International Trade and Monopolistic Competition without CES: Estimating Translog Gravity

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Abstract
This paper derives a micro-founded gravity equation in general equilibrium based on a translog demand system that allows for endogenous markups and rich substitution patterns across goods. In contrast to standard CES-based gravity equations, 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 strong empirical support in its favor. In an application to the currency union effect, I find that a currency union is only associated with substantially higher bilateral trade if the exporting country provides a small share of the destination country's imports. For other pairs, the currency union effect is modest or indistinguishable from zero.

JEL classification: F11, F12, F15
Keywords: Translog, Trade Costs, Gravity, Currency Union, Monopolistic Competition, Trade Cost Elasticity, Heterogeneity, Zero Trade

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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]

Yet, although the above trade models make different assumptions as to the motivation behind international trade, they all use constant elasticity of substitution (CES) preferences to describe the demand side of the economy.[2] This common feature translates into a *constant elasticity of trade with respect to trade costs*. It implies that a reduction in trade costs, for instance a ten percent 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 highlighted long-standing concerns over the CES demand specification and the implied constant markups. Attention has been drawn 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 and therefore lower markups. Melitz and Ottaviano (2008) demonstrate this effect theoretically. Feenstra and Weinstein (2010) provide theory as well as evidence for the US, Badinger (2007) provides evidence for European countries. This

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

line of research emphasizes flexible demand systems and variable markups that respond to changes in the competitive environment.

In this paper, I adopt such a flexible 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 of monopolistic competition. Translog preferences were introduced by Christensen, Jorgenson and Lau (1975) in a closed-economy study of consumer demand.[3] In contrast to CES, translog preferences are more flexible in that they allow for rich substitution patterns across varieties, yielding endogenous markups and price elasticities. When more goods are available for consumers to choose from, markups are lower and price elasticities are higher. This flexibility breaks the constant link between trade flows and trade costs.[4] Instead, the effect of trade frictions on trade flows varies, depending on how intensely two countries trade with each other. Trade frictions therefore have a heterogeneous trade-impeding impact across country pairs. Despite this increase in complexity, the resulting translog gravity equation is parsimonious and easy to implement with data.

In section 3, I attempt to empirically distinguish translog gravity from 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 CES preferences are not supported by the data. Instead, consistent with translog gravity, I find that the trade cost elasticity increases in absolute size, the less concentrated trade is between two countries. That is, 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.

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

[4] Although Melitz and Ottaviano (2008) work with quadratic preferences at the individual product level, their preferences have CES-like characteristics at the aggregate level in the sense that their gravity equation also features a constant trade cost elasticity. It has a zero income elasticity although population can be a demand shifter. Also see Behrens, Mion, Murata and Südekum (2009) for a model with non-homothetic preferences and variable markups but a constant trade cost elasticity. See Markusen (1986) and Bergstrand (1989) for other models with non-homothetic preferences.

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 example, it can help explain why trade liberalizations often lead to relatively larger trade creation amongst country pairs that previously traded relatively little.[5]

In section 4, I apply the insight about varying trade cost elasticities to one of the best-known topics of the gravity literature – the effect of currency unions on international trade. Following the seminal paper by Rose (2000), most estimates in the literature find that all else being equal, countries in a currency union trade substantially more with each other than with countries outside the currency union. I investigate whether the impact of a currency union is heterogeneous across country pairs. Guided by translog gravity theory, I ask whether currency unions have a larger impact on bilateral trade if the exporting country only ships a small fraction of the destination country's imports. In that case, translog gravity predicts that trade should react strongly to trade cost differences associated with currency unions. But if the exporting country is established as a major trading partner of the importing country, trade should not be much affected by currency unions. Using a large sample of bilateral trade flows, I find strong evidence that currency unions are indeed associated with significantly larger trade flows if the exporting country is a minor trading partner but not otherwise. Currency unions therefore have a heterogeneous impact on bilateral trade, depending on the size of the import share.

Although not explored in this paper, another feature of the translog demand system that is potentially useful in empirical analysis is its consistency with zero demand. It is well-known that zeros 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. 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).

A related paper in the literature is by Gohin and Femenia (2009) who develop a demand equation based on Deaton and Muellbauer's (1980) almost ideal demand system and estimate it

[5] Komorovska, Kuiper and van Tongeren (2007) refer to the 'small shares stay small' problem as the inability of CES-based demand systems to generate substantial trade creation in response to significant trade liberalization if initial trade flows were small. In contrast, translog demand predicts large trade responses if initial flows were 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.

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.

2. Translog Preferences and Trade Costs

This section outlines the general equilibrium translog model and derives the theoretical gravity equation based on a monopolistic competition framework. I assume there are J countries in the world with $j=1,\dots,J$ 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.[6] 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.

Following Diewert (1976), I assume a translog expenditure function. It 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. Given the interpretation of the translog model as a second-order approximation to an arbitrary expenditure system, it follows $\gamma_{km}=\gamma_{mk}$ due to Young's theorem.[7] 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 factory gate 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, that is, $t_{mj}=t_{ij}$ 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 homogeneity of degree one I impose the conditions:

[6] 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 arbitrarily across countries.

[7] The underlying function must be continuous and twice continuously differentiable, see Greene (2008, chapter 2).

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

In addition, I require that 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 condition 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}):

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

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 factory gate 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. The Technical Appendix provides a detailed derivation.

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

[8] The assumption of γ>0 ensures that the price elasticity of demand exceeds unity, as is necessary under monopolistic competition. The estimation results below confirm this assumption. The elasticity is also increasing in price (see Feenstra, 2003).

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

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

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

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

$$(9)\quad \beta_i \equiv \frac{y_i}{y^W} + \gamma n_i \sum_{s=1}^{J} \frac{y_s}{y^W} \ln\left(\frac{t_{is}}{T_s}\right).$$

But the third term on the right-hand side of equation (7), $\gamma n_i \ln\left(T_j\right)$, can only be captured as an importer fixed effect in the special case where n_i does not vary across countries, $n_i = n \forall i$.

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, not in logarithmic form. This stands in contrast to ‘traditional’ gravity equations that feature a constant elasticity of trade flows with respect to trade costs. For example, Anderson and van Wincoop (2003) derive the following gravity equation:

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

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 (10) 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 $x_{ij}=y_i y_j / y^W$.

$$(11)\quad \ln\left(\frac{x_{ij}}{y_j}\right) = -(\sigma-1)\ln(t_{ij}) + \tilde{\beta}_i + \tilde{\beta}_j,$$

where $\tilde{\beta}_i$ and $\tilde{\beta}_j$ are exporter and importer fixed effects defined as

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

The logarithmic form of the import share on the left-hand side of equation (11) is the key difference to the translog gravity equation (7). Likewise, the logarithmic form of the import share also follows as a feature of the Ricardian model by Eaton and Kortum (2002) as well as the heterogeneous firms model by Chaney (2008).[10] 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 (11) as the 'standard' or 'traditional' specification as opposed to the translog specification in equation (7).

The log-linear form of traditional gravity equations implies a trade cost elasticity η that is *constant*, where η is defined as[11]

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

Thus, gravity equation (11) implies η^{CES}=-(σ-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

[10] These models employ a CES preference structure. 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 definition of η ignores 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. Instead, the focus is on the direct effect of t_{ij} on x_{ij}/y_j.

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

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

3. Estimating the Translog Gravity Equation

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 (11). I then proceed to econometrically discriminate the two models 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 various years, 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.[13]

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

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

where ρ denotes the distance elasticity of trade costs. Since distance and adjacency do not vary over time, the focus is on cross-sectional variation in trade costs.

[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.

To estimate the 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 observe. However, Hummels and Klenow (2005) construct a measure of the extensive margin across countries based on shipments in more than 5,000 six-digit product categories from 126 exporting countries to 59 importing countries for the year 1995. The extensive margin is measured by weighting categories of goods by their overall importance in exports, consistent with the methodology developed by Feenstra (1994). Their Table A1 reports the extensive margin of country *i* relative to the rest of the world. I use this fraction as a proxy for n_i. Hummels and Klenow (2005) document that the extensive margin tends to be larger for big countries. For example, the extensive margin measure is 0.91 for the United States, 0.79 for Germany and 0.72 for Japan but only 0.05 for Iceland and 0.03 for Luxembourg.

3.2. Estimating Translog Gravity

I substitute the exporter fixed effect β_i from equation (9) into equation (7) to obtain

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

where I add a white noise error term ε_{ij}. Then I substitute the trade cost function (13) into the trade cost index term (8). This yields

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

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

$$(14)\quad \ln(T_j^{dist}) \equiv \sum_{s=1}^{J} \frac{n_s}{N} \ln(dist_{sj}) \quad \text{and} \quad T_j^{adj} \equiv \sum_{s=1}^{J} \frac{n_s}{N} adj_{sj}.$$

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

$$(15)\quad \frac{x_{ij}}{y_j} = -\gamma\rho n_i \ln(dist_{ij}) + \gamma\rho n_i \ln(T_j^{dist}) + n_i adj_{ij} - n_i T_j^{adj} + \beta_i + \varepsilon_{ij}.$$

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 trade cost index terms $\ln(T_j^{dist})$ and T_j^{adj} are constructed as weighted averages for each country *j* according to equation (14) and then also multiplied by the extensive margin proxy n_i.

Table 1 presents the regression results. Columns 1-4 present results under the simplifying assumption that each country is endowed with only one good (n_i=1 ∀ i).[14] In this case, I can capture the trade cost index terms by a simple importer fixed effect β_j, defined as $\beta_j \equiv \gamma\rho \ln(T_j^{dist}) - T_j^{adj}$. Columns 5-8 relax this assumption, allowing the number of goods to vary across countries. The trade cost index terms of the importing country multiplied by the extensive margin measure now enter as separate regressors, $n_i \ln(T_j^{dist})$ and $n_i T_j^{adj}$. Columns 1, 2, 5 and 6 focus on observations for the year 2000. Columns 3, 4, 7 and 8 expand the sample to annual observations from 1991 to 2000, in which case all fixed effects are time-varying.[15]

The baseline specifications in Columns 1, 3, 5 and 7 include bilateral distance as the only trade cost proxy. As expected, import shares tend to be significantly lower for more distant country pairs. Columns 2, 4, 6 and 8 add the adjacency dummy. As typically found in gravity estimations, this variable is positive and significant. In columns 5-8, the coefficients of the individual regressors and the corresponding multilateral resistance regressors are similar in magnitude as predicted by estimating equation (15). For example, the distance coefficient in column 5 is estimated at -0.0296, whereas the corresponding trade 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 adjacency regressors in columns 6 and 8 formal tests of their equality in absolute magnitude cannot be rejected (p-values=0.81 and 0.88, respectively). Overall, given the sizeable degree of explanatory power of the regressions with an R-squared of 50 percent or more, I conclude that the translog gravity equation passes its first test of being reasonable.

3.3. Testing Traditional vs. Translog Gravity

First, I substitute the trade cost function (13) into equation (11) to arrive at the estimating equation for 'traditional' gravity:

[14] 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.

[15] For the year 2000, the maximum number of bilateral observations is 28*27=756, but 7 are missing so that the sample includes 749 observations. From 1991 to 2000, the maximum number of observations is 28*27*10 years=7,560, but 864 are missing so that the sample includes 6,696 observations. Almost all missing observations are due to Eastern European countries who only started reporting in later years (Hungary, Poland, Slovak Republic), as well as to Belgium and Luxembourg who only reported jointly for most years.

$$(16)\quad \ln\left(\frac{x_{ij}}{y_j}\right) = -(\sigma-1)\rho\ln(dist_{ij}) + adj_{ij} + \tilde{\beta}_i + \tilde{\beta}_j + \xi_{ij},$$

where $\tilde{\beta}_i$ and $\tilde{\beta}_j$ are the exporter and importer fixed effects and I add a white noise error term ξ_{ij}.[16] The logarithmic form of the dependent variable is the key difference to the translog specification in equation (15).

I first run regressions of equation (16) that correspond to Table 1 and report the results in Table 2. Naturally, the coefficients differ in magnitude but the signs and the significance patterns are the same as in Table 1. In particular, the distance coefficient is in the vicinity of -1 and, as is typically found in the literature, the regressions have a high explanatory power with an R-squared close to 90 percent.[17]

As the next step, I test translog gravity against the traditional gravity specification. The test centers on the question of whether the trade cost elasticity is constant. As equation (12) shows, translog gravity implies that the absolute value of the trade cost elasticity decreases in the import share. Specifically,

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

To be precise, the absolute value of the trade cost elasticity decreases in the import share x_{ij}/y_j divided by the extensive margin measure n_i for the exporting country. The term $(x_{ij}/y_j)/n_i$ can be interpreted as the average import share per good of the exporting country, but to keep language concise I will simply refer to it as the 'import share' in this context. 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 (16), while hypothesis B is based on the translog gravity estimation as in equation (15).

The premise of hypothesis A is that the trade cost elasticities should not vary systematically across import shares. To implement this test, I allow the trade cost coefficients in

[16] An estimating equation based on Eaton and Kortum (2002) 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.

[17] The R-squared associated with the regressions in Table 1 is around 50 percent and thus lower, but it is not directly comparable to the R-squared in Table 2 as the dependent variables are not the same.

the traditional specification (16) to vary across import shares. For simplicity, I drop the adjacency dummy from the notation so that the estimating equation becomes

$$(17)\quad \ln\left(\frac{x_{ij}}{y_j}\right) = -\lambda_{ij}\ln(dist_{ij}) + \tilde{\beta}_i + \tilde{\beta}_j + \xi_{ij},$$

where the distance coefficients λ_{ij} may vary. Since estimating a separate distance coefficient for each observation would leave no degrees of freedom, I allow λ_{ij} to vary over import share intervals. That is, $\lambda_{ij}=\lambda_h$ if observation ij falls in the hth interval, where $h=1,...,H$. H denotes the interval with the largest import shares, and the number of intervals is sufficiently small to leave enough degrees of freedom in the estimation.[18] Hypothesis A states – as predicted by the traditional gravity model – that the λ_h distance coefficients should not vary across import share intervals, that is, $\lambda=\lambda_1=...=\lambda_H$. The alternative is – as predicted by the translog gravity model – that the λ_h distance coefficients should vary systematically across import share intervals as implied by equation (12). Specifically, the absolute elasticity should decrease across the import share intervals, that is, $\lambda_1> \lambda_2>...> \lambda_H$.

Table 3 presents regression results for equation (17). Based on the data for the year 2000, column 1 reports results under the assumption of $H=5$ where each interval contains an evenly balanced number of observations.[19] A clear pattern arises: the λ_h distance coefficients decline in absolute value for intervals with larger import shares, as predicted by the translog model. Hypothesis A, which states that the distance coefficients are equal to each other, can be clearly rejected (p-value=0.00).

The remaining columns of Table 3 provide additional checks. Column 2 adds the adjacency dummy as a control.[20] In columns 3 and 4, I repeat the regressions of columns 1 and 2 using the larger sample with annual observations from 1991 to 2000.[21] The results are qualitatively the same, exhibiting declining absolute values of the distance coefficients. Columns 5-8 repeat the regressions of columns 1-4 but based on alternative intervals. The intervals are

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[18] As explained above, the 'import share' in this context refers to $(x_{ij}/y_j)/n_i$.
[19] The import share thresholds that separate the five intervals are 0.116 percent, 0.378 percent, 0.912 percent and 2.4 percent. The first interval contains 149 observations, the remaining intervals contain 150 observations each. Although the choice of H is arbitrary, the results are not qualitatively affected when a different number of intervals is chosen. Neither are the results qualitatively affected if the intervals do not contain an equal number of observations, see columns 5-8.
[20] Although adjacency regressors are included for all intervals, due to space limitations Table 3 only reports one of their coefficients.
[21] The import share thresholds that separate the five intervals are the same as those for columns 1 and 2 of Table 3. The numbers of observations in the intervals are 1376, 1395, 1365, 1311 and 1249, respectively.

now defined by specific import share thresholds. In particular, I choose the following import share thresholds to form five intervals: 0.1 percent, 0.5 percent, 1 percent and 2 percent. The intervals thus defined no longer contain an evenly balanced number of observations.[22] Still, columns 5-8 produce the same pattern of declining absolute distance coefficients as in columns 1-4, and hypothesis A is clearly rejected in each regression (p-values=0.00). In summary, Table 3 provides strong evidence against the constant elasticity gravity specification and in favor of the translog gravity model.

Hypothesis B is based on the translog estimating equation (15). Its premise is that the trade cost coefficient in that estimation should not vary systematically across import shares if the translog specification is correct. For simplicity, I again drop the adjacency variable from the notation so that the estimating equation becomes

$$(18)\quad \frac{x_{ij}}{y_j} = -\kappa_{ij} n_i \ln(dist_{ij}) + \kappa_{ij} n_i \ln(T_j^{dist}) + \beta_i + \varepsilon_{ij},$$

where I allow the distance coefficients κ_{ij} to vary over the same import share intervals as for hypothesis A in Table 3. Hypothesis B states – as predicted by the translog gravity model – that the κ_h distance coefficients should not vary across import share intervals, that is, $\kappa=\kappa_1=\ldots=\kappa_H$. The alternative would be – as implied by the standard gravity model – that the κ_h distance coefficients should increase in the import share.[23]

Table 4 presents regression results for equation (18) that correspond to those of Table 3. As before, columns 1-4 refer to estimations with an evenly balanced number of observations across intervals. Columns 5-8 refer to the alternative intervals specified above. In general, there is no distinct pattern in the distance coefficients. For example, in column 1 the first four distance coefficients are -0.0132, -0.0118, -0.0131 and -0.0191. The hypothesis that these coefficients are equal to each other cannot be rejected (p-value=0.25). This confirms hypothesis B for these four coefficients. However, the fifth distance coefficient at -0.0327 is significantly different from the other distance coefficients (p-value=0.00), which is inconsistent with hypothesis B. As additional

[22] In columns 5 and 6 of Table 3, the intervals contain 249, 238, 85, 87 and 90 observations, respectively. In columns 7 and 8 the intervals contain 2217, 2187, 755, 751 and 786 observations, respectively. The results are robust to alternative thresholds.

[23] To see this, divide the constant elasticity gravity equation (10) by y_j and then take the derivative with respect to $\ln(t_{ij})$. The result is $d(x_{ij}/y_j)/d\ln(t_{ij})=-(\sigma-1)x_{ij}/y_j$. In the translog gravity equation (7), this derivative is given by $d(x_{ij}/y_j)/d\ln(t_{ij})=-\gamma n_i$, which corresponds to $-\kappa_{ij}n_i$ in equation (18). Thus, if constant elasticity gravity were the true specification, then the κ_h distance coefficients should increase in $(x_{ij}/y_j)/n_i$.

regressors, Table 4 also contains the trade cost index terms $\ln(T_j^{dist})$ multiplied by the extensive margin proxy n_i. As expected, their coefficients are positive. A similar pattern arises in that only the trade cost index term coefficient for the fifth interval in column 1 is significantly different from those for the other intervals.

However, the distance coefficients are no longer significantly different from each other once the adjacency regressors are added in column 2 of Table 4.[24] A test of coefficient equality can no longer be rejected (p-value=0.21), confirming hypothesis B. The coefficients in columns 2-8 of Table 4 are qualitatively similar in that they do not exhibit any distinct pattern, perhaps with the exception of the fifth coefficients that tend to be larger in absolute magnitude. As noted above, if gravity with a constant elasticity were the true underlying model, one should observe a monotonous increase in the absolute distance coefficients across import share intervals. However, such a pattern is generally not supported by the estimations.

3.4. Robustness

A concern about the regressions in Tables 3 and 4 is that the import share intervals are a function of the dependent variable. The estimated distance coefficients λ_h and κ_h vary across the import share intervals and might therefore suffer from an endogeneity bias. To address this problem, I adopt an instrumental variables approach. I continue to use observations for the year 2000 but I form five intervals based on predetermined import shares for the year 1980. Thus, the instruments are distance variables that are allowed to vary across 1980 import share intervals. These distance variables based on 1980 intervals are highly correlated with those based on 2000 intervals (the correlation coefficients are 0.62, 0.34, 0.35, 0.41 and 0.73, respectively), but I do not expect the 1980 intervals to be correlated with the error terms for the year 2000.[25] As additional instruments, I use distance variables that vary across five distance intervals as opposed to import share intervals. The motivation is that two countries with low bilateral trade shares tend to be far away from each other.

Table 5 presents IV regression results that correspond to columns 1 and 2 of Tables 3 and 4. There are 584 observations compared to 749 in columns 1 and 2 of Tables 3 and 4. The

[24] As in Table 3, to save space only one adjacency coefficient is reported in Table 4.
[25] These correlations refer to the $\ln(dist_{ij})$ regressors used in columns 1 and 2 of Table 5 over the intervals h=1,…,5. The corresponding correlations for the $n_i \ln(dist_{ij})$ regressors used in column 3 of Table 5 are 0.61, 0.39, 0.39, 0.51 and 0.77.

difference is due to missing import share data for the year 1980 that are required to construct the IV intervals. Although the magnitudes of individual coefficients in columns 1 and 2 are altered and the standard errors are slightly larger, the same overall pattern arises as in Table 3: the absolute values of the distance coefficients decline in the import share intervals, and the coefficients are significantly different from each other regardless of whether the adjacency variable is included as an additional control (p-values=0.00). Hypothesis A is therefore clearly rejected, confirming the evidence from Table 3 against the constant elasticity specification.

In the translog estimations in columns 3 and 4 of Table 5, the distance coefficients retain the expected negative sign. Although their magnitudes are similar to those in Table 4, they are no longer statistically significant in this IV specification with one exception in column 3. Still, tests of coefficient equality cannot be rejected (p-values=0.17 and 0.76 in columns 3 and 4, respectively), consistent with hypothesis B.

In an unreported 'placebo' test, I also run the constant elasticity specification (17) using distance variables that are allowed to have different coefficients across *distance* intervals. This is a placebo test in the sense that translog gravity predicts variation of distance coefficients across import shares, not across distance. I therefore do not expect any particular pattern in the distance coefficients. Indeed, the estimated distance coefficients are generally not significantly different from each other with values close to those in Table 2, and they do not exhibit any particular pattern. This stands in contrast to the results in Table 3. There, the distance regressors vary across import share intervals and their coefficients turn out systematically smaller in absolute magnitude for larger import shares. The contrast between the placebo test and the results in Table 3 demonstrates – as predicted by translog theory – that the crucial variation is across import shares.

Finally, I emphasize that the tests performed in Tables 3 through 5 are distinct from testing whether the distance coefficient in the trade cost function (13) varies across bilateral observations *ij* or across import share intervals *h*, that is, whether $\rho \neq \rho_{ij}$ or $\rho \neq \rho_h$. Both the distance coefficient in the translog regression (15), $-\gamma\rho n_i$, and the distance coefficient in the constant elasticity regression (16), $-(\sigma-1)\rho$, are functions of ρ. Thus, if ρ varied across observations *ij* or import share intervals *h*, one would expect similar distance coefficient patterns in the two regressions. But Tables 3 through 5 do not indicate such a similarity. Instead, the translog specification yields stable distance coefficients across import share intervals

($\kappa=\kappa_1=\ldots=\kappa_H$ in general), whereas the log-linear specification yields distance coefficients that decline in absolute magnitude across the same import share intervals ($\lambda_1 > \lambda_2 > \ldots > \lambda_H$).

As a robustness check, I abandon the log-linear trade cost function (13) and instead adopt a concave specification where the level of trade costs depends on logarithmic distance, $t_{ij} = \rho \ln(dist_{ij})$. The concave specification captures the idea that trade costs might rise disproportionately quickly at short distances and less quickly at longer distances (see Hillberry and Hummels, 2008). As a result, distance enters the CES-based gravity equation (11) in a double-logarithmic form. Naturally, this change in specification affects the magnitude of the distance coefficient. But, for example in a regression that corresponds to column 1 of Table 3 (not reported here), the (double-logarithmic) distance coefficients still decline in absolute value across import share intervals. This result provides further evidence against the notion that trade cost elasticities are equal across import shares.

3.5. Discussion

The crucial result from the preceding gravity estimations is that a constant ‘one-size-fits-all’ trade cost elasticity is rejected by 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 product of the translog parameter γ and the number of goods n_i, divided by the import share x_{ij}/y_j.

The values for n_i and x_{ij}/y_j are given by the data, and the translog parameter γ can be retrieved from the estimated coefficients on the variable $n_i \ln(dist_{ij})$ in the translog regressions. As the translog estimating equation (15) shows, this coefficient corresponds to the product of the translog parameter γ and the distance elasticity of trade costs ρ. As an illustration, I take 0.019 from column 6 of Table 1 as an absolute value of this coefficient, that is, $\gamma\rho$=0.019, as this value is roughly the average estimate of the regressions with multiple goods in Table 1. To be comparable to the gravity literature, I choose a value of ρ=1/7. This value corresponds to values implied by standard estimates.[26] In standard gravity equations based on equation (10), the distance coefficient is typically estimated to be around -1 (see Head and Disdier, 2008). This

[26] See Anderson and van Wincoop (2004, Figure 1) for further evidence that ρ=1/7 is a reasonable value.

coefficient corresponds to the parameter combination $-(\sigma-1)\rho$. It implies ρ=1/7 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). The value of the translog parameter then follows as $\gamma=0.019/\rho=0.133$.[27]

The trade cost elasticities can now be calculated across different import shares. Based on the sample underlying column 6 of Table 1, I first calculate the trade cost elasticity evaluated at the average import share. This average import share is x_{ij}/y_j =0.01. The sample average of the extensive margin measure is n_i =0.50. The trade cost elasticity therefore follows as $\eta_{ij} =-\gamma n_i /(x_{ij}/y_j)$=-0.133*0.50/0.01=-6.7. [28] Thus, if trade costs go down by one percent, the import share is expected to increase by 6.7 percent. This value is very close to the CES-based trade cost elasticity, $\eta^{CES}=-(\sigma-1)$, which equals 7 under the assumption of σ=8. For alternative values of σ it is also true that the translog trade cost elasticity evaluated at the average import share is close to the CES-based trade cost elasticity.[29]

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 an importing country. I choose New Zealand because its import shares vary across a relatively broad range so that the heterogeneity of trade cost elasticities can be demonstrated most clearly. Based on the sample used in column 6 of Table 1, 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 -1.0 for Australia, -3.2 for the US, -3.9 for Japan and -11.4 for the UK. Figure 1 plots these trade cost elasticities against the import shares, adding various additional countries that export to New

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[27] 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=0.133 is reasonably close and would match Feenstra and Weinstein's (2010) estimate exactly in the case of ρ=1/10.

[28] 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 (15) 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 ($\gamma N * n_i /N = \gamma n_i$).

[29] For instance, under the assumption of σ=5, it follows ρ=1/4 and γ=0.076 so that the trade cost elasticity evaluated at the average import share is -3.8. Under the assumption of σ=10, it follows ρ=1/9 and γ=0.171 so that the trade cost elasticity is -8.55.

Zealand.[30] Dotted lines represent 95 percent confidence intervals computed with the delta method based on the regression in column 6 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 where it is simply a constant (σ-1=7 in this case).

Finally, I add a general remark on the interpretation of the estimation results. Tables 3-5 provide empirical evidence that rejects the constant-elasticity CES specification but not the translog specification. Thus, the empirical results should first and foremost be interpreted as evidence against CES rather than in favor of translog. Of course, this evidence does not preclude the possibility that an alternative third specification could do even better than translog. But the translog specification can be handled conveniently in general equilibrium, and it indicates the direction in which the demand side of trade models could sensibly be modified to yield gravity equations with varying trade cost elasticities.

4. An Application to the Currency Union Effect

Inspired by Rose's (2000) seminal paper, a sizeable part of the gravity literature attempts to estimate whether a common currency increases bilateral trade. The vast majority of currency union papers find a statistically significant and economically large effect on bilateral trade. Rose and Stanley (2005) survey 754 point estimates and conclude that currency unions increase bilateral trade by between 30 and 90 percent, with some individual estimates significantly larger. Some researchers criticize the statistical evidence as being not representative. For example, Thom and Walsh (2002) argue that historically, most currency unions have involved small or poor countries so that panel estimates of currency union effects are unlikely to provide good guidance for many policy questions of interest, for example whether the UK should adopt the single European currency. Similarly, Nitsch (2002) worries that pooling observations across different currency unions tends to conceal underlying heterogeneity.

In this section, I formally investigate whether currency unions have a heterogeneous impact on country pairs. I am guided by the translog gravity framework that predicts varying

[30] In order of declining import shares, the other countries are Germany, Italy, Korea, France and Sweden. Other OECD countries such as Iceland and Austria are not included in the figure as their import shares are even smaller and their trade cost elasticities tend to be even higher.

trade cost elasticities across country pairs. As equation (12) shows, translog gravity implies that if the exporting country only ships a small amount of goods relative to the importing country's income, then bilateral trade is more sensitive to trade costs. Provided that currency unions lower trade costs, this sensitivity means that a currency union should have a bigger impact on trade flows associated with small import shares than on trade flows associated with large import shares.

To test this hypothesis, I modify the trade cost function (13) to include a currency union indicator variable, CU_{ij}. I follow the log-linear specification that is standard in the literature:

$$(19)\ \ln(t_{ij}) = \rho \ln(dist_{ij}) + CU_{ij},$$

where for simplicity I drop all other trade cost proxies apart from distance.[31] I follow the same empirical strategy as in Table 3. That is, I run CES-based gravity regressions where the trade cost coefficients are allowed to vary across import share intervals. The null hypothesis is the same as hypothesis A in Table 3: as predicted by the CES-based gravity model, the trade cost coefficients (in particular the currency union coefficient) should not vary across import share intervals. The alternative is – as predicted by the translog gravity model – that the currency union coefficient should decline across import shares, meaning that the currency union effect should be larger for small import shares than for large import shares.

To obtain results that are directly comparable to the literature, I use the well-known data set by Glick and Rose (2002).[32] It contains aggregate trade data from the International Monetary Fund's Direction of Trade Statistics for the post-World War II period. Since I am interested in cross-sectional variation, I focus on the latest cross section for which they report a currency union effect estimate, which is the year 1995. The sample includes 7,640 bilateral trade observations and involves 157 IMF country codes. Just over one percent of the sample covers currency unions (81 observations), a proportion which is the same as for Glick and Rose's (2002) entire post-World War II data set as well as for the United Nations data used by Rose (2000). Relying on IMF classifications, Glick and Rose (2002) define currency unions as money "interchangeable between the two countries at a 1:1 par for an extended period of time, so that there was no need to convert prices when trading between a pair of countries." With this definition, hard fixes such as Hong Kong's linked exchange rate system with the U.S. dollar are

[31] See below for a robustness check with additional trade cost proxies.
[32] The data as well as sample regression output are made available in exemplary fashion on Andrew K. Rose's website.

not counted as currency unions. I refer to Glick and Rose (2002) for a detailed description of the data set, and to their appendix for a full list of currency unions in the sample.

My initial aim is to replicate the magnitude of the currency union effect as estimated by Glick and Rose (2002). Column 1 of Table 6a follows their specification with logarithmic bilateral trade as the dependent variable apart from two minor differences. First, I allow for separate coefficients of the exporting and importing countries' GDPs as opposed to constraining them to be equal. Second, to keep the analysis parsimonious, I do not include the battery of additional controls such as contiguity, common language and colonial history dummies that Glick and Rose (2002) employ but that are not central to the question of interest.[33] My currency union point estimate of 1.46 with a standard error of 0.26 is very close to Glick and Rose's (2002) point estimate of 1.49 with a standard error of 0.23 for the year 1995.[34] The interpretation is that two countries joined by a common currency trade over four times as much with each other ($\exp(1.46) \approx 4.3$), all else being equal. This point estimate is confirmed in column 2 where I change the dependent variable to the logarithmic import share, $\ln(x_{ij}/y_j)$, as in Table 3. In column 3, I switch to exporter and importer fixed effects to control for multilateral resistance effects as warranted by the micro-founded gravity specification in equation (11). The currency union point estimate is slightly higher at 1.66 although not statistically different from the other estimates.

My next and primary aim is to establish whether the currency union effect differs across import share intervals. According to equation (12), translog gravity theory predicts a smaller currency union effect for larger import shares. To test this prediction, I split the sample into five equally large intervals of import shares x_{ij}/y_j, with the smallest import shares collected in interval h=1 and the largest import shares in interval h=5.[35] At this stage, I do not yet consider information on the exporting country's extensive margin, implicitly assuming n_i=1.[36] An example of an import share in the first interval is trade between Papua New Guinea and Poland as a fraction of Poland's GDP. An example for the second interval is trade between Kenya and Poland as a fraction of Poland's GDP. An example for the fifth interval is trade between the U.S. and Poland as a fraction of Poland's GDP. In fact, the fifth interval contains almost all import

[33] Robustness checks confirm that the results are not sensitive to the inclusion of these additional controls (see below).
[34] See Glick and Rose (2002, Table 3).
[35] Each interval contains 1,528 observations. The import share thresholds that separate the five intervals are 0.007 percent, 0.07 percent, 0.34 percent and 1.77 percent.
[36] This assumption is relaxed in Table 6b, see below.

shares that capture trade from the U.S. to other countries.[37] As explained earlier, the sample covers 81 observations with currency unions. 12 of these fall into the first interval, 13 into the second, 17 into the third, 16 into the fourth and 23 into the fifth interval.

Columns 4-8 of Table 6a report separate regression results for each interval. The coefficient pattern across intervals is consistent with the translog prediction of declining trade cost elasticities. In particular, the currency union estimate is positive and significant only in the first two intervals and insignificant in the remaining intervals. The point estimate is largest for the interval containing the smallest import shares, implying that two countries with a common currency trade more than three times as much with each other ($\exp(1.15) \approx 3.2$), all else being equal. Examples of currency union pairs in this interval are Bhutan and India as well as Chad and Togo. The point estimate for the second interval implies that two countries in a currency union still trade significantly more with each other, but in this case only about 70 percent more ($\exp(0.54) \approx 1.7$). Examples of currency union pairs in this interval include Benin and Mali as well as Niger and Senegal. Examples of currency union pairs in the last three intervals (none of which are associated with significantly larger trade flows) include Grenada and St. Lucia, Australia and Kiribati, the U.S. and the Bahamas as well the U.S. and Panama.

As the next step, I jointly estimate the currency union effects across import share intervals. This regression, which corresponds to the regressions in Table 3, is reported in column 1 of Table 6c. I allow both the currency union coefficients and the distance coefficients to vary across the five import share intervals.[38] The pattern of the currency union coefficients is broadly similar to the separate regressions in Table 6a. For the smallest import shares, a currency union is associated with trade flows that are more than three times as high ($\exp(1.27) \approx 3.6$). For the remaining intervals, a currency union is not associated with significantly higher trade flows, with the exception of the fourth interval where the coefficient is statistically significant (p-value=0.09) but economically not as large ($\exp(0.36) \approx 1.4$).

[37] For example, exceptions are the import shares associated with trade between the U.S. and Nepal as a fraction of Nepal's GDP and trade between the U.S. and Syria as a fraction of Syria's GDP. Those two import shares fall into the fourth interval.

[38] Since I am interested in the difference between currency union pairs and non-currency union pairs in each of the five intervals, there are ten different groups to be distinguished in the pooled regression. In contrast, in the separate regressions in columns 4-8 of Table 6a, there are only two different groups. I therefore need nine dummy variables (ten minus one omitted category). The currency union estimates reported in Table 6c represent the differences between the two groups in each interval with the corresponding standard errors.

So far, I divided the sample into five intervals based on simple import shares, x_{ij}/y_j. To be precise, the expression for the trade cost elasticity in equation (12) implies that in the translog framework, the absolute value of the elasticity should decline in the import share *per good*, $(x_{ij}/y_j)/n_i$. I therefore divide the sample into five alternative intervals based on import shares per good. As before, I take the data on the extensive margin of countries, n_i, from Hummels and Klenow (2005). As these data are not available for all countries in the Glick and Rose (2002) sample, I lose 768 observations so that the sample is reduced to 6,872 trade flows.[39] Again, just over one percent of the sample covers currency unions (70 observations). 5 of these fall into the first interval, 6 into the second, 7 into the third, 11 into the fourth and 41 into the fifth interval.[40]

Table 6b reports results for the same regressions as in Table 6a with the same dependent variables but based on the new intervals. The results are qualitatively the same. In particular, the currency union coefficients in columns 1-3 are positive and significant with comparable magnitudes. In the separate regressions for each interval in columns 4-8, a similar pattern arises as in Table 6a. That is, the currency union coefficient is significant and economically large for the first interval ($\exp(1.59) \approx 4.9$), but it is indistinguishable from zero in the remaining intervals.[41] In column 2 of Table 6c, the currency union coefficients are jointly estimated. As before, the largest estimate is for the interval that contains the smallest import shares ($\exp(1.05) \approx 2.9$ with p-value=0.06). The remaining currency union estimates are insignificant, with the exception of the fifth interval ($\exp(0.64) \approx 1.9$).[42]

Since the number of currency unions in each of the first four intervals is small (between 5 and 11), I check the robustness of the estimates in columns 4-8 of Table 6b by expanding the sample over time. Instead of only using data for 1995, I pool observations over the years 1990-1997. These are all the available data for the 1990s in Glick and Rose's (2002) data set. As before, I divide the sample into five intervals based on import shares per good. The total number of observations is increased to 52,129. There are now 545 observations with a currency union

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[39] Each interval contains 1,374 or 1,375 observations. The thresholds of $(x_{ij}/y_j)/n_i$ that separate the five intervals are 0.08 percent, 0.43 percent, 1.40 percent and 4.89 percent.

[40] See a robustness check below with a larger number of currency union observations.

[41] A difference is that the separate regressions in Table 6b have noticeably higher R-squareds than those in Table 6a. This suggests that the gravity model performs better at explaining within-interval variation if the intervals are based on import shares per good rather than 'aggregate' import shares.

[42] The fifth interval is also the one that contains the largest number country pairs in a currency union (41 out of 70). In contrast, there is no such imbalance for the intervals underlying column 1 of Table 6c where the currency union pairs are more evenly distributed.

instead of only 70. 46 fall into the first interval, 36 into the second, 64 into the third, 81 into the fourth and 318 into the fifth interval. The currency union estimates for the five intervals are similar to the ones reported in Table 6b: 1.42, 0.21, 0.13, 0.04 and 0.19.[43] Due to the larger number of observations they are all significant except for the fourth. These additional estimates confirm the economically strong association between a currency union and bilateral trade in the case of small import shares.

Further robustness checks have been carried out but are not reported in the tables. First, the results are not qualitatively affected by adding other explanatory variables that are typical in the gravity literature such as a contiguity dummy, a common language dummy, a colonial relationship dummy as well as a dummy that captures regional trade agreements. When these four dummy variables are added, for example the currency union estimate in column 3 of Table 6a is slightly reduced to 1.26 but retains its significance. Likewise, in column 1 of Table 6c, the currency union estimates remain very similar (1.12, 0.16, -0.07, 0.26, -0.12 with the first coefficient significant at the 1 percent level and the other coefficients insignificant).

A second robustness check concerns the functional form of the trade cost function. Instead of the log-linear specification in equation (19), I let bilateral distance enter in double-logarithmic form. This specification captures the idea that trade costs might increase disproportionately strongly at short distances and less strongly at longer distances (see Hillberry and Hummels, 2008). Naturally, the general magnitude of the (double-logarithmic) distance coefficient is different but the other coefficients in Tables 6a-6c are hardly affected. Most importantly, the pattern of the currency union estimates is the same as before in terms of magnitude and significance.

Overall, my results confirm a strong currency union effect as found by Glick and Rose (2002) and others in the literature but with one important qualification – the effect is only strong for a subgroup of country pairs. That is, a currency union retains its strong effect on bilateral trade if bilateral trade relative to the importing country's total expenditure is sufficiently small, but not otherwise. Thus, consistent with translog gravity theory, I find that currency unions have a heterogeneous impact on international trade.

Quah (2000) and Persson (2001) make the observation that currency unions and associated higher trade flows tend to involve small countries, which is also true in the sample

[43] Time dummies are added to the regressions.

used here. My results give a precise reason why currency unions tend to be associated with high bilateral trade if small countries are involved. That is, the results highlight that the import share has to be sufficiently small for a currency union to be associated with higher bilateral trade. For example, the US and Panama share the same currency in the sample. But their currency union is only associated with higher trade for imports from Panama to the US, in which case the import share is small (i.e., imports from Panama as a share of US GDP). For trade in the opposite direction, the import share is large (i.e., imports from the US as a share of Panama's GDP) so that the currency union is not associated with higher trade. Thus, small countries involved in a currency union are not necessarily associated with higher trade. Instead, the direction of bilateral trade and the size of the import share are crucial.

5. 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 common feature across models is related to the widespread use of CES demand systems. This paper adopts an alternative and more flexible demand system – translog preferences – and derives the corresponding micro-founded gravity equation in general equilibrium. Due to rich 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 trade costs.

I test the translog gravity specification and find strong evidence in its favor. Trade cost elasticities are heterogeneous across import shares, and the traditional specification with a constant trade cost elasticity can be clearly rejected. In an application to the currency union effect, I find further evidence in favor of the translog specification. That is, a currency union is only associated with substantially higher trade flows if two countries with a common currency have small bilateral import shares. In other cases, a currency union is not related to larger bilateral trade flows.

Apart from the currency union effect, the translog framework also predicts heterogeneity across country pairs in response to other institutional arrangements such as free trade agreements or WTO membership. Thus, the translog gravity framework opens up the opportunity to revisit the effects of these institutions on international trade. In addition, it seems promising for future research if the translog gravity framework were applied to more disaggregated data at the industry or product level, also by incorporating heterogeneous firms and fixed costs of exporting.

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Technical Appendix

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

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

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:

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

Table 1: Translog gravity

	One good per country (n_i=1)				*Multiple goods per country*			
	2000 sample		1991-2000 sample		2000 sample		1991-2000 sample	
Dependent variable	x_{ij}/y_j	x_{ij}/y_j	x_{ij}/y_j	x_{ij}/y_j	x_{ij}/y_j	x_{ij}/y_j	x_{ij}/y_j	x_{ij}/y_j
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(dist_{ij})$	-0.0149**	-0.0094**	-0.0122**	-0.0081**				
	(0.0022)	(0.0016)	(0.0020)	(0.0013)				
adj_{ij}		0.0273**		0.0212**				
		(0.0053)		(0.0047)				
$n_i \ln(dist_{ij})$					-0.0296**	-0.0190**	-0.0237**	-0.0155**
					(0.0041)	(0.0029)	(0.0035)	(0.0024)
$n_i \ln(T_j^{dist})$					0.0207**	0.0105**	0.0178**	0.0099**
					(0.0049)	(0.0034)	(0.0042)	(0.0030)
$n_i\, adj_{ij}$						0.0510**		0.0401**
						(0.0117)		(0.0097)
$n_i\, T_j^{adj}$						-0.0471*		-0.0381*
						(0.0192)		(0.0164)
R-squared	0.50	0.56	0.50	0.55	0.52	0.59	0.52	0.59
Observations	749	749	6,696	6,696	749	749	6,696	6,696

Notes: The dependent variable is the import share x_{ij}/y_j. Robust standard errors clustered around country pairs (378 clusters) reported in parentheses, OLS estimation. Columns 1-4: exporter and importer fixed effects not reported (time-varying in columns 3 and 4 plus annual dummies). Columns 5-8: exporter fixed effects not reported (time-varying in columns 7 and 8 plus annual dummies). * significant at 5% level. ** significant at 1% level.

Table 2: Constant elasticity gravity

	2000 sample		1991-2000 sample	
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)
$\ln(dist_{ij})$	-1.2390**	-1.1697**	-1.2641**	-1.1988**
	(0.0625)	(0.0713)	(0.0666)	(0.0739)
adj_{ij}		0.3440*		0.3380
		(0.1720)		(0.1743)
R-squared	0.89	0.89	0.88	0.88
Observations	749	749	6,696	6,696

Notes: The dependent variable is the logarithmic import share $\ln(x_{ij}/y_j)$. Robust standard errors clustered around country pairs (378 clusters) reported in parentheses, OLS estimation. Exporter and importer fixed effects not reported (time-varying in columns 3 and 4 plus annual dummies). * significant at 5% level. ** significant at 1% level.

Table 3: Testing constant elasticity gravity against translog gravity (Hypothesis A)

	Intervals with evenly balanced numbers of obs.				*Alternative intervals based on thresholds*			
	2000 sample		1991-2000 sample		2000 sample		1991-2000 sample	
Dependent variable	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(dist_{ij})$, h=1	-0.8299**	-0.7385**	-0.8680**	-0.7916**	-0.8907**	-0.8461**	-0.9421**	-0.9058**
	(0.0450)	(0.0410)	(0.0506)	(0.0470)	(0.0437)	(0.0454)	(0.0527)	(0.0530)
$\ln(dist_{ij})$, h=2	-0.6752**	-0.5804**	-0.7330**	-0.6536**	-0.7408**	-0.6957**	-0.8159**	-0.7808**
	(0.0461)	(0.0418)	(0.0525)	(0.0492)	(0.0461)	(0.0478)	(0.0559)	(0.0565)
$\ln(dist_{ij})$, h=3	-0.5994**	-0.5020**	-0.6647**	-0.5828**	-0.6868**	-0.6388**	-0.7681**	-0.7300**
	(0.0483)	(0.0443)	(0.0548)	(0.0516)	(0.0494)	(0.0509)	(0.0601)	(0.0604)
$\ln(dist_{ij})$, h=4	-0.5412**	-0.4402**	-0.6096**	-0.5254**	-0.6344**	-0.5935**	-0.7193**	-0.6932**
	(0.0520)	(0.0479)	(0.0585)	(0.0553)	(0.0510)	(0.0530)	(0.0611)	(0.0622)
$\ln(dist_{ij})$, h=5	-0.4385**	-0.3492**	-0.5216**	-0.4491**	-0.5599**	-0.5257**	-0.6598**	-0.6347**
	(0.0559)	(0.0513)	(0.0631)	(0.0596)	(0.0550)	(0.0558)	(0.0658)	(0.0652)
adj_{ij}, h=5		0.5472**		0.5156**		0.3550**		0.2807*
		(0.0917)		(0.1002)		(0.1342)		(0.1352)
R-squared	0.95	0.95	0.93	0.93	0.93	0.93	0.91	0.91
Observations	749	749	6,696	6,696	749	749	6,696	6,696

Notes: The dependent variable is the logarithmic import share $\ln(x_{ij}/y_j)$. The index h denotes import share intervals in order of ascending import shares. Columns 1-4 are based on intervals with evenly balanced numbers of observations. Columns 5-8 use alternative intervals based on thresholds as specified in the text. The adj_{ij} regressors for intervals h=1,...,4 are included in columns 2, 4, 6, and 8 but not reported. Robust standard errors clustered around country pairs (378 clusters) reported in parentheses, OLS estimation. Exporter and importer fixed effects not reported (time-varying in columns 3, 4, 7 and 8). * significant at 5% level. ** significant at 1% level.

Table 4: Testing translog gravity against constant elasticity gravity (Hypothesis B)

	Intervals with evenly balanced numbers of obs.				*Alternative intervals based on thresholds*			
	2000 sample		1991-2000 sample		2000 sample		1991-2000 sample	
Dependent variable	x_{ij}/y_j	x_{ij}/y_j	x_{ij}/y_j	x_{ij}/y_j	x_{ij}/y_j	x_{ij}/y_j	x_{ij}/y_j	x_{ij}/y_j
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$n_i \ln(dist_{ij})$, h=1	-0.0132**	-0.0141**	-0.0092**	-0.0106**	-0.0084**	-0.0077**	-0.0063**	-0.0063**
	(0.0031)	(0.0034)	(0.0024)	(0.0027)	(0.0020)	(0.0021)	(0.0016)	(0.0018)
$n_i \ln(dist_{ij})$, h=2	-0.0118**	-0.0112**	-0.0086**	-0.0086**	-0.0077**	-0.0069**	-0.0062**	-0.0057**
	(0.0026)	(0.0026)	(0.0021)	(0.0020)	(0.0020)	(0.0019)	(0.0017)	(0.0015)
$n_i \ln(dist_{ij})$, h=3	-0.0131**	-0.0112**	-0.0106**	-0.0093**	-0.0114**	-0.0106**	-0.0103**	-0.0098**
	(0.0038)	(0.0032)	(0.0035)	(0.0029)	(0.0041)	(0.0038)	(0.0038)	(0.0035)
$n_i \ln(dist_{ij})$, h=4	-0.0191**	-0.0150**	-0.0164**	-0.0134**	-0.0178**	-0.0150**	-0.0168**	-0.0148**
	(0.0055)	(0.0046)	(0.0051)	(0.0043)	(0.0057)	(0.0050)	(0.0053)	(0.0046)
$n_i \ln(dist_{ij})$, h=5	-0.0327**	-0.0174**	-0.0271**	-0.0151**	-0.0343**	-0.0195**	-0.0291**	-0.0165**
	(0.0071)	(0.0060)	(0.0064)	(0.0049)	(0.0074)	(0.0068)	(0.0069)	(0.0055)
$n_i \ln(T_j^{dist})$, h=1	0.0085**	0.0084**	0.0067**	0.0071**	0.0028	0.0021	0.0030*	0.0026
	(0.0026)	(0.0032)	(0.0021)	(0.0025)	(0.0018)	(0.0025)	(0.0014)	(0.0020)
$n_i \ln(T_j^{dist})$, h=2	0.0063*	0.0047	0.0057*	0.0045*	0.0017	0.0009	0.0026	0.0016
	(0.0028)	(0.0028)	(0.0022)	(0.0022)	(0.0027)	(0.0026)	(0.0022)	(0.0021)
$n_i \ln(T_j^{dist})$, h=3	0.0072	0.0047	0.0073	0.0051	0.0050	0.0042	0.0064	0.0056
	(0.0044)	(0.0036)	(0.0038)	(0.0031)	(0.0044)	(0.0039)	(0.0038)	(0.0034)
$n_i \ln(T_j^{dist})$, h=4	0.0127*	0.0078	0.0128*	0.0088*	0.0119*	0.0091	0.0133*	0.0109*
	(0.0059)	(0.0048)	(0.0053)	(0.0044)	(0.0059)	(0.0052)	(0.0052)	(0.0047)
$n_i \ln(T_j^{dist})$, h=5	0.0301**	0.0147**	0.0265**	0.0140**	0.0329**	0.0181**	0.0288**	0.0161**
	(0.0068)	(0.0053)	(0.0061)	(0.0045)	(0.0069)	(0.0060)	(0.0063)	(0.0049)
$n_i\, adj_{ij}$, h=5		0.0592**		0.0491**		0.0588**		0.0515**
		(0.0164)		(0.0138)		(0.0206)		(0.0174)
$n_i T_j^{adj}$, h=5		-0.1135		-0.1062*		-0.0904		-0.0978
		(0.0585)		(0.0507)		(0.0913)		(0.0791)
R-squared	0.61	0.66	0.61	0.67	0.65	0.69	0.64	0.69
Observations	749	749	6,696	6,696	749	749	6,696	6,696

Notes: The dependent variable is the import share x_{ij}/y_j. The index h denotes import share intervals in order of ascending import shares. Columns 1-4 are based on intervals with evenly balanced numbers of observations. Columns 5-8 use alternative intervals based on thresholds as specified in the text. The $n_i\, adj_{ij}$ and $n_i T_j^{adj}$ regressors for intervals h=1,...,4 are included in columns 2, 4, 6 and 8 but not reported. Robust standard errors clustered around country pairs (378 clusters) reported in parentheses, OLS estimation. Exporter fixed effects not reported (time-varying in columns 3, 4, 7 and 8). * significant at 5% level. ** significant at 1% level.

Table 5: IV regressions

	Constant elasticity		Translog	
Dependent variable	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	x_{ij}/y_j	x_{ij}/y_j
	(1)	(2)	(3)	(4)
$\ln(dist_{ij})$, h=1	-0.6391**	-0.5811**		
	(0.0722)	(0.0724)		
$\ln(dist_{ij})$, h=2	-0.4744**	-0.4142**		
	(0.0747)	(0.0758)		
$\ln(dist_{ij})$, h=3	-0.3665**	-0.3019**		
	(0.0831)	(0.0852)		
$\ln(dist_{ij})$, h=4	-0.3186**	-0.2448**		
	(0.0890)	(0.0907)		
$\ln(dist_{ij})$, h=5	-0.1568	-0.1078		
	(0.1015)	(0.0951)		
adj_{ij}, h=5		0.5835		
		(0.3900)		
$n_i \ln(dist_{ij})$, h=1			-0.0045	-0.0098
			(0.0038)	(0.0070)
$n_i \ln(dist_{ij})$, h=2			-0.0125	-0.0083
			(0.0068)	(0.0085)
$n_i \ln(dist_{ij})$, h=3			-0.0008	-0.0014
			(0.0071)	(0.0077)
$n_i \ln(dist_{ij})$, h=4			-0.0159	-0.0163
			(0.0112)	(0.0115)
$n_i \ln(dist_{ij})$, h=5			-0.0260**	-0.0061
			(0.0100)	(0.0117)
$n_i\, adj_{ij}$, h=5				0.0678**
				(0.0225)
R-squared	0.94	0.94	0.60	0.64
Observations	584	584	584	584

Notes: The dependent variable in columns 3 and 4 is the import share x_{ij}/y_j, and its logarithm in columns 1 and 2. Observations for the year 2000, where h indicates import share intervals in order of ascending import shares. The intervals have an evenly balanced number of observations. Instruments are based on 1980 import shares and distance intervals (see text for details). The adj_{ij} regressors for intervals h=1,...,4 are included in column 2 but not reported. The $n_i\, T_j^{dist}$ regressors for intervals h=1,...,5 are included in columns 3 and 4 but not reported. The $n_i\, adj_{ij}$ regressors for intervals h=1,...,4 are included in column 4 but not reported. The $n_i\, T_j^{adj}$ regressors for intervals h=1,...,5 are included in columns 4 but not reported. Robust standard errors clustered around country pairs (299 clusters) reported in parentheses, OLS estimation. Exporter fixed effects (all columns) and importer fixed effects (columns 1 and 2) not reported. ** significant at 1% level.

Table 6a: The currency union effect

	Pooled regressions			*Separate regressions for each interval (one good per country, n_i=1)*				
Dependent variable	$\ln(x_{ij})$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(gdp_i)$	1.09**	1.09**						
	(0.01)	(0.01)						
$\ln(gdp_j)$	0.97**							
	(0.01)							
CU_{ij}	1.46**	1.50**	1.66**	1.15*	0.54*	-0.23	-0.03	-0.11
	(0.26)	(0.26)	(0.28)	(0.53)	(0.23)	(0.18)	(0.24)	(0.36)
$\ln(dist_{ij})$	-1.39**	-1.39**	-1.67**	-0.61**	-0.22**	-0.18**	-0.24**	-0.86**
	(0.03)	(0.03)	(0.04)	(0.18)	(0.04)	(0.03)	(0.03)	(0.04)
Interval				h=1	h=2	h=3	h=4	h=5
R-squared	0.61	0.52	0.71	0.35	0.26	0.23	0.33	0.54
Observations	7,640	7,640	7,640	1,528	1,528	1,528	1,528	1,528

Notes: The sample is for the year 1995 based on the data set by Glick and Rose (2002). The dependent variable is the logarithmic trade flow $\ln(x_{ij})$ in column 1 and the logarithmic import share $\ln(x_{ij}/y_j)$ in all other columns. The index h in columns 4-8 denotes import share intervals with evenly balanced numbers of observations in order of ascending import shares under the assumption that each country is endowed with one good (n_i=1). Robust standard errors reported in parentheses, OLS estimation. Constants included in columns 1-2 but not reported. Exporter and importer fixed effects included in columns 3-8 but not reported. * significant at 5% level. ** significant at 1% level.

Table 6b: The currency union effect (ctd.)

	Pooled regressions			*Separate regressions for each interval (multiple goods per country)*				
Dependent variable	$\ln(x_{ij})$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(gdp_i)$	1.13**	1.13**						
	(0.02)	(0.01)						
$\ln(gdp_j)$	0.97**							
	(0.01)							
CU_{ij}	1.49**	1.52**	1.82**	1.59*	0.04	-0.04	-0.16	0.20
	(0.27)	(0.27)	(0.30)	(0.81)	(0.23)	(0.17)	(0.16)	(0.19)
$\ln(dist_{ij})$	-1.36**	-1.36**	-1.63**	-0.61**	-0.16**	-0.08**	-0.16**	-0.73**
	(0.03)	(0.03)	(0.04)	(0.18)	(0.04)	(0.02)	(0.02)	(0.04)
Interval				h=1	h=2	h=3	h=4	h=5
R-squared	0.63	0.53	0.71	0.56	0.90	0.93	0.93	0.79
Observations	6,872	6,872	6,872	1,374	1,374	1,375	1,374	1,375

Notes: The sample is for the year 1995 based on the data set by Glick and Rose (2002). The dependent variable is the logarithmic trade flow $\ln(x_{ij})$ in column 1 and the logarithmic import share $\ln(x_{ij}/y_j)$ in all other columns. The index h in columns 4-8 denotes import share intervals with evenly balanced numbers of observations in order of ascending import shares under the assumption that each country is endowed with multiple goods. Robust standard errors reported in parentheses, OLS estimation. Constants included in columns 1-2 but not reported. Exporter and importer fixed effects included in columns 3-8 but not reported. * significant at 5% level. ** significant at 1% level.

Table 6c: The currency union effect (ctd.)

	Pooled regressions	
Dependent variable	$\ln(x_{ij}/y_j)$	$\ln(x_{ij}/y_j)$
	(1)	(2)
CU_{ij}, h=1	1.27**	1.05[a]
	(0.41)	(0.56)
CU_{ij}, h=2	0.21	0.06
	(0.33)	(0.28)
CU_{ij}, h=3	0.07	0.15
	(0.26)	(0.22)
CU_{ij}, h=4	0.36[a]	0.28
	(0.22)	(0.24)
CU_{ij}, h=5	-0.05	0.64**
	(0.26)	(0.18)
$\ln(dist_{ij})$, h=1	-0.09	-0.05
	(0.10)	(0.11)
$\ln(dist_{ij})$, h=2	-0.36**	-0.30**
	(0.04)	(0.04)
$\ln(dist_{ij})$, h=3	-0.35**	-0.25**
	(0.03)	(0.03)
$\ln(dist_{ij})$, h=4	-0.36**	-0.26**
	(0.03)	(0.02)
$\ln(dist_{ij})$, h=5	-0.52**	-0.52**
	(0.03)	(0.03)
R-squared	0.89	0.90
Observations	7,640	6,872

Notes: The sample is for the year 1995 based on the data set by Glick and Rose (2002). The dependent variable is the logarithmic import share $\ln(x_{ij}/y_j)$. The index h denotes import share intervals with evenly balanced numbers of observations in order of ascending import shares. In column 1 it is assumed that each country is endowed with one good (n_i=1). In column 2 it is assumed that each country is endowed with multiple goods. Robust standard errors reported in parentheses, OLS estimation. Exporter and importer fixed effects included but not reported. [a] significant at the 10% level. * significant at 5% level. ** significant at 1% level.

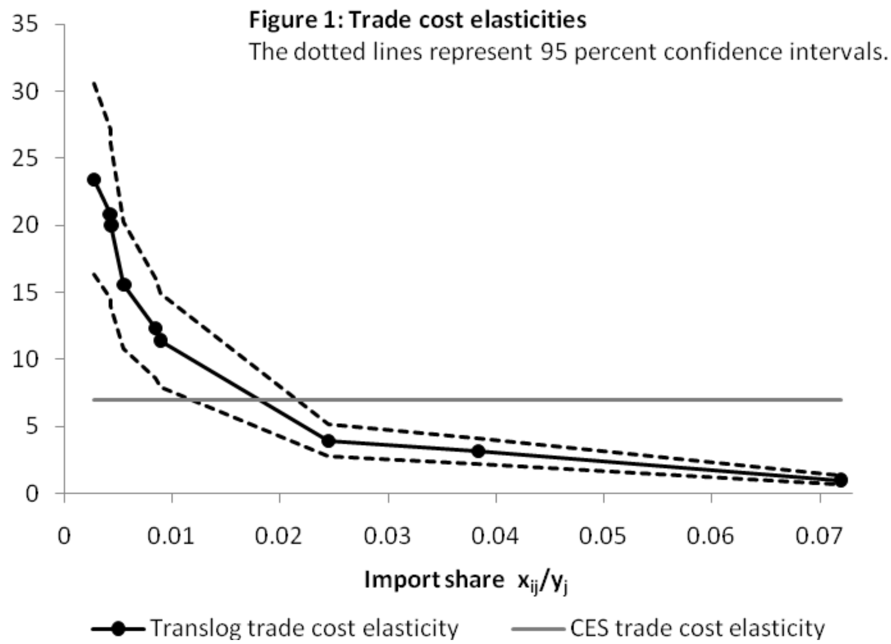

Figure 1: Trade cost elasticities

The dotted lines represent 95 percent confidence intervals.