Estimation of the gravity equation in the presence of zero flows

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Abstract
The gravity model is the workhorse model to describe and explain variation in bilateral trade empirically. Consistent with both Heckscher-Ohlin models and models of imperfect competition and trade, this versatile model has proven to be very successful, explaining a large part of the variance in trade flows. However, the loglinear model cannot straightforwardly account for the occurrence of zero-valued trade flows between pairs of countries. This paper investigates the various approaches suggested to deal with zero flows. Apart from the option to omit the zero flows from the sample, various extensions of Tobit estimation, truncated regression, probit regression and substitutions for zero flows have been suggested. We argue that the choice of method should be based on both economic and econometric considerations. The sample selection model appears to fit both considerations best. Moreover, we show that the choice of method may matter greatly for the results, especially if the fraction of zero flows in the sample is large. In the end, the results surprisingly suggest that the simplest solution, to omit zero flows from the sample, often leads to acceptable results, although the sample selection model is preferred theoretically and econometrically.

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1 Introduction

The gravity model has become the workhorse model to analyze patterns of bilateral trade (Eichengreen and Irwin, 1998). Originally inspired by Newton's gravity equation in physics, the gravity model has become common knowledge in regional science for describing and analyzing spatial flows, and was pioneered in the analysis of international trade by Tinbergen (1962), Pöyhönen (1963) and Linneman (1966). The model has worked well empirically, yielding sensible parameter estimates and explaining a large part of the variation in bilateral trade (Rose, 2005). However, it has long been disputed for a lack of theoretical foundation. More recently, the gravity model has made a comeback in the international trade literature, after developments in the modelling of bilateral trade have provided the model with a more satisfying theoretical underpinning in trade theory (see, e.g., Feenstra, 2005 and Anderson and Van Wincoop, 2004, for an overview).

In conjunction with the expanding theoretical literature on the gravity model, a number of recent contributions have addressed issues concerning the correct specification and interpretation of the gravity equation in empirical estimation. These deal with, for example, the specification of panel gravity equations, the estimation of cross-section gravity equations, and the correct interpretation of the distance effect on patterns of bilateral trade. All in all, these developments have improved our understanding of the gravity equation as a tool to model and analyze bilateral trade patterns. However, a number of questions with regard to bilateral trade and the gravity equation remain to be investigated (see Anderson and Van Wincoop, 2004). One of these is the question how to deal with zero-flow observations, country-pairs that do not trade at all in a certain sector or industry, or even at the macroeconomic level. The gravity model predicts that countries have positive trade in both directions, even if this predicted trade may be small. Moreover, in the usual double-logarithmic formulation, the model cannot include zero flows either. This paper deals with the question how to amend the gravity model in order to be able to deal with zero flows. It discusses the theoretical and econometric problems for the gravity model generated by the occurrence of zero flows, and presents an overview of the solutions commonly proposed and applied in the literature. Subsequently, it argues that these solutions are at odds with both a sound theoretical treatment of zero flows in the gravity model and with proper econometric modelling of zero flows in bilateral trade. Finally, the paper proposes an alternative method to deal with zero-valued trade flows, which has been widely used in other fields of applied economics: the sample selection model. This approach is rather novel to the literature on bilateral trade, and therefore deserves more attention in applied work. Moreover, this paper also presents a comparison of the results using various alternative approaches, and thus provides an explicit check of the sensitivity of the empirical outcomes for the approach chosen. This allows us to asses whether the general consensus in the literature that zero flows do not have much impact on the estimation results (see, e.g., Baldwin, {Baldwin, 1994 686 /id}1994 and Frankel, {Frankel, 1997 556 /id}1997) is corroborated.

2 The gravity model

The traditional gravity model relates bilateral trade flows to the GDP levels of the countries and their geographic distance. The levels of GDP reflect the market size in both countries, as a measure of 'economic mass'. The market size of the importing country reflects the potential demand for bilateral imports, while GDP in the exporting country represents the potential supply of goods from that country; geographic distance reflects resistance to bilateral trade. The familiar functional form from physics is then used to relate bilateral trade to these variables of economic mass and distance:

$$T_{ij} = K \cdot \frac{Y_i^{\alpha} Y_j^{\beta}}{D_{ij}^{\delta}}, \tag{1}$$

where T_{ij} stands for export from country i to country j; K is a scalar; Y represents the level of GDP and D_{ij} reflects physical distance between the countries.

Usually, the gravity equation is expressed in logarithmic form, for the purpose of empirical estimation. The transformed basic gravity equation, used in estimation, then looks as follows:

$$\ln(T_{ij}) = \ln K + \alpha \ln(Y_i) + \beta \ln(Y_j) + \delta \ln(D_{ij}) + \varepsilon_{ij}, \qquad (2)$$

where ε_{ij} is a disturbance term that reflects random deviations from the underlying relation.

We will follow the literature in extending the basic gravity equation with several variables that proxy different aspects of economic distance. These comprise, among others, dummies for common language and colonial history, to proxy cultural familiarity, a dummy for membership in a common trade bloc, to reflect economic integration, and a religion dummy to indicate similarity in cultural values and norms. The benchmark version of the disaggregated gravity equations estimated below looks as follows:

$$\begin{aligned} \ln(T_{ij}) &= \beta_0 + \beta_1 \ln(Y_i) + \beta_2 \ln(Y_j) + \beta_3 \ln(D_{ij}) + \beta_4 Adj_{ij} \\ &+ \beta_5 RIA_{ij} + \beta_6 Lan_{ij} + \beta_7 Col_{ij} + \beta_8 Rel_{ij} + \varepsilon_{ij} \end{aligned}, \qquad (3)$$

where *i* and *j* denote the exporting and importing country, respectively. The dataset comprises 127 countries (listed in the Data Appendix). The dependent variable T_{ij} is merchandise exports (in '000 US$) from *i* to *j*, for 1999. The independent variables are: GDP (*Y*), the distance between *i* and *j* (D_{ij}) and dummies reflecting whether *i* and *j*: share a land border (*Adj*), are both member in a regional integration agreement (*RIA*), have the same primary language (*Lan*) or main religion (*Rel*), and whether they were part of a common colonial empire (*Col*).

3 Zero flows

A logarithmic formulation of the gravity model, as in equation (3), cannot include zero trade, because the logarithm of zero is undefined. However, in our data set of bilateral trade, some of the potential trade flows are recorded as zero or missing.[2] At the aggregate level, zero flows mostly occur for trade between small or distant countries, which are expected to trade little (Frankel, 1997). However, omitting zero flows can bias the empirical results, if they do not occur randomly. Omitting zero-entried observations implies we loose information on the causes of (very) low trade. Specifically, if geographic distance, low levels of national income, and a lack of cultural or historical links lead to lower trade, omitting zero flows tends to reduce the estimated effects of these variables on trade. Rauch (1999) argues that disregarding zero flows leads to an underestimation of the impact of distance and historical and cultural links on trade, "[i]f zero observations tend to occur between countries that are far apart and do not share a common language/colonial tie" (pp. 18–19).

Several approaches have been applied or suggested in the literature to address the problem of zero flows (see, e.g., Frankel, 1997, pp. 145–146; Bikker, 1982, pp. 371–372). The most common solution in the literature confines the sample to non-zero observations to avoid the estimation problems related to zero trade. However, the omission of zero flows can give rise to biased results. The zero-valued flows contain relevant information about the pattern of trade. Throwing away zero entries implies that one loses any information contained in these flows on why these low levels of trade are observed (Eichengreen and Irwin, 1998, p. 41). Alternatively, (part of the) zero values may be substituted by a small constant, so that the double-log model can be estimated without throwing these country pairs out of the sample. Examples in the literature that followed this approach are Linnemann (1966), Van Bergeijk

[2] Most of these flows are recorded as missing in the source database (UN COMTRADE); some have explicitly been recorded as zero. We assume that all missing observations in principle indicate that bilateral exports are considered to be absent by the reporting country. Countries that do not report any trade statistics in the database have been omitted from our sample. As described in the Data Appendix, we have confronted flows from country i to j as reported by both countries to check for reporting errors in missing flows. Apart from flows that are truly zero, missing trade may also reflect imperfections in measurement as a consequence of rounding processes. Trade flows can be too small to register if reporting of trade involves rounding to the nearest integer amount of predetermined size (e.g., rounded to thousands of US$; this would imply that trade is censored from below at US$ 500). However, the data do not appear to be generally censored below a fixed amount, as flows have been reported as low as US$ 1.

and Oldersma (1990), Wang and Winters (1991) and Raballand (2003). Substituting small values prevents omission of observations from the sample, but is essentially ad hoc. The inserted value is arbitrary and does not necessarily reflect the underlying expected value. Thus, inserting arbitrary values close to zero does not provide any formal guarantee that the resulting estimates of the gravity equation are consistent. Both approaches are hence generally unsatisfactory.

Dealing properly with zero flows, then, would involve that the information provided by these flows is taken into account, without using ad-hoc methods. The censored regression model (Tobit model) is often employed to analyse data sets in which a substantial fraction of the observations cluster at the (zero-) limit. Several studies have used the standard Tobit model to estimate the gravity equation with zero flows (e.g., Rose, 2004; Soloaga and Winters, 2001; Anderson and Marcouiller, 2002). The Tobit model describes a situation in which part of the observations on the dependent variable is censored (unobservable) and represented instead by mapping them to a specific value, generally zero. The model applies to situations in which outcomes cannot be observed over some range, either because actual outcomes cannot reflect desired outcomes (e.g., actual trade cannot be negative), or because of measurement inaccuracy (e.g., rounding). Thus, whether the Tobit model can be applied to study zero flows in the conventional gravity framework depends on two questions. First, 'Can desired trade be negative?' and second, 'Is rounding of trade flows an important concern?'.

The gravity model, in its conventional specification, does not explain the occurrence of zero-flow observations. This can be illustrated by considering the gravity model in levels, rather than logs. Equation (5) presents a typical specification of the gravity model, with explanatory variables GDP (*Y*), geographic distance (*D*), and a set of variables (*x*) that includes institutional variables as well as the bilateral dummy variables, under the assumption of a log-normally distributed disturbance term.

$$T_{ij} = AY_i^{\beta_1} Y_j^{\beta_2} D_{ij}^{-\beta_3} e^{x_{ij}'\gamma_k} e^{\varepsilon_{ij}} . \quad (4)$$

As can easily be seen, the gravity model as conventionally specified would only predict zero trade if the GDP of one or both countries equaled zero. This is only a hypothetical situation, of course, which will not occur in practice.[3] If we specified equation (4) with an additive, normally distributed error term, instead of a log-normal error structure, the gravity model could in principle generate negative trade, by means of the random error. This negative trade would then be censored at zero, and actual zero trade might reflect desired negative trade. Note, however, that the predicted, non-stochastic part of the gravity model can never be negative. Given that the non-stochastic part can be derived from economic optimization, it is unclear which optimizing framework would justify negative desired trade, even if caused by randomly distributed factors not explicitly identified in the model.[4] The first question can thus be answered negatively.

Usually, the gravity model is restated in terms of natural logarithms for the purpose of estimation. The censoring model, given that rounding occurs at some fixed value (*a*), would then look as follows:

$$\begin{aligned} &\ln(\tilde{T}_{ij}) = \beta_0 + \beta_1 \ln(Y_i) + \beta_2 \ln(Y_j) - \beta_3 \ln(D_{ij}) + x_{ij}'\gamma + \varepsilon_{ij} \\ &\ln(T_{ij}) = \ln(\tilde{T}_{ij}) \qquad \text{if } \ln(\tilde{T}_{ij}) > \ln(a) \\ &\ln(T_{ij}) = \ln(a) \qquad \text{if } \ln(\tilde{T}_{ij}) \leq \ln(a) \end{aligned} \quad . \tag{5}$$

In this formulation, censoring at zero trade (a=0) causes technical problems because the logarithm of zero is not defined. Though censoring cannot occur at zero, it can occur at some positive fixed value (*a*), as shown in equation (5), due to rounding. If trade flows were rounded to zero below some censoring value, the Tobit model might be useful to estimate the gravity equation. However, rounding of trade flows in general does not seem to occur in our

[3] One could imagine this to describe the tautological situation of trade with an uninhibited island, which would be zero almost per definition.

[4] In fact, this implies that an additive error term might better be regarded as truncated from below. Zero flows then always represent desired zero flows, and the model is consistent with economic optimization. However, this solution does not accord with the Tobit model anymore.

data set. As noted before, trade flows are reported up to an accuracy of US$ 1 (although this differs somewhat across countries). Therefore, the second question can be answered negatively as well. In other words, the Tobit model is not the appropriate model to explain why some trade flows are missing.

Given that the conventional gravity model in equation (4) is not capable to generate zero-valued bilateral trade nor desired negative trade, and in the absence of rounding below some positive value, zero flows have to be interpreted otherwise. In this context, zero flows result from binary decision making rather than censoring (Sigelman and Zeng, 1999). The appropriate way to proceed, then, is "to model the decisions that produce the zero observations rather than use the Tobit model mechanically" (Maddala, 1992, cf. Sigelman and Zeng, 1999, p. 170). This can be done by modelling the decision whether or not to trade as a Probit model. The outcome of that decision determines whether or not we observe actual trade flows in the sample, or trade is zero (or, equivalently, missing). The size of potential trade is determined by the gravity model. We only observe positive trade in case the selection model resulted in a positive outcome. This structure has been framed in the sample selection model (see, e.g., Greene, 2000, section 20.4; Verbeek, 2000, section 7.4), to which we will now turn for a solution to the problems associated with zero flows in a gravity model context.

4 The sample selection model

The selection model is often used in micro-econometric research, especially in labour economics. Its use can be traced back, for example, to Gronau (1974). A rather small number of gravity model studies of bilateral trade have used the selection model to deal with zero flows. For example, Bikker (1982) and Bikker and De Vos (1992) make extensive use of a selection model, similar to the one used here. Rose (2000) estimates a variant of the model in a robustness section of the paper, without explicating the model. Hillberry (2002) motivates and estimates a more restricted variant, in which an independent selection and, as he prefers to call it, truncated regression equation are estimated (cf. Cragg, 1971). The sample selection model of bilateral trade is specified as follows:

Selection mechanism:

$$\tilde{\pi}_{ij}=\gamma_0+\gamma_1\ln(Y_i)+\gamma_2\ln(Y_j)+\gamma_3\ln(y_i)+\gamma_4\ln(y_j)+\gamma_5\ln(D_{ij})+\gamma_6 Adj_{ij}$$
$$+\gamma_7 RIA_{ij}+\gamma_8 Lan_{ij}+\gamma_9 Col_{ij}+\gamma_{10} Rel_{ij}+\gamma_{11} IQ_i+\gamma_{12} IQ_j+\gamma_{13} ID_{ij}+\mu_{ij}$$
$$s_{ij}=1 \text{ if } \tilde{\pi}_{ij}>0$$
$$s_{ij}=0 \text{ if } \tilde{\pi}_{ij}\leq 0$$

Regression model:

$$\ln(\tilde{T}_{ij})=\beta_0+\beta_1\ln(Y_i)+\beta_2\ln(Y_j)+\beta_3\ln(y_i)+\beta_4\ln(y_j)+\beta_5\ln(D_{ij})+\beta_6 Adj_{ij}$$
$$+\beta_7 RIA_{ij}+\beta_8 Lan_{ij}+\beta_9 Col_{ij}+\beta_{10} Rel_{ij}+\beta_{11} IQ_i+\beta_{12} IQ_j+\beta_{13} ID_{ij}+\varepsilon_{ij}$$

$$\ln(T_{ij})=\ln(\tilde{T}_{ij}) \text{ if } s_{ij}=1$$
$$\ln(T_{ij})=\text{not observed if } s_{ij}=0$$

$$(\mu_{ij},\varepsilon_{ij})\sim \text{bivariate normal}[0,0,1,\sigma_\varepsilon^2,\rho_{\varepsilon\mu}] \qquad (6)$$

The model in equation (6) can be estimated using maximum likelihood (ML) estimation (for further details, see the Technical Appendix at the end). The selection equation determines whether or not we observe bilateral trade between two countries in the sample. The regression model determines the potential size of bilateral trade. In general, the selection equation should at least contain all variables that are reflected in the regression equation (Verbeek, 2000). We assume that the selection process reflects decisions made at the microeconomic level on the basis of comparing costs and benefits of bilateral transactions (see Bikker and De Vos, 1992). Anderson and Van Wincoop (2004) point at the importance of fixed costs associated with international trade to explain zero flows in trade, such as border costs (Hillberry, 2002), search costs and other specific investments to enter foreign markets (Romer, 1994). At the macroeconomic level, we assume an underlying latent variable, say profitability, which depends on the same variables as the gravity equation. This can be motivated by the fact that profitability will generally rise if the potential size of trade gets larger. However, this does not imply that profitability only reflects the potential size of the flow. For example, some variables may be more important in determining the profitability of flows rather than the potential size of these flows. Moreover, the disturbance term of the selection equation will capture all (microeconomic) factors that influence profitability of bilateral transactions. Therefore, we expect that the coefficients in the selection and regression equation will not perfectly match and that the correlation between the disturbance terms will be positive, but not necessarily one.[5]

The basic idea behind the sample selection model is as follows. If a variable, such as institutional quality, becomes so low that firms decide to stop exporting to a country because it is no longer profitable, we do not observe (potential) bilateral trade. Therefore, the effect of low institutional quality could be underestimated from the available data (cf. Verbeek, 2000, p. 207). The effect would be underestimated if the correlation between the disturbance terms of both equations in the model is positive, in this case. Those trade flows that we do observe for low institutional quality levels will have a positive expected value for the disturbance term in the selection equation, μ_{ij}, in order for the selection decision to be positive. Because of the positive correlation, $\rho_{\varepsilon\mu}$, the expected disturbance term in the regression model, ε_{ij}, will be positive as well. As a result, observed trade will be expected to be higher than potential trade, which is unconditional on being observed or not. The observed sample will be biased upward at low levels of institutional quality. OLS estimates of the regression coefficients, for the observed sample of positive trade, will be biased toward zero if $\rho_{\varepsilon\mu} > 0$. This is technically known as sample selection bias. The sample selection model allows us to tackle this problem,

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[5] As noted by Bikker and De Vos (1992), for $\gamma_k = \beta_k / \sigma_\varepsilon, k \in \{1,..K\}$, $\gamma_0 = (\beta_0 - \ln(a)) / \sigma_\varepsilon$ and $\rho_{\varepsilon\mu} = 1$, the sample selection model transforms into the Tobit model in equation (5) (see also Verbeek, 2000 and Greene, 2000 for similar observations for the standard Tobit model). The only difference with equation (5) is that the selection equation has a variance normalized to one and includes a linear transformation with the censoring threshold, because the selection limit is set at zero. Because, in the Tobit model, the latent selection variable and the potential size of the action are perfectly correlated, we can map the latent variable to the observed variable and do not need to normalize the selection equation. This leads to the formulation of the observation rule in equation (5) (with the exception, not of importance to estimation, that equation (5) sets all missing observations equal to $\ln(a)$). Note that, if the estimated sample selection model would (approximately) lead to the stated relations regarding parameters and cross-equation correlation, we would observe trade *as if* it were censored at a positive value. Strictly speaking, this is not a case of censoring, because the observed sample is not limited by non-observability (e.g., due to rounding) of trade below this value.

noted earlier in the paper: disregarding zero flows may lead to an underestimation of the effect of regressors such as distance and GDP on bilateral trade.

5 Empirical results

The previous sections have argued that, on theoretical grounds, the sample selection model is the preferred approach to deal with zero flows, over censored regression (Tobit) or truncated regression, and substitution of arbitrary small values for zero flows. This section estimates the gravity equation using these different approaches for zero flows, to assess the sensitivity of the results for using different methods. The regression results presented in Table 1 compare the various solutions for dealing with zero flows. The first specification represents simple OLS regression on a sample excluding the zero flow observations. All variables have the expected sign, and are highly significant statistically. These findings are in line with the existing literature. Trade increases with GDP and decreases with physical distance. Moreover, other proxies for economic proximity, such as the cultural familiarity variables and the common trade bloc indicator, positively affect trade. Specification (2) reflects the sample selection model set forward in the previous section. Column (2a) presents the regression equation, and column (2b) the corresponding selection equation. The results are surprisingly similar to the straight OLS results. There is only marginal indication that OLS is biased downward, due to sample selection bias. The correlation between both stages in the selection model ($\rho_{\varepsilon\mu}$) is positive, as expected, but small (although significantly different from zero at $p<0.05$). The impact of some independent variables in the selection stage is quite comparable to the regression stage, after correcting for the re-scaling involved in the selection stage (see footnote 5 above). This implies that their effect on the expected potential size of the flow also translates into expected profitability. However, this does not hold for several regressors, notably adjacency, language, religion and common trade bloc membership. These findings imply that the extent of sample selection bias will be relatively small (confirming our earlier statement comparing specifications (1) and (2)), and that, apart from its theoretical unsuitability, the Tobit model is no supported as a reduced form either. Specification (3) shows the results of a Tobit estimation. We have substituted 1 (=$1000) for the zeros, and subsequently put the censoring limit to ln(1)=0, censoring all flows below $1000 including the zero observations. The parameter estimates generally tend to overestimate the results from the sample selection model. This reflects that maximizing the Tobit likelihood function implies that the expected value for all zero flows is forced as closely as possible to (or below) $1000. Clearly, this value is arbitrary and not representative for all zero flows. Specification (5) uses truncated regression. All flows (including the zero flows) are truncated at $1000. This approach disregards all truncated flows, and assumes that those flows observed around the truncation limit will on average have positive disturbance terms. As a result, it should correct for a downward bias in OLS estimation. The outcomes from truncated regression (4) are more in line with the Heckman results than the corresponding Tobit model in specification (3), because they are not burdened with the zero flows that are ill-fit to the imposed censoring or truncation limit. However, truncated regression does not appear to sufficiently correct for the bias that results from the arbitrarily imposed truncation at $1000. The estimates are lower in absolute terms than the benchmark estimates in specifications (1) and (2). Both Tobit and truncated regression require arbitrarily imposing a censoring limit to the sample, because actual trade flows are not censored at any value in the logarithmic gravity model. The artificial censoring furthermore implies that the information contained in the positive observations of trade below the censoring limit of, e.g., $1000 is lost. These observations are thrown onto a pile of limit observations in Tobit, and are completely discarded in truncated regression. Moreover, the estimation results will depend on the (arbitrarily chosen) lower limit. The last specification in Table 1, model (5), estimates an OLS after substituting an arbitrary, small value for all zero flows. We have chosen the smallest recorded value in the COMTRADE database, $1. The rationale for this approach is that zero flows tend to reflect low expected potential trade. The substituted values need to be even lower than the average expected value for zero flows that follow from the OLS results on the non-zero sample. Thus, these low values will tend to correct for the upward bias assumed to follow from estimation using the non-zero observations. The results in Table 1 illustrate, however, that the approach leads to an overcorrection of the assumed bias. Most parameter estimates are unrealistically high in absolute terms, and overestimate the benchmark results from the sample selection model. Of course, the results from this approach are not robust to the value chosen to substitute for zeros.

Table 1: Estimation Results

	(1)	(2a)	(2b)	(3)	(4)	(5)
	OLS	Heckman	Heckman selection	Tobit	Truncated	OLS incl. zeros
Log GDP exporter	1.23***	1.24***	0.49***	1.48***	1.17***	1.76***
	(133.93)	(139.90)	(41.81)	(140.56)	(137.26)	(129.73)
Log GDP importer	1.01***	1.02***	0.40***	1.21***	0.97***	1.45***
	(109.45)	(114.37)	(37.87)	(116.03)	(113.58)	(106.82)
Log Distance	-1.12***	-1.14***	-0.46***	-1.39***	-1.09***	-1.68***
	(50.08)	(50.95)	(17.08)	(49.71)	(52.39)	(47.98)
Border Dummy	0.93***	0.92***	-0.36	0.69***	0.85***	0.51**
	(7.25)	(7.13)	(1.36)	(4.33)	(6.85)	(2.26)
Language Dummy	0.38***	0.39***	0.51***	0.57***	0.32***	0.76***
	(4.15)	(4.24)	(4.83)	(5.23)	(3.60)	(5.34)
Colonial Dummy	0.81***	0.83***	0.41***	1.15***	0.77***	1.53***
	(10.30)	(10.53)	(4.73)	(12.63)	(10.28)	(12.14)
Religion Dummy	0.13***	0.13***	0.14***	0.28***	0.14***	0.42***
	(2.64)	(2.79)	(3.12)	(4.87)	(3.31)	(5.60)
Trade area Dummy	0.57***	0.56***	0.76***	0.41***	0.61***	0.18*
	(7.94)	(7.77)	(5.13)	(4.22)	(9.20)	(1.66)
Constant	-36.91***	-37.41***	-15.73***	-46.43***	-34.84***	-56.88***
	(96.35)	(100.49)	(36.89)	(107.83)	(98.05)	(100.83)
Observations	13682	16002	16002	16002	13249	16002
censored:		2320		2753	2753	
Adjusted R-squared	0.68					0.64
log likelihood	-30282.40	-34313.15		-34253.03	-27572.54	-44071.15
F-statistic	3950.22			19470.05		3530.48
$\rho_{\varepsilon\mu}$		0.08				
sigma		2.21				
lambda		0.18				
Wald-statistic		37094.18			33407.61	

Robust t statistics in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%.
Dependent variable: log bilateral export (1999)

Table 2 includes some additional estimations, as a robustness check. Specifications (1) and (2) again apply Tobit and truncated regression. The lower limit has been put equal to the average value of zero flows following from the benchmark OLS estimation for the non-zero sample. The results show that these methods are not robust for the chosen limit. The Tobit results are more in line with the benchmark outcomes from the sample selection model, because the censoring limit imposed is a more realistic representation of the zero-flow observations. However, these approaches remain empirically unsatisfactory as well as theoretically unfounded for the situation at hand. Arbitrary censoring and truncation is an ad-hoc, crude method that does not guarantee any quantitative accurateness in terms of results, compared to the preferred and flexible sample selection model. Specifications (3) and (4) provide robustness checks using country-specific fixed effects in the regression equation, to correct for the potential bias in the estimates of the conventional gravity equation that does not include theoretically derived country-specific price levels (Anderson and Van Wincoop, 2004; Feenstra, 2004). Although the results indeed differ quantitatively from the conventional gravity outcomes, the OLS and sample selection models remain highly comparable. The correlation term between regression and selection equation does not differ statistically from zero anymore, suggesting that the probit selection model and the linear regression model are independent. This implies that simply performing OLS on the non-zero sample does not bias the results in this context.

Table 2: Robustness

	(1)	(2)	(3)	(4a)	(4b)
	Tobit at mean exp. value†	Truncated at mean exp. value†	OLS FE	Heckman FE	Heckman selection
Log GDP exporter	1.32***	1.08***			0.49***
	(147.84)	(131.61)			(67.32)
Log GDP importer	1.09***	0.92***			0.40***
	(123.12)	(112.82)			(67.30)
Log Distance	-1.23***	-1.00***	-1.31***	-1.31***	-0.46***
	(53.23)	(52.13)	(41.68)	(42.31)	(32.79)
Border Dummy	0.75***	0.85***	0.87***	0.87***	-0.32***
	(5.80)	(7.63)	(6.70)	(6.75)	(3.36)
Language Dummy	0.47***	0.35***	0.49***	0.49***	0.51***
	(5.16)	(4.22)	(5.21)	(5.28)	(10.64)
Colonial Dummy	0.93***	0.71***	0.72***	0.72***	0.41***
	(12.37)	(10.20)	(8.73)	(8.84)	(11.74)
Religion Dummy	0.22***	0.10**	0.35***	0.35***	0.14***
	(4.64)	(2.48)	(6.99)	(7.07)	(6.17)
Trade area Dummy	0.55***	0.69***	0.24***	0.24***	0.75***
	(6.84)	(11.43)	(3.11)	(3.12)	(13.22)
Constant	-40.56***	-31.92***	10.98***	10.98***	-15.58***
	(111.45)	(93.15)	(27.59)	(27.86)	(58.71)
Observations	16002	12039	13682	16002	16002
of which censored:	3963	3963		2320	
log likelihood	-29120.83	-22801.03	-28752.54	-32788.54	
F-statistic	20998.82		173.79		
Wald-statistic		30423.08		48028.97	
$\rho_{\varepsilon\mu}$				0.01	
sigma				1.98	
lambda				0.03	
Adjusted R-squared			0.74		

Absolute value of t statistics in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. Dependent variable: log bilateral export (1999). †: Mean expected value for zero flows ($18916) is based on the OLS results for the non-zero sample.

6 Conclusions

Zero flows may bias the estimation results for the gravity equation of bilateral trade. This paper has argued that a careful choice of the method to deal with zero flows is needed. The solutions often applied, substituting small values for zero flows or using Tobit or truncated regression are not suited to the gravity model of trade. First, zeros do not reflect unobservable trade values. In the gravity model with lognormal disturbance term, desired trade cannot be negative, making censoring at zero an unsuitable reason for observed zeros. Second, rounding of trade flows as a cause of censoring does not appear to be an important explanation for zero flows either. Instead, zero flows are the result of economic decisions that partly depend on the size of potential trade, explained by the gravity equation. If decisions lead to zero trade, potential trade is unobserved, but positive, satisfying the gravity model theoretically. This combination of simultaneous and partly interdependent economic decisions regarding bilateral trade should be explicitly modelled at the macroeconomic level. The sample selection model forms a well-established approach to model bilateral trade in the presence of zero flows. It allows for correlation between both decisions, as the profitability of trade depends on the size of potential flows, but does not require that profitability perfectly reflects potential trade. Other, microeconomic factors that do not affect the size of trade can be important for profits.

We have estimated a sample selection model as well as alternative approaches to deal with zero flows. This paper shows the sensitivity of the results with respect to the method chosen to deal with zero flows. Because the regression outcomes differ, it is important to make a well-motivated decision on how to deal with zero flows. We have seen that, in our context, censored or truncated regression and replacement of zero flows with arbitrary numbers are not preferable. These approaches may yield misleading results, as they rely on ad-hoc assumptions, or artificial truncation. Sample selection models, on the other hand, allow zero flows to be explained separately, as the outcome of, in principle, independent economic decisions of traders. This method correctly takes into account the information provided by zero-valued observations. Moreover, it encompasses censored regression as well as independent probit and (truncated) regression as special cases. Starting from an explicit theoretical framework on the causes of zero flows, sample selection allows for all kinds of data structures to emerge in practice, and provides information on the decision processes underlying zero flows as well.

Apart from the extra information provided by the selection model, the results for the level regressions suggest that OLS on a non-zero sample may not lead to much bias in practice. The results have shown only limited residual correlation between the decision whether to trade at all and the decision how much to trade. Hence, OLS does not suffer greatly from selection bias. As a result, we draw the conclusion that omitting zero flows from the regression sample leads to satisfactory results in our case, even at disaggregated levels of trade, and is preferred to the use of a Tobit model or ad-hoc substitutions for zero flows. One has to keep in mind, however, that the OLS estimates only consider the non-zero sample. In this context, Greene (2000) notes that the extent of bias in OLS estimates depends on the distribution of the regressors in this sub-sample. So, it is not possible to determine beforehand whether the bias of OLS is likely to be serious. Therefore, even though the OLS results prove to be fairly close to the results in the sample selection model in our case, it is preferable to use the sample selection model.

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Technical Appendix **Estimation of the sample selection model**

In this appendix, we present the likelihood function of the sample selection model estimated in section 5. We will illustrate sample selection bias when the correlation between the selection and regression model is positive.

Let us repeat the sample selection model, defined in equation (6):

$$\begin{aligned}
&\ln(T_{ij}) = \ln(\tilde{T}_{ij}); s_{ij} = 1 \quad \text{if } \tilde{\pi}_{ij} > 0\\
&\ln(T_{ij}) = \text{not observed}; s_{ij} = 0 \quad \text{if } \tilde{\pi}_{ij} \leq 0\\
&\text{where:}\\
&\ln(\tilde{T}_{ij}) = x'_{1i}\beta_1 + x'_{2j}\beta_2 + x'_{3ij}\beta_3 + \varepsilon_{ij}\\
&\tilde{\pi}_{ij} = x'_{1i}\gamma_1 + x'_{2j}\gamma_2 + x'_{3ij}\gamma_3 + \mu_{ij}\\
&x_1, x_2 \text{ and } x_3 \text{ are vectors of exporter- and importer specific and bilateral regressors}\\
&\beta_k \text{ and } \gamma_k, k \in \{1,2,3\} \text{ are vectors of regression and selection parameters, and:}\\
&(\varepsilon, \mu) \sim \text{bivariate normal}\left(0, 0, \sigma_\varepsilon, \sigma_\mu, \rho_{\varepsilon\mu}\right)
\end{aligned} \quad . \qquad (7)$$

The parameters in equation (7) can be estimated using maximum likelihood. We follow Verbeek (2000, section 7.4.2) to derive the likelihood functions for an individual observation. Although both decisions in the model are most naturally thought of as occurring simultaneously, it is instructive to view the two parts separately when constructing the likelihood function. The selection equation essentially describes a binary choice problem. Therefore, the contribution to the likelihood is the probability of observing $s_{ij} = 1$ ($\tilde{\pi}_{ij} > 0$), if trade is non-zero, and $s_{ij} = 0$ ($\tilde{\pi}_{ij} \leq 0$), if trade is zero. The contribution for non-zero trade furthermore consists of the conditional probability density of observed trade given that trade is actually taking place, $f(\ln(T_{ij}) \mid s_{ij} = 1)$. This results in the following log likelihood function:

$$\ln L(\beta, \gamma, \sigma_\varepsilon, \rho_{\varepsilon\mu}) = \sum_{T_{ij}=0} \ln P\{s_{ij} = 0\} + \sum_{T_{ij}>0} \left[\ln f\left(\ln(T_{ij}) \mid s_{ij} = 1\right) + \ln P\{s_{ij} = 1\}\right]. \qquad (8)$$

The conditional distribution of $\ln(T_{ij})$, given that $s_{ij} = 1$, is rather complicated. However, a reformulation simplifies matters substantially (Verbeek, 2000; Bikker and De Vos, 1992). We can use a general rule for joint distributions, that is:

$$f\left(\ln(T_{ij}) \mid s_{ij} = 1\right) P\{s_{ij} = 1\} = P\{s_{ij} = 1 \mid \ln(T_{ij})\} f\left(\ln(T_{ij})\right). \tag{9}$$

The probability density of log trade follows a normal distribution, whereas the probability in the first term on the right-hand side is from a conditional normal density function. Using the underlying latent selection variable, this conditional normal density function has the following mean and variance.

$$\begin{aligned} E\{\tilde{\pi}_{ij} \mid \ln(T_{ij})\} &= x'_{1i}\gamma_1 + x'_{2j}\gamma_2 + x'_{3ij}\gamma_3 + E\{\mu_{ij} \mid \varepsilon_{ij}\} \\ &= x'_{1i}\gamma_1 + x'_{2j}\gamma_2 + x'_{3ij}\gamma_3 + \frac{\sigma_{\varepsilon\mu}}{\sigma_\varepsilon^2}\left(\ln(T_{ij}) - x'_{1i}\beta_1 - x'_{2j}\beta_2 - x'_{3ij}\beta_3\right) \\ V\{\tilde{\pi}_{ij} \mid \ln(T_{ij})\} &= 1 - \frac{\sigma_{\varepsilon\mu}^2}{\sigma_\varepsilon^2} = 1 - \rho_{\varepsilon\mu}^2 \end{aligned} \quad . \tag{10}$$

Thus:

$$\tilde{\pi}_{ij} \mid \ln(T_{ij}) = x'_{1i}\gamma_1 + x'_{2j}\gamma_2 + x'_{3ij}\gamma_3 + \frac{\sigma_{\varepsilon\mu}}{\sigma_\varepsilon^2}\left(\ln(T_{ij}) - x'_{1i}\beta_1 - x'_{2j}\beta_2 - x'_{3ij}\beta_3\right) + \eta_{ij}$$

$$\eta_{ij} \sim \text{independent } N\left(0, (1 - \rho_{\varepsilon\mu}^2)\right)$$

With the modification in equation (9) and the conditional distribution in equation (10), the log likelihood can be written as follows.

$$\ln L(\beta, \gamma, \sigma_\varepsilon, \rho_{\varepsilon\mu}) = \sum_{T_{ij}=0} \ln P\{s_{ij} = 0\} + \sum_{T_{ij}>0} \left[\ln f\left(\ln(T_{ij})\right) + \ln P\{s_{ij} = 1 \mid \ln(T_{ij})\}\right]. \tag{11}$$

The relevant probabilities and probability density for an individual observation, with either observed trade or zero trade, directly result from equations (7) and (10):

$$
\begin{aligned}
P\{s_{ij}=0\} &= P\{\tilde{\pi}_{ij}\le 0\} = P\{\mu_{ij}\le -x'_{1i}\gamma_1 - x'_{2j}\gamma_2 - x'_{3ij}\gamma_3\} \\
&= 1-\Phi\left(x'_{1i}\gamma_1 + x'_{2j}\gamma_2 + x'_{3ij}\gamma_3\right) \\
P\{s_{ij}=1 \mid \ln(T_{ij})\} &= P\{\tilde{\pi}_{ij}>0 \mid \ln(T_{ij})\} = P\{\eta_{ij} > -x'_{1i}\gamma_1 - x'_{2j}\gamma_2 - x'_{3ij}\gamma_3 \\
&\quad -\frac{\sigma_{\varepsilon\mu}}{\sigma_\varepsilon^2}\left(\ln(T_{ij}) - x'_{1i}\beta_1 - x'_{2j}\beta_2 - x'_{3ij}\beta_3\right)\} = \\
&= \Phi\left(\frac{x'_{1i}\gamma_1 + x'_{2j}\gamma_2 + x'_{3ij}\gamma_3 + \left(\sigma_{\varepsilon\mu}/\sigma_\varepsilon^2\right)\left(\ln(T_{ij}) - x'_{1i}\beta_1 - x'_{2j}\beta_2 - x'_{3ij}\beta_3\right)}{\sqrt{1-\rho_{\varepsilon\mu}^2}}\right) \\
f\left(\ln(T_{ij})\right) &= \frac{1}{\sigma_\varepsilon}\phi\left(\frac{\ln(T_{ij}) - x'_{1i}\beta_1 - x'_{2j}\beta_2 - x'_{3ij}\beta_3}{\sigma_\varepsilon}\right)
\end{aligned}
\quad , \qquad (12)
$$

where $\phi(.)$ and $\Phi(.)$ stand for the standard normal probability density and cumulative distribution function, respectively.

The log likelihood function in equation (11), maximized with respect to the unknown parameters from the sample selection model, leads to consistent and asymptotically efficient estimators for the parameters of the selection and regression equations (Verbeek, 2000, p. 211).

The most important property of the sample selection model is its flexibility with respect to the influence of zero-trade observations. The model includes separate explanatory equations for selection and potential size of the action of primary interest, but allows correlation between both stages. If the residuals in both stages are correlated, the non-random sampling implied by the selection equation leads to sample selection bias in the observed (non-zero trade) sample. We can illustrate this by confining ourselves to the model in equation (7), as it applies to the non-zero trade observations in our sample. In particular, consider the conditional expectation of log trade, given that trade is profitable to begin with (for further details, see Greene, 2000; Verbeek, 2000):

$$
\begin{aligned}
E\{\ln(T_{ij}) \mid \ln(T_{ij}) \text{ is observed}\} &= E\{\ln(T_{ij}) \mid \tilde{\pi}_{ij} > 0\} \\
&= E\{\ln(T_{ij}) \mid \mu_{ij} > -x'_{1i}\gamma_1 - x'_{2j}\gamma_2 - x'_{3ij}\gamma_3\} \\
&= x'_{1i}\beta_1 + x'_{2j}\beta_2 + x'_{3ij}\beta_3 + E\{\varepsilon_{ij} \mid \mu_{ij} > -x'_{1i}\gamma_1 - x'_{2j}\gamma_2 - x'_{3ij}\gamma_3\} \\
&= x'_{1i}\beta_1 + x'_{2j}\beta_2 + x'_{3ij}\beta_3 + \frac{\sigma_{\varepsilon\mu}}{\sigma_\mu^2} E\{\mu_{ij} \mid \mu_{ij} > -x'_{1i}\gamma_1 - x'_{2j}\gamma_2 - x'_{3ij}\gamma_3\} \\
&= x'_{1i}\beta_1 + x'_{2j}\beta_2 + x'_{3ij}\beta_3 + \frac{\sigma_{\varepsilon\mu}}{\sigma_\mu} \frac{\phi\left(x'_{1i}\gamma_1 + x'_{2j}\gamma_2 + x'_{3ij}\gamma_3 / \sigma_\mu\right)}{\Phi\left(x'_{1i}\gamma_1 + x'_{2j}\gamma_2 + x'_{3ij}\gamma_3 / \sigma_\mu\right)} \qquad . \qquad (13) \\
&= x'_{1i}\beta_1 + x'_{2j}\beta_2 + x'_{3ij}\beta_3 + \rho_{\varepsilon\mu}\sigma_\varepsilon\lambda\left(\alpha_{ij}\right)
\end{aligned}
$$

with $\sigma_\mu \equiv 1; \alpha_{ij} = -x'_{1i}\gamma_1 - x'_{2j}\gamma_2 - x'_{3ij}\gamma_3$

and $\lambda\left(\alpha_{ij}\right) = \dfrac{\phi\left(x'_{1i}\gamma_1 + x'_{2j}\gamma_2 + x'_{3ij}\gamma_3\right)}{\Phi\left(x'_{1i}\gamma_1 + x'_{2j}\gamma_2 + x'_{3ij}\gamma_3\right)}$

The expectation of the conditional disturbance term in the selection equation (μ_{ij}) exceeds zero, given that it is truncated from below in the observed-trade sample. To judge whether this leads to sample selection bias in the regression equation, we have to consider the expectation of the regression disturbance term (ε_{ij}), conditional on the truncation in the selection equation. From equation (13), the expectation of ε_{ij}, given that μ_{ij} is truncated from below, exceeds zero if $\rho_{\varepsilon\mu}$ is positive. The estimates in the main text of this paper indeed show a positive correlation between ε_{ij} and μ_{ij}. Thus, the conditional expected value of (log) trade, given that trade is observed, exceeds expected potential trade, unconditional on being observed or not. In other words, OLS regression of log trade on the regressor variables, using only non-zero trade observations, produces inconsistent estimates of the regression parameters in $\beta_k, k \in \{1,2,3\}$. This bias is known as sample selection bias. It can be seen most intuitively by summarizing the complete model as it applies to the non-zero sub sample.

$$
\begin{aligned}
\ln\left(T_{ij}\right) \mid \left(s_{ij} = 1\right) &= E\{\ln\left(T_{ij}\right) \mid \left(s_{ij} = 1\right)\} + \nu_{ij} \\
&= x'_{1i}\beta_1 + x'_{2j}\beta_2 + x'_{3ij}\beta_3 + \beta_\lambda\lambda\left(\alpha_{ij}\right) + \nu_{ij}, \qquad (14)
\end{aligned}
$$

where $\beta_\lambda = \rho_{\varepsilon\mu}\sigma_\varepsilon$

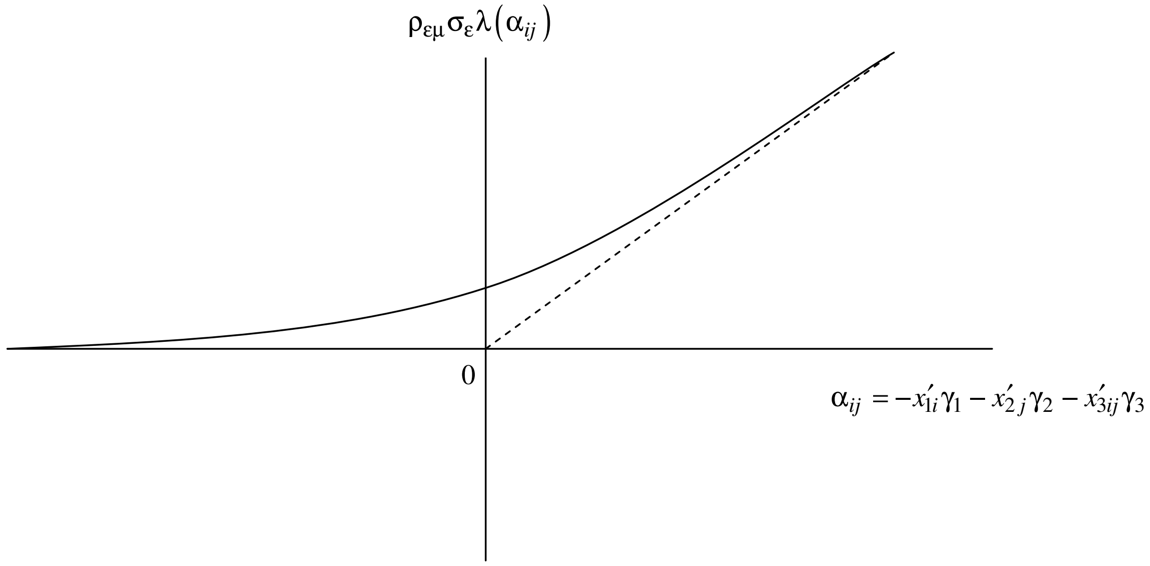
If $\beta_\lambda \neq 0$, an OLS regression omitting λ from the model suffers from omitted variable bias. On the other hand, if we can include λ in the specification, OLS will produce consistent estimates of $\beta_k \left(k \in \{1,2,3\}\right)$, although inefficient because ν_{ij} is heteroskedastic (see Greene, 2000, section 20.4.1 for more details). This concept is the basis for an alternative method often used in empirical applications to estimate the selection model, without the need to estimate the full model by maximum likelihood. The two-step estimation procedure, due to Heckman (1979) and also known as the 'Heckit' estimator, estimates equation (14) by OLS. However, λ_{ij} is not directly observed. Therefore, the first step is to estimate the selection equation as a binary Probit model, using maximum likelihood. The estimates for $\gamma_k \left(k \in \{1,2,3\}\right)$ can then be used to compute $\hat{\lambda}_{ij}$, as estimates of λ_{ij}, and substitute these in the second-step OLS regression. This method is often simpler to apply than full maximum likelihood. However, it has some drawbacks. Apart from heteroskedasticity, the fact that $\hat{\lambda}_{ij}$ is estimated leads to less efficiency, and inconsistency of OLS standard errors. Most importantly, the method may not give reliable results if the share of zero flows is very large (Hillberry, 2002). Because the explanatory variables in the selection and regression equations are identical, the second-step OLS regression is only identified because $\hat{\lambda}_{ij}$ is nonlinear (see Verbeek, 2000). A large share of 'limit' observations (i.e., zero flows) may imply little variation in $\hat{\lambda}_{ij}$ across the sample, such that $\hat{\lambda}_{ij}$ is close to a linear function of the regressor variables. Because of these problems with the Heckit procedure, we have relied on full maximum likelihood estimation in this paper, also because it turned out to work well in practice.[6]

As shown by equations (13) and (14), the conditional expectation of log trade is different from the unconditional expectation of potential trade, because of the term $\lambda\left(\alpha_{ij}\right) = \lambda\left(-x'_{1i}\gamma_1 - x'_{2j}\gamma_2 - x'_{3ij}\gamma_3\right) > 0$. For positive $\rho_{\varepsilon\mu}$, the conditional expected value

[6] Results based on the Heckit two-step procedure are not reported, but are available upon request. The regression parameters did not differ much qualitatively. There are some quantitative differences in parameter estimates, though. Most importantly, the estimates for ρ are much larger.

exceeds unconditional expected potential trade. Figure 5.1 below illustrates how the size of this difference depends on the expected value of the latent selection variable (profitability).[7]

Figure 5.1 $\mathrm{E}\left[\ln\left(\mathrm{T_{ij}}\right) \mid \ln(\mathrm{T_{ij}})\,\text{is observed}\right] - \mathrm{E}\left[\ln\left(\tilde{\mathrm{T}}_{\mathrm{ij}}\right)\right]$ *as a function of* $-E\left[\tilde{\pi}_{ij}\right]$.



The figure shows that conditional expected trade is highest, compared to unconditional expected trade, for low values of expected profitability. Given the positive correlation $\rho_{\varepsilon\mu}$, this makes sense. In order to assure profitability, the realization for the disturbance term μ_{ij} should be high. Given the truncation in the selection equation, the expected value of trade will be high as well.

Apart from the relationship between expected profitability and conditional expected trade, it is important to establish the potential consequences of truncation in the selection equation for sample selection bias of OLS. We may conclude from our estimation results in Section 5 that the difference between conditional and unconditional expected trade is highest for low values of unconditional expected trade, because most explanatory variables in our model have the same sign in both the selection and the regression equation. This corresponds to the intuitive argument in the main text. A low expected profitability goes together with low

[7] The figure is based on Figure 20.2 in Greene (2000).

expected trade. Therefore, trade flows that we observe between countries that have, for example, low institutional quality levels, or are distant from each other, will be most above their unconditional expected value, on average. The regression plane tends to be flattened by the sample selection process. As a result, the effect of these explanatory variables on expected trade in the 'observed' sample of non-zero bilateral trade will underestimate the true effect on unconditional expected potential trade.