International Trade without CES: Estimating Translog Gravity

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 consistent with its predictions.

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Keywords: Translog, Gravity, Trade Costs, Distance, Trade Cost Elasticity, Trade 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 very grateful to the editor and three anonymous referees for helpful comments. I am also 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, Alan Taylor, Christian Volpe Martincus, David Weinstein and Adrian Wood. I am also grateful for comments by seminar participants at Central European University, Kiel, the London School of Economics, Loughborough, Oxford, the Paris Trade Seminar, 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 exporters and importers such as economic size, and to bilateral characteristics such as trade frictions between the trading partners. 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 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. Translog preferences were introduced by Christensen, Jorgenson and Lau (1975) in a closed-economy study of consumer demand.[2] 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.[3] 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 is their bilateral trade 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 strong evidence against the constant elasticity specification. The results demonstrate that 'one-size-fits-all' trade cost elasticities as implied by standard gravity models are not supported by the data. Instead, consistent with translog gravity, 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 shed new light on the effect of institutional arrangements such as free trade agreements or WTO membership on international trade. For

[2] 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.

[3] 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.

example, it can help explain why trade liberalizations often lead to relatively larger trade creation amongst country pairs that previously traded relatively little.[4]

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.[5] 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 varying 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 Pareto distribution. This parametric assumption is crucial in generating a log-linear gravity

[4] 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.

[5] 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.

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.[6] 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.[7] Let $[N_{j-1}+1,N_j]$ denote the range of goods of country j, with $N_{j-1}\leq N_j$ 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:

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

[6] I follow Anderson and van Wincoop (2003) in calling this framework general equilibrium (also see section 3.5).
[7] 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.

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

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

It can be easily verified that these additional restrictions satisfy the homogeneity conditions in (2).[8]

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

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

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:

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

To close the model, I impose market clearing:

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

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 provides a detailed derivation.

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

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

[8] 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).

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.[9] 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

[9] 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 for a discussion).

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

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).[10] It implies a trade cost elasticity η that is constant, where η is defined as[11]

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

Thus, the traditional gravity equation (10) implies $\eta^{CES}=-(\sigma-1)$.[12]

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 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

[10] 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.

[11] 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.

[12] The gravity equation by Eaton and Kortum (2002) implies $\eta^{EK}=-\theta$. 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.

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 testing the hypothesis 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.[13] 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 one 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.

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

[13] 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.

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.[14] As expected, 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.[15] 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 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 country. The resulting variable can be interpreted as the average import share per good of the exporting country. From equation (16) I obtain

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

[14] I cluster around country pairs regardless of the direction of trade. For example, one cluster is formed for the trade flows from the United States to Canada and from Canada to the United States.

[15] 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.

where v_{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.[16] As an additional check, I refer to Appendix B.2 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 $\forall$ i).[17] 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:

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

where I add an error term ξ_{ij}.[18] $\tilde{S}_i$ and $\tilde{S}_j$ are exporter and importer fixed effects defined as

[16] 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.
[17] 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.
[18] 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.

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

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 typical, bilateral distance is negatively related to import shares with a coefficient in the vicinity of -1, whereas adjacency is associated with higher shares.[19] 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 and also the corresponding residuals. 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 19). 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 and compute the residuals as their difference. I thus obtain import shares and residuals 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 two panels on the left-hand side are based on the translog model, and the right-hand side panels are based on the standard model. The top panels plot the fitted against the actual import shares, and the bottom panels plot the corresponding residuals. Both models do fairly well in fitting small import shares in the sense that the corresponding residuals are clustered closely around zero. For intermediate import shares in the range from 0.05 to 0.15 the translog model still generates a reasonably good fit, whereas the

[19] For completeness, I rerun the regressions in columns 1 and 2 of Table 2 with the log 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.

residuals for the standard model tend to grow. For 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. 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 tests that center on the question of whether the trade cost elasticity is constant.

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.,

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

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. 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., $\lambda_1 > \lambda_2 > ... > \lambda_H$.[20]

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.[21]

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

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[20] To be clear, equation (19) does not represent a formal test of non-nested hypotheses. The same applies to equation (20).

[21] 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.

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.[22]

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.[23] 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 numbers of intervals, in particular H=3 and H=10 (not reported here). The results are not qualitatively affected and the same coefficient patterns arise as in Table 3. This suggests that the systematic inequality of trade cost elasticities across import

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

share intervals is a robust feature of the data. In summary, therefore, the results provide evidence against the constant elasticity gravity specification.

Hypothesis B is based on the translog gravity estimating equation (17). Its premise is that the translog specification is correct and that 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 h=1,...,H of import shares per good, also adding interval fixed effects. For simplicity, I again drop the adjacency variable from the notation so that the estimating equation becomes

$$(20)\quad \frac{x_{ij}/y_j}{n_i} = -\kappa_h \ln(dist_{ij}) + \hat{S}_i + \hat{S}_j + \hat{S}_h + \upsilon_{ij},$$

where κ_h denotes the trade cost coefficients, $\hat{S}_h$ denotes the interval fixed effect and υ_{ij} is an error term. Hypothesis B states – as predicted by the translog gravity model – that the κ_h distance coefficients should not vary across intervals of import shares per good, i.e., $\kappa_1= \kappa_2=...=\kappa_H$. The alternative is – consistent with the standard gravity model – that the magnitude of the κ_h distance coefficients should increase in the import share per good.[24]

As with hypothesis A, one needs to be careful in constructing the intervals. If they were chosen based on *observed* values of import shares per good, one would incur an upward endogeneity bias in the coefficients of interest, κ_h. But this bias can be avoided if one first estimates equation (17) to obtain common trade cost coefficients, predicts the corresponding import shares and then divides the sample into H intervals of *predicted* import shares per good. I verified the validity of this estimation strategy with Monte Carlo simulations.[25]

Table 4a presents regression results for equation (20) under the assumption of H=5, i.e., with five import share intervals. In column 1 where distance is the only trade cost regressor, the

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[24] To see this, divide the constant elasticity gravity equation (9) by y_j and take the derivative with respect to $\ln(t_{ij})$. The result is $d(x_{ij}/y_j)/d\ln(t_{ij})=-(\sigma-1)x_{ij}/y_j$, implying that the absolute value of this derivative is increasing in x_{ij}/y_j. In the translog gravity equation (7), this derivative is given by $d(x_{ij}/y_j)/d\ln(t_{ij})=-\gamma n_i$. If constant elasticity gravity were the true specification, then γn_i should also be increasing in x_{ij}/y_j, or equivalently γ should be increasing in $(x_{ij}/y_j)/n_i$. Thus, in equation (20) the κ_h distance coefficients should be increasing in $(x_{ij}/y_j)/n_i$.

[25] I simulated import shares under the assumption that the translog gravity equation (7) is the true model, using distance as the trade cost proxy based on the trade cost function (13) and assuming various arbitrary values for the distance elasticity ρ and the translog parameter γ. The variance of the error term was chosen to match the R-squared of around 55 percent as in Table 1. I divided the sample into intervals based on either the simulated import shares or predicted import shares from a first-stage regression of equation (17). I then ran regression (20) with both types of intervals, replicating this procedure 1000 times. Forming intervals based on the simulated import shares leads to a severe upward bias in the κ_h coefficients.

distance coefficients appear to generally rise in magnitude across import shares and the hypothesis that they are equal can be rejected (p-value=0.00). However, this rejection is driven by the coefficient for the first interval (equal to -0.0449), which deviates most from the other coefficients. Indeed, the hypothesis that the coefficients for intervals 2-5 are equal cannot be rejected (p-value=0.44). Neither can the hypothesis of equality between all distance coefficients be rejected when I rerun regression (20) with more intervals.[26]

In column 2, I add adjacency. Since all adjacent country pairs in the sample fall into the fifth interval, the adjacency variables for the other intervals drop out. With adjacency included, I no longer obtain a monotonic pattern of distance coefficients. In fact, the point estimates for intervals 4 and 5 are smaller in magnitude than for interval 3, and they are not statistically different from each other (p-value=0.69). This evidence is inconsistent with the pattern of distance coefficients that one would expect under the constant elasticity gravity model.[27]

In Table 4b I present corresponding results based on equation (16) with x_{ij}/y_j as the dependent variable. Multilateral resistance terms now appear as regressors. As in Table 4a, in columns 1 and 2 intervals are chosen based on predicted import shares per good. As a robustness check, the intervals in columns 3 and 4 are chosen based on predicted import shares only. Distance is the only trade cost regressor in columns 1 and 3. Adjacency is added in columns 2 and 4.

As noted above, if gravity with a constant elasticity were the true underlying model, one should observe a monotonic increase in the absolute distance coefficients across the intervals. However, such a pattern is generally not supported by the estimations. For example, in column 1 the distance coefficient for the first interval (equal to -0.0535) is larger in absolute size than those for intervals 2 and 3 but smaller than those for intervals 4 and 5. In column 2 the smallest distance coefficient is associated with the second interval (equal to -0.0351); in column 3 the smallest coefficient is for the fourth interval (equal to -0.0332); in column 4 the smallest coefficient is for the second interval (equal to -0.0327). Nevertheless, formal tests of coefficient equality across intervals (i.e., hypothesis B) can still be rejected because the coefficients are tightly estimated.

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[26] For example, with H=10 the test of coefficient equality cannot be rejected (p-value=0.24).

[27] I also estimated equation (20) with nonlinear least squares and a multiplicative error term instead of the additive error term (see Appendix B.2 for details of this estimation procedure). The results are qualitatively similar to those in Table 4a.

Overall, the tests of heterogeneous distance coefficients in Tables 3, 4a and 4b appear inconsistent with coefficient patterns one should expect under the constant elasticity gravity model. They are instead consistent with the predictions of the translog gravity model.

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 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 somewhat higher than 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.

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. In particular, based on equation (17) the translog model can be written as

$$\frac{x_{ij}/y_j}{n_i} = -\gamma\rho \ln(dist_{ij}) + \hat{S}_i + \hat{S}_j + v_{ij}.$$

Rewriting equation (18) for the standard model yields

$$\ln\left(\frac{x_{ij}/y_j}{n_i}\right) = -(\sigma-1)\rho \ln(dist_{ij}) + \tilde{S}_i' + \tilde{S}_j + \xi_{ij},$$

where the dependent variable is $\ln((x_{ij}/y_j)/n_i)$ instead of $\ln(x_{ij}/y_j)$ and where the exporter fixed effect absorbs the n_i term as

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

For simplicity I drop the adjacency dummy. The advantage of the two above specifications is that they share the same right-hand side regressors in the estimation (logarithmic distance as well as exporter and importer fixed effects). 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=0 corresponds to log-linearity as

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

and θ=1 corresponds to the linear case. The right-hand side variables are not transformed. A regression with the Box-Cox transform as the dependent variable 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 0 and 1, and both the log-linear and the linear cases are rejected (p-values=0.00).[28] 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, 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=0 and θ=1. My interpretation is that whilst the results cannot be seen as a statistical endorsement of the translog model, they still highlight weaknesses of the standard log-linear gravity model. 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 varying trade cost elasticities.

3.4. Discussion

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.,

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[28] Sanso, Cuairan and Sanz (1993) also estimate a generalized functional form of the gravity equation defined by a Box-Cox transformation, also transforming the 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.

$\gamma\rho$=0.0296. To be comparable to the gravity literature, I choose a value of ρ that is consistent with typical estimates, ρ=0.177.[29] The value of the translog parameter then follows as γ=0.0296/ρ=0.167.[30] To be clear about my approach, 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.[31] Thus, if trade costs go down by one percent, ceteris paribus the average import share is expected to increase by 8.4 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, $\eta^{CES}=-(\sigma-1)$, which equals 7.[32]

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

[29] I obtain this value as follows. In standard gravity equations such as equation (18), the distance coefficient corresponds to the parameter combination $-(\sigma-1)\rho$. 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.

[30] 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.

[31] 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 (N) so that their product is not affected ($N\gamma * n_i / N = \gamma n_i$).

[32] 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.

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.[33] 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

The trade cost elasticity η as defined in equation (11) focuses on the direct impact of a change in trade costs t_{ij} on the import share x_{ij}/y_j. However, it does not take into account the indirect impact of a trade cost change through general equilibrium effects, as forcefully demonstrated by Anderson and van Wincoop (2003). 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

$$(21)\quad \Delta \ln\left(\frac{x_{ij}}{y_j}\right) = (1-\sigma)\Delta \ln(t_{ij}) + \Delta \ln\left(\frac{y_i}{y^W}\right) + (\sigma - 1)\Delta \ln(P_i P_j).$$

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

The left-hand side of equation (21) 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 most importantly the change in multilateral resistance terms scaled by (σ-1).

I am interested in how the decomposition in equation (21) varies across import shares. To that end, I first compute an initial equilibrium of trade flows based on the income data for the year 2000 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 that observation have decreased by one percent, i.e., $\Delta\ln(t_{ij})=-0.01$, assuming an elasticity of substitution of $\sigma=8$. I use the trade cost function (13) with distance as the only trade cost variable, assuming a distance elasticity of $\rho = 1/7$.[34]

Table 5 presents the decomposition results that correspond to equation (21). The rows report the average changes for each import share interval. Given the parameter assumption of $\sigma=8$, 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

[34] 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. This 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.

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 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 6 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.[35] The purpose is to check whether the distance coefficient patterns in Tables 3 and 4a 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 6. Clearly, the pattern of declining absolute distance coefficients is still in place. The distance coefficients monotonically

[35] The language dummy takes on the value one 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.

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, I rerun the regression in column 1 of Table 4a with the added variables. The result is reported in column 2 of Table 6. As in Table 4a 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). Table 6 thus confirms the earlier results.

Table 7 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,

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

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 in the distance coefficients in Tables 4a and 4b was therefore 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 7 is to substitute an alternative, more flexible trade cost function. Apart from logarithmic distance I add a quadratic in logarithmic distance:

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

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 (22) 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 7 reports a standard gravity regression as in equation (18) but with the additional quadratic distance term based on trade cost function (22). The estimate for $-(\sigma-1)\rho$ 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, 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 (22) 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 7 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.[36] 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 $\left(\ln(dist_{ij})\right)^2$ should not vary across intervals.

Column 2 of Table 7 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 $\left(\ln(dist_{ij})\right)^2$ coefficients are -0.0773, -0.0707 and -0.0611. Thus,

[36] 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.

their absolute values exhibit the same declining pattern as already found in section 3.3, 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 7 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 $\left(\ln(dist_{ij})\right)^2$ coefficients are 0.0057, 0.0068 and 0.0066. Although the differences are significant (p-values=0.00) as the coefficients 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 strongly supports this prediction. That is, trade cost elasticities are heterogeneous across import shares, and the traditional specification with a constant trade cost elasticity can be clearly rejected.

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 varying trade cost elasticities are 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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Appendix A. Deriving the Translog Gravity Equation

This appendix outlines the derivation of the translog gravity equation (7). Substituting the expenditures shares implied by (4) into the market-clearing condition (6) yields

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

Use $p_{kj}=t_{kj}p_k$ and define world income as $y^W \equiv \sum_{j=1}^{J} y_j$ to obtain

$$y_i = \sum_{j=1}^{J} y_j \sum_{m=N_{i-1}+1}^{N_i} \left(\alpha_m + \sum_{k=1}^{N} \gamma_{km} \ln(t_{kj}) \right) + y^W \sum_{m=N_{i-1}+1}^{N_i} \left(\sum_{k=1}^{N} \gamma_{km} \ln(p_k) \right),$$

which can be rearranged as

$$\sum_{m=N_{i-1}+1}^{N_i} \left(\sum_{k=1}^{N} \gamma_{km} \ln(p_k) \right) = \frac{y_i}{y^W} - \sum_{s=1}^{J} \frac{y_s}{y^W} \sum_{m=N_{i-1}+1}^{N_i} \left(\alpha_m + \sum_{k=1}^{N} \gamma_{km} \ln(t_{ks}) \right),$$

where the first summation index on the right-hand side is changed from j to s. Then substitute the last equation back into the import share (5):

$$\begin{aligned}
\frac{x_{ij}}{y_j} &= \sum_{m=N_{i-1}+1}^{N_i} \left(\alpha_m + \sum_{k=1}^{N} \gamma_{km} \ln(t_{kj}) \right) + \frac{y_i}{y^W} - \sum_{s=1}^{J} \frac{y_s}{y^W} \sum_{m=N_{i-1}+1}^{N_i} \left(\alpha_m + \sum_{k=1}^{N} \gamma_{km} \ln(t_{ks}) \right) \\
&= \frac{y_i}{y^W} + \sum_{s=1}^{J} \frac{y_s}{y^W} \sum_{m=N_{i-1}+1}^{N_i} \left(\sum_{k=1}^{N} \gamma_{km} \ln(t_{kj}) - \sum_{k=1}^{N} \gamma_{km} \ln(t_{ks}) \right) \\
&= \frac{y_i}{y^W} + \sum_{s=1}^{J} \frac{y_s}{y^W} \sum_{m=N_{i-1}+1}^{N_i} \left(\sum_{k=1}^{N} \gamma_{km} \ln\left(\frac{t_{kj}}{t_{ks}} \right) \right).
\end{aligned}$$

Use (3) to arrive at

$$\begin{aligned}
\frac{x_{ij}}{y_j} &= \frac{y_i}{y^W} + \sum_{s=1}^{J} \frac{y_s}{y^W} \sum_{m=N_{i-1}+1}^{N_i} \left(\sum_{k=1,k\neq m}^{N} \frac{\gamma}{N} \ln\left(\frac{t_{kj}}{t_{ks}} \right) - \frac{\gamma}{N} (N-1) \ln\left(\frac{t_{mj}}{t_{ms}} \right) \right) \\
&= \frac{y_i}{y^W} + \sum_{s=1}^{J} \frac{y_s}{y^W} \sum_{m=N_{i-1}+1}^{N_i} \left(\sum_{k=1}^{N} \frac{\gamma}{N} \ln\left(\frac{t_{kj}}{t_{ks}} \right) - \gamma \ln\left(\frac{t_{mj}}{t_{ms}} \right) \right).
\end{aligned}$$

To ease notation define the geometric mean of trade costs in country j as

$$T_j \equiv \left(\prod_{k=1}^{N} t_{kj} \right)^{1/N}$$

so that

$$\frac{x_{ij}}{y_j} = \frac{y_i}{y^W} + \sum_{s=1}^{J} \frac{y_s}{y^W} \sum_{m=N_{i-1}+1}^{N_i} \left(\gamma \ln\left(\frac{T_j}{T_s} \right) - \gamma \ln\left(\frac{t_{mj}}{t_{ms}} \right) \right).$$

Recall that $t_{mj}=t_{ij}$ if $m \in [N_{i-1}+1,N_i]$ so that the previous equation can be rewritten as

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

where $n_i \equiv N_i - N_{i-1}$ denotes the number of goods of country *i*. Note that $\ln(T_j)$ can be rewritten as a weighted average of trade costs over the trading partners of country *j*:

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

Appendix B. Empirical Appendix

B.1. Robustness checks for the extensive margin measure

The right-hand side variables of translog gravity equation (16) contain a measure of the extensive margin, n_i. But the specific measure based on Hummels and Klenow (2005) that I use for n_i in the regressions in columns 1 and 2 of Table 1 might not be suitable. As a robustness check, I therefore re-estimate equation (16) non-parametrically in two ways.

First, I replace n_i by a set of exporter dummy variables. Thus, I interact the bilateral distance and adjacency variables with these dummy variables. But given that $\ln(T_j^{dist})$ and T_j^{adj} are importer-specific, it becomes impossible to estimate the two variables involving these terms because all degrees of freedom would be exhausted. They are therefore dropped. All 28 resulting distance coefficients are negative and almost all of them are significant at the one percent level. The average distance coefficient is 0.0062 in absolute value. The smallest distance coefficient in absolute value is 0.0001 for Iceland, and the largest distance coefficient in absolute value is 0.0310 for Australia followed by 0.0286 for Germany. As to the interacted adjacency variables, some drop out of the estimation because the corresponding exporting countries are not adjacent to any other countries in the sample. These countries are Australia, Greece, Iceland, Japan, Korea and New Zealand. But the estimated interacted adjacency coefficients have the expected positive sign and most of them are significant. Only one coefficient has a negative sign but it is insignificant. Overall, the R-squared stands at 77 percent.

The translog model in equation (16) suggests that the trade cost coefficients should be correlated with the extensive margin. I therefore compare the interacted distance and adjacency coefficients to empirical measures of the extensive margin. Specifically, I compute the correlation between the estimated coefficients and three different measures. First, I consider the extensive margin measure by Hummels and Klenow (2005). The correlation is 44 percent with the absolute values of the distance coefficients and 50 percent with the adjacency coefficients. Second, I consider the unweighted count of six-digit product categories as an extensive margin measure (see section 3.2). The correlations are 47 percent and 53 percent, respectively. Third, I use (the logarithm of) the exporting country's income (GDP), $\ln(y_i)$, as a simple proxy of the extensive margin. This proxy captures the idea that larger countries tend to export a larger range of goods. The correlations are 58 percent and 64 percent, respectively. Figure B1 plots the individual distance and adjacency coefficients against the three extensive margin measures. In general I find that the trade cost coefficients are related to the extensive margin proxies as suggested by the translog model.

As the second, related way of re-estimating equation (16), I stratify based on intervals of the extensive margin. I divide the sample into five intervals and allow the coefficients on distance and adjacency to vary across these intervals. This stratification is carried out for the three extensive margin measures mentioned above. As the translog model suggests, the intervals representing the smallest extensive margins, denoted by h=1, are expected to have the lowest coefficients in absolute value, and vice versa for the intervals representing the largest extensive margins, denoted by h=5.

The regression results are reported in Table B1. In all three specifications the distance coefficients are lowest in absolute value for the first interval and highest for the fifth interval. In column 2 the distance coefficients are strictly increasing in absolute value, although the pattern is more varied in columns 1 and 3. Formal tests of whether the distance coefficients are equal are rejected for all three specifications (p-values=0.00). A broadly similar pattern arises for the adjacency coefficients. As expected, the highest coefficients are estimated for the fifth intervals, and they tend to become lower for intervals representing smaller extensive margins. Formal tests of whether the adjacency coefficients are equal can be rejected for all specifications (the p-values range between 0.00 and 0.02). As a final remark, I obtain identical distance and adjacency coefficients if I run separate regressions for each interval instead of the joint regressions in columns 1 to 3 of Table B1.

In summary, I therefore conclude that the non-parametric regressions of equation (16) yield results that are consistent with the translog model.

B.2. A multiplicative error term

The traditional gravity specification, for instance in equation (18), typically has the trade flow variable in logarithmic form as the dependent variable with an additive error term. That is, in levels this would correspond to a multiplicative lognormal error term. However, the translog gravity equations (16) and (17) have the trade flow in levels as the dependent variable plus an additive error term.

Here I introduce a multiplicative error term for the translog specification. Instead of the additive error term in equation (14), I assume a multiplicative error term of the following form:

$$\frac{x_{ij}}{y_j} = \left[-\gamma n_i \ln(t_{ij}) + \gamma n_i \ln(T_j) + S_i\right] e^{\varepsilon_{ij}},$$

where ε_{ij} is assumed normally distributed. That is, $e^{\varepsilon_{ij}}$ and x_{ij}/y_j are log-normally distributed.

I carry out the estimation with nonlinear least squares (NLS) running the regressions that correspond to columns 1-4 of Table 1. The results are reported in Table B2. As expected, distance is negatively and adjacency is positively related to import shares. The signs and significance of the coefficients are exactly the same as in Table 1. But the values of the individual coefficients are of course not the same because the error term is specified differently (multiplicative in Table B2 as opposed to additive in Table 1). For example, the distance coefficient in column 1 is -0.0133 compared to -0.0296 in the corresponding column of Table 1.

The R-squareds are substantially higher. They fall in the range of 0.91-0.93 compared to the range of 0.50-0.59 in Table 1, indicating that the multiplicative error term produces a better fit. How can this fit be compared to that of the traditional gravity equations in Table 2? Instead of the log-linear specification underlying Table 2, the traditional gravity equations can also be estimated in levels with nonlinear least squares, based on equation (9) with the usual multiplicative error term. This yields exactly the same coefficients and R-squareds as reported in Table 2. Therefore, as the dependent variables are the same, the R-squareds in the range of 0.91-0.93 in Table B2 are directly comparable to the value of 0.89 in Table 2 for the traditional gravity specification. Based on a multiplicative error term the goodness of fit is thus not worse in the translog model than in the traditional model.[37]

B.3. An alternative stratification procedure

The issue of stratification in the context of equations (19) and (20) is important. Stratifying in terms of *observed* import shares would come down to selection on the endogenous variable and would thus lead to an estimation bias. In line with results from Monte Carlo simulations, in the main part of the paper I resort to a two-step procedure whereby the sample is stratified in terms of intervals of *predicted* import shares. Nevertheless, it might still be a concern that the stratification is in terms of the (predicted) dependent variable. As a robustness check, I

[37] Note that a logarithmic version of the above equation (i.e., taking logarithms on both sides) could also be estimated with nonlinear least squares. The crucial difference would be that the fitted values for import shares would have to be positive as the conditional expectation of import shares would be constrained to be positive due to the logarithmic form. This constraint would lead to lower R-squareds in the range of 0.43-0.74.

therefore adopt an alternative stratification procedure in terms of the right-hand side gravity variables.

Translog gravity theory implies that trade cost elasticities vary across import shares (see equation 12). To be consistent with the guidance from theory, the stratification should thus be based on an indicator of right-hand side variables that is closely related to the import shares. But a problem with the estimating equations is that most right-hand side variables are fixed effects. It therefore makes sense to focus on right-hand side variables that are observable. More specifically, the standard gravity equation (18) has three such variables. The first two are logarithmic distance and the adjacency dummy. The third is the logarithmic income of the exporting country, which is part of the exporter fixed effect $\tilde{S}_i$. The remaining variables embedded in the fixed effects would be the multilateral resistance terms but those are unobservable.

I proceed by constructing an indicator based on these three variables. Adjacency and the exporter's income are supposed to be positively related to import shares, while distance is expected to be negatively related. The difficulty is how to combine these three variables. I first standardize them to remove differences in units of measurement. I then construct a simple unweighted indicator for import shares by adding the standardized variables for adjacency and exporter's income and subtracting the standardized variable for distance. The resulting indicator has a correlation of 77 percent with the observed logarithmic import shares. For example, the three biggest values of the indicator are for the US share of Canadian imports, the Austrian share of Slovakian imports and the French share of Belgian imports, all of which seem sensible. Most importantly, the indicator is based on a combination of arguably exogenous right-hand side variables. It is not based on a first-stage prediction of import shares.

As the final step, I construct five import share intervals based on the indicator and run regression (19). The results are reported in columns 1 and 2 of Table B3. They correspond to columns 1 and 2 of Table 3. The smallest import shares according to the indicator are in interval h=1, and the largest import shares are in interval h=5. As before, hypothesis A puts forward the equality of distance coefficients, i.e., $\lambda_1 = \lambda_2 = \ldots = \lambda_5$. The alternative, consistent with the translog gravity model, is a declining pattern in the absolute distance coefficients, i.e., $\lambda_1 > \lambda_2 > \ldots > \lambda_5$. In column 1 of Table B3 the distance coefficients clearly decline in absolute value except for the last interval. But once adjacency is added as a control in column 2, the last coefficient shrinks in magnitude and becomes the smallest. The hypotheses that the distance coefficients are equal are rejected (the p-values are 0.02 and 0.00 in columns 1 and 2, respectively). As in section 3.3, I therefore find evidence against hypothesis A.

I carry out a similar procedure for translog gravity and hypothesis B. Specifically, I focus on observable right-hand side variables in equation (17). These are distance, adjacency and the exporter's income and, through the importer fixed effect $\hat{S}_j$, also the two multilateral resistance terms $\ln(T_j^{dist})$ and T_j^{adj}. I standardize them and construct an indicator by adding the variables for adjacency, exporter's income and the multilateral resistance term for distance and by subtracting the variables for distance and the multilateral resistance term for adjacency. I then run regression (20). The results are reported in columns 3 and 4 of Table B3. They correspond to columns 1 and 2 of Table 4a. Hypothesis B states that the distance coefficients should be equal, i.e., $\kappa_1 = \kappa_2 = \ldots = \kappa_5$. In column 3 the distance coefficients show an increasing pattern in absolute value although their equality marginally cannot be rejected (p-value=0.14). Once adjacency is added as a control in column 4, the monotonically increasing pattern disappears and the equality of the coefficients clearly cannot be rejected (p-value=0.35).

Overall, I conclude that the alternative stratification procedure in terms of right-hand side variables leads to similar results as those discussed in section 3.3.

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 4a: Testing translog gravity (Hypothesis B)

	Intervals based on $(x_{ij}/y_j)/n_i$	
Dependent variable	$(x_{ij}/y_j)/n_i$	$(x_{ij}/y_j)/n_i$
	(1)	(2)
$\ln(dist_{ij})$, h=1	-0.0449***	-0.0347***
	(0.0068)	(0.0039)
$\ln(dist_{ij})$, h=2	-0.0518***	-0.0383***
	(0.0077)	(0.0042)
$\ln(dist_{ij})$, h=3	-0.0516***	-0.0412***
	(0.0078)	(0.0046)
$\ln(dist_{ij})$, h=4	-0.0543***	-0.0411***
	(0.0079)	(0.0045)
$\ln(dist_{ij})$, h=5	-0.0567***	-0.0380***
	(0.0084)	(0.0057)
adj_{ij}, h=5		0.0608***
		(0.0103)
R-squared	0.64	0.71
Observations	749	749

Notes: The index h denotes intervals in order of ascending predicted import shares. The intervals are based on predicted import shares divided by n_i. The adj_{ij} regressors for intervals h=1-4 drop out in column 2 since no adjacent country pair falls into these 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 1% level.

Table 4b: Testing translog gravity (Hypothesis B)

	Intervals based on $(x_{ij}/y_j)/n_i$		Intervals based on (x_{ij}/y_j)	
Dependent variable	x_{ij}/y_j	x_{ij}/y_j	x_{ij}/y_j	x_{ij}/y_j
	(1)	(2)	(3)	(4)
$n_i \ln(dist_{ij})$, h=1	-0.0535***	-0.0406***	-0.0403***	-0.0369***
	(0.0090)	(0.0064)	(0.0085)	(0.0061)
$n_i \ln(dist_{ij})$, h=2	-0.0446***	-0.0351***	-0.0338***	-0.0327***
	(0.0081)	(0.0052)	(0.0075)	(0.0054)
$n_i \ln(dist_{ij})$, h=3	-0.0507***	-0.0376***	-0.0334***	-0.0337***
	(0.0085)	(0.0054)	(0.0069)	(0.0053)
$n_i \ln(dist_{ij})$, h=4	-0.0585***	-0.0406***	-0.0332***	-0.0343***
	(0.0095)	(0.0062)	(0.0061)	(0.0055)
$n_i \ln(dist_{ij})$, h=5	-0.0627***	-0.0476***	-0.0601***	-0.0439***
	(0.0087)	(0.0077)	(0.0079)	(0.0084)
$n_i \ln(T_j^{dist})$, h=1	0.0430***	0.0286***	0.0291***	0.0258***
	(0.0076)	(0.0049)	(0.0065)	(0.0047)
$n_i \ln(T_j^{dist})$, h=2	0.0300***	0.0189***	0.0201***	0.0183***
	(0.0067)	(0.0037)	(0.0057)	(0.0039)
$n_i \ln(T_j^{dist})$, h=3	0.0343***	0.0199***	0.0195***	0.0189***
	(0.0072)	(0.0043)	(0.0058)	(0.0040)
$n_i \ln(T_j^{dist})$, h=4	0.0391***	0.0207***	0.0184***	0.0163***
	(0.0085)	(0.0055)	(0.0055)	(0.0044)
$n_i \ln(T_j^{dist})$, h=5	0.0417***	0.0256***	0.0413***	0.0242***
	(0.0084)	(0.0067)	(0.0083)	(0.0079)
$n_i\, adj_{ij}$, h=5		0.0536***		0.0529***
		(0.0161)		(0.0161)
$n_i T_j^{adj}$, h=5		-0.1309**		-0.0933*
		(0.0647)		(0.0501)
R-squared	0.64	0.69	0.64	0.68
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 $n_i\, adj_{ij}$ regressors for intervals h=1-4 drop out in column 2 since no adjacent country pairs fall into these intervals (intervals h=1, 2 and 4 in column 4). The $n_i\, T_j^{adj}$ regressors for intervals h=1-4 in columns 2 and 4 are included but not reported here. Robust standard errors clustered around country pairs (378 clusters) reported in parentheses, OLS estimation. Exporter fixed effects and interval fixed effects not reported. * significant at 10% level. ** significant at 5% level. *** significant at 1% level.

Table 5: 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	$\Delta \ln(x_{ij}/y_j)$	=	$(1\text{-}\sigma)\ \Delta \ln(t_{ij})$	+	$\Delta \ln(y_i/y^W)$	+	$(\sigma\text{-}1)\ \Delta \ln(P_iP_j)$	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 6: Additional trade cost variables

	Constant elasticity gravity	Translog gravity
Dependent variable	$\ln(x_{ij}/y_j)$	$(x_{ij}/y_j)/n_i$
	(1)	(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 7: 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.

Table B1: Non-parametric estimation of equation (16)

	Intervals based on different extensive margin measures n_i		
	n_i=HK (2005)	n_i=unweighted count	$n_i=\ln(y_i)$
Dependent variable	x_{ij}/y_j (1)	x_{ij}/y_j (2)	x_{ij}/y_j (3)
$n_i \ln(dist_{ij})$, h=1	-0.0009*** (0.0003)	-0.0011*** (0.0003)	-0.0011*** (0.0003)
$n_i \ln(dist_{ij})$, h=2	-0.0150*** (0.0042)	-0.0040*** (0.0011)	-0.0061*** (0.0015)
$n_i \ln(dist_{ij})$, h=3	-0.0085*** (0.0033)	-0.0041*** (0.0011)	-0.0144*** (0.0048)
$n_i \ln(dist_{ij})$, h=4	-0.0074*** (0.0021)	-0.0106*** (0.0022)	-0.0066* (0.0035)
$n_i \ln(dist_{ij})$, h=5	-0.0201*** (0.0047)	-0.0338*** (0.0075)	-0.0268*** (0.0056)
$n_i\, adj_{ij}$, h=1	0.0019 (0.0011)	0.0046** (0.0019)	0.0046** (0.0019)
$n_i\, adj_{ij}$, h=2	0.0187* (0.0110)	0.0049* (0.0027)	0.0017 (0.0028)
$n_i\, adj_{ij}$, h=3	0.0137 (0.0097)	0.0182*** (0.0060)	0.0245** (0.0098)
$n_i\, adj_{ij}$, h=4	0.0174*** (0.0063)	0.0205* (0.0115)	0.0227 (0.0159)
$n_i\, adj_{ij}$, h=5	0.0568*** (0.0181)	0.0392*** (0.0136)	0.0451*** (0.0147)
R-squared	0.62	0.68	0.66
Observations	749	749	749

Notes: The index h denotes intervals in order of ascending extensive margin measures. The intervals in column 1 are based on the measure by Hummels and Klenow (2005). The intervals in column 2 are based on the unweighted count of six-digit product categories. The intervals in column 3 are based on the logarithmic income of the exporter. The $n_i\, T_j^{dist}$ and $n_i\, T_j^{adj}$ regressors are included but not reported here. Robust standard errors clustered around country pairs (378 clusters) reported in parentheses, OLS estimation. Exporter fixed effects not reported. * significant at 10% level. ** significant at 5% level. *** significant at 1% level.

Table B2: Translog gravity, nonlinear least squares estimation

Dependent variable	x_{ij}/y_j	x_{ij}/y_j	$(x_{ij}/y_j)/n_i$	$(x_{ij}/y_j)/n_i$
	(1)	(2)	(3)	(4)
$n_i \ln(dist_{ij})$	-0.0133***	-0.0119***		
	(0.0008)	(0.0010)		
$n_i \ln(T_j^{dist})$	0.0027***	0.0029***		
	(0.0004)	(0.0010)		
$n_i\, adj_{ij}$		0.0226***		
		(0.0050)		
$n_i\, T_j^{adj}$		-0.0071**		
		(0.0033)		
$\ln(dist_{ij})$			-0.0164***	-0.0133***
			(0.0011)	(0.0008)
adj_{ij}				0.0174***
				(0.0042)
R-squared	0.91	0.93	0.92	0.92
Observations	749	749	749	749

Notes: Robust standard errors clustered around country pairs reported in parentheses, NLS estimation. Columns 1 and 2: exporter fixed effects not reported. Columns 3-4: exporter and importer fixed effects not reported. ** significant at 5% level. *** significant at 1% level.

Table B3: Stratification in terms of right-hand side variables

	Constant elasticity gravity (Hypothesis A)		Translog gravity (Hypothesis B)	
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)
$\ln(dist_{ij})$, h=1	-1.4742***	-1.4788***	-0.0122***	-0.0137***
	(0.1613)	(0.1570)	(0.0022)	(0.0021)
$\ln(dist_{ij})$, h=2	-1.3132***	-1.3366***	-0.0135***	-0.0164***
	(0.1323)	(0.1189)	(0.0041)	(0.0038)
$\ln(dist_{ij})$, h=3	-1.0595***	-1.1110***	-0.0170***	-0.0214***
	(0.1181)	(0.1115)	(0.0047)	(0.0044)
$\ln(dist_{ij})$, h=4	-0.8761***	-0.8920***	-0.0177***	-0.0207***
	(0.1366)	(0.1229)	(0.0049)	(0.0044)
$\ln(dist_{ij})$, h=5	-1.0044***	-0.7824***	-0.0285***	-0.0219***
	(0.1114)	(0.1187)	(0.0074)	(0.0067)
adj_{ij}, h=4				0.0211***
				(0.0079)
adj_{ij}, h=5		0.8003***		0.0501***
		(0.1745)		(0.0104)
R-squared	0.89	0.89	0.56	0.59
Observations	749	749	749	749

Notes: The index h denotes intervals in order of ascending stratified import shares. See Appendix B.3 for details of the stratification. The adj_{ij} regressors for intervals h=1-4 in column 2 drop out since no adjacent country pair falls into these intervals (intervals h=1-3 in column 4). 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 1% level.

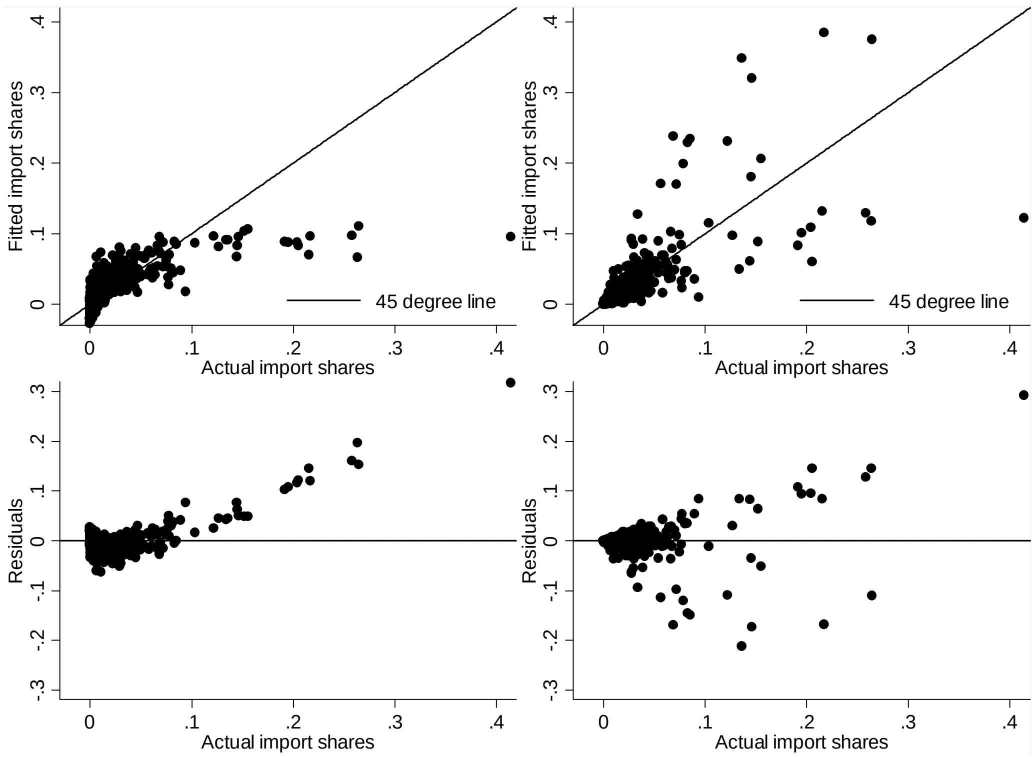

Figure 1: Fitted import shares and residuals plotted against actual import shares. The left-hand side panels are based on the translog gravity model, and the right-hand side panels are based on the standard gravity model.

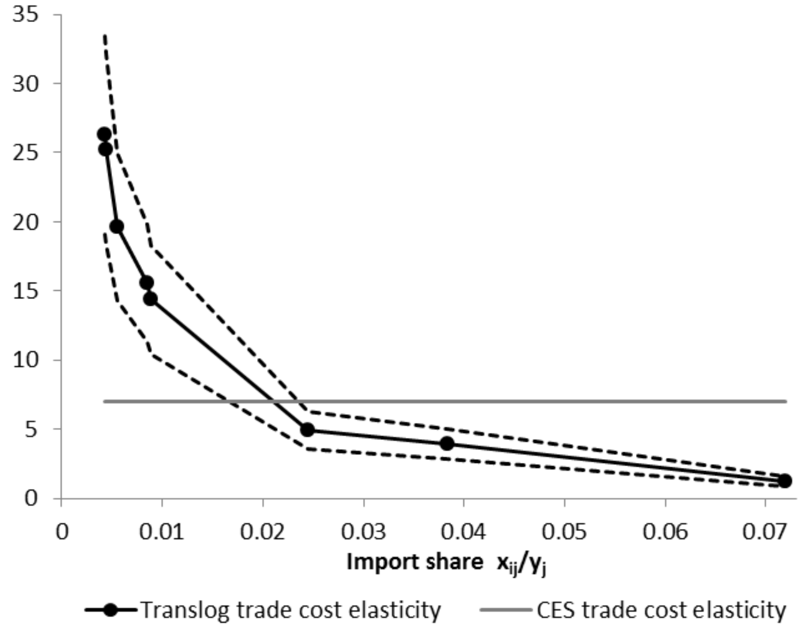

Figure 2: Trade cost elasticities (in absolute value) plotted against import shares for the case of New Zealand. The dashed lines represent 95 percent confidence intervals.

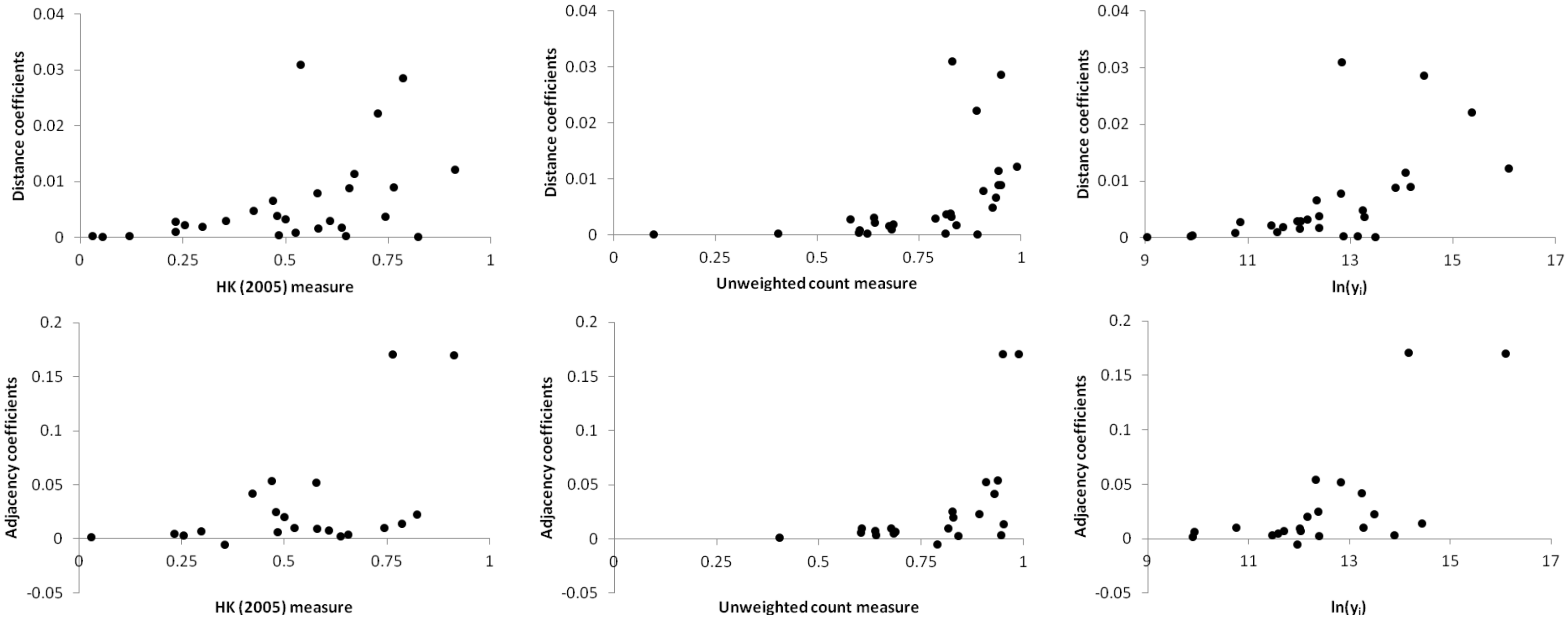

Figure B1: Non-parametric estimates of distance and adjacency coefficients. In the top panels the absolute values of distance coefficients are plotted against three extensive margin measures, and in the bottom panels the values of adjacency coefficients are plotted against the three measures. The extensive margin measures are by Hummels and Klenow (2005) in the left-hand side panels, an unweighted count of six-digit product categories in the middle panels and the logarithmic income of the exporter in the right-hand side panels.