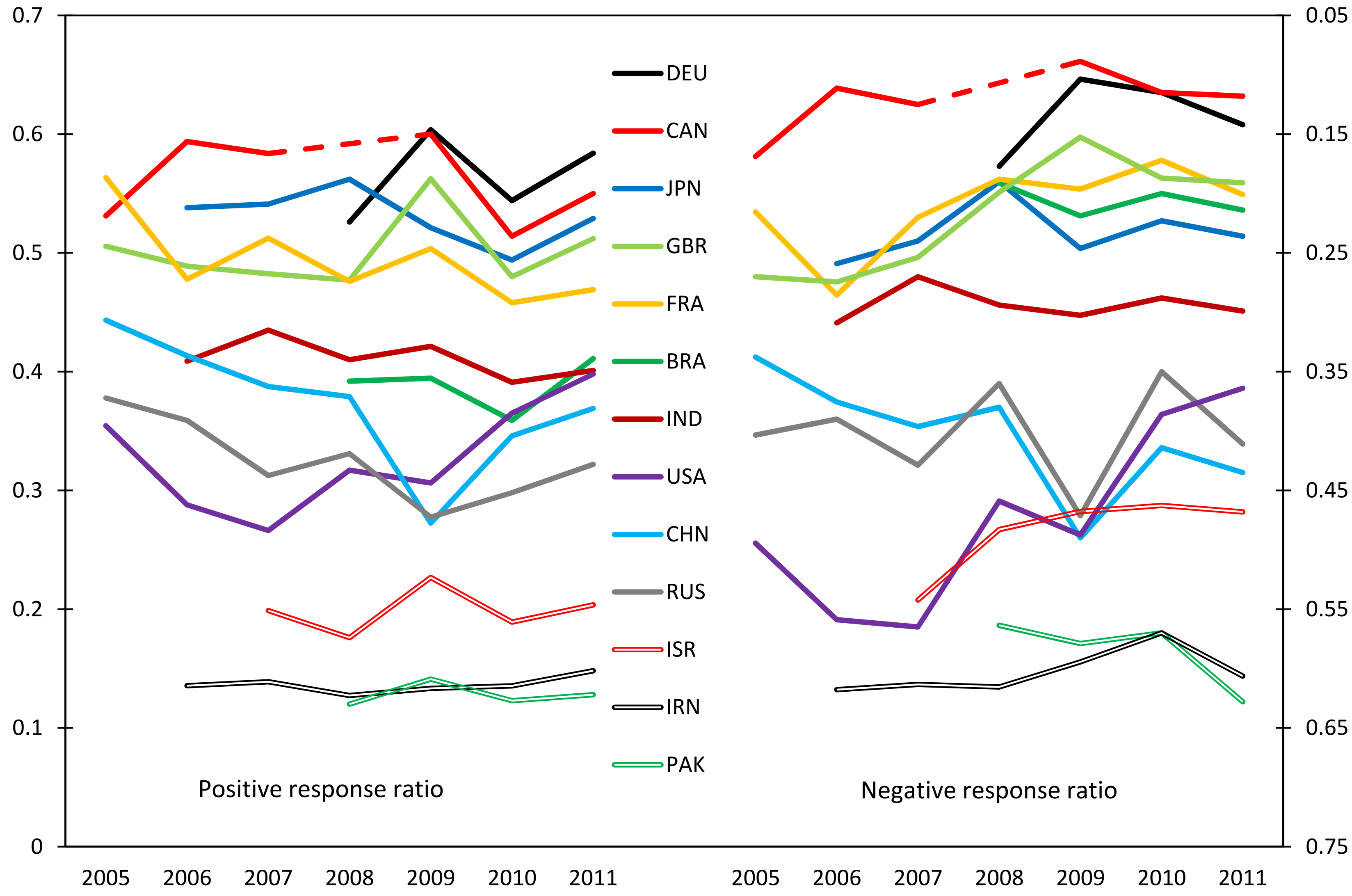

Figure 1: Average positive response ratio $\overline{PS}_{i\cdot\tau}$ and average negative response ratio $\overline{NG}_{i\cdot\tau}$ calculated with the restricted sample.

with the change of administration from Bush to Obama. Second, the country image of China hits the bottom in 2009, after which there is a sign of improvement. The turning point coincides with a decline in the reported cases of food scandals in China.[13]

To see how the negative and positive responses are related, we run three-way fixed effect regressions of $PS_{ij\tau}$ and $NG_{ij\tau}$, where the fixed effects are with respect to the evaluated country i, the evaluating country j, and the time τ. For both evaluating and evaluated countries, we take the United States as the base country. Figure 2 gives the estimated fixed effects for each evaluated and evaluating country using the whole sample. The countries that appear on the right of the vertical axis in Figure 2(a) [Figure 2(b)] tend to receive [give] a higher positive response ratio than the United States after controlling for the time fixed effect and the evaluating-country [evaluated-country] fixed effect. Similarly, the countries that appear above the horizontal axis tend to receive [give] a higher negative response ratio than the United States after controlling for the time fixed effect and the evaluating-country [evaluated-country] fixed effect.

Figure 2(a) suggests that countries with a high positive response ratio are those with a low negative response ratio. It also shows that, even after controlling for the evaluating-country fixed effect and time fixed effect, Canada and Germany have a better country image than others, while Iran and Pakistan have a worse country image than others. Note that all the points in Figure 2(a) are below the negative 45-degree line. This means that people in the surveyed countries tend to have a more non-neutral (positive/negative) view about the United States than they do about other countries. This may be because the United States is the most well-known country in the world.

In comparison, Figure 2(b) shows that most countries are less positive/negative than the United States towards other countries. However, some countries such as Finland, Germany, and Turkey tend to view other countries more negatively than the United States, whereas other countries such as Afghanistan and Senegal tend to view other countries more positively. The presence of these fixed effects, however, does not pose a problem to our estimation because the panel structure of the data allows us to control for them.

[13]We have used Factiva to count the number of articles that contain the words "China" and "food scandal" in major news and business publications. The number was over 150 between 2005 and 2008, but it dropped to 29 in 2009 and stayed below 50 until 2011.

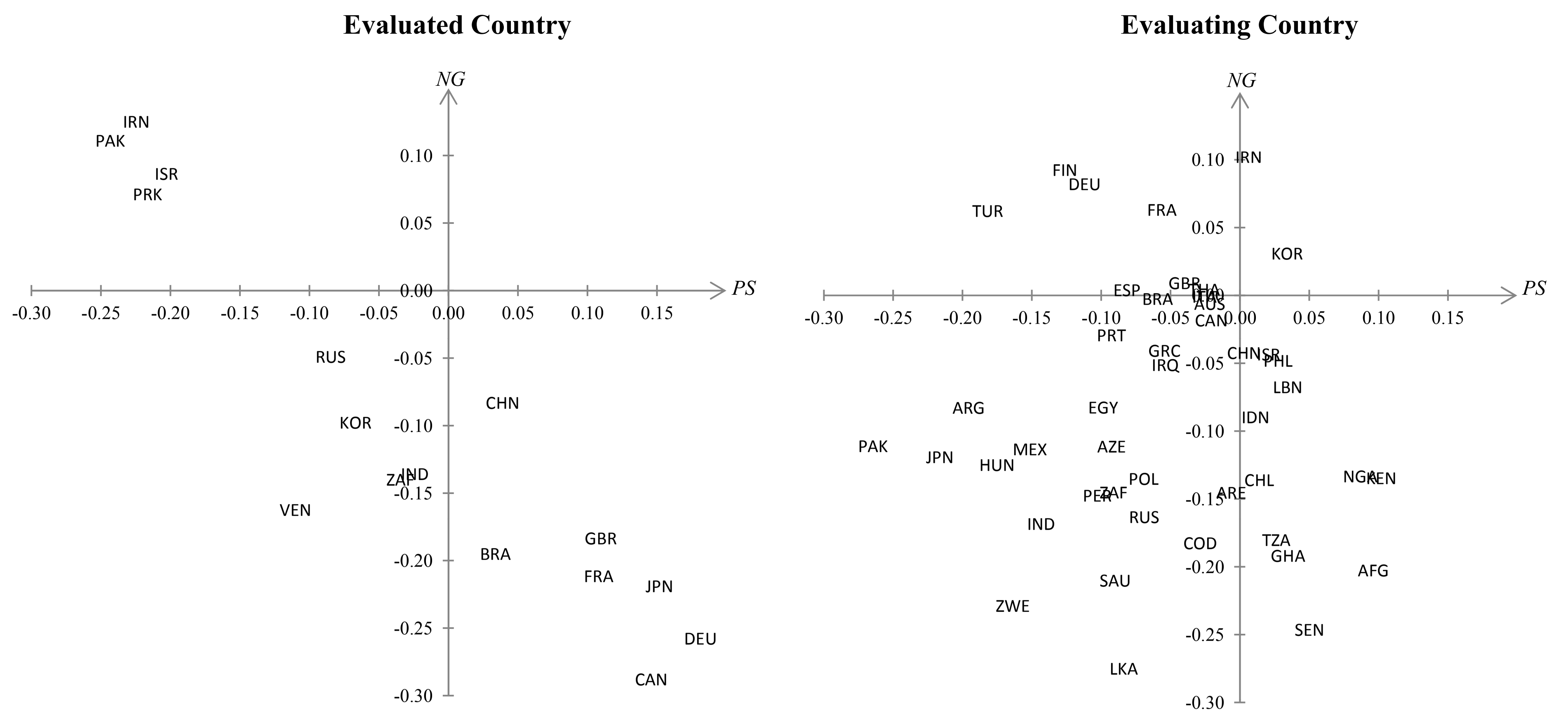

Figure 2: (a) Fixed effects for the evaluated countries (left) and (b) the evaluating countries (right) relative to the United States. The horizontal and vertical axes are the fixed effects for positive and negative response ratios, respectively.

In most of our estimations, we use the positive response ratio $PS_{ij\tau}$ as a measure of country image. This measure has the advantage that it can be readily interpreted as the approximate percentage change in trade flows in response to a one percentage point increase in $PS_{ij\tau}$. In Section 5, we consider a few alternative measures of country image and verify that the main results are robust to the choice of measure.

5 Results

Benchmark Specification

In the benchmark specification, we include a measure of country image ($CI_{ij\tau}$), the logarithmic distance between the two trading countries (LD_{ij}), and a constant in the set of regressors, where $CI_{ij\tau}$ is the evaluation of country i by country j in year τ. Except for robustness checks, we set $CI_{ij\tau} = PS_{ij\tau}$. We favor a parsimonious model, because an additional covariate increases the number of parameters in eq. (6) by the number of types of goods, which makes the IILS estimation difficult in the subsequent disaggregate analysis.

Table 2 presents the benchmark estimation results for aggregate trade flows with the restricted sample. The upper and lower panels of the table report the estimation results for aggregate trade flows based on eqs. (7) and (8), respectively.[14] The fixed-effects estimation reported in Column (2a) shows that an increase in positive response ratio by one percentage point is associated with a 1.5 percent increase in trade flow, which we treat as the baseline estimate. On the other hand, a one percent increase in distance is associated with a 0.7 percent decrease in international trade. The impact of the positive response ratio is both statistically and economically significant. The results based on the log-linear approximation approach proposed by Baier and Bergstrand (2009) are similar as reported in Column (2i).

In Columns (2b)-(2g) and (2j)-(2o), we report the estimations of eqs. (7) and (8) separately for each year. Their results are generally similar across years, although the estimates based on eq. (7) tend to be less significant, which is likely because of the large set of dummy variables used in these regressions. The estimates without including the fixed-effects terms are also similar as reported in Columns (2h) and (2p).

[14]Standard errors reported in this paper are robust standard errors unless otherwise stated.

Table 2: Benchmark regression results for aggregate trade flows based on eq. (7) (top) and eq. (8) (bottom). Restricted sample.

Year	2005-10	2005	2006	2007	2008	2009	2010	2005-10
Column	(2a)	(2b)	(2c)	(2d)	(2e)	(2f)	(2g)	(2h)
PS	1.53***	0.20	1.52*	1.67*	1.22	2.23***	2.00***	1.06***
	(0.32)	(0.50)	(0.81)	(0.91)	(0.77)	(0.83)	(0.72)	(0.22)
LD	-0.72***	-0.73***	-0.91***	-0.87***	-0.65***	-0.60***	-0.66***	-0.60***
	(0.04)	(0.07)	(0.11)	(0.10)	(0.09)	(0.09)	(0.08)	(0.04)
R^2	0.583	0.861	0.629	0.606	0.486	0.542	0.571	0.291
#Obs	577	54	81	83	120	108	131	577
Fixed Effects	$\eta_{i\tau}, \delta_{j\tau}$	η_i, δ_j	η_i, δ_j	η_i, δ_j	η_i, δ_j	η_i, δ_j	η_i, δ_j	No
Column	(2i)	(2j)	(2k)	(2l)	(2m)	(2n)	(2o)	(2p)
$\widetilde{PS}$	1.81***	1.33**	1.74**	1.94**	1.58**	1.91**	2.27***	1.90***
	(0.30)	(0.55)	(0.77)	(0.90)	(0.80)	(0.77)	(0.59)	(0.30)
$\widetilde{LD}$	-0.58***	-0.48***	-0.65***	-0.64***	-0.58***	-0.51***	-0.57***	-0.56***
	(0.05)	(0.13)	(0.12)	(0.12)	(0.12)	(0.11)	(0.10)	(0.05)
R^2	0.265	0.287	0.264	0.241	0.194	0.252	0.317	0.244
#Obs	577	54	81	83	120	108	131	577
Fixed Effects	ι_τ	No	No	No	No	No	No	No

Note: Standard errors in parenthesis. *, **, and *** indicate statistical significance at a 10%, 5%, and 1% level, respectively.

One obvious issue with a parsimonious model is that the estimates may suffer from omitted variable biases. Therefore, we also consider controlling for the contiguity of the two trading countries (CTG), whether the two countries are both island states (ILD), whether the two countries have a regional trade agreement (RTA), whether the two countries are both in the World Trade Organization (WTO), whether the two countries have ever had a colonial link (COL), whether the two countries share a common official language (LNG), whether the two countries share a common currency (CUR), and the genetic distance between plurality groups in the two countries (GEN). These covariates have been used and often found to be significant in the empirical trade literature.

In Table 3, we add one covariate at a time to the benchmark specification using eq. (8). None of these variables are consistently significant in the year-by-year regressions between 2005 and 2010, whereas PS is significant in most years. Further, the inclusion of the additional covariate does not affect the estimated coefficient on PS much. Using eq. (7) instead of eq. (8) does not alter this conclusion, either.[15] Thus, our main finding that the country image is an important determinant of trade flows remains valid. Consistent with the existing empirical literature, the logarithmic distance is highly significant and economically important in almost all specifications.

Instead of adding additional covariates one by one, we have also estimated a full model with all the additional covariates. Column (4a) and (4b) in Table 4 present the estimation results based on eqs. (7) and (8). The estimated coefficient on PS is still significantly positive and not significantly different from our baseline estimate of 1.5. Thus, even if the country image in the benchmark model may reflect the effects of some of the additional covariates such as common language and colonial ties, the effect of country image remains economically and statistically significant after controlling for these additional covariates.

Specification Tests and Robustness Checks

The gravity equation eq. (4) implicitly imposes a unit elasticity of trade flow with respect to each trading country's income. We relax this restriction by using $\ln C_{ij\tau}$ as the dependent

[15] See Table 9 in Appendix B.

Table 3: Estimation of the benchmark specification with one additional covariate based on eq. (8). Restricted sample.

Year	2005-10	2005	2006	2007	2008	2009	2010
$\widetilde{PS}$	1.85***	1.23*	1.79**	1.95*	1.68**	2.05**	2.23***
$\widetilde{LD}$	-0.59***	-0.44***	-0.69***	-0.65***	-0.62***	-0.56***	-0.56***
$\widetilde{CTG}$	-0.08	0.17	-0.17	-0.03	-0.22	-0.23	0.05
R^2	0.266	0.289	0.266	0.242	0.196	0.255	0.317
$\widetilde{PS}$	1.85***	1.35**	1.74**	1.95**	1.66**	1.93**	2.31***
$\widetilde{LD}$	-0.57***	-0.47***	-0.65***	-0.64***	-0.57***	-0.50***	-0.56***
$\widetilde{ILD}$	-0.53***	-0.61	-0.11	-0.11	-0.61	-0.69**	-0.69**
R^2	0.268	0.293	0.265	0.242	0.198	0.259	0.322
$\widetilde{PS}$	1.84***	1.38**	1.79**	2.02**	1.69**	1.89**	2.26***
$\widetilde{LD}$	-0.61***	-0.31	-1.14***	-0.76***	-0.63***	-0.49***	-0.57***
$\widetilde{RTA}$	-0.15	0.54	-1.72**	-0.45	-0.24	0.10	0.01
R^2	0.266	0.293	0.298	0.248	0.196	0.253	0.317
$\widetilde{PS}$	1.85***	1.56***	1.84**	1.98**	1.59**	2.00**	2.27***
$\widetilde{LD}$	-0.59***	-0.47***	-0.68***	-0.66***	-0.59***	-0.53***	-0.58***
$\widetilde{WTO}$	-1.11***	8.01	-0.79*	-1.03	-1.23**	-1.75***	-1.50***
R^2	0.275	0.317	0.274	0.250	0.203	0.277	0.331
$\widetilde{PS}$	1.75***	1.35**	1.63**	1.91**	1.61**	1.79**	2.21***
$\widetilde{LD}$	-0.60***	-0.46***	-0.68***	-0.68***	-0.61***	-0.54***	-0.60***
$\widetilde{COL}$	0.26**	-0.06	0.21	0.26	0.43*	0.25	0.28
R^2	0.269	0.287	0.267	0.245	0.203	0.256	0.321
$\widetilde{PS}$	1.68***	1.44**	1.70**	1.80*	1.36	1.67**	2.16***
$\widetilde{LD}$	-0.58***	-0.48***	-0.65***	-0.65***	-0.60***	-0.52***	-0.58***
$\widetilde{LNG}$	0.33**	-0.22	0.08	0.28	0.56*	0.54*	0.44
R^2	0.273	0.292	0.265	0.246	0.212	0.273	0.330
$\widetilde{PS}$	1.80***	1.26**	1.76**	1.93**	1.59*	1.86**	2.27***
$\widetilde{LD}$	-0.57***	-0.46***	-0.66***	-0.64***	-0.58***	-0.50***	-0.57***
$\widetilde{CUR}$	0.07	0.45	-0.27	0.11	-0.03	0.24	0.01
R^2	0.265	0.290	0.265	0.242	0.194	0.253	0.317
$\widetilde{PS}$	1.51***	1.16**	1.28*	1.58	1.22	1.70**	2.03***
$\widetilde{LD}$	-0.65***	-0.55***	-0.72***	-0.68***	-0.68***	-0.57***	-0.67***
$\widetilde{GEN}$	0.56***	0.77	0.63	0.40	0.60	0.37	0.63*
R^2	0.276	0.323	0.273	0.245	0.205	0.258	0.334
#Obs	577	54	81	83	120	108	131
Fixed Effects	ι_τ	No	No	No	No	No	No

Note: *, **, and *** indicate statistical significance at a 10%, 5%, and 1% level, respectively.

Table 4: Specification tests and robustness checks. Restricted Sample.

Column	(4a)	(4b)	(4c)	(4d)	(4e)	(4f)
PS^*	0.98***	1.29***	1.79***	0.63*	1.74***	0.77***
	(0.37)	(0.35)	(0.30)	(0.33)	(0.37)	(0.22)
LD^*	-1.07***	-0.89***	-0.58***	-0.65***	-0.73***	-0.64***
	(0.10)	(0.11)	(0.05)	(0.03)	(0.04)	(0.03)
CTG^*	-0.74***	-0.43***				
	(0.18)	(0.16)				
ILD^*	0.09	-0.34				
	(0.14)	(0.22)				
RTA^*	-0.03	-0.20				
	(0.16)	(0.18)				
WTO^*	-0.77**	-1.35***				
	(0.33)	(0.30)				
COL^*	0.25**	0.32**				
	(0.12)	(0.14)				
LNG^*	0.81***	0.44***				
	(0.13)	(0.15)				
CUR^*	0.26	0.35				
	(0.16)	(0.22)				
GEN^*	0.86***	0.98***				
	(0.15)	(0.22)				
$\ln y_i$			1.05***			
			(0.04)			
$\ln y_j$			1.00***			
			(0.05)			
Est. Eq.	eq. (7)	eq. (8)	eq. (8)	eq. (7)	eq. (7)	eq. (7)
R^2	0.640	0.315	0.748	0.811	0.598	0.848
#Obs	577	577	577	295	430	257
Fixed Effects	$\eta_{i\tau}, \delta_{j\tau}$	ι_τ	ι_τ	$\eta_{i\tau}, \delta_{j\tau}$	$\eta_{i\tau}, \delta_{j\tau}$	$\eta_{i\tau}, \delta_{j\tau}$
Instrumental Variables				$LSP_{ij\tau}$	$\overline{PS^*}_{ij\tau}$ $PS_{ij\tau-1}$	$LSP_{ij\tau}$ $\overline{PS^*}_{ij\tau}$ $PS_{ij\tau-1}$
Robust score χ^2 test				0.860	0.378	0.569
Robust OIR test					0.836	0.880

Note: Standard errors in parentheses. *, **, and *** indicate statistical significance at a 10%, 5%, and 1% level, respectively. $x^* = \tilde{x}$ for Columns (4b) and (4c), and $x^* = x$ for all the other columns. P-value is reported for the robust score χ^2 test of endogeneity and robust overidentification restriction (OIR) test.

variable and adding $\ln y_{i\tau}$ and $\ln y_{j\tau}$ as independent variables in eq. (8).[16] We find that the estimated coefficients on the logarithmic incomes are not significantly different from unity as shown in Column (4c). More importantly, the estimated coefficients on PS are robust to the unit-elasticity restriction.[17]

One potentially important issue in the estimation of eq. (7) is the endogeneity issue. We address this issue with IV estimations and Granger-causality tests. We identify the following three time-varying instruments for country image $PS_{ij\tau}$: the leadership support rate $LSP_{ij\tau}$, the country image from the previous year (i.e., $PS_{ij\tau-1}$) and the leave-one-out average (i.e., $\overline{PS}^{*}_{ij\tau} \equiv \sum_{j'\neq j} PS_{ij'\tau}/(N-1)$).

The leadership support rate $LSP_{ij\tau}$ measures the rate of approval of country i's leadership by country j. The WOP data suggests that the leadership plays an important role for the formation of country image. The negative view towards Iran and Pakistan around the world, for example, is not because most respondents have first-hand experience in these countries but because of their leadership. While leadership may play a pivotal role in promoting bilateral trade flows, its impact on trade flow is mainly through country image, a point for which we will provide some empirical support below. Thus, this variable would qualify as a candidate for a valid instrument. The country image in the previous year and the leave-one-out average can be good instruments because the former captures the recent attitude of country j towards country i, and the latter the current attitude towards country i in the rest of the world. Both are likely to be correlated with country j's current view of country i, but not directly affect the current bilateral trade flow between the two countries.

The two-stage least-squares estimates with some or all of these instruments are reported in Columns (4d)-(4f). We cannot reject the null hypothesis that the country image is exogenous by the robust score χ^2 test of endogeneity. In Columns (4e) and (4f), we cannot find evidence that the IV's used are invalid based on the robust test of overidentifying restrictions. These results are also consistent with our argument above that the impact of leadership on bilateral trade flows is mainly through the country image.

[16]The estimates based on eq. (7) are not influenced by this restriction because of the exporter-year- and importer-year-specific fixed-effect terms.

[17]This conclusion also holds when we run the regressions without time-specific fixed effects or separately for each year. Details of these regressions are given in Table 11 in Appendix B.

Table 5: Alternative measures of country image.

Column	(5a)	(5b)	(5c)	(5d)	(5e)	(5f)	(5g)	(5h)
$PS_{ij\tau}$							1.07***	0.99***
							(0.33)	(0.34)
$NNG_{ij\tau}$	1.55***							
	(0.31)							
$PS_{ij\tau}/RS_{ij\tau}$		1.40***						
		(0.29)						
$RS_{ij\tau}$		0.27						
		(1.26)						
$PS^E_{ij\tau}$			1.51***					
			(0.31)					
PS^{2011}_{ij}				1.87***	1.85***	0.91***		
				(0.33)	(0.30)	(0.21)		
$\Delta PS_{ij\tau}$				0.36	0.32	1.25***		
				(0.50)	(0.39)	(0.42)		
$PS_{ji\tau}$								0.35
								(0.34)
LD_{ij}	-0.75***	-0.73***	-0.71***	-0.70***	-0.70***	-0.60***	-0.74***	-0.74***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.06)	(0.06)
#Obs	577	568	577	561	561	561	120	120
R^2	0.584	0.583	0.592	0.594	0.580	0.298	0.892	0.894
Fixed Effects	$\eta_{i\tau}, \delta_{j\tau}$	$\eta_{i\tau}, \delta_{j\tau}$	$\eta_{i\tau}, \delta_{j\tau}$	$\eta_{i\tau}, \delta_{j\tau}$	$\eta_i, \delta_j, \iota_\tau$	ι_τ	$\eta_{i\tau}, \delta_{j\tau}$	$\eta_{i\tau}, \delta_{j\tau}$

Note: Standard errors in parentheses. *, **, and *** indicate statistical significance at a 10%, 5%, and 1% level, respectively.

In the Technical Appendix, we derive panel Granger-causality tests and a Wald specification test under the assumption of possible autocorrelation in ϵ and reverse causality (i.e., Granger-causality running from the normalized trade to the positive response ratio). Using lag orders of one, two, and three, we find no evidence of reverse causality or misspecification.[18] In sum, we find no evidence that the benchmark estimates suffer from an endogeneity bias.

Finally, we verify our conclusions with alternative measures of country image. In Column (5a), we replace $PS_{ij\tau}$ by the non-negative response ratio $NNG_{ij\tau} \equiv 1 - NG_{ij\tau}$ and find that the results are similar to the baseline estimates. It could be argued that those who give a negative response have some familiarity with the evaluated country but those who give no answer do not. Thus, it may make sense to use the conditional positive response ratio $PS_{ij\tau}/RS_{ij\tau}$ and the response ratio $RS_{ij\tau}$ separately. However, we find that the coefficient on $RS_{ij\tau}$ is insignificant as shown in Column (5b). On the other hand, the coefficient on $PS_{ij\tau}/RS_{ij\tau}$ is

[18]In contrast, the positive response ratio is found to Granger-cause trade flow when the lag-order is three.

positive and significant.

Because the country image is measured at the beginning of the year, it may not reflect important events during the year that affect the subsequent trade flows for that year. As a robustness check, we take the next-year positive response ratio $PS_{ij\tau+1}$ as a year-end measure of country image for the current year $PS^E_{ij\tau}(\equiv PS_{ij\tau+1})$. As Column (5c) shows, the coefficient on $PS^E_{ij\tau}$ is significant and positive. It is also quantitatively similar to the baseline estimate.

In Column (5d), we decompose the country image into the positive response ratio in year 2011, PS^{2011}_{ij}, and the deviation from it, $\Delta PS \equiv PS_{ij\tau} - PS^{2011}_{ij}$. They represent the cross-sectional and time-series variations in country image, respectively. We choose year 2011 as the base year because we do not use the trade flow for this year and almost all the country pairs in our restricted sample have an observation for this year. We find that most of the impacts come from the cross-sectional dimension after controlling for the multilateral resistance.

The results in Column (5d) do not imply that changes in the exporting country's *overall* image have no impact on trade flows, because the exporter-year fixed effect captures the impact of such changes. To investigate the importance of overall country image, we depart from the theory and replace $\eta_{i\tau}$ and $\delta_{j\tau}$ with the importer- and exporter-specific fixed-effect terms η_i and δ_j, respectively, and add a year-specific fixed-effect term ι_τ. The estimates under this specification, which are reported in Column (5e), are very similar to those in Column (5d). Only when we drop the importer- and exporter-specific effects does $\Delta PS_{ij\tau}$ become significant as reported in Column (5f). These results suggest that "country branding" is unlikely to have a discernible impact on trade flows at least in the short run unless the improvement in country image is substantial.

Thus far, we have assumed that country image matters for the importers but not for the exporters. However, how the exporting country views the importing country may also matter, because the exporters may not wish to deal with the countries they view negatively. To verify whether this is the case, we include $PS_{ji\tau}$ in the set of regressors, which is the evaluation of importing country j by exporting country i in year τ. However, the challenge is that our restricted sample is not a balanced sample in the sense that the sets of evaluated and evaluating countries do not match each year. To make a fair comparison between $PS_{ij\tau}$ and $PS_{ji\tau}$, we further restrict our sample to the five core countries in the WOP dataset—China, France, Russia, UK, and USA—for which we have observations of both $PS_{ij\tau}$ and $PS_{ji\tau}$ for each country pair since the beginning of the survey in 2005. As the estimates based on the benchmark specification reported in Column (5g) show, using the sample of five core countries does not alter our main results. In Column (5h), we report the estimates with both $PS_{ij\tau}$ and $PS_{ji\tau}$ included. The former is statistically significant but not the latter, providing no evidence of serious misspecification.

While we have focused on the restricted sample to avoid the confounding effects due to changes in the set of countries in the sample, our main finding remains true when the whole sample is used.[19] In conclusion, the positive effects of country image on trade flows found in the baseline estimates are robust and unlikely to be due to reverse causality or inappropriate choice of the measure of country image.

Disaggregation of the Impacts

We now evaluate the effects of country image allowing for heterogeneous impacts across different types of goods. We first consider the classification proposed by Rauch (1999). In his classification, goods with and without a reference price are classified as homogeneous (HOM) and differentiated (DIF) goods, respectively.[20] We follow his "conservative" definition, which minimizes the number of goods treated as homogeneous goods. Using a conversion table between the four-digit Standard International Trade Classification Rev. 2 used by Rauch (1999) and the six-digit Harmonized System (HS) product codes used in the UN COMTRADE trade flow dataset, we classify each HS product as homogeneous or differentiated. Trade flows are then aggregated by homogeneous and differentiated goods.

The estimation results with Rauch's classification are reported in Table 6. Columns (6a), (6b), and (6c) are based on estimation equations eqs. (6), (9) and (10), respectively. To estimate these equations, we measure $z^p_{ij\tau k}$ [$z^c_{ij\tau k}$] by the FOB [CIF] trade value reported by the exporting [importing] country where $k \in \{HOM, DIF\}$. Eq. (6) is estimated with the ILLS estimator and the reported standard errors are based on Blundell and Robin (1999).[21] Column (6a) gives

[19] See Table 10 in Appendix B.

[20] Rauch (1999) further divides homogeneous goods into those goods that are traded on organized exchanges and those that are not. Because we did not find significant difference between these two categories, we do not distinguish them in this study. Further discussion on Rauch's classification can be found in the Data Appendix.

[21] See also Appendix A.4.

Table 6: Regression with disaggregation of goods by the homogeneity of goods after Rauch (1999). Restricted Sample.

Column	(6a)	(6b)	(6c)
PS	2.66***	0.65***	
	(0.24)	(0.14)	
$PS \times DIF$	-2.62***	-0.42***	0.43*
	(0.31)	(0.14)	(0.25)
LD	-1.11***	-0.05***	
	(0.01)	(0.02)	
$LD \times DIF$	0.82***	-0.06***	0.07*
	(0.02)	(0.02)	(0.04)
Est. eq.	eq. (6)	eq. (9)	eq. (10)
#Obs	1128	1048	1080
R^2	0.659	0.338	0.894

Note: Standard errors in parenthesis.
*, **, and *** indicate statistical significance at a 10%, 5%, and 1% level, respectively.

an estimate of $\gamma_{kl}(= [\sigma - 1]\gamma_{kl}^0)$ whereas Column (6b) gives an estimate of γ_{kl}^0. Notice also that the coefficients based on eq. (10) reported in Column (6c) can be identified only relative to the reference type, which is the homogeneous goods in Table 6.

Before interpreting the results, it should be pointed out that there are at least five reasons why we expect discrepancies across the columns in Table 6 even after accounting for $\sigma - 1$. First, Columns (6a), (6c), and (6b) rely on the CIF trade value, FOB trade value, and the difference between them, respectively. This means that they are subject to different sources of measurement errors. In particular, the estimates in Column (6b) are subject to the reporting errors in both exports and imports. Such errors could arise not only from the accounting errors but also from the discrepancy in the timing of reporting. The timing issue may be particularly important for the estimation of the coefficient on PS because different types of goods may have different shipping times.

Second, we have derived the estimation equations assuming $\beta_{ij} = \beta_i$ for all j. However, this assumption may not hold in practice. As noted earlier, it is possible to relax this assumption when deriving eq. (6) by replacing the left-hand-side of eq. (5) with $\beta_{ij\tau}t_{ij\tau k}$. However, this essentially leads to the same estimation equation. As a result, Column (6a) captures the combined effects of taste and trade resistance. On the other hand, Columns (6b) and (6c) only capture the effects on trade resistance.

Third, the derivation of estimation equations eqs. (6) and (9) relies on the equality of the elasticity of substitution σ across countries.[22] However, the elasticity of substitution may vary across countries in practice, in which case these estimates are biased. On the other hand, the heterogeneity in the elasticity is absorbed by $\psi_{ij\tau}$ in eq. (10). Therefore, eq. (10) is robust to the potential heterogeneity in the elasticity of substitution.

Fourth, because we do not observe trade values at domestic producer prices in the data, we measure $z^p_{ij\tau k}$ by the FOB trade values. However, the domestic producer prices are likely to be different from the FOB prices in practice. Any discrepancy is particularly worrisome for the estimation of eq. (9), because the impact of covariates is identified essentially through the differences between the FOB and CIF prices.

That said, we believe that eq. (9) is still worth estimating for the following reason. If exporters find it more costly to carry out a transaction with a hostile country (i.e., an importing country that views the exporting country very negatively), the price difference between the domestic producer price and CIF price reflects the higher transaction cost. If the FOB price fully internalizes the transaction costs, our identification will not work, because the difference between the FOB and CIF prices provides no information about the transaction cost. However, it is likely that some of the transaction costs (e.g., the cost to find and negotiate with trading partners) are directly borne by the importer, in which case the insurance cost may partially reflect the transaction cost. This is because, in practice, the insured sum typically exceeds the CIF value of imports to cover indirect costs such as transaction costs and a fraction of the importer's expected profit. Thus, it is plausible that the difference in FOB and CIF prices reflects some of the transaction cost, which allows us to correctly identify the signs of the coefficients of interest.[23]

Fifth, estimation equations eqs. (6), (9) and (10) capture in fact different sources of variations in trade flow. As mentioned above, eq. (9) captures the price variations. On the other hand, eq. (10) relies on the quantity variations across types, because the fixed-effects term a_{ik} in eq. (10) captures the variations in domestic producer prices and $\psi_{ij\tau}$ captures the general

[22] This point can be easily verified by writing σ_j instead of σ in eq. (1).

[23] For example, suppose that the FOB price can be written as $p^F_{ij\tau k} \approx [p_{i\tau k}]^\kappa [p^c_{ij\tau k}]^{1-\kappa}$ for some $\kappa \in (0,1)$. Then, the left-hand-side of eq. (9) is approximately $-\kappa \ln t$ instead of $-\ln t$. We can, therefore, identify $\kappa\gamma^0_{kl}$ instead of γ^0_{kl}.

trade resistance between countries i and j in year τ. In contrast, eq. (6) captures both price and quantity variations across the combination of i, j, and τ.

With these points in mind, let us return to Table 6. While we are not aware of a theory directly linking country image and the homogeneity of goods, two competing effects can be expected. On one hand, if we believe that country image reflects similarities in tastes or the strength of informal ties between the two trading countries, country image would give a higher impact on differentiated goods than on homogeneous goods. This is because taste similarities may make the marketing of goods easier, and the informational gaps between two trading countries may be mitigated by the presence of complementary networks and social capital.

On the other hand, the presence of a reference price may indicate that the buyers of the product can easily find substitutes in the international market. If close substitutes produced in another country are widely available, the cost of favoring or boycotting the products of a particular country would be small. In this view, the (positive) impact of PS on differentiated goods is expected to be smaller than on homogeneous goods. Therefore, we can test these two competing hypotheses with the data.

In Columns (6a) and (6b), we see that the impact of country image on trade flows is positive and the impact of distance is negative for homogeneous goods. On the other hand, the impact of country image on differentiated goods is small and not significant. The trade flow of homogeneous goods increases by more than 2 percent when the positive response ratio increases by one percentage point. In contrast to Columns (6a) and (6b), the impacts of country image on differentiated goods are bigger than for homogeneous goods in Column (6c), although the coefficient on $PS \times DIF$ is only marginally significant.

Although instructive, the previous analysis may mask a high level of heterogeneity in the degree of substitutability within each of the two types of goods. Thus, we conduct the analysis at the six-digit HS level to look further into the relative importance of tastes/networks vis-à-vis substitutability. We measure the availability of substitutes in the international market for each six-digit HS product by the logarithmic number of countries exporting that product, $LNX_{\tau k}$. We let LNX interact with PS and LD and use the interaction terms as regressors.

Because we have too many different combinations of exporting countries and types at the six-digit HS level, the estimation of eq. (6) (with a_{ik}) is not feasible. For the same reason, we

Table 7: Regression with disaggregation of goods at the six-digit HS level.

Column	(7a)	(7b)	(7c)	(7d)
PS	0.58***	-0.32		
	(0.03)	(0.23)		
$PS \times DIF$	0.03	0.14	0.53***	0.42***
	(0.03)	(0.30)	(0.14)	(0.13)
$PS \times LNX$		0.21***		-0.02
		(0.05)		(0.28)
$PS \times DIF \times LNX$		-0.04		1.56***
		(0.07)		(0.24)
LD	-0.07***	0.03		
	(0.00)	(0.02)		
$LD \times DIF$	-0.09***	-0.09***	0.00	-0.89***
	(0.00)	(0.03)	(0.02)	(0.05)
$LD \times LNX$		-0.03***		0.23***
		(0.01)		(0.02)
$LD \times DIF \times LNX$		0.00		0.41***
		(0.01)		(0.03)
Est. eq.	eq. (9)	eq. (9)	eq. (10)	eq. (10)
#Obs	966792	966792	1147775	1147775
R^2	0.070	0.070	0.110	0.116

Note: Standard errors in parenthesis. *, **, and *** indicate statistical significance at a 10%, 5%, and 1% level, respectively.

slightly modify eq. (10) to enable the estimation. We first subtract the mean over j and τ from both dependent and independent variables (e.g., $x_{ij\tau k} - \sum_j \sum_\tau x_{ij\tau k}[NT]^{-1}$ instead of $x_{ij\tau k}$). We then regress the mean-subtracted dependent variable on the mean-subtracted independent variables with error terms clustered by the combination of j and τ.

Table 7 reports the estimation results with goods disaggregated at the six-digit HS level. Columns (7a) and (7b) based on eq. (9) measure the price effects of PS whereas Columns (7c) and (7d) based on eq. (10) capture the quantity effects of PS. As shown in Columns (7a), the coefficient on PS is positive and significant as with the corresponding aggregate estimate in Column (6b) in Table 6. However, the estimated coefficient on $PS \times DIF$ is not statistically significant, suggesting that the effect of PS on bilateral trade resistance—as measured by the difference between the FOB and CIF prices—does not differ between homogeneous and differentiated goods. The distance effects in Column (7a) are similar to those reported in Column (6b) in Table 6.

In Column (7b), we incorporate the measure of substitutability, LNX, to allow different degrees of substitutability within each broad category of HOM and DIF goods. Note that the point estimate (not reported) of the marginal effect of PS, including the main effect and the interaction effects, is significantly positive for an overwhelming majority of observations. In addition, the estimated coefficient on $PS \times LNX$ is positive and significant. Hence, when the market for a good is served by a larger number of exporters, the price effect of PS on that good tends to be bigger. Further, the coefficient on $PS \times DIF \times LNX$ is insignificant. This implies that the magnitude of the impact of country image through the price channel is primarily determined by the availability of substitutes and not by the presence of a reference price.

In Columns (7c) and (7d), we report the estimation results based on the modified eq. (10) described above. These columns show that the *quantity* of differentiated goods tends to respond more strongly to country image than homogeneous goods, suggesting the importance of the effects of tastes and network. The availability of substitutes is also an important determinant of the marginal impact of country image on the trade flow for differentiated goods as the estimated coefficient on $PS \times DIF \times LNX$ indicates. However, the same does not hold for homogeneous goods.

In conclusion, the availability of substitutes intensifies the positive effect of country image on trade. Its effect on differentiated goods via the quantity channel appears to be larger than on homogeneous goods, although its price effects are similar regardless of product differentiation.

6 Conclusion

In this paper, we have investigated the impact of country image on trade flows. The impact is significant both economically and statistically, and this finding is robust. In the majority of our estimates for aggregate trade flows, a one percentage point increase in the positive response ratio in the importing country is associated with a more than one percent increase in the bilateral trade flow. This is at least as large as the impact of a one percent change in the bilateral distance in most estimates. The impact of country image is mainly due to cross-sectional variations rather than time-series variations.

While our contribution is primarily empirical, we extend the gravity model and disaggregate the trade flow by the type of goods and derive three different estimation equations consistent with the theory. Analysis conducted at the six-digit HS level suggests that the substitutability of the good in the international market is an important determinant of the marginal impact of country image on trade flow. These findings are of interest not only to academic researchers but to country leaders and policy-makers who intend to promote trade flows by improving their country image.

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Data Appendix

Country Image

To measure country image, we use the seven rounds of the World Opinion Poll survey data between 2005 and 2011. The survey was conducted for BBC by GlobeScan and the Program on International Policy Attitudes of the Center for International and Security Studies at the

University of Maryland. In each country surveyed, about one thousand respondents or more are interviewed. The respondents are asked to answer whether they think the country to be evaluated is having a mainly positive or mainly negative influence in the world. Other than "mainly positive" and "mainly negative", the recorded responses include "depends", "neither, neutral", "DK/NA (don't know or no answer)", even though these choices are not volunteered by the interviewer. We treat both "depends" and "neither, neutral" answers as "neutral" because these two answers are not distinguished from each other for some countries and years.

The exact timing of the survey slightly varies from year to year and from country to country, but the survey is conducted in less than two weeks in January of the reference year (i.e., year τ) or December of the previous year (i.e., year $\tau - 1$) in most cases. In a few cases, the survey was conducted slightly earlier or later. Therefore, the country image variables in our data refer to the country image around the beginning of the year. We exclude non-countries such as the European Union and Central America from the data. The set of countries included in the whole sample is as follows:

Evaluated countries Brazil (2008-2011); Canada (2005-2007, 2009-2011); China (2005-2011); France (2005-2011); Germany (2008-2011); India (2006-2011); Iran (2006-2011); Israel (2007-2011); Japan (2006-2011); North Korea (2007-2011); Pakistan (2007-2011); Russia (2005-2011); South Africa (2009-2011); South Korea (2010-2011); United Kingdom (2005-2011); United States (2005-2011); Venezuela (2007).

Evaluating countries Afghanistan (2006); Argentina (2005-2008); Australia (2005-2011); Azerbaijan (2010); Brazil (2005-2011); Canada (2005-2011); Chile (2005-2011); China (2005-2011); Congo (2006); Egypt (2006-2011); Finland (2006); France (2005-2011); Germany (2005-2011); Ghana (2006, 2008-2011); Greece (2007); Hungary (2007); India (2005-2011); Indonesia (2005-2011); Iran (2006); Iraq (2006); Israel (2008); Italy (2005-2011); Japan (2005, 2008-2011); Kenya (2006-2011); Lebanon (2005, 2007-2008); Mexico (2005-2011); Nigeria (2006-2011); Pakistan (2010-2011); Peru (2011); Philippines (2005-2011); Poland (2005-2007); Portugal (2007-2011); Russia (2005-2011); Saudi Arabia (2006); Senegal (2006); South Africa (2005-2006, 2011); South Korea (2005-2008, 2010-2011); Spain (2005-2006, 2008-2011); Sri Lanka (2006); Tanzania (2006); Thailand (2010);

Table 8: The number of evaluating and evaluated countries and their GDP and population shares in the whole sample.

Year	Evaluated Country			Evaluating Country		
	# Country	% GDP	% Pop	# Country	% GDP	% Pop
2005	6	46.4	29.4	23	81.7	64.9
2006	9	57.7	49.2	35	74.6	70.7
2007	12	57.2	50.0	27	71.5	65.7
2008	13	62.1	55.5	28	79.8	67.7
2009	15	66.6	56.5	22	75.2	63.1
2010	16	68.3	57.1	27	78.6	70.3
2011	16	—	—	27	—	—

Turkey (2005-2011); United Arab Emirates (2007-2008); United Kingdom (2005-2011); United States (2005-2011); Zimbabwe (2006).

Table 8 is the same table as Table 1, except that the statistics are calculated for the whole sample. As the table shows, the number of evaluated countries has increased from 6 in 2005 to 16 in 2011. These countries account for about half or more of the Gross World Product (GWP). The number of evaluating countries is between 22 and 35, and their economies account for at least 70 percent of the GWP.

We have compiled data from BBC, PIPA and Globescan websites, which include the proportion of "mainly positive" and "mainly negative" answers. Globescan kindly made more detailed data with "neutral" and "DK/NA" answers available to us. For a small proportion of records, the data compiled from the websites and the data we received from Globescan were not consistent. In such cases, we used the data from Globescan following its suggestion.

Trade Flow

For disaggregate trade flows at the level of six-digit HS product code, we use the UN COMTRADE data compiled by the United Nations Statistical Division. We downloaded the data from the World Integrated Trade Solution (WITS) website[24] under the H0 nomenclature (HS 1988/1992 version) for years 2005-2010 (See also, Amjadi et al. (2011)). For aggregate trade flows, we use the DOTS data maintained by the International Monetary Fund for 2005-2010. All the trade statistics are reported in current US dollars.

[24] `http://wits.worldbank.org`.

Gross Domestic Product and Other Country-Specific Variables

The Gross Domestic Product figures expressed in current US dollars are taken from the World Development Indicators (WDI) except for Iran for 2010, for which WDI data are not available and thus the estimate published in the CIA Factbook is used instead. GDP figures in the WDI and CIA Factbook are generally close.

Classification of Goods

We follow Rauch (1999) for the "conservative" definitions of homogeneous and differentiated goods.[25] We downloaded the goods classification data from Jon Haveman's website.[26] Because the downloaded data gives the categorization of goods for four-digit Standard International Trade Classification Rev. 2 (SITC2) codes, we link the six-digit HS product codes to the four-digit SITC2 codes. We have dropped from our analysis those records for which we could not find Rauch's categorization. They account for about 13 percent of the total trade flow in the restricted sample.

Bilateral Resistance Data

The WTO membership data was compiled from the WTO website.[27] We assume that the country is a WTO member in year τ if the country joined the WTO in or before June of year τ. For the currency union and regional trade agreement data, we downloaded data compiled by de Sousa (2012) from his website.[28] The downloaded currency union data primarily come from Appendix B of Glick and Rose (2002) but are updated to include the Euro currency. The regional trade agreement data are derived from Table 3 of Baier and Bergstrand (2007), Frankel (1997), and the Regional Trade Agreements Information System (RTA-IS) of the World Trade Organization.[29] Because the original downloaded data reflect RTAs until 2008, we have updated the data using the current RTA-IS. The resulting data we use for our analysis contain currency union and RTA information up to year 2010.

[25] Using "liberal" definitions does not change our results much.

[26] http://www.macalester.edu/research/economics/PAGE/HAVEMAN/Trade.Resources/TradeData.html.

[27] http://www.wto.org/english/thewto_e/whatis_e/tif_e/org6_e.htm.

[28] http://jdesousa.univ.free.fr/data.htm.

[29] http://rtais.wto.org/UI/PublicAllRTAList.aspx

A number of bilateral-resistance variables were obtained from the website of CEPII,[30] a French research center in international economics. The downloaded data include contiguity, distance, language, and colonial link. The distance is based on the great circle formula, which uses latitudes and longitudes of the most important cities in the two countries. The genetic distance data after Spolaore and Wacziarg (2009) are downloaded from Romain Wacziarg's website.[31] We use F_{ST} distance between the plurality ethnic groups in each of the two countries. We normalize it by dividing it by one thousand.

Support of Leadership

The GALLUP Worldview data includes the data on the approval of leadership in major economies including China, France, Germany, Japan, Russia, United Kingdom, and United States for years 2006-2010. Each respondent is asked whether he approves or disapproves of the job performance of the leadership of each of these seven evaluated countries. The GALLUP Worldview covers a large number of evaluating countries and about one thousand people are interviewed in most countries.

Technical Appendix

In Section 3, we have implicitly assumed that the covariates x and the error term ϵ are uncorrelated. However, this assumption is violated when reverse causation and autocorrelation in the error term are simultaneously present. Hence, we now allow for the possibility of reverse causation and autocorrelation, and develop Granger-causality tests and a Wald specification test. Because we have a short panel dataset, we keep the model structure as simple as possible.

We hereafter assume that the first covariate is a measure of country image $CI_{ij\tau} \equiv x^1_{ij\tau}$. Because the country image is likely to be persistent and to depend on the characteristics specific to the country pair and possibly on the year-specific fixed effect, we adopt the following model that allows for reverse causation:

$$CI_{ij\tau} = R^1_z \ln z^c_{ij\tau-1} + R^1_c CI_{ij\tau-1} + \upsilon^c_{ij} + \phi^c_\tau + \nu^c_{ij\tau}, \tag{11}$$

[30] http://www.cepii.fr/anglaisgraph/bdd/distances.htm

[31] http://www.anderson.ucla.edu/faculty_pages/romain.wacziarg/papersum.html

where R_z^1 and R_c^1 are parameters, υ_{ij}^c is a country-pair-specific fixed effect, ϕ_τ^c is a year-specific fixed effect, and $\nu_{ij\tau}^c$ is an independently and identically distributed error term. We assume that $\epsilon_{ij\tau}$ follows an AR(1) process such that we have $\epsilon_{ij\tau} = \rho\epsilon_{ij\tau-1} + \nu_{ij\tau}^z$. We further assume that ν and ϵ are uncorrelated with each other regardless of their subscripts and superscripts except that $E[\epsilon_{ij\tau}\nu_{ij\tau}^z] = V[\nu_{ij\tau}^z] \neq 0$. Under these simple but plausible assumptions, we have $E[CI_{ij\tau} \cdot \epsilon_{ij\tau}] = R_z^1\rho$. Therefore, when both reverse causality (i.e., $R_z^1 \neq 0$) and autocorrelation (i.e., $\rho \neq 0$) are present, we will have a biased estimate of γ.

Suppose now that $x_{ij\tau}^l$ for $l \geq 2$ is time-invariant. Then, the following form of augmented dynamic panel equations can be obtained from the AR(1) process of $\epsilon_{ij\tau}$ and eqs. (8) and (11):

$$\begin{aligned}
\ln z_{ij\tau}^c &= \sum_{h=1}^{H} r_z^h \ln z_{ij\tau-h}^c + \sum_{h=0}^{H} r_c^h \widetilde{CI}_{ij\tau-h} + \upsilon_{ij}^z + \phi_\tau^z + \nu_{ij\tau}^z && (12)\\
CI_{ij\tau} &= \sum_{h=0}^{H} R_z^h \ln z_{ij\tau-h}^c + \sum_{h=1}^{H} R_c^h CI_{ij\tau-h} + \upsilon_{ij}^c + \phi_\tau^c + \nu_{ij\tau}^c. && (13)
\end{aligned}$$

We estimate these equations piecewise by the one-step dynamic-panel-data system estimator (DPD-SYS) derived by Blundell and Bond (1998). This estimator builds on the dynamic-panel-data difference (DPD-DIF) estimator proposed by Arellano and Bond (1991) and extends the idea to use lagged differences as instruments for the level equation originally proposed by Arellano and Bover (1995). We adopt the DPD-SYS estimator in this paper because the DPD-DIF estimator tends to perform poorly when the panel fixed-effect term υ_{ij} has a much larger variance than the idiosyncratic error term $\nu_{ij\tau}$.

Eqs. (12) and (13) suggest panel Granger-causality tests, in which the rejection of the null hypothesis $H_0 : R_z^h = 0$ $[r_c^h = 0]$ for all $h \in \{0, \ldots, H\}$ is taken as the evidence for the presence of Granger causality running from the normalized trade [the country image] to the country image [the normalized trade]. In addition, the following equation holds under the assumptions stated above:

$$r_c^0 r_z^1 + r_c^1 = 0 \qquad (14)$$

We use this equation for the Wald specification test.[32]

[32] The derivation of eqs. (12), (13), and (14) are provided in Appendix A.5.

A Derivation of Equations

A.1 Derivation of eq. (2)

Let $V_{ij} \equiv \prod_k c_{ijk}^{\alpha_{ik}}$ and $W_j \equiv \sum_i \beta_{ij}^{\frac{1-\sigma}{\sigma}} V_{ij}^{\frac{\sigma-1}{\sigma}}$. We can form the Lagrangian L_j for eq. (1) as follows:

$$L_j \equiv W_j^{\frac{\sigma}{\sigma-1}} + \mu \left[y_j - \sum_i \sum_k p_{ik} t_{ijk} c_{ijk} \right], \tag{15}$$

where μ is the Lagrange multiplier. Taking the first order conditions, we have:

$$\frac{\partial L_j}{\partial c_{ijk}} = W_j^{\frac{1}{\sigma-1}} \beta_{ij}^{\frac{1-\sigma}{\sigma}} V_{ij}^{\frac{\sigma-1}{\sigma}} \alpha_{ik}/c_{ijk} - \mu p_{ik} t_{ijk} = 0. \tag{16}$$

Multiplying eq. (16) by c_{ijk}, summing over i and k, and solving for μ, we have $\mu = W_j^{\frac{\sigma}{\sigma-1}}/y_j$. Plugging this in eq. (16) and solving for c_{ijk}, we have:

$$c_{ijk} = \frac{\alpha_{ik} y_j \beta_{ij}^{\frac{1-\sigma}{\sigma}} V_{ij}^{\frac{\sigma-1}{\sigma}}}{W_j p_{ik} t_{ijk}}. \tag{17}$$

Therefore, substituting this in the definition of V_{ij} and solving for V_{ij}, we have:

$$V_{ij} = \frac{y_j^{\sigma} \beta_{ij}^{1-\sigma}}{W_j^{\sigma} T_{ij}^{\sigma} P_i^{\sigma}}. \tag{18}$$

Substituting this in the definition of W_j, we have:

$$W_j = y^{\frac{\sigma-1}{\sigma}} \left[\sum_i [\beta_{ij} T_{ij} P_i]^{1-\sigma} \right]^{1/\sigma} \tag{19}$$

Plugging eqs. (18) and (19) into eq. (16), we have:

$$c_{ijk} = \frac{\alpha_{ik} y_j}{p_{ik} t_{ijk}} \cdot \frac{[\beta_{ij} T_{ij} P_i]^{1-\sigma}}{\sum_{i'} [\beta_{i'j} T_{i'j} P_{i'}]^{1-\sigma}}. \tag{20}$$

Applying the definition of Π_j^0, we have eq. (2). $\square$

A.2 Derivation of eqs. (3) and (4)

Because the derivation is similar to Anderson and van Wincoop (2003), we only describe the main steps. Using $\sum_k \alpha_{ik} = 1$, eq. (2), and the definitions of p^c_{ijk}, C_{ijk}, and Π^1_i, we have:

$$y_i = \sum_j \sum_k C_{ijk} = \sum_j \sum_k \alpha_{ik} y_j \left[\frac{\omega_{ij} P_i}{\Pi^0_j}\right]^{1-\sigma} = P_i^{1-\sigma} \sum_j y_j \left[\frac{\omega_{ij}}{\Pi^0_j}\right]^{1-\sigma} = P_i^{1-\sigma} y_w \left[\Pi^1_i\right]^{1-\sigma}. \quad (21)$$

Solving this for $P_i^{1-\sigma}$ and plugging in the definition of Π^0_j and eq. (2), we have eqs. (3) and (4), respectively. □

A.3 Derivation of eq. (8)

By the Maclaurin approximation of eq. (3) with respect to $\ln \omega_{ij\tau}$ and $\ln \Pi^1_{i\tau}$, we have:

$$\ln \Pi^0_{j\tau} = \frac{1}{1-\sigma} \ln \left[\sum_i s_{i\tau} \exp\left[(1-\sigma)\ln \omega_{ij\tau} - (1-\sigma)\ln \Pi^1_{i\tau}\right]\right] \simeq \sum_i s_{i\tau}\left[\ln \omega_{ij\tau} - \ln \Pi^1_{i\tau}\right]. \quad (22)$$

Similarly, we have $\ln \Pi^1_{i\tau} \simeq \sum_j s_{j\tau}[\ln \omega_{ij\tau} - \ln \Pi^0_{j\tau}]$. It is straightforward to verify that the following expressions give a solution to these equations:

$$\ln \Pi^0_{j\tau} = \sum_i s_{i\tau}[\ln \omega_{ij\tau} - \ln \omega_{i1\tau}] + \ln \Pi^0_{1\tau} \quad \text{for } j \geq 2, \quad (23)$$

$$\ln \Pi^1_{i\tau} = \sum_j s_{j\tau}[\ln \omega_{ij\tau} + \ln \omega_{j1\tau}] - \sum_{i'} \sum_j s_{i'\tau} s_{j\tau} \ln \omega_{i'j\tau} + \ln \Pi^0_{1\tau} \quad \text{for } i \geq 2, \quad (24)$$

where $\ln \Pi^0_{1\tau}$ is arbitrarily chosen as the numeraire and $\ln \Pi^1_{1\tau}$ follows its approximate expressions above. Because the dataset used by Baier and Bergstrand (2009) does not have a time dimension, they adopt the following normalization: $\ln \Pi^0_1 = 0$. However, this normalization is inappropriate in our case because the prices may vary over time. Plugging eqs. (23) and (24) into eq. (7) and using eq. (5), we have eq. (8). Eq. (8) shows that the variation of $\ln \Pi^0_{1\tau}$ over time can be modelled as a year-specific fixed effect. □

A.4 Derivation of the ILLS estimator

We provide here an alternative derivation of the ILLS estimator originally proposed by Blundell and Robin (1999). This is necessary because the number of regressors increases as N and T increase and thus their asymptotics do not apply to our problem. We assume that the regressors are fixed and examine the properties of the first-order approximation of the estimator.

It is convenient to express eq. (6) in a matrix form. To this end, we introduce some additional notations. First, let us denote an $N(K-1)$-vector of a_{ik} by $\boldsymbol{a} \equiv [a_{11}, \ldots, a_{N(K-1)}]^T$, where a_{iK} is omitted for all i. Similarly, we denote the parameter vectors for γ_{kl}, $\eta_{i\tau}$, and $\delta_{j\tau}$ by $\boldsymbol{\gamma} \equiv [\gamma_{11}, \ldots, \gamma_{KL}]^T$, $\boldsymbol{\eta} \equiv [\eta_{11}, \ldots, \eta_{NT}]^T$, and $\boldsymbol{\delta} \equiv [\delta_{11}, \ldots, \delta_{(N-1)T}]^T$, respectively. Let $\boldsymbol{\alpha}$ be an $N \times K$-matrix whose (i,k)-element is α_{ik} and $\boldsymbol{X}$ be an $N^2T \times L$-matrix whose $(iNT+jT+\tau, l)$-element is $x^l_{ij\tau}$. Because there is a bijective relationship between $\boldsymbol{a}$ and $\boldsymbol{\alpha}$, we can write $\boldsymbol{\alpha}(\boldsymbol{a})$. We let the vector forms of the logarithmic normalized trade flow and error terms be $\boldsymbol{Z} \equiv [\ln z_{1111}, \ldots, \ln z_{NNTK}]^T$. $\boldsymbol{\epsilon} \equiv [\epsilon_{1111}, \ldots, \epsilon_{NNTK}]^T$, respectively.

We denote the $n \times n$ identity matrix by $\boldsymbol{I}_n$, and n-column vectors of zeros and ones by $\mathbf{0}_n$ and $\mathbf{1}_n$, respectively. We use $\circ$ and $\otimes$ to denote the elementwise and Kronecker products, respectively. Using these notations, we define the following matrices:

$$\boldsymbol{G}_1 \equiv \boldsymbol{I}_N \otimes \mathbf{1}_{NT} \otimes \begin{bmatrix} \boldsymbol{I}_{K-1} \\ \mathbf{0}^T_{K-1} \end{bmatrix}, \ \boldsymbol{G}_3 \equiv \boldsymbol{I}_N \otimes \mathbf{1}_{NK} \otimes \boldsymbol{I}_T, \text{ and } \boldsymbol{G}_4 \equiv \mathbf{1}_N \otimes \begin{bmatrix} \boldsymbol{I}_{N-1} \\ \mathbf{0}^T_{N-1} \end{bmatrix} \otimes \mathbf{1}_K \otimes \boldsymbol{I}_T, \tag{25}$$

where $\boldsymbol{G}_1$ is an $N^2TK \times N(K-1)$-matrix of the exporter-type-specific dummy variables, $\boldsymbol{G}_3$ an $N^2TK \times NT$-matrix of the exporter-year-specific dummy variables, and $\boldsymbol{G}_4$ an $N^2TK \times (N-1)T$-matrix of the importer-year-specific variables. Further let $\boldsymbol{G}_2(\boldsymbol{a}) \equiv [\boldsymbol{\alpha}(\boldsymbol{a}) \otimes \mathbf{1}_{NTK \times L}] \circ [\mathbf{1}^T_K \otimes \boldsymbol{X} \otimes \mathbf{1}_K]$ be an $N^2TK \times KL$-matrix of regressors for $\boldsymbol{\gamma}$. Then, the parameter vector $\boldsymbol{\theta} \equiv [\boldsymbol{a}^T, \boldsymbol{\gamma}^T, \boldsymbol{\eta}^T, \boldsymbol{\delta}^T]^T$ has a dimension of $D \equiv N(2T+K-1)-T+KL$. Letting the $N^2TK \times D$ design matrix be $\boldsymbol{G}(\boldsymbol{\theta}) \equiv [\boldsymbol{G}_1 \ \boldsymbol{G}_2(\boldsymbol{a}) \ \boldsymbol{G}_3 \ \boldsymbol{G}_4]$, we can rewrite eq. (4) as follows:

$$\boldsymbol{Z} = \boldsymbol{G}(\boldsymbol{\theta})\boldsymbol{\theta} + \boldsymbol{\epsilon}. \tag{26}$$

As with Blundell and Robin (1999), we assume that $E[\boldsymbol{\epsilon}\boldsymbol{\epsilon}^T] = \boldsymbol{I}_{N^2T} \otimes \boldsymbol{\Omega}$, where $\boldsymbol{\Omega}$ is a $K \times$

K variance matrix for the vector $\boldsymbol{\varepsilon}_{ijk} \equiv [\epsilon_{ij\tau 1}, \ldots, \epsilon_{ij\tau K}]^T$ of idiosyncratic terms for a given combination of i, j, and τ.

Eq. (26) is linear in $\boldsymbol{\theta}$ when $\boldsymbol{G}(\boldsymbol{\theta})$ is taken as given. Therefore, if we have an estimate $\hat{\boldsymbol{\theta}}^{(q)}$ of $\boldsymbol{\theta}$ in the qth round of iteration, we can update it by the ordinary least squares such that $\hat{\boldsymbol{\theta}}^{(q+1)} \leftarrow [\boldsymbol{G}^T(\hat{\boldsymbol{\theta}}^{(q)})\boldsymbol{G}(\hat{\boldsymbol{\theta}}^{(q)})]^{-1}\boldsymbol{G}^T(\hat{\boldsymbol{\theta}}^{(q)})\boldsymbol{Z}$, assuming $[\boldsymbol{G}^T(\hat{\boldsymbol{\theta}}^{(q)})\boldsymbol{G}(\hat{\boldsymbol{\theta}}^{(q)})]$ is a non-singular matrix. When the iteration converges, the ILLS estimator $\hat{\boldsymbol{\theta}}$ satisfies $\hat{\boldsymbol{\theta}} = [\boldsymbol{G}^T(\hat{\boldsymbol{\theta}})\boldsymbol{G}(\hat{\boldsymbol{\theta}})]^{-1}\boldsymbol{G}^T(\hat{\boldsymbol{\theta}})\boldsymbol{Z}$.

Now, let us define the estimate of residual by $\hat{\boldsymbol{\epsilon}} \equiv \boldsymbol{Z} - \boldsymbol{G}(\hat{\boldsymbol{\theta}})\hat{\boldsymbol{\theta}}$. Then, premultiplying this equation by $-\boldsymbol{G}^T(\hat{\theta})/N^2TK$, we have:

$$\boldsymbol{F}(\hat{\boldsymbol{\theta}}) \equiv \frac{-\boldsymbol{G}^T(\hat{\boldsymbol{\theta}})\hat{\boldsymbol{\epsilon}}}{N^2TK} = \frac{-[\boldsymbol{G}^T(\hat{\boldsymbol{\theta}})\boldsymbol{G}(\hat{\boldsymbol{\theta}})][\boldsymbol{G}^T(\hat{\boldsymbol{\theta}})\boldsymbol{G}(\hat{\boldsymbol{\theta}})]^{-1}\boldsymbol{G}^T(\hat{\boldsymbol{\theta}})\boldsymbol{Z} + [\boldsymbol{G}^T(\hat{\boldsymbol{\theta}})\boldsymbol{G}(\hat{\boldsymbol{\theta}})]\hat{\boldsymbol{\theta}}}{N^2TK} = \mathbf{0}_D. \tag{27}$$

We let $\boldsymbol{e}_d$ be a D-vector whose dth element is one and all the other elements are zero. Then, we can write the derivative of $\boldsymbol{F}(\hat{\boldsymbol{\theta}})$ as follows:

$$\begin{aligned} \left.\frac{\partial \boldsymbol{F}(\hat{\boldsymbol{\theta}})}{\partial \hat{\boldsymbol{\theta}}^T}\right|_{\hat{\boldsymbol{\theta}}=\boldsymbol{\theta}} &= \frac{1}{N^2TK} \cdot \left[\boldsymbol{G}^T(\boldsymbol{\theta})\boldsymbol{G}(\boldsymbol{\theta}) + \sum_{d=1}^{D}\left[\boldsymbol{G}^T(\boldsymbol{\theta})\frac{\partial \boldsymbol{G}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}_d}\boldsymbol{\theta} - \frac{\partial \boldsymbol{G}^T(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}_d}\boldsymbol{\epsilon}\right]\boldsymbol{e}_d\right] \\ &\simeq \frac{1}{N^2TK} \cdot \left[\boldsymbol{G}^T(\boldsymbol{\theta})\boldsymbol{G}(\boldsymbol{\theta}) + \sum_{d=1}^{D}\left[\boldsymbol{G}^T(\boldsymbol{\theta})\frac{\partial \boldsymbol{G}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}_d}\boldsymbol{\theta}\right]\boldsymbol{e}_d\right] \equiv \boldsymbol{B}(\boldsymbol{\theta}), \end{aligned} \tag{28}$$

where the approximation in the last line is justified by the Law of Large Numbers provided N^2TK is sufficiently large and some regularity conditions are satisfied. Using this and the first-order approximation of $\boldsymbol{F}(\hat{\boldsymbol{\theta}})$ around the true parameter value $\boldsymbol{\theta}$ in eq. (27), we have:

$$\boldsymbol{F}(\boldsymbol{\theta}) + \boldsymbol{B}(\boldsymbol{\theta})(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}) \simeq \mathbf{0}_D, \text{ or } \hat{\boldsymbol{\theta}} \simeq \boldsymbol{\theta} - \boldsymbol{B}^{-1}(\boldsymbol{\theta})\boldsymbol{F}(\boldsymbol{\theta}) = \boldsymbol{\theta} + \boldsymbol{B}^{-1}(\boldsymbol{\theta})\boldsymbol{G}^T(\boldsymbol{\theta})\boldsymbol{\epsilon}. \tag{29}$$

Taking an expectation and variance, we have:

$$E[\hat{\boldsymbol{\theta}}] \simeq \boldsymbol{\theta} \tag{30}$$

$$V[\hat{\boldsymbol{\theta}}] \simeq \boldsymbol{B}^{-1}(\boldsymbol{\theta})\boldsymbol{G}^T(\boldsymbol{\theta})[\boldsymbol{I}_{N^2T} \otimes \boldsymbol{\Omega}]\boldsymbol{G}(\boldsymbol{\theta})\boldsymbol{B}^{-T}(\boldsymbol{\theta}) \tag{31}$$

We estimate $\boldsymbol{\Omega}$ by $\hat{\boldsymbol{\Omega}} = [N^2T]^{-1}\sum_i\sum_j\sum_\tau \hat{\boldsymbol{\varepsilon}}_{ij\tau}\hat{\boldsymbol{\varepsilon}}_{ij\tau}^T$, where $\hat{\boldsymbol{\varepsilon}}_{ij\tau}$ is constructed from the regression residuals. Then, $V[\hat{\boldsymbol{\theta}}]$ can be estimated by $\hat{V}[\hat{\boldsymbol{\theta}}] \equiv \boldsymbol{B}^{-1}(\hat{\boldsymbol{\theta}})\boldsymbol{G}^T(\hat{\boldsymbol{\theta}})[\boldsymbol{I}_{N^2T} \otimes \hat{\Omega}]\boldsymbol{G}(\hat{\boldsymbol{\theta}})\boldsymbol{B}^{-T}(\hat{\boldsymbol{\theta}})$. □

A.5 Derivation of eqs. (12), (13), and (14)

Let us first consider the case where $H = 1$. Then, by adding $R_z^0 \ln z_{ij\tau}^c$ to eq. (11), we have eq. (13).

Now, let $\tilde{\xi}_{ij} \equiv \sum_{l \geq 2} \gamma_l \tilde{x}_{ij}$. Notice that we do not need the subscript τ here because of the assumption that $x_{ij\tau}^l$ is time-invariant for $l \geq 2$. Using this and AR(1) process of ϵ, we can transform eq. (8) as follows:

$$\begin{aligned} \ln z_{ij\tau}^c &= \gamma_1 \widetilde{CI}_{ij\tau} + \tilde{\xi}_{ij} + \iota_\tau + \rho \epsilon_{ij\tau-1} + \nu_{ij\tau}^z & (32) \\ &= \gamma_1 \widetilde{CI}_{ij\tau} + \tilde{\xi}_{ij} + \iota_\tau + \rho[\ln z_{ij\tau-1}^c - \gamma_1 \widetilde{CI}_{ij\tau-1} - \tilde{\xi}_{ij} - \iota_{\tau-1}] + \nu_{ij\tau}^z & (33) \end{aligned}$$

By letting $r_z^1 \equiv \rho$, $r_c^0 \equiv \gamma_1$, $r_c^1 \equiv -\rho\gamma_1$, $\upsilon_{ij}^z \equiv (1-\rho)\tilde{\xi}_{ij}$, and $\phi_\tau^z \equiv \iota_\tau - \rho\iota_{\tau-1}$, we have eq. (12). The Wald specification test equation eq. (14) directly follows from these definitions. When $H \geq 2$, we simply need to add higher-order lag terms. $\square$

B Additional Tables

Table 9 shows the benchmark estimation results with one additional covariate based on eq. (7). Table 10 is the whole-sample version of Table 2. We only present the results based on eq. (7), because the estimation of eq. (8) is vulnerable to changes in the set of countries in the sample. Table 11 provides additional regression results without the restriction of unit elasticity of trade flow with respect to each trading country's income.

Table 9: Estimation of the benchmark specification with one additional covariate based on eq. (7). Restricted sample.

Year	2005-10	2005	2006	2007	2008	2009	2010
PS	1.72***	0.10	1.66*	1.85*	1.41*	2.63***	2.16***
LD	-0.80***	-0.70***	-1.01***	-0.97***	-0.72***	-0.72***	-0.71***
CTG	-0.35**	0.15	-0.50	-0.46	-0.41	-0.58	-0.23
R^2	0.588	0.862	0.637	0.613	0.491	0.555	0.573
PS	1.55***	0.21	1.51*	1.66*	1.29	2.25***	2.02***
LD	-0.72***	-0.72***	-0.91***	-0.87***	-0.63***	-0.59***	-0.65***
ILD	-0.30**	-0.35	0.11	0.02	-0.47	-0.40	-0.47**
R^2	0.584	0.863	0.629	0.606	0.488	0.544	0.574
PS	1.53***	0.14	1.69*	1.73*	1.15	2.20**	1.98***
LD	-0.72***	-0.87***	-1.44***	-0.94***	-0.62***	-0.56***	-0.65***
RTA	0.00	-0.43	-1.84**	-0.25	0.13	0.18	0.06
R^2	0.583	0.864	0.658	0.608	0.486	0.543	0.572
PS	1.53***	0.20	1.53*	1.66*	1.21	2.26***	1.98***
LD	-0.73***	-0.73***	-0.91***	-0.87***	-0.65***	-0.61***	-0.67***
WTO	-0.35	-0.64***	-0.14	0.09	-0.28	-0.87	-0.90
R^2	0.584	0.861	0.629	0.606	0.486	0.547	0.576
PS	1.42***	0.09	1.30*	1.62*	1.28	2.08**	1.91***
LD	-0.76***	-0.77***	-0.95***	-0.91***	-0.69***	-0.63***	-0.69***
COL	0.33***	0.20	0.38	0.35	0.53**	0.28	0.27
R^2	0.589	0.864	0.635	0.612	0.498	0.546	0.575
PS	1.16***	-0.03	1.14	1.26	0.82	1.72**	1.77**
LD	-0.74***	-0.74***	-0.92***	-0.89***	-0.67***	-0.62***	-0.67***
LNG	0.74***	0.40	0.60*	0.67*	1.03***	0.80***	0.71***
R^2	0.613	0.873	0.644	0.628	0.542	0.581	0.602
PS	1.55***	0.20	1.61*	1.71*	1.20	2.22**	2.00**
LD	-0.73***	-0.73***	-0.93***	-0.88***	-0.64***	-0.60***	-0.66***
CUR	-0.11	0.00	-0.64	-0.26	0.07	0.06	-0.02
R^2	0.583	0.861	0.631	0.607	0.486	0.542	0.571
PS	1.32***	0.18	1.32	1.52	0.98	2.07**	1.84**
LD	-0.79***	-0.79***	-0.95***	-0.90***	-0.71***	-0.66***	-0.75***
GEN	0.41***	0.45**	0.31	0.18	0.33	0.30	0.50*
R^2	0.588	0.870	0.630	0.607	0.488	0.545	0.579
#Obs	577	54	81	83	120	108	131
Fixed Effects	$\eta_{i\tau}, \delta_{j\tau}$	η_i, δ_j	η_i, δ_j	η_i, δ_j	η_i, δ_j	η_i, δ_j	η_i, δ_j

Note: *, **, and *** indicate statistical significance at a 10%, 5%, and 1% level, respectively.

Table 10: Benchmark regression results for aggregate trade flows based on eq. (7). Whole sample.

Year	2005-10	2005	2006	2007	2008	2009	2010	2005-10
Column	(10a)	(10b)	(10c)	(10d)	(10e)	(10f)	(10g)	(10h)
PS	0.71***	0.35	0.58	0.31	0.64	0.95**	1.30***	1.21***
	(0.21)	(0.67)	(0.49)	(0.54)	(0.46)	(0.44)	(0.48)	(0.14)
LD	-0.86***	-0.87***	-1.03***	-1.00***	-0.79***	-0.77***	-0.75***	-0.69***
	(0.04)	(0.10)	(0.10)	(0.14)	(0.09)	(0.10)	(0.08)	(0.03)
R^2	0.505	0.661	0.453	0.516	0.504	0.491	0.506	0.215
# Obs	1694	129	285	287	321	297	375	1694
Fixed Effects	$\eta_{i\tau}, \delta_{j\tau}$	η_i, δ_j	η_i, δ_j	η_i, δ_j	η_i, δ_j	η_i, δ_j	η_i, δ_j	No

Note: Standard errors in parenthesis. *, **, and *** indicate statistical significance at a 10%, 5%, and 1% level, respectively.

Table 11: Benchmark regression results without the unit-income-elasticity constraints based on eq. (8). Restricted Sample.

Year	2005	2006	2007	2008	2009	2010	2005-10
Column	(11a)	(11b)	(11c)	(11d)	(11e)	(11f)	(11g)
$\ln y_{i\tau}$	0.71***	1.06***	0.99***	1.11***	1.08***	1.06***	1.06***
	(0.11)	(0.16)	(0.11)	(0.08)	(0.08)	(0.07)	(0.04)
$\ln y_{j\tau}$	1.18***	1.20***	1.13***	0.86***	0.92***	0.97***	0.99***
	(0.13)	(0.15)	(0.20)	(0.09)	(0.15)	(0.08)	(0.05)
$\widetilde{PS}$	1.60***	2.09**	2.05**	1.64**	1.86**	2.24***	1.86***
	(0.56)	(0.83)	(0.88)	(0.79)	(0.73)	(0.58)	(0.30)
$\widetilde{LD}$	-0.49***	-0.66***	-0.64***	-0.58***	-0.52***	-0.57***	-0.56***
	(0.13)	(0.12)	(0.13)	(0.11)	(0.11)	(0.10)	(0.05)
R^2	0.756	0.716	0.715	0.756	0.766	0.794	0.741
#Obs	54	81	83	120	108	131	577
$P(\ln y_{i\tau} = \ln y_{j\tau} = 1)$	0.020**	0.291	0.813	0.126	0.554	0.655	0.376
Fixed Effects	No	No	No	No	No	No	No

Note: *, **, and *** indicate statistical significance at a 10%, 5%, and 1% level, respectively.