The Importance of Dynamics in Panel Gravity Models of Trade

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Abstract

Existing gravity models of trade based on panel data are often static, that is, they only allow for contemporaneous effects of regressors on trade. However, there are numerous economic arguments suggesting that trade is a dynamic process. Hence, we extend the static model by including lags of the regressors and lags of trade. Using a panel of 221 annual bilateral OECD trade flows over 48 years, we find that dynamics are strongly significant, so that static models are misspecified. The resulting dynamic panel gravity model leads to sensible short-term and long-term trade dynamics. We also show that the simple least squares dummy variable estimator, which is typically used in static panels, yields accurate estimates for our dynamic model and outperforms the popular generalized method of moments estimator of Arellano and Bond (1991).

Key words: dynamic panel data model, export, gravity model, LSDV estimator, trade elasticities.

JEL classification: C13; C23; F10.

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1 Introduction

The gravity model is often used in international economics. It goes back to Tinbergen (1962) and Pöyhönen (1963), who suggest to use the Newtonian gravity concept to explain bilateral trade (attraction) by the national incomes of the trading countries (mass) and the distance between them (same in physics). This standard gravity model has later been augmented with many other explanatory variables, such as population size, dummies for trade bloc and currency union membership, and indicators for common cultural characteristics (De Grauwe and Skudelny, 2000; Glick and Rose, 2001; and many others). The main reason for the popularity of the gravity model is its success in empirical applications. In addition, several authors have also provided an economic theoretical backing of the model (Bergstrand, 1985; Deardorff, 1998).

Although early empirical studies used cross-section data to estimate gravity models (Aitken, 1973; Bergstrand, 1985), most researchers nowadays use panel data (Mátyás, 1997; De Grauwe and Skudelny, 2000; Wall, 2000; Glick and Rose, 2001). One reason is that the extra time series observations result in more accurate estimates. Moreover, in a cross-section analysis unobserved trade determinants that are country-pair specific and invariant over time are necessarily captured by the disturbance term. As these variables are likely correlated with observed regressors, the usual least squares estimator is inconsistent. In contrast, with panel data the effects of such unobserved determinants can be modelled by including country-pair specific constant terms, so that the source of inconsistency just mentioned is avoided. Mátyás (1997) and Wall (2000) stress the importance of including country-pair "individual" effects.

Existing gravity models based on panel data, however, ignore one potentially important aspect of trade, namely dynamics (as far as we know, the only exception is De Grauwe and Skudelny, 2000). For countries that traded a lot in the past, businesses have set up distribution and service networks in the partner country, which has lead to entrance and exit barriers due to sunk costs. In addition, consumers have grown accustomed to the partner country's products (habit formation). It is therefore very likely that current bilateral trade between those countries is also high (Eichengreen and Irwin, 1997). Hence, lagged trade affects current trade. Ignoring this may lead to incorrect inference.

Eichengreen and Irwin (1997) therefore add lagged trade as a regressor to their gravity model and show that lagged trade is indeed important. However, they use a cross-section model. This implies that the estimate for lagged trade represents not only dynamic effects, but also the impact of unobserved country-pair specific time invariant factors, as these factors are present in both current and lagged trade. It is thus not clear how important dynamics truly are.

The current paper brings the separate static panel and dynamic cross-section developments in the gravity literature together by using a panel data model with both country-pair effects and dynamics. The main goal is to demonstrate the need for a sufficiently rich dynamic structure in panel gravity models, both from an econometric and an economic point of view. The static panel gravity model is our benchmark model. We use a panel data set of $N = 221$ annual bilateral OECD trade flows over $T = 48$ years (1950-1997), which is abstracted from the Glick and Rose (2001) data set.

To model the dynamics we use an autoregressive distributed lag (ADL) model, which is commonly used in time series econometrics. One feature of ADL models is the inclusion of lagged dependent variables as regressors to model the relation between current and past trade. However, it is unlikely that this autoregressive structure completely describes the dynamics, because it is well-known that explanatory variables such as income affect trade with a lag (Goldstein and Kahn, 1985). ADL models allow for such distributed lag effects, as both contemporaneous and lagged income can be included as regressors. In addition to the ADL structure, we include time specific constants to allow for dynamics that are the same for all country-pairs, such as the world-wide economic situation. We thus use a dynamic panel model with both country-pair effects and time effects. We treat both effects as fixed instead of random, to allow for correlation with other explanatory variables.

Our dynamic panel structure generalizes the De Grauwe and Skudelny (2000) model in several respects. First, we allow for more than one lag of trade. Because De Grauwe and Skudelny find serial correlation in the residuals from their first-order autoregressive approach, our use of higher order lags is presumably worthwhile. The second generalization is our allowance for lagged income. Finally, we account for time effects. These generalizations make it possible to obtain a more detailed idea of the importance of trade dynamics.

The second contribution of the paper concerns the method of estimation for dynamic panel gravity models. In general, the estimation of dynamic models for panel data with fixed effects is not straightforward, see Baltagi (2001) for a recent overview. Least-squares methods for static models, such as the Least Squares Dummy Variables (LSDV) estimator, are inconsistent for dynamic panels when the number of time periods T is finite and the number of cross-section observations N goes to infinity. Since panel data used to estimate gravity models usually have a moderately large T and a large N, this inconsistency may be a problem in practice. Therefore, various authors have proposed GMM (Generalized Method of Moments) alternatives, which are consistent for finite T

and infinite N (see Arellano and Bond, 1991; Blundell and Bond, 1998). In dynamic panel data models the number of moment conditions available increases in T. To enhance asymptotic efficiency one should use all available moment conditions. However, it is well-known that this may increase the finite sample bias. Since one typically has substantial values of T in panel gravity studies, this bias may be problematic.

Because it is not a priori clear which estimator is preferable for our data and to obtain a robust answer to the question whether dynamics are important, we estimate our model by both LSDV and a particularly popular GMM estimator, namely the one of Arellano and Bond (1991). In addition, we perform a simulation study to analyze the accuracy of both estimators in our application to suggest which method is best suited for the estimation of dynamic panel gravity models.

The set up of the paper is as follows. In section 2 we describe our dynamic panel gravity model and discuss the two estimation methods (LSDV and GMM). Section 3 answers the question whether dynamics are important and examines the quality of both methods of estimation. Section 4 concludes.

2 Dynamic panel gravity model

This section shows how we use the ADL approach to allow for trade dynamics in panel gravity models. We then discuss how one can estimate the resulting dynamic panel model.

2.1 Model

The variable to be explained is $TRADE_{ijt}$, the logarithm of the real bilateral trade (sum of exports and imports) between countries i and j in year t; this definition is based on Glick and Rose (2001), as we will use their data in the empirical part of our paper. The core explanatory variables in gravity models are measures for the economic size of both countries and for the distance between the countries. These are often augmented by typical variables such as population size and dummies for common language, common border, free trade area and currency union membership, depending on the research question of interest. In this paper we include size, proxied by the logarithm of the product of the countries' real gross domestic products, denoted by GDP_{ijt}; this definition is again based on Glick and Rose (2001). In addition, since we have panel data, we can account for the effects of all possible time invariant determinants of trade by an "individual" effect η_{ij} for country-pair ij. This term thus encompasses the effects of typical time invariant regressors such as distance, common language and common border dummies. Likewise, we use a time effect λ_t to correct for the impact of all possible country-pair invariant trade determinants, such as the general economic situation in the world. The λ_t also correct for a potential trend in trade that is not explained by GDP.

In the standard, static panel gravity model one only finds the contemporaneous value of GDP_{ijt} to explain $TRADE_{ijt}$. As argued in the introduction, there are many economic arguments that suggest that also lagged income and lagged trade are relevant for current trade. To allow for such dynamic effects, we extend the static panel gravity model using an ADL model. For ease of exposition we restrict both ADL orders to two, because that will suffice in the empirical part of this paper. Hence, our model is

$$TRADE_{ijt} = \alpha + \sum_{p=1}^{2} \gamma_p TRADE_{ij,t-p} + \sum_{q=0}^{2} \beta_q GDP_{ij,t-q} + \eta_{ij} + \lambda_t + \varepsilon_{ijt}, \qquad (1)$$

where we assume a stable dynamic relationship between $TRADE$ and GDP, which implies $\gamma_1 + \gamma_2 < 1$. Since η_{ij} is obviously correlated with lagged trade and since λ_t contains elements such as the general state of the world economy that are correlated with current income, we treat η_{ij} and λ_t as fixed instead of random effects. The error term ε_{ijt} in (1) is a zero mean random variable uncorrelated over time, which may have arbitrary heteroskedasticity across country-pairs and time. We ignore any correlation of ε_{ijt} across country-pairs. This is the usual procedure in both the panel data and gravity model literature, and it would go beyond the purpose of this paper to correct also for spatial correlation. Note that ε_{ijt} is presumably correlated with GDP_{ijt}, because ε_{ijt} affects trade (export plus import) and the export from country i to j is part of GDP of country i and the import of i from j is part of GDP of j, so that ε_{ijt} affects GDP_{ijt}. Since the trade variable only concerns bilateral trade and is thus only a small part of the GDP variable, this endogeneity is usually ignored in the literature. We follow that approach and thus assume exogeneity for GDP_{ijt} (we will check the robustness of our results with respect to this assumption).

Model (1) allows for a range of dynamic effects. We distinguish a transitory, one-period external shock through ε_{ijt} and a permanent shock in income. A shock through ε_{ijt} not only affects contemporaneous trade, but also trade next year, by a factor γ_1. Two years later the impact is $\gamma_1^2 + \gamma_2$. Though there is no effect on the long-run level of trade, the cumulation of all contemporaneous and medium-run effects leads to a total impact of $(1 - \gamma_1 - \gamma_2)^{-1}$. Hence, $\gamma_1 + \gamma_2$ measures the persistence of shocks in trade.

A permanent income shock has a contemporaneous effect on trade of β_0. The effect on next period's trade (in addition to the impact β_0 caused by the increment of next period's income) is not only the direct effect β_1, but also the indirect effect through the lagged trade term, which yields a combined effect of $\beta_1 + \gamma_1\beta_0$. The income shock affects the long-run level of trade by the multiplier $\frac{\beta_0+\beta_1+\beta_2}{1-\gamma_1-\gamma_2}$.

One may be tempted to view these income effects as usual income elasticities, because trade and GDP are both specified in logarithms. However, one should be careful with that. One commonly defines income elasticities as, for instance, the elasticity of exports from country i to j with respect to income of the country of demand j; in formula $\frac{\partial X_{ij}}{\partial GDP_j}$, where X_{ij} is log real exports and GDP_j is log real income (time indices are suppressed for simplicity). The income effect in our model is $\frac{\partial TRADE_{ij}}{\partial GDP_{ij}}$, where $TRADE_{ij}$ and GDP_{ij} are based on the definitions of our data source (Glick and Rose (2001)), as given at the beginning of this subsection. Expressing $TRADE_{ij}$ and GDP_{ij} in variables such as X_{ij} and GDP_j yields $TRADE_{ij} = \log(\exp(X_{ij}) + \exp(X_{ji}))$ and $GDP_{ij} = GDP_i + GDP_j$. Hence, our income effect is not the usual income elasticity.

Despite these differences, there is a simple relation $\frac{\partial TRADE_{ij}}{\partial GDP_{ij}} = \frac{1}{2}\left(\frac{\partial X_{ij}}{\partial GDP_i} + \frac{\partial X_{ij}}{\partial GDP_j}\right)$, where $\frac{\partial X_{ij}}{\partial GDP_i}$ is the elasticity of exports with respect to income of the country of supply.[1] The latter elasticity can be zero, as assumed in the often-used imperfect substitutes model (Goldstein and Kahn, 1985); it can also be positive, and then it is very likely bounded by the elasticity with respect to income of the country of demand $\frac{\partial X_{ij}}{\partial GDP_j}$. Hence, $\frac{\partial TRADE_{ij}}{\partial GDP_{ij}} \leq \frac{\partial X_{ij}}{\partial GDP_j} \leq 2\frac{\partial TRADE_{ij}}{\partial GDP_{ij}}$. The income elasticity in the usual meaning is thus bounded by once and twice our income effect. We cannot model the income elasticity itself, because we have no data on exports and imports separately as we only have data on their sum. To avoid any possibility of confusion, we will maintain the separation between the terms "income effect" and "income elasticity" throughout the paper.

2.2 Estimation

Static panel gravity models, such as model (1) under the restriction $\gamma_1 = \gamma_2 = \beta_1 = \beta_2 = 0$, are usually estimated by the LSDV estimator, also called fixed effect or within estimator. LSDV consists of removing the country-pair effects η_{ij} by taking deviations from country-pair means, which is called the within transformation, and then applying least squares on the centered variables. If trade is a static process, so that the static model is correct, the LSDV estimator is consistent for a finite time dimension T and

[1] One can derive $\frac{\partial TRADE_{ij}}{\partial GDP_{ij}} = \frac{1}{2}\left(\frac{\partial X_{ij}}{\partial GDP_i} + \frac{\partial X_{ij}}{\partial GDP_j}\right)$ as follows. Define $u_{ij} = GDP_i + GDP_j$ and $v_{ij} = GDP_i - GDP_j$. Then $\frac{\partial TRADE_{ij}}{\partial GDP_{ij}} = \frac{\partial \log(\exp(X_{ij})+\exp(X_{ji}))}{\partial u_{ij}} = \frac{1}{\exp\left(X_{ij}\right)+\exp\left(X_{ji}\right)} * \left[\exp\left(X_{ij}\right)\left(\frac{\partial X_{ij}}{\partial GDP_i}\frac{\partial GDP_i}{\partial u_{ij}} + \frac{\partial X_{ij}}{\partial GDP_j}\frac{\partial GDP_j}{\partial u_{ij}}\right) + \exp\left(X_{ji}\right)\left(\frac{\partial X_{ji}}{\partial GDP_i}\frac{\partial GDP_i}{\partial u_{ij}} + \frac{\partial X_{ji}}{\partial GDP_j}\frac{\partial GDP_j}{\partial u_{ij}}\right)\right]$. Using $GDP_i = \frac{u_{ij}+v_{ij}}{2}$, $GDP_j = \frac{u_{ij}-v_{ij}}{2}$ and the homogeneity assumption implicit in (1), so that $\frac{\partial X_{ij}}{\partial GDP_i} = \frac{\partial X_{ji}}{\partial GDP_j}$ and $\frac{\partial X_{ij}}{\partial GDP_j} = \frac{\partial X_{ji}}{\partial GDP_i}$, yields the result.

an infinite number of country-pairs N, the asymptotics we consider throughout this paper.[2]

If trade is a dynamic process and one uses a dynamic panel model such as (1), estimation is potentially more difficult. The basic reason is that the transformation needed to wipe out the country-pair fixed effects (within or first difference operator) leads to correlation between the transformed lagged dependent variable regressors and the transformed error term. For a finite T and an infinite N this correlation renders least squares methods on the transformed model biased and inconsistent. The correlation, however, vanishes as T gets large. Given the fairly large T for our data set, the bias and inconsistency of the LSDV estimator may thus be limited. This is an empirical issue, which is further addressed in subsection 3.3.

To bypass the inconsistency of LSDV, numerous alternative estimators have been proposed, see for example Baltagi (2001) for a broad overview. A class of estimators, which is nowadays popular by practitioners, is GMM. The particular GMM estimator we use here is due to Arellano and Bond (1991). For this estimator, the model is transformed into first differences instead of deviations from country-pair means to remove the country-pair effects η_{ij}. This gives correlation between the transformed regressor $TRADE_{ij,t-1} - TRADE_{ij,t-2}$ and the transformed disturbance term $\varepsilon_{ijt} - \varepsilon_{ij,t-1}$. This correlation does not vanish when T gets large. However, valid instruments can be constructed from at least two-periods-lagged levels of the dependent variable. The Arellano-Bond estimator uses these instruments to define the moment conditions. The resulting GMM estimator is consistent for finite T and $N \to \infty$. Note that in dynamic panel data models the number of valid moment conditions increases with the number of time periods T and that for asymptotic efficiency reasons one should use all available moment conditions. However, it is well-known that finite sample bias of GMM estimators increases as the number of moment conditions gets larger, in other words, as T gets larger. Because our data set has a fairly large T, finite sample bias may be substantial. Hence, in the empirical section we will not use all available moment conditions, but only those based on ten lagged values of the dependent variable, that is, lags two through eleven.

[2] As we consider fixed T, large N asymptotics, the number of time specific effects λ_t is finite, so that their inclusion poses no further complications for estimation. One might argue, however, that for our empirical application, where $T = 48$ and $N = 221$, asymptotic results for large T and large N are also worthwhile. In that case, the discussion of the relative merits of the various estimators below is tentative only. However, a complete theory on large T, large N asymptotics for the dynamic panel data model with both country-pair and time specific effects has not yet been developed, and its derivation would go beyond the scope of this paper.

3 Empirical results

In this section we first briefly describe the data. Second, to examine the importance of dynamics in trade equations, we present estimation results for model (1) using both LSDV and GMM estimators. Finally, we analyze the accuracy of both estimators by simulation to assess which estimator is preferable in our application.

3.1 Data

The data set we use is a subset from the data of Glick and Rose (2001), which is available from their website (http://haas.berkeley.edu/~arose). The Glick and Rose data set contains annual data over 1948-1997 on bilateral trade flows between 217 countries. We have selected the sample of the 24 OECD countries that have been member of the OECD for more than a decade. Furthermore, the years 1948 and 1949 have been excluded, as there are many missing observations for these years. Finally, we have balanced the panel by discarding all country-pairs with missing observations for the years 1950-1997.[3] As a result, we are left with $T = 48$ years for each of the $N = 221$ pairs of trading partners. For more details on the data we refer to Glick and Rose (2001).

3.2 Are dynamics important in panel gravity models?

The benchmark model in this paper is the static panel gravity model with both country-pair and time specific effects, which has been used in many other studies (Mátyás, 1997; Wall, 2000). This model is a special case of (1), because it restricts $\gamma_1 = \gamma_2 = \beta_1 = \beta_2 = 0$. As usual, we estimate it by LSDV. We compute all estimates with the DPD package of Ox (Doornik, Arellano and Bond, 2001). The estimation results are in Table 1. It shows that, as expected, the estimate for the income effect (β_0) is positive. The standard error suggests that the effect is strongly significant.

As a first insight into the importance of dynamics, we test for first-order autocorrelation in the residuals of the static model. We use a Lagrange Multiplier (LM) test based on the LSDV residuals, which is asymptotically χ^2_1-distributed (Baltagi, 2001). The value of the LM statistic is 21230.63, so that there is very strong evidence of autocorrelation. Hence, the static panel gravity model is misspecified and leads to incorrect inference, for instance because the estimated contemporaneous income effect is biased

[3]For 45 of the 276 (24*23/2) possible country-pairs the original data set contains no observations. In addition, there are incomplete time series for 10 country-pairs.

Table 1: Estimation results for model (1)

		STATIC MODEL	DYNAMIC MODEL	
		LSDV	LSDV	GMM
$TRADE_{ij,t-1}$	γ_1		0.74 (0.01)	0.57 (0.02)
$TRADE_{ij,t-2}$	γ_2		0.13 (0.01)	0.06 (0.02)
GDP_{ijt}	β_0	0.92 (0.01)	0.80 (0.05)	0.82 (0.11)
$GDP_{ij,t-1}$	β_1		−0.44 (0.07)	−0.33 (0.10)
$GDP_{ij,t-2}$	β_2		−0.24 (0.05)	−0.06 (0.08)
Long-run income effect	$\frac{\beta_0+\beta_1+\beta_2}{1-\gamma_1-\gamma_2}$	0.92 (0.01)	1.02 (0.06)	1.21 (0.24)
R^2		0.83	0.96	–
Residual autocorr. test		21230.63 [0.00]	0.01 [0.91]	−1.40 [0.16]

Standard errors in parentheses and p-values in square brackets. The standard error for the long-run income effect is computed by the delta-method. All standard errors and p-values are robust for heteroskedasticity, both across individuals and over time. The R^2 is unknown for GMM. The residual autocorrelation test for LSDV is the first-order autocorrelation LM test from Baltagi (2001). For GMM it is the second-order autocorrelation test of Arellano and Bond (1991); see footnote 6 for details.

and because the standard errors are invalid.[4]

One potential source of residual autocorrelation is underspecification of the dynamics. As argued in the introduction, there are good economic reasons to allow for trade dynamics. Therefore, we now leave the dynamics parameters γ_1, γ_2, β_1 and β_2 in (1) unrestricted and thus turn to a dynamic panel gravity model. We estimate the model both by LSDV and GMM to verify the robustness of our conclusions.[5]

The last two columns of Table 1 show the estimation results for the dynamic specification. Now the residuals do not exhibit significant autocorrelation for both estimation

[4] Several authors, for instance Doel and Kiviet (1994), have analyzed the consequences of estimating a static panel data model by LSDV when the true model is in fact dynamic. Some results point out that the estimates may be interpreted as long-run effects. However, the models analyzed are very specific, so that it is difficult to draw general conclusions.

[5] We have further checked the robustness by estimating the model without the exogeneity assumption for income, that is, by GMM with an alternative set of moment conditions that remains valid if income is endogenous. Because the estimation results do not change notably, we conclude that endogeneity of income is not a major issue in this application and continue as if income is exogenous.

methods.[6] Moreover, longer lags of dependent and explanatory variables yield insignificant estimates (not reported). Hence, second-order dynamics seems adequate.[7] We also see that the estimates of the dynamics parameters are substantial and almost all clearly significant, for both estimation methods. The dynamics also raise R^2 substantially. We conclude that including dynamics is important to obtain a proper gravity model specification from an econometric point of view.[8] This is in line with the strong economic arguments for the relevance of dynamics in trade relations.

Concerning the economic characteristics of trade flows, we see that the coefficient of the first lagged dependent variable (γ_1) is large and highly significant for both LSDV and GMM. Also the second-order term (with coefficient γ_2) is significant, although of moderate magnitude. The sum of γ_1 and γ_2 equals 0.87 for LSDV and 0.63 for GMM. This implies a half-life of one-time exogenous shocks of five years and one and a half years, respectively. Though there are considerable differences between the two estimators regarding the precise dynamic effects, it is clear that shocks are persistent in trade flows.

The estimated contemporaneous income effect is around 0.80 for both estimators. Income also has a dynamic impact on trade. This not only goes through the lagged trade terms, but also directly. The effect of a permanent income shock on next year's trade in addition to the impact β_0 caused by the increment of next period's income, $(\beta_1+\gamma_1\beta_0)$, is estimated at around 0.15 for both estimators. This is much lower than the contemporaneous impact. Moreover, after two years the effect is virtually zero. Hence, income affects trade rather quickly. This result is in line with the common opinion on trade dynamics (Goldstein and Khan, 1985). The estimated long-run income effect on the level of trade, $\frac{\beta_0+\beta_1+\beta_2}{1-\gamma_1-\gamma_2}$, is 1.02 for LSDV and 1.21 for GMM.

As explained at the end of subsection 2.1, the income effects should not be viewed as income elasticities in the usual meaning of for instance $\frac{\partial X_{ij}}{\partial GDP_j}$, the elasticity of exports

[6] The test used for GMM is based on Arellano and Bond (1991). It differs from the test used for LSDV, because under the null of no serial correlation in ε_{ijt}, there is first-order serial correlation in the first differenced residuals by construction. However, the null implies that higher-order autocorrelation is absent. The test therefore checks for second-order autocorrelation in the first differenced residuals. It is asymptotically standard normally distributed under the null.

[7] We have also estimated a first-order dynamic model in the spirit of De Grauwe and Skudelny (2000), that is, with γ_1 unrestricted but $\gamma_2 = \beta_1 = \beta_2 = 0$. The LM test is 150.04 indicating significant residual autocorrelation. Hence, higher-order dynamic terms are relevant in this application.

[8] Another possible source of the residual autocorrelation in static models is neglected heterogeneity, that is, heterogeneous slope coefficients across country-pairs. Hence, estimating a dynamic model such as (1) with homogeneous slope coefficients may lead to spurious dynamics. To examine this, we have estimated model (1) for all 221 country-pairs separately, thus allowing for unrestricted heterogeneity. We find that all country-pair models contain significant dynamics. Hence, even after accounting for heterogeneity we find strong evidence of dynamics.

from country i to j with respect to income of the country of demand j. Instead, we have suggested a bound for the elasticities in terms of our income effects: $\frac{\partial TRADE_{ij}}{\partial GDP_{ij}} \leq \frac{\partial X_{ij}}{\partial GDP_j} \leq 2\frac{\partial TRADE_{ij}}{\partial GDP_{ij}}$. For the long-run income elasticity the estimation results thus imply an interval from 1.02 to 2.04 for LSDV and from 1.21 to 2.42 for GMM. This corroborates the common idea that income elasticities for industrial countries fall in the range of one to two (Goldstein and Kahn, 1985).

In summary, including dynamics in panel gravity models is not only important from an econometric point of view, but also yields estimation results that are reasonable in an economic sense.

3.3 Accuracy of the LSDV versus the GMM estimator

Although our conclusion concerning the importance of including dynamics is robust regarding the use of LSDV or GMM, there are some differences in the exact magnitude of the dynamics between the two estimation methods. These differences may originate from either the inconsistency of LSDV for finite T, or the finite sample bias of GMM, or both (see also subsection 2.2). In this section we investigate by simulation which method yields the most accurate estimates for our data.

The finite sample properties of both estimators have already been analyzed by extensive simulation studies (Arellano and Bond, 1991; Kiviet, 1995; Blundell and Bond, 1998). The results from these Monte Carlo experiments show that for the LSDV and GMM estimators the quality of the asymptotic approximations in finite samples depends heavily on the actual parameter values of the model and on the dimensions of the available data set.

In most of the simulation studies short time series and reasonably large cross-section samples have been examined. The performance of LSDV and GMM when both dimensions are moderate or large is much less understood. Judson and Owen (1999) provide some evidence that also in these types of samples LSDV and GMM estimators can exhibit sizeable biases.

To evaluate the accuracy of the estimators for our application, we perform a Monte Carlo experiment using artificial data for $TRADE_{ijt}$ generated from the empirical model of the previous section. More precisely, we use (1) with the LSDV estimates of $\alpha, \gamma_1, \gamma_2, \beta_1, \beta_2, \beta_3, \eta_{ij}$ and λ_t as true parameters (using the GMM estimates does not affect the conclusions). We take the data on GDP as given, use the observed actual values of $TRADE$ for 1950 and 1951 as initial observations and draw independent homoskedastic disturbances ε_{ijt} from the normal distribution with mean zero and a variance equal to the sample variance of the LSDV residuals. This gives simulated data

Table 2: Simulation results

		TRUE	STATIC MODEL LSDV	DYNAMIC MODEL LSDV	DYNAMIC MODEL GMM
$TRADE_{ij,t-1}$	γ_1	0.74		0.71	0.60
				(0.01)	(0.04)
$TRADE_{ij,t-2}$	γ_2	0.13		0.12	0.16
				(0.01)	(0.04)
GDP_{ijt}	β_0	0.80	0.91	0.79	0.82
			(0.01)	(0.05)	(0.06)
$GDP_{ij,t-1}$	β_1	−0.44		−0.41	−0.33
				(0.07)	(0.08)
$GDP_{ij,t-2}$	β_2	−0.24		−0.22	−0.22
				(0.05)	(0.06)
Long-run income effect	$\frac{\beta_0+\beta_1+\beta_2}{1-\gamma_1-\gamma_2}$	1.02	0.91	0.98	1.13
			(0.01)	(0.04)	(0.16)

Mean and standard deviation (in parentheses) over 500 replications. The true and estimated model is (1).

on $TRADE_{ijt}$. We then estimate model (1) by LSDV and GMM and, for completeness, we also estimate the static model used above by LSDV. We replicate this procedure 500 times.

Table 2 shows the mean and standard deviation of the LSDV and GMM coefficient estimators over the 500 replications. We first conclude that estimating a static panel gravity model for a dynamic data generating process yields a biased estimate in the sense that the long-run income effect is underestimated.

The second result is that LSDV reproduces the true parameters quite well, even though some bias is visible, such as 0.03 for γ_1, which is in accordance with the theoretical inconsistency of LSDV in dynamic panel models with finite T. Apparently, the inconsistency of LSDV is small in our study.

At first sight, this conclusion differs from the Judson and Owen (1999) results, as they still find sizeable finite sample bias. However, they investigate data sets with $T \leq 30$, whereas for our data the number of time periods is substantially larger, namely $T = 48$. It is well-known that the bias decreases as T gets larger. For instance, for the autoregressive parameter in their first-order ADL model, Judson and Owen report a decline in the bias from about 70% of the true parameter value to 8.5% as T goes from 5 to 30. Hence, the small biases we find, for instance 4.1% for the corresponding parameter γ_1 in our ADL model, seem in line with the Judson and Owen results after all.

The final result from Table 2 is that the finite sample bias of the GMM estimator is relatively large, particularly regarding the first lagged trade coefficient γ_1. Moreover, the dispersion in the GMM estimates is larger than for LSDV. Both characteristics show that LSDV is here superior to GMM, asserting the conclusion of Judson and Owen (1999) that for moderate or large T the LSDV estimator is recommended. Hence, regarding the estimation results discussed in the previous subsection we prefer the LSDV estimates to indicate the magnitude of the trade dynamics.

4 Conclusion

The panel gravity model for trade has often been estimated without taking account of the effects of past trade and income on current trade flows. However, there are numerous economic reasons for the fact that trade is a dynamic process. Using yearly data on 221 bilateral trade flows between OECD countries from 1950 through 1997, we indeed find that the residuals from a static model exhibit strong patterns of autocorrelation.

In this study we have therefore extended the standard static gravity model with dynamics, both by including lagged trade and lagged income terms. Both types of dynamics are strongly significant. Hence, our first conclusion is that trade is a dynamic process and that panel gravity models should allow for that, by including both lagged trade and lagged income terms.

The second contribution of this paper concerns the method to estimate dynamic panel gravity models. We have examined two estimation methods, namely LSDV and the GMM estimator due to Arellano and Bond (1991). A simulation experiment shows that for this application the LSDV technique is accurate and outperforms GMM. This is important from a practical point of view, because it allows one to employ the same simple LSDV estimator used in static panel gravity models.

Concerning the magnitude of the trade dynamics, we conclude that transitory shocks to trade persist for a long time, with an estimated persistence parameter (sum of autoregressive parameters) of 0.87. This implies a half-life of five years. Income shocks also have a dynamic impact, but their effect on trade is rather quickly; the contemporaneous effect of a permanent shock is estimated at 0.80, while the additional effect after one year is 0.15 only. The long-run income effect on the level of trade is 1.02, which corresponds to income elasticities of trade between 1.02 and 2.04. Such point estimates are reasonable from an economic point of view.

We expect that our conclusions will be relevant for future research on trade using the gravity model. First, dynamic terms will be important for many other data sets, because trade is inherently dynamic. Moreover, many trade panels have substantial cross-section and time series dimensions, so that we expect LSDV to be an accurate estimation method for those data as well.

Though the transition from a static to a dynamic panel gravity model is important, the dynamic model we have used is, of course, not perfect. For instance, it can presumably be improved by allowing for richer heterogeneity and for correlation between country-pairs. Such issues are left for future research.

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