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Dennis Novy

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Abstract
This paper derives a micro-founded gravity equation based on a translog demand system that allows for flexible substitution patterns across goods. In contrast to the standard CES-based gravity equation, translog gravity generates an endogenous trade cost elasticity. Trade is more sensitive to trade costs if the exporting country only provides a small share of the destination country's imports. As a result, trade costs have a heterogeneous impact across country pairs, with some trade flows predicted to be zero. I test the translog gravity equation and find empirical evidence that is in many ways consistent with its predictions.

JEL classification: F11, F12, F15
Keywords: Translog, Gravity, Trade Costs, Distance, Trade Cost Elasticity, Import Share

* University of Warwick, Department of Economics, Coventry CV4 7AL, United Kingdom, Centre for Economic Policy Research (CEPR), Centre for Economic Performance (CEP) and CESifo, d.novy@warwick.ac.uk. I am grateful for comments by Ana Cecília Fieler, Alberto Behar, Jeffrey Bergstrand, Johannes Bröcker, Natalie Chen, Robert Feenstra, Kyle Handley, Gordon Hanson, Christopher Meissner, Peter Neary, Krishna Pendakur, Joel Rodrigue, João Santos Silva, Alan Taylor, Silvana Tenreyro, Christian Volpe Martincus, David Weinstein and Adrian Wood. I am also grateful for comments by seminar participants at the Central European University, the Chinese Academy of Social Sciences, Kiel, the London School of Economics, Loughborough, Oxford, the Paris Trade Seminar, Shanghai University of Finance and Economics, Valencia, Warwick, the 2010 CESifo Global Economy conference, the 2010 Econometric Society World Congress, the 2010 NBER Summer Institute, the 2010 Rocky Mountain Empirical Trade conference and the 2011 European Meeting of the Urban Economics Association. I gratefully acknowledge research support from the Economic and Social Research Council, Grant RES-000-22-3112.

1. Introduction

For decades, gravity equations have been used as a workhorse model of international trade. They relate bilateral trade flows to country-specific characteristics of the trading partners such as economic size, and to bilateral characteristics such as trade frictions between exporters and importers. A large body of empirical literature is devoted to understanding the impact of trade frictions on international trade. The impact of distance and geography, currency unions, free trade agreements and WTO membership have all been studied in great detail with the help of gravity equations.

Theoretical foundations for gravity equations are manifold. In fact, various prominent trade models of recent years predict gravity equations in equilibrium. These models include the Ricardian framework by Eaton and Kortum (2002), the multilateral resistance framework by Anderson and van Wincoop (2003), as well as the model with heterogeneous firms by Chaney (2008). Likewise, Deardorff (1998) argues that a gravity equation also arises from a Heckscher-Ohlin framework where trade is driven by relative resource endowments.[1]

The above trade models all result in gravity equations with a *constant elasticity of trade with respect to trade costs*. This feature means that all else being equal, a reduction in trade costs – for instance a uniform tariff cut – has the same proportionate effect on bilateral trade regardless of whether tariffs were initially high or low or whether a country pair traded a little or a lot. This is true when the supply side is modeled as a Ricardian framework (Eaton and Kortum, 2002), as a framework with heterogeneous firms (Chaney, 2008) or simply as an endowment economy (Anderson and van Wincoop, 2003).

Recent research has drawn attention to the idea that a reduction in trade costs, for example through a free trade agreement or falling transportation costs, may lead to an increase in competition. Melitz and Ottaviano (2008) and Behrens and Murata (2012) demonstrate this effect theoretically. Feenstra and Weinstein (2010) provide theory as well as evidence for the US. Badinger (2007) as well as Chen, Imbs and Scott (2009) provide evidence for European countries. This line of research emphasizes more flexible demand systems that respond to changes in the competitive environment.

[1] Also see Bergstrand (1985). Feenstra, Markusen and Rose (2001) as well as Evenett and Keller (2002) also show that various competing trade models lead to gravity equations.

In this paper, I adopt such a demand system and argue that it is fundamental to understanding the trade cost elasticity. In particular, in section 2 I depart from the constant elasticity gravity model and derive a gravity equation from homothetic translog preferences in a general equilibrium framework.[2] Translog preferences were introduced by Christensen, Jorgenson and Lau (1975) in a closed-economy study of consumer demand.[3] In contrast to CES, translog preferences are more flexible in that they allow for richer substitution patterns across varieties. This flexibility breaks the constant link between trade flows and trade costs.[4] Instead, the resulting translog gravity equation features an *endogenous elasticity of trade with respect to trade costs*. The effect of trade costs on trade flows varies depending on how intensely two countries trade with each other. Specifically, the less the destination country imports from a particular exporter, the more sensitive are its bilateral imports to trade costs. Trade costs therefore have a heterogeneous trade-impeding impact across country pairs. Despite this increase in complexity, the translog gravity equation is parsimonious and easy to implement with data.

In section 3, I attempt to empirically contrast translog gravity with the traditional constant elasticity specification. Based on trade flows amongst OECD countries, I find evidence that seems inconsistent with the constant elasticity specification. The results demonstrate that 'one-size-fits-all' trade cost elasticities as implied by standard gravity models are typically not supported by the data. Instead, consistent with translog gravity, in many applications I find that the trade cost elasticity increases in absolute size, the less trade there is between two countries. To be precise, all else being equal bilateral trade is more sensitive to trade costs if the exporting country provides a smaller share of the destination country's imports. An implication is that a given trade cost change, for instance a reduction of trade barriers through a free trade agreement, has a heterogeneous impact across country pairs. The translog gravity framework can therefore

[2] An online appendix that accompanies this paper provides further details both on the theory and the empirics.

[3] Recent applications of translog preferences include Feenstra and Weinstein (2010) who are concerned with estimating the welfare gains from increased variety through globalization, Feenstra and Kee (2008) who estimate the effect of expanding export variety on productivity, as well as Bergin and Feenstra (2009) who estimate exchange rate pass-through. More generally, the translog functional form has been used widely in other fields, for example in the productivity literature. See Christensen, Jorgenson and Lau (1971) for an early reference.

[4] Although Melitz and Ottaviano (2008) work with quadratic preferences at the individual product level, their preferences have CES-like characteristics at the aggregate level in the sense that their gravity equation also features a constant trade cost elasticity. It has a zero income elasticity although population can be a demand shifter. Also see Behrens, Mion, Murata and Südekum (2009) for a model with non-homothetic preferences and variable markups but a constant trade cost elasticity. The constant trade cost elasticity is also a feature of the 'generalized gravity equation' based on the nested Cobb-Douglas/CES/Stone-Geary utility function in Bergstrand (1989). See Markusen (1986) for an additional specification with non-homothetic preferences.

shed new light on the effect of institutional arrangements such as free trade agreements or WTO membership on international trade. For example, it can help explain why trade liberalizations often lead to relatively larger trade creation amongst country pairs that previously traded relatively little.[5]

Although not explored in this paper, another potentially useful feature of the translog demand system is that it is in principle consistent with zero demand. It is well-known that zeroes are widespread in large samples of aggregate bilateral trade, and even more so in samples at the disaggregated level. If bilateral trade costs are sufficiently high, the corresponding import share in translog gravity is zero.[6] This feature is a straightforward implication of the fact that the price elasticity of demand is increasing in price and thus increasing in variable trade costs. In contrast, a CES-based demand system is not consistent with zero trade flows unless fixed costs of exporting are assumed on the supply side (see Helpman, Melitz and Rubinstein, 2008).

The paper builds on the gravity framework by Anderson and van Wincoop (2003), but instead of CES it relies on the homothetic translog demand system employed by Feenstra (2003). Another related paper in the literature is by Gohin and Féménia (2009) who develop a demand equation based on Deaton and Muellbauer's (1980) almost ideal demand system and estimate it with data on intra-European Union trade in cheese products. They also find evidence against the restrictive assumptions underlying the CES-based gravity approach and stress the role of variable price elasticities. But in contrast to my paper, they adopt a partial equilibrium approach and abstract from trade costs. Volpe Martincus and Estevadeordal (2009) use a translog revenue function to study specialization patterns in Latin American manufacturing industries in response to trade liberalization policies, but they do not consider gravity equations. Lo (1990) models shopping travel behavior in a partial equilibrium spatial translog model with variable elasticities of substitution across destination pairs. But her approach does not lead to a gravity equation.

The theoretical note by Arkolakis, Costinot and Rodríguez-Clare (2010) examines the relationship between translog gravity and gains from trade based on the continuous translog expenditure function by Rodríguez-López (2011). They assume that firm productivity follows a

[5] Komorovska, Kuiper and van Tongeren (2007) refer to the 'small shares stay small' problem as the inability of CES-based demand systems to generate substantial trade creation in response to significant trade liberalization if initial trade flows are small. In contrast, translog demand predicts large trade responses if initial flows are small. Kehoe and Ruhl (2009) find evidence consistent with this prediction in an analysis of trade growth at the four-digit industry level in the wake of the North American Free Trade Agreement and other major trade liberalizations.

[6] The translog demand system allows for choke prices beyond which demand is zero. See Melitz and Ottaviano (2008) for a specification with choke prices in a linear demand system.

Pareto distribution. This parametric assumption is crucial in generating a log-linear gravity equation with the standard constant trade cost elasticity. In contrast, my translog gravity equation gives rise to variable and endogenous trade cost elasticities.

2. Translog preferences and trade costs

This section outlines the general equilibrium translog model and derives the theoretical gravity equation based on an endowment economy framework.[7] Following Diewert (1976) and Feenstra (2003), I assume a translog expenditure function. As Bergin and Feenstra (2000) note, the translog demand structure employed here is more concave than the CES. It can be rationalized as a second-order approximation to an arbitrary expenditure system (see Diewert, 1976).

I assume there are J countries in the world with $j=1,\ldots,J$ and $J \geq 2$. Each country is endowed with at least one differentiated good but may have arbitrarily many, and the number of goods may vary across countries.[8] Let $[N_{j-1}+1,N_j]$ denote the range of goods of country j, with $N_{j-1}<N_j$ and $N_0 \equiv 0$. $N_J \equiv N$ denotes the total number of goods in the world. The translog expenditure function is given by

$$(1)\quad \ln(E_j) = \ln(U_j) + \alpha_{0j} + \sum_{m=1}^{N} \alpha_m \ln(p_{mj}) + \frac{1}{2}\sum_{m=1}^{N}\sum_{k=1}^{N} \gamma_{km} \ln(p_{mj}) \ln(p_{kj}),$$

where U_j is the utility level of country j with m and k indexing goods and $\gamma_{km}=\gamma_{mk}$. The price of good m when delivered in country j is denoted by p_{mj}. I assume trade frictions such that $p_{mj}=t_{mj}p_m$, where p_m denotes the net price for good m and $t_{mj} \geq 1\ \forall\ m,j$ is the variable trade cost factor. I furthermore assume symmetry across goods from the same origin country i in the sense that $p_m=p_i$ if $m \in [N_{i-1}+1,N_i]$, and that trade costs to country j are the same for all the goods from origin country i, i.e., $t_{mj}=t_{ij}$ if $m \in [N_{i-1}+1,N_i]$. But I allow trade costs t_{ij} to be asymmetric for a given country pair such that $t_{ij} \neq t_{ji}$ is possible.

As in Feenstra (2003), to ensure an expenditure function with homogeneity of degree one I impose the conditions:

[7] I follow Anderson and van Wincoop (2003) in calling this framework general equilibrium (also see section 3.5).
[8] CES can be rationalized as an aggregator for a set of underlying goods so that the assumption of one differentiated good per country as in Anderson and van Wincoop (2003) is reasonable. However, that assumption would not be harmless with translog demand. The number of goods is therefore allowed to vary across countries.

$$(2)\ \sum_{m=1}^{N}\alpha_m = 1, \text{ and } \sum_{k=1}^{N}\gamma_{km} = 0.$$

In addition, I let all goods enter 'symmetrically' in the γ_{km} coefficients. Following Feenstra (2003), I therefore impose the additional restrictions:

$$(3)\ \gamma_{mm} = -\frac{\gamma}{N}(N-1)\forall m \text{ and } \gamma_{km} = \frac{\gamma}{N}\forall k \neq m \text{ with } \gamma > 0.$$

It can be easily verified that these additional restrictions satisfy the homogeneity conditions in (2).[9]

The expenditure share s_{mj} of country j for good m can be obtained by differentiating the expenditure function (1) with respect to $\ln(p_{mj})$:

$$(4)\ s_{mj} = \alpha_m + \sum_{k=1}^{N}\gamma_{km}\ln(p_{kj}).$$

This share must be non-negative, of course. Let x_{ij} denote the value of trade from country i to country j, and y_j is the income of country j equal to expenditure E_j. The import share x_{ij}/y_j is then the sum of expenditure shares s_{mj} over the range of goods that originate from country i:

$$(5)\ \frac{x_{ij}}{y_j} = \sum_{m=N_{i-1}+1}^{N_i} s_{mj} = \sum_{m=N_{i-1}+1}^{N_i}\left(\alpha_m + \sum_{k=1}^{N}\gamma_{km}\ln(p_{kj})\right).$$

To close the model, I impose market clearing:

$$(6)\ y_i = \sum_{j=1}^{J} x_{ij}\forall i.$$

2.1. The translog gravity equation

To obtain the gravity equation, I substitute the import shares from equation (5) into the market-clearing condition (6) to solve for the general equilibrium. Using $p_{kj}=t_{kj}p_k$, I then solve for the net prices p_k and substitute them back into the import share (5). This solution procedure is similar to the one adopted by Anderson and van Wincoop (2003) for their CES-based model. Appendix A, which can be found in an online appendix that accompanies this paper, provides a detailed derivation.

As the final result, I obtain a translog 'gravity' equation for import shares as

[9] The assumption of $\gamma>0$ ensures that the price elasticity of demand exceeds unity. The estimation results below confirm this assumption. The elasticity is also increasing in price (see Feenstra, 2003).

$$(7)\quad \frac{x_{ij}}{y_j} = \frac{y_i}{y^W} - \gamma n_i \ln(t_{ij}) + \gamma n_i \ln(T_j) + \gamma n_i \sum_{s=1}^{J} \frac{y_s}{y^W} \ln\left(\frac{t_{is}}{T_s}\right),$$

where y^W denotes world income, defined as $y^W \equiv \sum_{j=1}^{J} y_j$, and $n_i \equiv N_i - N_{i-1}$ denotes the number of goods of country *i*. The variable $\ln(T_j)$ is a weighted average of (logarithmic) trade costs over the trading partners of country *j* akin to inward multilateral resistance in Anderson and van Wincoop (2003). As Appendix A shows, it is given by

$$(8)\quad \ln(T_j) = \frac{1}{N}\sum_{k=1}^{N} \ln(t_{kj}) = \sum_{s=1}^{J} \frac{n_s}{N} \ln(t_{sj}).$$

Note that the last term on the right-hand side of equation (7) only varies across the exporting countries *i* but not across the importing countries *j*. However, the third term on the right-hand side of equation (7), $\gamma n_i \ln\left(T_j\right)$, varies across both.

To be clear, I refer to expression (7) as a 'gravity' equation although its appearance differs from traditional gravity equations in two respects. First, the left-hand side variable is the import share x_{ij}/y_j and not the bilateral trade flow x_{ij}. Second, the right-hand side variables are not multiplicatively linked. However, expression (7) and traditional gravity equations have in common that they relate the extent of bilateral trade to both bilateral variables such as trade costs as well as to country-specific variables such as the exporter's and importer's incomes and multilateral resistance.

2.2. A comparison to gravity equations with a constant trade cost elasticity

The important feature of the translog gravity equation is that the import share on the left-hand side of equation (7) is specified in levels, while logarithmic trade costs appear on the right-hand side. This stands in contrast to 'traditional' gravity equations. For example, Anderson and van Wincoop (2003) derive the following gravity equation:

$$(9)\quad x_{ij} = \frac{y_i y_j}{y^W}\left(\frac{t_{ij}}{\Pi_i P_j}\right)^{1-\sigma},$$

where Π_i and P_j are outward and inward multilateral resistance variables, respectively, and σ is the elasticity of substitution from the CES utility function on which their model is based.[10] To be more easily comparable to the translog gravity equation (7), I divide the standard gravity equation (9) by y_j and take logarithms to arrive at

$$(10)\quad \ln\left(\frac{x_{ij}}{y_j}\right) = \ln\left(\frac{y_i}{y^W}\right) - (\sigma-1)\ln(t_{ij}) + (\sigma-1)\ln(\Pi_i) + (\sigma-1)\ln(P_j).$$

Although the dependent variable of gravity equations in the literature is typically $\ln(x_{ij})$ as opposed to the logarithmic import share $\ln(x_{ij}/y_j)$, I will nevertheless refer to the CES-based gravity equation (10) as the 'standard' or 'traditional' specification as opposed to the translog specification in equation (7).

The log-linear form of equation (10) is the key difference to the translog gravity equation (7). The log-linear form is also a feature of the Ricardian model by Eaton and Kortum (2002) as well as the heterogeneous firms model by Chaney (2008).[11] It implies a trade cost elasticity η that is constant, where η is defined as[12]

$$(11)\quad \eta \equiv \frac{\mathrm{d}\ln(x_{ij}/y_j)}{\mathrm{d}\ln(t_{ij})}.$$

Thus, the traditional gravity equation (10) implies η^{CES}=-(σ-1).[13]

However, translog gravity breaks this constant link between trade flows and trade costs. The translog (TL) trade cost elasticity follows from equation (7) as

$$(12)\quad \eta_{ij}^{TL} = -\gamma n_i/(x_{ij}/y_j).$$

It thus varies across observations. Specifically, ceteris paribus the absolute value of the elasticity, $\left|\eta_{ij}^{TL}\right|$, decreases as the import share grows larger. Intuitively, given the size y_j of the importing

[10] Note that in the absence of trade costs (t_{ij}=1$\forall i,j$), the CES and translog gravity equations coincide as $x_{ij}/y_j=y_i/y^W$. With positive trade costs the models are non-nested (see section 3.3.3 for a discussion).

[11] The trade cost coefficient in Eaton and Kortum (2002) is governed by the technology parameter θ, which is the shape parameter from the underlying Fréchet distribution. The trade cost elasticities in Chaney (2008) and Melitz and Ottaviano (2008) are governed by the parameter that determines the degree of firm heterogeneity, drawn from a Pareto distribution. Other differences include, for instance, the presence of bilateral fixed trade costs in the Chaney gravity equation.

[12] The elasticity η as defined here focuses on the direct effect of t_{ij} on x_{ij}/y_j. It abstracts from the indirect effect of t_{ij} on x_{ij}/y_j through the multilateral resistance terms. These are general equilibrium effects that operate in both the CES and the translog frameworks. See section 3.5 for a discussion.

[13] The gravity equation by Eaton and Kortum (2002) implies η^{EK}=-θ. Likewise, the gravity equations by Chaney (2008) and Melitz and Ottaviano (2008) also imply a constant trade cost elasticity, given by the Pareto shape parameter.

country and the number of exported goods n_i, a large trade flow x_{ij} means that the exporting country enjoys a relatively powerful market position. Demand for the exporter's goods is buoyant, and consumers do not react strongly to price changes induced by changes in trade costs. On the contrary, a small trade flow x_{ij} means that demand for an exporting country's goods is weak, and consumers are sensitive to price changes. As a result, small exporters are hit harder by rising trade costs and find it more difficult to defend their market share.

3. Estimation

In this section, I first estimate a translog gravity regression as derived in equation (7), and separately I also estimate a traditional gravity regression as in equation (10). I then proceed by examining whether the trade cost elasticity is constant (as predicted by the traditional gravity model) or variable (as predicted by the translog gravity model).

3.1. Data

I use exports amongst 28 OECD countries for the year 2000, sourced from the IMF Direction of Trade Statistics and denominated in US dollars. These include all OECD countries except for the Czech Republic and Turkey. The maximum number of bilateral observations is 28*27=756, but seven are missing so that the sample includes 749 observations in total.[14] Income data for the year 2000 are taken from the IMF International Financial Statistics.

I follow the gravity literature by modeling the trade cost factor t_{ij} as a log-linear function of observable trade cost proxies (see Anderson and van Wincoop, 2003 and 2004). For the baseline specification, I use bilateral great-circle distance $dist_{ij}$ between capital cities as the sole trade cost proxy, taken from www.indo.com/distance. For other specifications I add an adjacency dummy adj_{ij} that takes on the value 1 if countries i and j share a land border. The trade cost function can thus be written as

$$(13)\quad \ln(t_{ij}) = \rho \ln(dist_{ij}) + \delta\, adj_{ij},$$

where ρ denotes the distance elasticity of trade costs and δ is the adjacency coefficient.

[14] The countries are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Korea, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, the Slovak Republic, Spain, Sweden, Switzerland, the United Kingdom and the United States. As some data for the Czech Republic and Turkey were missing, these countries were dropped from the sample.

To estimate translog gravity equation (7), I also require data on n_i, the number of goods that originate from country i. Naturally, such data are not easy to obtain and the theory does not provide guidance as to how it should be measured. However, Hummels and Klenow (2005) construct a measure of the extensive margin across countries based on shipments in more than 5,000 six-digit product categories from 126 exporting countries to 59 importing countries for the year 1995. The extensive margin is measured by weighting categories of goods by their overall importance in exports, consistent with the methodology developed by Feenstra (1994). Their Table A1 reports the extensive margin of country i relative to the rest of the world. I use this fraction as a proxy for n_i. Hummels and Klenow (2005) document that the extensive margin tends to be larger for big countries. For example, the extensive margin measure is 0.91 for the United States, 0.79 for Germany and 0.72 for Japan but only 0.05 for Iceland. I will also go through a number of robustness checks to ensure that my results do not solely depend on this particular extensive margin measure.

3.2. Estimating translog gravity

The first and last terms on the right-hand side of equation (7) can be captured by an exporter fixed effect S_i since they do not vary over the importing country j:

$$S_i \equiv \frac{y_i}{y^W} + \gamma n_i \sum_{s=1}^{J} \frac{y_s}{y^W} \ln\left(\frac{t_{is}}{T_s}\right).$$

I substitute this exporter fixed effect into equation (7) to obtain

$$(14)\quad \frac{x_{ij}}{y_j} = -\gamma n_i \ln(t_{ij}) + \gamma n_i \ln(T_j) + S_i + \varepsilon_{ij},$$

where I also add a mean-zero error term ε_{ij}. Then I substitute the trade cost function (13) into the multilateral resistance term (8). This yields

$$\ln(T_j) = \rho \ln(T_j^{dist}) + \delta T_j^{adj},$$

where the terms on the right-hand side are defined as

$$(15)\quad \ln(T_j^{dist}) \equiv \sum_{s=1}^{J} \frac{n_s}{N} \ln(dist_{sj}) \text{ and } T_j^{adj} \equiv \sum_{s=1}^{J} \frac{n_s}{N} adj_{sj}.$$

Using the trade cost function (13) once again for $\ln(t_{ij})$, the translog estimating equation follows as

$$(16)\quad \frac{x_{ij}}{y_j} = -\gamma\rho n_i \ln(dist_{ij}) + \gamma\rho n_i \ln(T_j^{dist}) - \gamma\delta n_i adj_{ij} + \gamma\delta n_i T_j^{adj} + S_i + \varepsilon_{ij}.$$

I construct the explanatory variables $n_i \ln(dist_{ij})$ and $n_i adj_{ij}$ by multiplying the underlying trade cost variables by the extensive margin proxy n_i taken from Hummels and Klenow (2005). The $\ln(T_j^{dist})$ and T_j^{adj} terms are constructed for each country j according to equation (15) and then multiplied by the extensive margin proxy n_i.

Table 1 presents the regression results. Column 1 estimates equation (16) with bilateral distance as the only trade cost proxy.[15] As one would expect, import shares tend to be significantly lower for more distant country pairs. Column 2 adds the adjacency dummy. As typically found in gravity estimations, this coefficient is positive and significant. The coefficients of the individual regressors and the corresponding multilateral resistance regressors are similar in magnitude as predicted by estimating equation (16). For example, the distance coefficient in column 1 is estimated at -0.0296, whereas the corresponding trade cost index term is 0.0207. These two values are reasonably close in absolute magnitude, although a formal test of their equality is rejected (p-value=0.00). However, for the two adjacency regressors in column 2 a test of their equality in absolute magnitude cannot be rejected (p-value=0.81).

As an alternative to the Hummels and Klenow (2005) measure, I devise an unweighted count of six-digit product categories to account for the extensive margin. The correlation between the two measures stands at 77 percent.[16] I use this alternative measure as a robustness check to re-estimate columns 1 and 2 of Table 2, finding qualitatively very similar results. Furthermore, in Appendix B.1 in the online appendix I estimate equation (16) non-parametrically in order to provide further robustness checks that do not rely on the Hummels and Klenow (2005) measure. Overall, I yield results that are consistent with the translog model.

As an additional specification, I adopt a related estimating equation where the dependent variable is the import share x_{ij}/y_j divided by the extensive margin measure n_i for the exporting

[15] I cluster around bilateral country pairs. For example, one joint cluster is formed for the trade flows between the United States and Canada, regardless of the direction.

[16] I use UN Comtrade bilateral export data at the six-digit level for the year 2000 (HS 1996 classification). I exclude very small bilateral trade flows (those with values below 10,000 US dollars) since those tend to disappear frequently from one year to the next. Following Hummels and Klenow (2005), I normalize the extensive margin measure by constructing it relative to the total number of six-digit product categories that exist across all countries (5130 categories). This alternative measure is 0.99 for the US, 0.95 for Germany, 0.89 for Japan and 0.10 for Iceland.

country. The resulting variable can be interpreted as the average import share per good of the exporting country. From equation (16) I obtain

$$(17)\quad \frac{x_{ij}/y_j}{n_i} = -\gamma\rho\ln(dist_{ij}) - \gamma\delta adj_{ij} + \hat{S}_i + \hat{S}_j + \nu_{ij},$$

where ν_{ij} denotes the error term. The exporter fixed effect $\hat{S}_i = S_i / n_i$ now absorbs the extensive margin measure n_i, and the multilateral resistance terms associated with distance and adjacency can be captured by an importer fixed effect $\hat{S}_j$ given by

$$\hat{S}_j \equiv \gamma\rho\ln(T_j^{dist}) + \gamma\delta T_j^{adj}.$$

I prefer specification (17) to (16) because any possible measurement error surrounding n_i is passed on to the left-hand side and estimation can be carried out with both exporter and importer fixed effects, as is frequently done in the gravity literature.

The regression results are reported in columns 3 and 4. As before, distance enters with the expected negative coefficient and adjacency with a positive coefficient.[17] As an additional check, I refer to Appendix B.2 in the online appendix where I estimate specifications similar to equations (16) and (17) but with a multiplicative error term instead of the additive error term. That estimation is carried out with nonlinear least squares.

As a final check, in columns 5 and 6 I make the simplifying assumption that each country is endowed with only one good (n_i=1 ∀ i).[18] Naturally, the magnitudes of the coefficients shift but they retain their signs and significance. Overall, given an R-squared of 50 percent or more, I conclude that the translog gravity equation passes its first test of being reasonable.

Apart from translog gravity, I also estimate the standard gravity specification. I substitute the trade cost function (13) into equation (10) to arrive at the estimating equation for traditional gravity:

$$(18)\quad \ln\left(\frac{x_{ij}}{y_j}\right) = -(\sigma-1)\rho\ln(dist_{ij}) - (\sigma-1)\delta\, adj_{ij} + \tilde{S}_i + \tilde{S}_j + \xi_{ij},$$

[17] As an additional robustness check, I re-estimate columns 1-4 of Table 1 with an alternative measure of the extensive margin. In particular, I use both y_i and ln(y_i) as measures of n_i. The results are qualitatively similar and therefore not reported here.

[18] Alternatively, I could also set n_i=n where n is any arbitrary positive integer. Since the regression is linear, the estimated coefficients would simply be scaled by the factor 1/n.

where I add an error term ξ_{ij}.[19] $\tilde{S}_i$ and $\tilde{S}_j$ are exporter and importer fixed effects defined as

$$\tilde{S}_i \equiv \ln\left(\frac{y_i}{y^W}\right) + (\sigma - 1)\ln(\Pi_i),$$
$$\tilde{S}_j \equiv (\sigma - 1)\ln(P_j).$$

The logarithmic form of the dependent variable is the key difference to the translog specification.

Regression results for equation (18) are presented in columns 1 and 2 of Table 2. As usual, bilateral distance is negatively related to import shares with a coefficient in the vicinity of -1, whereas adjacency is associated with higher shares.[20] Consistent with the gravity literature, the log-linear regressions in Table 2 have a high explanatory power with R-squareds close to 90 percent.

Although the R-squareds associated with the regressions in Table 1 are around 55 percent and thus lower, they are not directly comparable to those in Table 2 because the dependent variables are not the same. It is therefore useful to get a visual impression of the fit of the two models. For that purpose, I plot the fitted values against the actual values of import shares for each model. For the translog specification, I use column 3 of Table 1. For the standard specification, I use a regression that corresponds to column 1 of Table 2 but with $\ln((x_{ij}/y_j)/n_i)$ as the dependent variable (see footnote 20). These two specifications are similar in the sense that apart from various fixed effects, the log of distance is the only regressor. The dependent variable of the translog specification is $(x_{ij}/y_j)/n_i$. To generate visual impressions of the two models that are more easily comparable, I exponentiate the fitted and actual values for the standard model. I thus obtain import shares expressed in the same units for both specifications, that is, in units of $(x_{ij}/y_j)/n_i$.

The results can be seen in Figure 1. The left panel is based on the translog model, and the right panel is based on the standard model. Both models do fairly well in fitting small import shares. For intermediate import shares in the range from 0.05 to 0.15 the translog model still generates a reasonably good fit, whereas the residuals for the standard model tend to grow. For

[19] An estimating equation based on the Eaton and Kortum (2002) model would merely replace σ-1 by θ. Here, the crucial feature is that the trade cost elasticity is constant. This feature would also arise for the other gravity models mentioned above.

[20] For completeness, I rerun the regressions in columns 1 and 2 of Table 2 with the logarithmic import share per good of the exporting country, $\ln((x_{ij}/y_j)/n_i)$, as the dependent variable. The measure for n_i is entirely absorbed by the exporter fixed effects so that the coefficients of interests and their standard errors remain the same. However, the R-squareds are reduced to 85 percent.

large import shares both models produce larger residuals, and the translog model in particular underpredicts the actual import shares.

Those large residuals can in part be explained by the nature of the dependent variable, $(x_{ij}/y_j)/n_i$. Using x_{ij}/y_j instead as in column 1 of Table 1 and column 1 of Table 2 implies a smaller range of values for the dependent variable so that the residuals would be smaller. The reason is that Hummels and Klenow (2005) express the extensive margin measure n_i relative to the rest of the world so that $0<n_i<1$, pushing up values for $(x_{ij}/y_j)/n_i$ compared to x_{ij}/y_j. For example, the largest value for $(x_{ij}/y_j)/n_i$ is 0.41 for imports to Luxembourg from Belgium but the corresponding value for x_{ij}/y_j would only be 0.19.

3.3. Comparing traditional and translog gravity

The next objective is to examine how the data relate to different aspects of the traditional gravity model on the one hand and translog gravity on the other. The difficulty is that the two competing models are non-nested. This problem arises because the traditional gravity model has the logarithmic trade share as the dependent variable, whereas the dependent variable of the translog model has the trade share in levels. Before I compare the performance of the two models more directly at the end of this section, I first turn towards more informal checks that center on the question of whether the trade cost elasticity is constant.

3.3.1. Does the trade cost elasticity vary?

As equation (12) shows, translog gravity implies that the absolute value of the trade cost elasticity decreases in the import share per good, i.e.,

$$\frac{\partial\left|\eta_{ij}^{TL}\right|}{\partial\left(\dfrac{x_{ij}/y_j}{n_i}\right)}<0.$$

In contrast, standard gravity equations imply a constant trade cost elasticity. I form two hypotheses, A and B, to test whether the elasticity is indeed constant under the maintained assumption of the log-linear trade cost function (13). Hypothesis A is based on the standard gravity estimation as in equation (18), while hypothesis B is based on the translog gravity estimation as in equation (17).

The premise of hypothesis A is that the standard gravity model is correct and that trade cost elasticities should not vary systematically. To implement this test, I allow the trade cost coefficients in the traditional specification (18) to vary across import shares per good. Since estimating a separate distance coefficient for each observation would leave no degrees of freedom, I allow the distance coefficient to vary over intervals of import shares per good. That is, I set the distance coefficient for observation *ij* equal to λ_h if this observation falls in the *h*th interval with $h=1,...,H$. H denotes the interval with the largest import shares per good, and the number of intervals is sufficiently small to leave enough degrees of freedom in the estimation. I also add interval fixed effects. For simplicity, I drop the adjacency dummy from the notation so that the estimating equation becomes

$$(19)\quad \ln\left(\frac{x_{ij}}{y_j}\right) = -\lambda_h \ln(dist_{ij}) + \tilde{S}_i + \tilde{S}_j + \tilde{S}_h + \omega_{ij},$$

where $\tilde{S}_h$ denotes the interval fixed effect and ω_{ij} is an error term. Hypothesis A states – as predicted by the traditional gravity model – that the λ_h distance coefficients should not vary across import share intervals, i.e., $\lambda_1 = \lambda_2 = ... = \lambda_H$. The alternative is – consistent with the translog gravity model – that the λ_h distance coefficients should vary systematically across intervals as implied by equation (12). Specifically, the absolute elasticity should decrease across the intervals, i.e., $\lambda_1 > \lambda_2 > ... > \lambda_H$.[21]

How exactly should the intervals be chosen? If the intervals were chosen based on *observed* values for import shares, this selection would be based on the dependent variable and would lead to an endogeneity bias in the coefficients of interest, λ_h. More specifically, I carried out Monte Carlo simulations demonstrating that this selection procedure would lead to an upward bias in the distance coefficients (i.e., λ_h coefficients closer to zero) since both the dependent variable and the interval classification would be positively correlated with the error term.[22]

[21] To be clear, equation (19) does not represent a formal test of non-nested hypotheses.

[22] I simulated import shares under the assumption that the Anderson and van Wincoop (2003) gravity equation (10) is the true model, using distance as the trade cost proxy based on the trade cost function (13) and assuming various arbitrary parameter values for the distance elasticity ρ and the elasticity of substitution σ. The variance of the log-normal error term was chosen to match the R-squared of around 90 percent as in Table 2. I then divided the sample into intervals based on the simulated import shares and ran regression (19) with OLS, replicating this procedure 1000 times. The resulting bias can be severe, in some cases halving the magnitudes of coefficients compared to their true values.

The endogeneity bias can be avoided if intervals are chosen based on *predicted* import shares. In particular, I first estimate equation (18) and obtain trade cost coefficients that are common across all observations. Based on those regression results I then predict import shares and divide the sample into H intervals of predicted import shares. By construction, this interval classification is uncorrelated with the residuals of regression (18). Indeed, Monte Carlo simulations confirm that with this two-stage procedure, estimating equation (19) no longer imparts a bias on the λ_h coefficients.[23]

Table 3 presents regression results for equation (19) under the assumption of H=5, i.e., with five import share intervals. Consistent with equation (12), the intervals in columns 1 and 2 are chosen based on predicted import shares per good, $(x_{ij}/y_j)/n_i$. As a robustness check, the intervals in columns 3 and 4 are chosen based on predicted import shares only, x_{ij}/y_j.

Columns 1 and 3 report results with distance as the only trade cost regressor. A clear pattern arises: the λ_h distance coefficients decline in absolute value for intervals with larger import shares, as consistent with the translog model. For example, in column 1 the distance elasticity for the smallest import shares is -1.4960 whereas it shrinks in magnitude to -1.0790 for the largest import shares. Hypothesis A, which states that the distance coefficients are equal to each other, can be clearly rejected (p-value=0.01 in column 1, p-value=0.00 in column 3).

Columns 2 and 4 add adjacency. Since no adjacent country pair in the sample falls into the interval capturing the smallest predicted import shares, the corresponding regressor drops out. The addition of the adjacency dummies does not alter the pattern of distance coefficients. Those still decline monotonically in magnitude across all specifications and their equality can be rejected (p-values=0.00). There is no such monotonic pattern for the adjacency coefficients, but their point estimates for intervals 2 and 3 are substantially larger than those for intervals 4 and 5.[24] Overall, their equality can be clearly rejected in column 2 (p-value=0.00) although not in column 4 (p-value=0.34). But the specification in column 2 is preferable since it is based on intervals of predicted import shares per good, as warranted by equation (12).

I also experimented with different interval numbers, in particular H=3 and H=10 (not reported here). The results are not qualitatively affected and the same coefficient patterns arise as

[23] In Appendix B.3 in the online appendix I present an alternative stratification procedure in terms of right-hand side variables, not in terms of predicted import shares.

[24] A clear monotonic pattern for the adjacency coefficients does emerge in column 2 of Table 3 if the alternative, unweighted measure is used for the extensive margin n_i.

in Table 3. This suggests that the systematic inequality of trade cost elasticities across import share intervals is a robust feature of the data. In summary, therefore, the results seem inconsistent with the constant elasticity gravity specification, at least in combination with the log-linear trade cost function (13).[25]

Hypothesis B is based on the translog gravity estimating equation (17). Its premise is that the translog specification is correct and that the trade cost coefficients in that estimation should not vary systematically across import shares. I adopt the same strategy as above in that I allow the trade cost coefficients to vary across intervals. A more detailed description and the results can be found in Appendix B.4 in the online appendix. I show that distance coefficients are typically more stable in the translog specification although in most cases the hypothesis of constant coefficients can be rejected at conventional levels of significance. But at least qualitatively, those results seem in line with the predictions of the translog gravity model under the maintained assumption of a log-linear trade cost function.

3.3.2. Comparing the goodness of fit

I now turn towards comparing the performance of the two models more directly. As their dependent variables differ, their associated R-squareds are not directly comparable. To facilitate a comparison I estimate the standard gravity equation in levels as opposed to logarithms. The left-hand side variable then becomes the same as for the translog specification.

Specifically, I take the standard gravity equation (9), divide it by y_j on both sides so that the left-hand side variable becomes x_{ij}/y_j. I carry out the estimation with nonlinear least squares, using (exponentiated) exporter and importer fixed effects to absorb y_i and the multilateral resistance terms and using distance as the only trade cost regressor (based on the exponentiated version of trade cost function 13).

I estimate two specifications. The first uses a multiplicative error term $e^{\xi_{ij}}$ where ξ_{ij} is assumed normally distributed. As this specification is the levels analog of the logarithmic regression in equation (18), it yields exactly the same results as reported in column 1 of Table 2. In particular, this specification yields an R-squared of 0.89. The second specification is also

[25] As I further discuss in section 3.6, a specification as in equation (19) combines two restrictions that are difficult to separate: the log-linearized standard gravity equation on the one hand and a constant elasticity of trade costs with respect to trade costs on the other.

estimated in levels but with an additive error term. This makes it comparable to the translog estimations reported in Table 1, which are also based on an additive error term. The result is a slightly larger distance coefficient in absolute value (-1.4258 instead of -1.2390 in column 1 of Table 2) but a similar R-squared of 0.88. In summary, the levels specification is characterized by essentially the same degree of explanatory power as the logarithmic specification, regardless of whether it is estimated with a multiplicative or an additive error term.

Which translog specifications are the relevant points of comparison? The relevant comparison for the first specification is a translog regression with x_{ij}/y_j as the dependent variable and a multiplicative error term. This regression is reported in column 1 of Table B2 (see Appendix B.2 for details). The associated R-squared is 0.91 and thus in the same ballpark as 0.89. The relevant comparison for the second specification is the translog regression in column 1 of Table 1 since it is also estimated with an additive error term. The R-squared there is only 0.52 and thus lower than 0.88. Overall, I therefore conclude that in terms of explanatory power, the translog model performs worse with an additive error term but equally well as the standard model when a multiplicative error term is used.

3.3.3. A Box-Cox transformation of the dependent variable

The difficulty in distinguishing the two models econometrically in a more formal way is that they are non-nested with different functional forms of the left-hand side variable. Specifically, as in equation (17) the translog model can be expressed with $(x_{ij}/y_j)/n_i$ as the dependent variable. Akin to equation (18) the standard model can be rewritten with $\ln((x_{ij}/y_j)/n_i)$ as the dependent variable, in which case the exporter fixed effect absorbs the n_i term. The two specifications share the same right-hand side regressors in the estimation, i.e., logarithmic distance as well as exporter and importer fixed effects (the adjacency dummy is dropped for simplicity). Thus, they only differ on the left-hand side in terms of their functional form.

I adopt the popular Box-Cox transformation of the dependent variable according to

$$\left(\frac{x_{ij}/y_j}{n_i}\right)^{(\theta)} = \frac{\left(\frac{x_{ij}/y_j}{n_i}\right)^{\theta} - 1}{\theta}.$$

The case of θ=1 corresponds to the linear (translog) case, and θ=0 corresponds to log-linearity as

$$\lim_{\theta \to 0} \frac{\left(\frac{x_{ij} / y_j}{n_i} \right)^{\theta} - 1}{\theta} = \ln\left(\frac{x_{ij} / y_j}{n_i} \right).$$

The right-hand side variables are not transformed. A regression with the Box-Cox transform as the dependent variable and an additive error structure yields a point estimate of 0.1201 for θ with a standard error of 0.0108. This result means that θ is significantly different from 1 and 0, and both the linear and log-linear cases are rejected (p-values=0.00).[26] The coefficient on logarithmic distance follows as -0.6871 and is thus roughly in the middle of the corresponding coefficients for the translog model in column 3 of Table 1 (equal to -0.0250) and the standard model in column 1 of Table 2 (equal to -1.2390).

Overall, from a purely statistical point of view the Box-Cox procedure therefore produces an inconclusive outcome. Such outcomes often occur with non-nested tests as well as in Box-Cox applications (see the discussion in Pesaran and Weeks, 2007). The reason is that these tests typically involve two different null hypotheses that can each be rejected, in this case the hypotheses θ=1 and θ=0.

However, from an economic point of view a common sense conclusion is that the standard specification seems favored. The intuition is that the standard form with an additive error term yields an R-squared in the region of 90 percent (see Table 2), whereas the translog form with an additive term yields an R-squared in the region of only 50 percent (see Table 1).

My overall interpretation is that whilst the results certainly cannot be seen as an endorsement of the translog model, they still highlight weaknesses of the standard log-linear gravity model. While some features of the data are suggestive of the standard form, others are more consistent with the variable elasticity specification implied by the translog functional form. There are bound to be models that fit the data even better than the one-parameter translog model developed in this paper. But nevertheless, the translog specification indicates the direction in which the demand side of trade models could be sensibly modified to yield gravity equations with variable trade cost elasticities.

[26] Sanso, Cuairan and Sanz (1993) also estimate a generalized functional form of the gravity equation defined by a Box-Cox transformation with transformed regressors. Consistent with my results, they find evidence against the standard log-linear specification based on trade flows amongst 16 OECD countries over the period from 1964 to 1987. However, they do not provide a theory that might justify the non-loglinear functional form.

3.4. Illustration: some numbers for trade cost elasticities

The crucial result from the preceding gravity estimations is that a constant 'one-size-fits-all' trade cost elasticity is inconsistent with the data. Instead, the trade cost elasticities vary with the import share, as predicted by translog gravity. What are the implied values for these elasticities? This question can be answered by considering the elasticity expression in equation (12). The elasticities η_{ij} depend on the translog parameter γ, the import share x_{ij}/y_j and the number of goods of the exporting country n_i.

The values for x_{ij}/y_j and n_i are given by the data, and the translog parameter γ can be retrieved from the estimated distance coefficient in a translog regression. As the translog estimating equation (16) shows, the coefficient on the variable $n_i \ln(dist_{ij})$ corresponds to the negative product of the translog parameter γ and the distance elasticity of trade costs ρ. As an illustration, I take 0.0296 from column 1 of Table 1 as an absolute value for this coefficient, i.e., $\gamma\rho$=0.0296. To be comparable to the gravity literature, I choose a value of ρ that is consistent with typical estimates, ρ=0.177.[27] The value of the translog parameter then follows as γ=0.0296/ρ=0.167.[28] To be clear, I only choose a value of ρ for illustrative purposes. The analysis below does not qualitatively depend on this particular value.

The trade cost elasticities can now be calculated across different import shares. I first calculate the trade cost elasticity evaluated at the average import share in the sample. This average share is x_{ij}/y_j=0.01. The average of the extensive margin measure is n_i=0.50. The trade cost elasticity therefore follows as $\eta_{ij} = -\gamma n_i / (x_{ij}/y_j)$=-0.167*0.50/0.01=-8.4.[29] Thus, if trade costs go down by one percent, ceteris paribus the average import share is expected to increase by 8.4

[27] I obtain this value as follows. In standard gravity equations such as equation (18), the distance coefficient corresponds to the parameter combination -(σ-1)ρ. It is typically estimated to be around -1 (see Disdier and Head, 2008), and in column 1 of Table 2 I obtain a reasonably close estimate of -1.239 for my sample of OECD countries. Under the assumption of an elasticity of substitution equal to σ=8, the distance coefficient estimate implies ρ=1.239/(8-1)=0.177. But one does not have to rely on a standard gravity regression to obtain a parameter value for ρ. Limão and Venables (2001, Table 2) report values for ρ in the range of 0.21-0.38 based on regressions of logarithmic c.i.f./f.o.b. ratios on logarithmic distance. See Anderson and van Wincoop (2004, Figure 1) for further evidence that ρ=0.177 is a reasonable value.

[28] Based on an estimation of supply and demand systems at the 4-digit industry level, Feenstra and Weinstein (2010) yield a median translog coefficient of γ=0.19. My value of γ=0.167 is reasonably close and would match Feenstra and Weinstein's (2010) estimate exactly in the case of ρ=0.156.

[29] The extensive margin measure taken from Hummels and Klenow (2005) more closely corresponds to the fraction n_i/N since they report the extensive margin of country i relative to the rest of the world. However, this does not affect the implied trade cost elasticities. The reason is that the elasticities as expressed in equation (12) depend on the product γn_i. If n_i is multiplied by a constant ($1/N$), the linear estimation in regression (16) leads to a point estimate of γ that is scaled up by the inverse of the constant (i.e., scaled up by N) so that their product is not affected ($N\gamma * n_i / N = \gamma n_i$).

percent. Under the assumption of an elasticity of substitution equal to σ=8, which falls approximately in the middle of the range [5,10] as surveyed by Anderson and van Wincoop (2004), this value would be close to the CES-based trade cost elasticity, η^{CES}=-(σ-1), which equals 7.[30]

However, in contrast to the CES specification, the trade cost elasticities based on the translog gravity estimation vary across import shares. A given trade cost reduction therefore has a heterogeneous impact on import shares. As an example, I illustrate this heterogeneity with import shares that involve New Zealand as the importing country. I choose New Zealand because its import shares vary across a relatively broad range so that the heterogeneity of trade cost elasticities can be demonstrated succinctly. Of course, the analysis would be qualitatively similar for other importing countries.

Specifically, the Australian share of New Zealand's imports is the biggest (7.2 percent), followed by the US share (3.8 percent), the Japanese share (2.4 percent) and the UK share (0.9 percent). The corresponding trade cost elasticities, computed in the same way as before, are -1.3 for Australia, -4.0 for the US, -5.0 for Japan and -14.4 for the UK. Figure 2 plots these trade cost elasticities in absolute value against the import shares, adding various additional countries that export to New Zealand.[31] Dashed lines represent 95 percent confidence intervals computed with the delta method based on the regression in column 1 of Table 1. The figure shows that trade flows are more sensitive to trade costs if import shares are small. The impact of a given trade cost change is therefore heterogeneous across country pairs. This key feature stands in contrast to the trade cost elasticity in the standard CES-based gravity model, which is simply a constant (σ-1=7 in this case).

3.5. General equilibrium effects

If bilateral trade costs t_{ij} change, this has a direct effect on the corresponding import share x_{ij}/y_j. But the change in t_{ij} also has an indirect effect on x_{ij}/y_j through a change in price indices, which is the famous multilateral resistance effect highlighted by Anderson and van Wincoop

[30] Based on the above way of calculating ρ, for alternative values of σ it would also be true that the translog trade cost elasticity evaluated at the average import share is close to the underlying CES-based trade cost elasticity. For instance, under the assumption of σ=5, it follows ρ=0.31 and γ=0.095 so that the trade cost elasticity evaluated at the average import share is -4.8. Under the assumption of σ=10, it follows ρ=0.138 and γ=0.214 so that the trade cost elasticity is -10.7.

[31] In order of declining import shares, the other countries are Germany, Italy, Korea and France.

(2003). Another indirect effect is through a change in income shares. I refer to the indirect effects as general equilibrium effects.

The trade cost elasticity η as defined in equation (11) only captures the direct effect of a change in t_{ij} on x_{ij}/y_j. To illustrate the role of general equilibrium, I decompose how import shares are affected by the direct and indirect effects and how this decomposition varies across import share intervals. But as I clarify further below, general equilibrium effects are not able to explain the pattern of declining distance coefficients as found in Table 3.

I demonstrate the role of general equilibrium effects based on the constant elasticity gravity model in equation (10). As a simplification I assume trade cost symmetry such that outward and inward multilateral resistance terms are equal ($\Pi_i = P_i \ \forall \ i$). As a counterfactual experiment, I will assume a reduction in trade costs t_{ij} for a specific country pair. To understand the effect on the import share, I take the first difference of equation (10) to arrive at

$$(20) \quad \Delta \ln\left(\frac{x_{ij}}{y_j}\right) = (1-\sigma)\Delta \ln(t_{ij}) + \Delta \ln\left(\frac{y_i}{y^W}\right) + (\sigma - 1)\Delta \ln(P_i P_j).$$

The left-hand side of equation (20) indicates the percentage change of the import share. It can be decomposed into three components. The first term on the right-hand side is the direct effect of the change in bilateral trade costs scaled by (1-σ). The second and third terms are the general equilibrium effects, i.e., the change in the exporting country's income share and the change in multilateral resistance terms scaled by (σ-1).

I am interested in how the decomposition in equation (20) varies across import shares. To that end, I first compute an initial equilibrium of trade flows based on the income data and bilateral distance data for the 28 countries in the sample. Then, for each of the 28*27=756 bilateral observations I compute a counterfactual equilibrium under the assumption that all else being equal, bilateral trade costs for the observation have decreased by one percent, i.e., $\Delta\ln(t_{ij})$=-0.01, assuming an elasticity of substitution of σ=8. I use the trade cost function (13) with distance as the only trade cost variable, assuming a distance elasticity of ρ =1/7.[32]

[32] The counterfactual equilibria are computed in the same way as in Anderson and van Wincoop (2003, Appendix B). The required domestic distance data are taken from the CEPII, see http://www.cepii.fr/anglaisgraph/bdd/distances.htm. The distance elasticity is close to the value chosen in section 3.4 for illustrative purposes. The results are qualitatively not sensitive to alternative values. I also experimented with alternative parameter assumptions for the substitution elasticity (σ=5 and σ=10) and different trade cost declines (5 percent and 10 percent). The overall results are qualitatively very similar.

Table 4 presents the decomposition results that correspond to equation (20). The rows report the average changes for each import share interval. Given the parameter assumption of σ=8, the direct effect of a one percent drop in bilateral trade costs is an increase in the import share of seven percent across all intervals (see column 2). While changes in the income shares in column 3 do not vary systematically across import shares, the multilateral resistance effects in column 4 are largest in absolute size for the interval capturing the largest import shares. In total, the general equilibrium effects dampen the direct effect for larger import shares (see the total effect in column 1). Intuitively, large countries like Japan and the US are less dependent on international trade such that changes in bilateral trade costs have little effect on multilateral resistance. As large countries are typically associated with small bilateral import shares (they mainly import from themselves), the indirect general equilibrium effects are often negligible for small import shares. However, for small countries like Iceland and Luxembourg a given change in bilateral trade costs shifts multilateral resistance relatively strongly. As those countries are typically associated with larger import shares, general equilibrium effects tend to be stronger in that case so that the total effect is dampened. The trade cost elasticities in columns 5a and 5b summarize these effects. Columns 6a and 6b report the implied distance elasticities. From equation (18) the direct distance elasticity is simply given by $-(\sigma-1)\rho$, which equals -1 in this case.

It is important to stress that the distance elasticities in Tables 2 and 3 only represent the direct elasticities. General equilibrium effects work in addition to the direct effect and are absorbed by exporter and importer fixed effects. To verify this claim, I conduct Monte Carlo simulations as in section 3.3.1 for the constant elasticity model. The simulations are now based on the counterfactual scenario that all bilateral trade costs decline by one percent, leaving domestic distances unchanged. Thus, the simulated import shares are shifted by both direct and indirect effects. I then re-estimate gravity regression (19), dividing the sample into five import share intervals and allowing the distance elasticities to vary across these intervals. The results show that the distance coefficients are consistently estimated as the parameter combination $-(\sigma-1)\rho$ across all five intervals. They do not reflect general equilibrium effects. Thus, general equilibrium effects cannot account for the systematic pattern of distance elasticities reported in Table 3.

3.6. Alternative trade cost specifications

The log-linear trade cost function (13) is the standard specification in the gravity literature. However, I also examine other specifications to ensure that the coefficient patterns in the regression tables do not hinge on this particular functional form.

In Table 5 I add more trade cost variables apart from distance and adjacency. In particular, I add three variables that are commonplace in the gravity literature: a common language dummy, a currency union dummy and a dummy capturing a common colonial history.[33] The purpose is to check whether the distance coefficient patterns in Table 3 are driven by the omission of these trade cost variables. I therefore add them to those regressions.

In particular, for the standard gravity case I rerun the regression in column 1 of Table 3 with the added variables. The result is reported in column 1 of Table 5. Clearly, the pattern of declining absolute distance coefficients is still in place. The distance coefficients monotonically decline in absolute value from 1.4463 to 0.8155. Their equality is rejected (p-value=0.00). The added trade cost regressors have the expected (positive) signs but are not always significant. For the translog gravity case, the result is reported in column 2 of Table 5. There is no clear pattern of distance coefficients. For example, the distance coefficient in the second interval (equal to -0.0473) is larger in absolute value than the one in the first interval (equal to -0.0398) but smaller than those in the third, fourth and fifth intervals (equal to -0.0464, -0.0460 and -0.0447). The fact that there is no trend in the coefficients is consistent with the translog gravity prediction (see Appendix B.4 in the online appendix for a more detailed discussion of this aspect).

Table 6 attempts to address a more fundamental identification problem. The elasticity of trade with respect to distance is the combination of the elasticity of trade with respect to trade costs and the elasticity of trade costs with respect to distance. That is,

$$\frac{\mathrm{d}\ln(x_{ij}/y_j)}{\mathrm{d}\ln(dist_{ij})} = \frac{\mathrm{d}\ln(x_{ij}/y_j)}{\mathrm{d}\ln(t_{ij})}\frac{\mathrm{d}\ln(t_{ij})}{\mathrm{d}\ln(dist_{ij})}.$$

[33] The language dummy takes on the value 1 if two countries have at least one official language in common according to the CIA World Factbook. Given the countries listed in section 3.1 the currency union dummy only captures the Euro, whose member countries irrevocably fixed their exchange rates in 1999. The colonial dummy captures relationships between the United Kingdom as the colonizer and Australia, Canada, Ireland, New Zealand and the United States.

It is challenging to distinguish a standard constant elasticity gravity model with a more flexible trade cost function on the one hand from a translog gravity model with a variable trade cost elasticity on the other. Both these models could be observationally equivalent.[34]

The standard gravity case yields $\mathrm{d}\ln(x_{ij}/y_j)/\mathrm{d}\ln(t_{ij}) = -(\sigma-1)$. The basic trade cost function (13) implies a constant distance elasticity, $\mathrm{d}\ln(t_{ij})/\mathrm{d}\ln(dist_{ij}) = \rho$. But as can be seen in equation (18), estimation only yields an estimate of their product, $-(\sigma-1)\rho$. To separately identify variation in $\mathrm{d}\ln(x_{ij}/y_j)/\mathrm{d}\ln(t_{ij})$ and $\mathrm{d}\ln(t_{ij})/\mathrm{d}\ln(dist_{ij})$ when I allowed for heterogeneous distance coefficients in Table 3, some structure needed to be imposed on the trade cost function. For that purpose I maintained the assumption that trade cost function (13) is correct. That is, I held ρ constant. Due to this identifying assumption all variation in the distance coefficients was attributed to variation in $\mathrm{d}\ln(x_{ij}/y_j)/\mathrm{d}\ln(t_{ij})$. A similar reasoning applies to the translog case. Running regression (17) yields an estimate of $-\gamma\rho$. Given trade cost function (13) all the variation across distance coefficients would therefore be attributed to variation in γ.

Of course, this identification procedure is only valid to the extent that trade cost function (13) is correct. The purpose of Table 6 is to substitute an alternative, more flexible trade cost function. Apart from logarithmic distance I add a quadratic in logarithmic distance:

$$(21)\quad \ln(t_{ij}) = \rho\ln(dist_{ij}) + \tilde{\rho}\left(\ln(dist_{ij})\right)^2.$$

The distance elasticity of trade costs follows as $\mathrm{d}\ln(t_{ij})/\mathrm{d}\ln(dist_{ij}) = \rho + 2\tilde{\rho}\ln(dist_{ij})$ and is thus no longer constant (a non-CES transport technology). For the standard gravity case the elasticity of trade with respect to distance is therefore equal to $-(\sigma-1)\left(\rho + 2\tilde{\rho}\ln(dist_{ij})\right)$.

Methodologically, I want to be clear that equation (21) represents only one specific trade cost function (albeit arguably a reasonable one) out of an infinite number of potential possibilities. Since gravity estimates only yield products of structural elasticity parameters and trade cost parameters, identification in this context inevitably has to rely on a particular assumed functional form.

Column 1 of Table 6 reports a standard gravity regression as in equation (18) but with the additional quadratic distance term based on trade cost function (21). The estimate for $-(\sigma-1)\rho$

[34] As an extreme example, it would always be possible to choose a matrix of trade costs such that the standard model fits the data perfectly with an R-squared of 1.

is negative at -0.2677 but not significant. The estimate for $-(\sigma-1)\tilde{\rho}$ is -0.0644 and significant at the five percent level.

Then, as in section 3.3.1, I allow the distance coefficients to vary across import share intervals. The intervals are given by predicted import shares based on the results in column 1. As before, the identifying assumption is that the trade cost function is correct. In the context of specification (21) this means that I have to hold ρ and $\tilde{\rho}$ constant. Of course, I do not know the values for ρ and $\tilde{\rho}$ as column 1 of Table 6 only reveals their products with $-(\sigma-1)$. However, based on the point estimates I can calculate their ratio as $\rho/\tilde{\rho}$=-0.2677/-0.0644=4.16.[35] To be consistent with the identifying assumption of a constant ρ and a constant $\tilde{\rho}$, I constrain the ratio of the two distance regressors in each interval to this particular value. All variation in the elasticity of trade with respect to distance is therefore attributed to $\mathrm{d}\ln(x_{ij}/y_j)/\mathrm{d}\ln(t_{ij})$. If standard gravity is the true model, the coefficients on $\ln(dist_{ij})$ and $(\ln(dist_{ij}))^2$ should not vary across intervals.

Column 2 of Table 6 reports the results. To reduce the number of parameters to be estimated, I only adopt three intervals instead of five. The $\ln(dist_{ij})$ coefficients are -0.3216, -0.2942 and -0.2542, and the $(\ln(dist_{ij}))^2$ coefficients are -0.0773, -0.0707 and -0.0611. Thus, their absolute values exhibit the same declining pattern as already found in section 3.3.1, and the differences are statistically significant (p-value=0.00). As before, this result casts doubt on the standard gravity specification but it is consistent with the translog model.

The remaining two columns of Table 6 go through the same procedure for the translog specification as in equation (17) with the additional quadratic distance term. Based on the results in column 3 the estimates for $-\gamma\rho$ and $-\gamma\tilde{\rho}$ are -0.0933 and 0.0045, respectively. Their ratio follows as $\rho/\tilde{\rho}$=-20.73. Column 4 allows the coefficients to vary across import share intervals, with the ratio of the two distance regressors constrained to the value of -20.73. The $\ln(dist_{ij})$ coefficients are -0.1182, -0.1407 and -0.1355, and the $(\ln(dist_{ij}))^2$ coefficients are 0.0057, 0.0068 and 0.0066. Although the differences are significant (p-values=0.00) as the coefficients

[35] As ρ in particular is imprecisely estimated, a concern might be that the true ratio could be different. The 95 percent confidence interval for the ratio is given by the values -12.91 and 20.42. The results are qualitatively the same based on either of those two values.

are tightly estimated, there is no monotonic pattern. This finding is consistent with the translog model.

4. Conclusion

Leading trade models from the current literature imply a gravity equation that is characterized by a constant elasticity of trade flows with respect to trade costs. This paper adopts an alternative demand system – translog preferences – and derives the corresponding gravity equation. Due to more flexible substitution patterns across goods, translog gravity breaks the constant trade cost elasticity that is the hallmark of traditional gravity equations. Instead, the elasticity becomes endogenous and depends on the intensity of trade flows between two countries.

In particular, all else being equal, the less two countries trade with each other and the smaller their bilateral import shares, the more sensitive they are to bilateral trade costs. I test the translog gravity specification and find evidence that tends to support this prediction. That is, trade cost elasticities appear heterogeneous across import shares under the standard assumption of a log-linear trade cost function.

The empirical results presented in this paper are based on aggregate trade flows. A natural extension would be an application to more disaggregated data. In that regard, I have obtained some preliminary results based on import shares between OECD countries at the level of 3-digit industries. When I allow gravity distance coefficients for individual industries to vary across import shares in CES-based gravity equations, their absolute values are characterized by the same declining pattern as in Table 3 for industries as diverse as food products, plastic products and electric machinery. This additional evidence suggests that variable trade cost elasticities might be a distinct feature of international trade data also at the industry level. Exploring industry-level data in more detail along those lines is thus an important topic for future research.

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Table 1: Translog gravity

	Multiple goods per country				One good per country (n_i=1)	
Dependent variable	x_{ij}/y_j	x_{ij}/y_j	$(x_{ij}/y_j)/n_i$	$(x_{ij}/y_j)/n_i$	x_{ij}/y_j	x_{ij}/y_j
	(1)	(2)	(3)	(4)	(5)	(6)
$n_i \ln(dist_{ij})$	-0.0296***	-0.0190***				
	(0.0041)	(0.0029)				
$n_i \ln(T_j^{dist})$	0.0207***	0.0105***				
	(0.0049)	(0.0034)				
$n_i\, adj_{ij}$		0.0510***				
		(0.0117)				
$n_i\, T_j^{adj}$		-0.0471**				
		(0.0192)				
$\ln(dist_{ij})$			-0.0250***	-0.0159***	-0.0149***	-0.0094***
			(0.0033)	(0.0021)	(0.0022)	(0.0016)
adj_{ij}				0.0450***		0.0273***
				(0.0090)		(0.0053)
R-squared	0.52	0.59	0.50	0.57	0.50	0.56
Observations	749	749	749	749	749	749

Notes: Robust standard errors clustered around country pairs (378 clusters) reported in parentheses, OLS estimation. Columns 1 and 2: exporter fixed effects not reported. Columns 3-6: exporter and importer fixed effects not reported. ** significant at 5% level. *** significant at 1% level.

Table 2: Constant elasticity gravity

Dependent variable	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$
	(1)	(2)
$\ln(dist_{ij})$	-1.2390***	-1.1697***
	(0.0625)	(0.0713)
adj_{ij}		0.3440**
		(0.1720)
R-squared	0.89	0.89
Observations	749	749

Notes: Robust standard errors clustered around country pairs (378 clusters) reported in parentheses, OLS estimation. Exporter and importer fixed effects not reported. ** significant at 5% level. *** significant at 1% level.

Table 3: Testing constant elasticity gravity (Hypothesis A)

	Intervals based on $(x_{ij}/y_j)/n_i$		Intervals based on (x_{ij}/y_j)	
Dependent variable	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$
	(1)	(2)	(3)	(4)
$\ln(dist_{ij})$, h=1	-1.4960***	-1.4490***	-1.6523***	-1.5970***
	(0.1377)	(0.1313)	(0.1080)	(0.1044)
$\ln(dist_{ij})$, h=2	-1.4636***	-1.3405***	-1.3936***	-1.3190***
	(0.1223)	(0.1117)	(0.1180)	(0.1140)
$\ln(dist_{ij})$, h=3	-1.3668***	-1.2502***	-1.3369***	-1.2131***
	(0.1092)	(0.1043)	(0.1123)	(0.1017)
$\ln(dist_{ij})$, h=4	-1.2235***	-1.0662***	-1.3311***	-1.1551***
	(0.1024)	(0.0968)	(0.0947)	(0.0946)
$\ln(dist_{ij})$, h=5	-1.0790***	-0.8297***	-1.0662***	-0.8251***
	(0.1000)	(0.1045)	(0.0910)	(0.0972)
adj_{ij}, h=2		1.9499***		1.1283*
		(0.2279)		(0.6657)
adj_{ij}, h=3		2.3218***		1.6318***
		(0.2150)		(0.5925)
adj_{ij}, h=4		0.7333***		0.5197***
		(0.2345)		(0.1910)
adj_{ij}, h=5		0.6221***		0.6359***
		(0.1500)		(0.1556)
R-squared	0.90	0.90	0.89	0.90
Observations	749	749	749	749

Notes: The index h denotes intervals in order of ascending predicted import shares. The intervals in columns 1 and 2 are based on predicted import shares divided by n_i. The intervals in columns 3 and 4 are based on predicted import shares only. The adj_{ij} regressor for interval h=1 drops out since no adjacent country pair falls into this interval. Robust standard errors clustered around country pairs (378 clusters) reported in parentheses, OLS estimation. Exporter and importer fixed effects and interval fixed effects not reported. * significant at 10% level. *** significant at 1% level.

Table 4: General equilibrium effects in response to a counterfactual decline in trade costs

	Total effect		Direct effect		Indirect GE effect			Trade cost elasticity		Distance elasticity	
Import share interval	$\Delta \ln(x_{ij}/y_j)$	=	$(1-\sigma)\,\Delta \ln(t_{ij})$	+	$\Delta \ln(y_i/y^W)$	+	$(\sigma-1)\,\Delta \ln(P_iP_j)$	Total	Direct	Total	Direct
	(1)		(2)		(3)		(4)	(5a)	(5b)	(6a)	(6b)
h=1	0.0702	=	0.07	+	-0.0007	+	0.0009	-7.02	-7	-1.00	-1
h=2	0.0699	=	0.07	+	-0.0007	+	0.0007	-6.99	-7	-1.00	-1
h=3	0.0696	=	0.07	+	-0.0008	+	0.0003	-6.96	-7	-0.99	-1
h=4	0.0690	=	0.07	+	-0.0006	+	-0.0003	-6.90	-7	-0.99	-1
h=5	0.0637	=	0.07	+	-0.0007	+	-0.0056	-6.37	-7	-0.91	-1

Notes: This table reports logarithmic differences of variables between the initial equilibrium and the counterfactual equilibrium. The initial equilibrium is based on country income shares y_i/y^W for the year 2000 and bilateral distance data for the 28 countries in the sample (28*27=756 bilateral observations). For each bilateral observation a counterfactual equilibrium is computed under the assumption that bilateral trade costs t_{ij} for this observation have decreased by one percent all else being equal, yielding 756 counterfactual scenarios. The table reports the logarithmic differences between the initial and the counterfactual equilibria averaged across five import share intervals denoted by h. Import share intervals are in ascending order and based on the initial equilibrium. Assumed parameter values: σ=8 and ρ=1/7. Column 1: change in the import share; column 2: change in bilateral trade costs scaled by the substitution elasticity; column 3: change in the exporting country's income share; column 4: change in multilateral resistance scaled by the substitution elasticity; columns 5a and 5b: implied trade cost elasticities based on total effect and direct effect (=1-σ); columns 6a and 6b: implied distance elasticities based on total effect and direct effect (=(1-σ)*ρ).

Table 5: Additional trade cost variables

Dependent variable	Constant elasticity gravity $\ln(x_{ij}/y_j)$ (1)	Translog gravity $(x_{ij}/y_j)/n_i$ (2)
$\ln(dist_{ij})$, h=1	-1.4463***	-0.0398***
	(0.1369)	(0.0061)
$\ln(dist_{ij})$, h=2	-1.3789***	-0.0473***
	(0.1168)	(0.0068)
$\ln(dist_{ij})$, h=3	-1.2841***	-0.0464***
	(0.1030)	(0.0068)
$\ln(dist_{ij})$, h=4	-1.0150***	-0.0460***
	(0.0992)	(0.0068)
$\ln(dist_{ij})$, h=5	-0.8155***	-0.0447***
	(0.1060)	(0.0072)
adj_{ij}	0.5859***	0.0292***
	(0.1711)	(0.0071)
common $language_{ij}$	0.1999	0.0091**
	(0.1356)	(0.0045)
currency $union_{ij}$	0.0159	0.0073**
	(0.1128)	(0.0034)
$colonial_{ij}$	0.6286**	0.0146
	(0.2509)	(0.0159)
R-squared	0.90	0.69
Observations	749	749

Notes: The index h denotes intervals in order of ascending predicted import shares. The adj_{ij}, common $language_{ij}$, currency $union_{ij}$ and $colonial_{ij}$ regressors do not vary across intervals. Robust standard errors clustered around country pairs (378 clusters) reported in parentheses, OLS estimation. Exporter and importer fixed effects and interval fixed effects not reported. ** significant at 5% level. *** significant at 1% level.

Table 6: Alternative distance specification

	Constant elasticity gravity		Translog gravity	
Dependent variable	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$(x_{ij}/y_j)/n_i$	$(x_{ij}/y_j)/n_i$
	(1)	(2)	(3)	(4)
$\ln(dist_{ij})$	-0.2677		-0.0933**	
	(0.4176)		(0.0442)	
$(\ln(dist_{ij}))^2$	-0.0644**		0.0045	
	(0.0278)		(0.0028)	
$\ln(dist_{ij})$, h=1		-0.3216***		-0.1182***
		(0.0191)		(0.0209)
$\ln(dist_{ij})$, h=2		-0.2942***		-0.1407***
		(0.0196)		(0.0231)
$\ln(dist_{ij})$, h=3		-0.2542***		-0.1355***
		(0.0184)		(0.0284)
$(\ln(dist_{ij}))^2$, h=1		-0.0773***		0.0057***
		(0.0046)		(0.0010)
$(\ln(dist_{ij}))^2$, h=2		-0.0707***		0.0068***
		(0.0047)		(0.0011)
$(\ln(dist_{ij}))^2$, h=3		-0.0611***		0.0066***
		(0.0044)		(0.0014)
R-squared	0.89	0.89	0.52	0.59
Observations	749	749	749	749

Notes: The index h denotes intervals in order of ascending predicted import shares. Robust standard errors clustered around country pairs (378 clusters) reported in parentheses, OLS estimation. Exporter and importer fixed effects and interval fixed effects not reported. ** significant at 5% level. *** significant at 1% level.

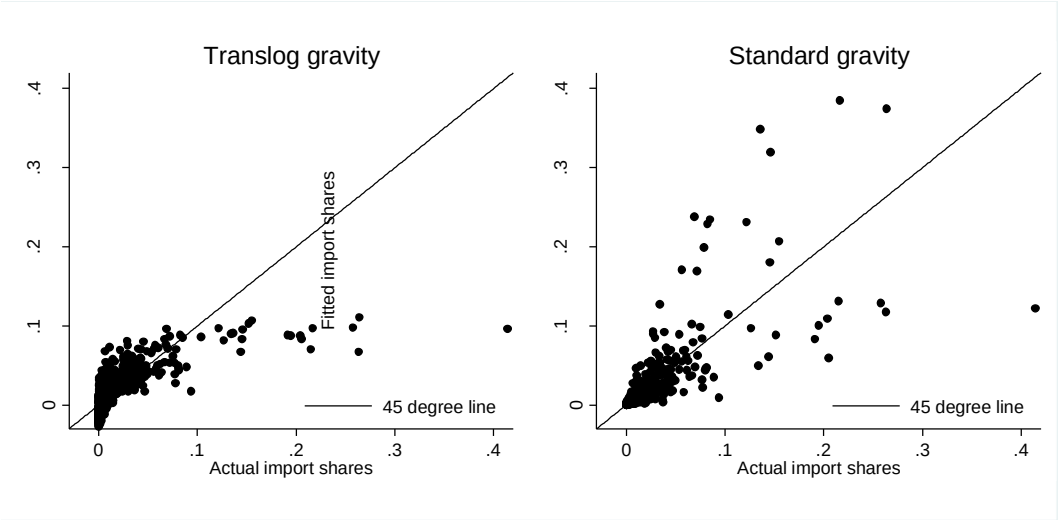

Figure 1: Fitted import shares plotted against actual import shares. The left panel is based on the translog gravity model, and the right panel is based on the standard gravity model.

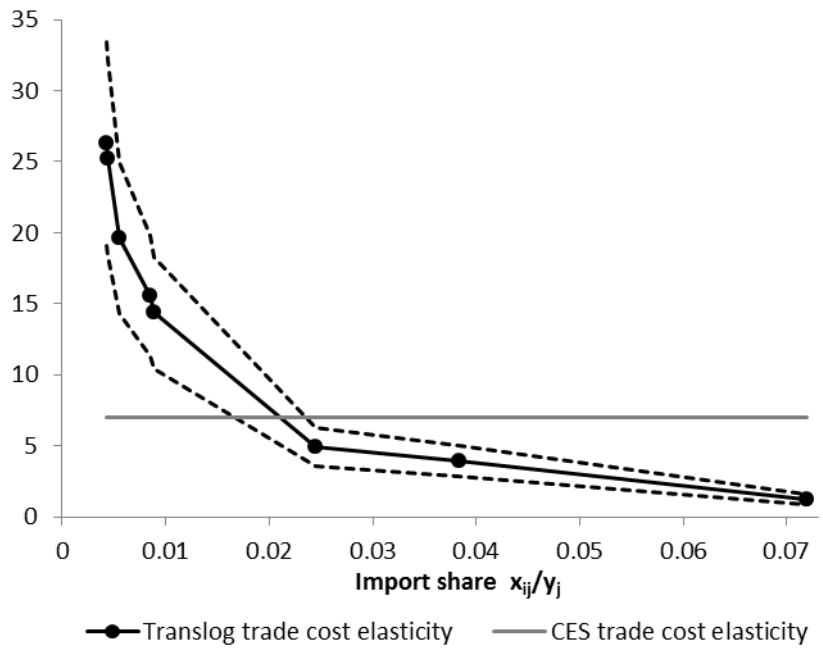

Figure 2: Trade cost elasticities (in absolute value) plotted against import shares for the case of New Zealand. The dashed lines represent 95 percent confidence intervals.