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Gravity Models of the Intra-EU Trade: Application of the Hausman-Taylor Estimation in Heterogeneous Panels with Common Time-specific Factors*

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Abstract

In this paper we follow recent developments of panel data studies and explicitly allow for the existence of unobserved common time-specific factors where their individual responses are also allowed to be heterogeneous across cross section units. In the context of this extended panel data framework we generalize the Hausman-Taylor estimation methodology and develop the associated econometric theory. We apply our proposed estimation technique along with the conventional panel data approaches to a comprehensive analysis of the gravity equation of bilateral trade flows amongst the 15 European countries over 1960-2001. Empirical results clearly demonstrate that our proposed approach fits the data reasonably well and provides much more sensible results than the conventional approach based on the fixed time dummies. These findings may highlight the importance of allowing for a certain degree of cross section dependence through unobserved heterogeneous time specific common effects, otherwise the resulting estimates would be severely biased.

JEL Classification: C33, F14.

Key Words: Gravity Models of Trade, Heterogeneous Panel Data, Hausman-Taylor Estimation, Time-specific Common Factors, Intra-EU Trade.

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1 Introduction

The gravity model of international trade flows has been widely used as a baseline model for estimating the impact of a variety of policy issues related to regional trading groups, currency unions and various trade distortions, *e.g.* Bougheas, Demetriades and Morgenroth (1999), De Grauwe and Skudelny (2000), Glink and Rose (2002), Martinez-Zaroso and Nowak-Lehmann (2003) and De Sousa and Disdier (2002). Since the seminal paper by Anderson (1979), some attempts have also been made explicitly to derive the prediction of the gravity model from different theoretical models such as Ricardian models, Heckscher-Olin models and Increasing Returns to Scale models, *e.g.* Bergstrand (1990), Markusen and Wigle (1990) and Leamer (1992). As argued by Davis (2000), it is nowadays remarkable to observe that in the space of a little more than a decade the gravity model has gone from theoretical orphan to having several competing claims to maternity.

Recently, it is criticised that the use of conventional cross-section estimation is misspecified since it is not able to deal with bilateral (exporter and/or importer) heterogeneity, which is extremely likely to be present in bilateral trade flows. In this regard a panel-based approach will be desired because heterogeneity issues can be modelled by including country-pair "individual" effects. In particular, Matyas (1997) argues that the correct econometric specification should be the so-called "triple-way model", where time, exporter and importer effects are specified as fixed and unobservable. But, Egger and Pfaffermayr (2002) demonstrate that when the Matays' triple-way model is extended to include bilateral trade interaction effects, then this three-way specification reduces to a conventional two-way model with time and bilateral effects only. Although a number of panel estimation techniques such as the pooled OLS, the Fixed Effects Model, the Random Effects Model have been applied in various contexts, the assumption that unobserved individual effects are uncorrelated with all the regressors is convincingly rejected in almost all studies. Therefore, the Fixed Effects estimation has been the most preferred estimation method in order to avoid the potentially biased estimation, *e.g.* Cheng and Wall (2002).

However, it is worth noting that the Fixed Effects approach does not allow for estimating coefficients on time invariant variables such as distance or common language dummies, though the consistent estimation of such effects are equally important in many situations. Cheng and Wall (2002) simply suggest to estimate the regression of the (estimated) individual effects on individual-specific variables by the OLS, though this approach clearly ignores the potential correlation between individual specific variables and (unobserved) individual effects such that the resulting estimates are likely to be severely biased. In order to properly address this issue we need to employ the Hausman and Taylor (1981, hereafter HT) instrumental variable estimation technique, see for example Brun, Carrere, Guillaumont and de Melo (2002) for the HT estimation of gravity models of international trade. Most recent empirical studies also emphasise the importance of explicitly allowing for the presence of time specific effects in order to capture business cycle effects or to deal with globalization issues. The conventional approach extends the benchmark model simply by incorporating the fixed $T-1$ time dummies in the panel regression, *e.g.* Matyas (1997), De Sousa and Disdier (2002) and Egger (2002).

In this paper we follow recent developments of panel data studies surrounding the use of unobserved common time effects, *e.g.* Ahn, Lee and Schmidt (2001), Bai and Ng (2002), Pesaran (2002) and Phillips and Sul (2002), and advance an alternative estimation framework in which we explicitly allow for the existence of observed and/or unobserved common time-specific factors and also allow the individual responses to those common factors to be heterogeneous across country pairs. This approach has an additional advantage in accommodating certain degrees of cross section dependence through heterogeneous time-specific factors, in which case we may avoid the potential bias of the uncorrected estimates. In particular, we aim to generalize the HT estimation in this extended panel data setup, develop the underlying econometric theory but also propose an alternative source of instruments in addition to the (internal) instruments suggested by HT; namely, some of (consistently estimated) heterogeneous time-specific factors under the assumption that they are correlated with individual specific variables but not with unobserved individual effects.

We apply our proposed HT estimation technique along with the conventional panel data approaches to a comprehensive analysis of the sources of bilateral trade amongst the 15 European countries over 1960-2001. We use both the triple and the double indexed versions of the gravity equation, where we consider as the dependent variable the logarithm of real export in the former and the logarithm of total trade in the latter. *First*, we use the basic specification and consider the impacts of core explanatory variables such as GDP and population, and the distance. We *then* augment the basic specification by adding various variables such as common language, common border, free trade area and currency union membership dummies. *Finally*, we follow recent theoretical developments [*e.g.* Helpman (1987) and Egger (2002)] and include variables measuring both similarity in relative size of trading countries and differences in relative factor endowments.

Our main empirical findings are summarised below. *First*, the impact of the GDP variables is always significantly positive, whereas the impact of population variables is found to be mostly insignificant. *Second*, the impacts of free custom union membership are all positively significant, whilst the results are mixed for the impacts of EMU. *Third*, the impact of similarity in relative size of trading countries are mostly significant and positive, while the impact of differences in relative factor endowments (RLF) are somewhat ambiguous. Turning to the estimation results for individual specific variables, the impacts of distance, common language dummy and common border dummy are mostly significantly negative, positive and positive, respectively, as expected. A notable finding is that once the correlation between the common language dummy and unobserved individual effect is accommodated by the HT estimation, there is evidence that the effects of the variables that may proxy for geographical distance, *i.e.* distance and common border dummy, might be compensated each other, whereas the role of cultural affinities proxied by common language dummy becomes more significant. On the other hand, when using the conventional approach using the $T-1$ fixed time dummies, the HT estimates of the impact of distance are surprisingly positive but insignificant, the impacts of common language dummy are significant but seem to be too large, and common border dummy loses its statistical significance. This observation may reflect the practical importance of properly incorporating the time-specific effects.

Furthermore, we find that our proposed HT estimation results produce more sensible predictions on the impacts of differences in factor endowments and of the common currency dummy on intra-EU trade flows than the conventional approach; namely the impacts of both

EMU and *RLF* are found to be convincilngly insignificant only in the extended HT model. *First*, considering that the total trade flows are the sum of inter- and intra-industry trades, and *RLF* is positively correlated only with the intra-industry trade, we may argue that the impact of *RLF* on total trade flows would not be unambiguous. *Secondly*, empirical evidence on the impact of *EMU* on trade flows has been at most mixed in the literature, see Rose (2002) and Glink and Rose (2002) for a rather large positive effect of currency union on trade, and Persson (2001), Pakko and Wall (2002) and De Nardis and Vicarelli (2003) for its negative or insignificant effects on trade. In particular, as argued by de Souza (2002), the (evaluation) periods are too short after an introduction of the Euro to use the *EMU* dummy as an adequate proxy for monetary union membership and therefore, we also expect that the impacts of *EMU* are yet to be significantly materialised. This observation may indicate the importance of properly accommodating a certain degree of cross section dependence through unobserved heterogeneous time effects, otherwise the resulting estimates would be severely biased.

The plan of the paper is as follows: Section 2 presents an overview on gravity models of international trade flows. Section 3 develops the extended HT estimation methodology for heterogeneous panels with both observed and unobserved common factors. Section 4 presents a comprehensive empirical application to the gravity model of an intra-EU trade. Section 5 concludes with further discussions.

2 Overview on Gravity Models of International Trade

Since early 1940s, the gravity model has been applied to a wide variety of goods and factors of production moving across regional and national boundaries under differing circumstances. For example, the model has been successfully applied to explain the determinants of varying types of flows, such as migration, flows of buyers to shopping centers, recreational traffic or commuting flows and patient flows to hospitals. In the context of international trade flows, the gravity model states that the size of trade flows between two countries is determined by supply conditions at the origin, demand conditions at the destination and stimulating or restraining forces related to the trade flows between the two countries. Empirically, the gravity model has been well suited for trade policy analysis and thus it has been widely used as a baseline for estimating the impact of a variety of policy issues regarding regional trading groups, currency unions and various trade distortions, *e.g.* Bougheas *et al.* (1999), De Grauwe and Skudelny (2000), Glink and Rose (2002) and De Sousa and Disdier (2002). Core explanatory variables used to explain the volume of trade across a pair of countries are measures of economic size of trading partners and of the distance between them. Moreover, empirical works to date are often augmented by various variables such as common language, common border, free trade area and currency union membership dummies.

Despite its widespread empirical use, the gravity model was earlier criticized because it lacked theoretical foundations. Nowadays, it is certainly no longer true that the gravity model is without a theoretical basis. Since the seminal paper by Anderson (1979) it has been increasingly recognized that the prediction of the gravity model can be derived from different structural models such as Ricardian models, Heckscher-Olin (H-O) models and increasing returns to scale (IRS) models of the New Trade Theory. These three types of models differ by the way product specialization is obtained in equilibrium: technology differences across countries in Ricardian model, factor proportion differences in the H-O model, and increasing returns at the firm level in the IRS model, see Helpman (1987), Bergstrand (1990), Markusen and Wigle (1990), Leamer (1992) and Eaton and Kortum (2002).

Although the gravity model per se cannot be used to test the validity any of these trade theories against each other, its empirical success is mainly due to its ability to incorporate most of empirical phenomena observed in international trade. In order to reconcile theory and empirical evidence, Evenett and Keller (2002) address the so called 'model identification' issue and try to determine which models generate gravity-like trade predictions. The H-O model predicts that the trade will be exclusively inter-industry (defined as trade in goods with different factor intensities), whereas the IRS model anticipates that trade is intra-industry. Using a cross-sectional study on a sample of almost all industrialized countries Evenett and Keller find a robust evidence that an IRS-based trade theory provides an important reason why the gravity equation fits trade flows well. This implies that volume of international trade among industrialized countries is likely to be determined mainly by the extent of product specialization and factor proportions differences, though it is also acknowledged that these findings do not rule out the possibility that Ricardian technology differences might be what is really behind intra-industry trade. See also Deardorff (1998). As highlighted by Davis (2000), it is remarkable to observe that in the space of a little more than a decade the gravity model has gone from a theoretical orphan to having several competing claims to maternity.

We now turn to the issue of econometric specifications in details. Most of earlier empirical studies relied upon the use of cross-section estimation techniques. We begin with the following typical gravity equation of the international trade:

$$y_{hft} = \alpha_0 + \theta_t + \boldsymbol{\beta}'_{1t}\mathbf{x}_{hft} + \boldsymbol{\beta}'_{2t}\mathbf{x}_{ht} + \boldsymbol{\beta}'_{3t}\mathbf{x}_{ft} + \boldsymbol{\beta}'_{4t}\mathbf{z}_{hf} + u_{hft}, \tag{2.1}$$

for $h = 1, ..., N$, $f = 1, ..., N$, $h \neq f$, $t = 1, ..., T$, where y_{hft} is the dependent variable (say, the volume of trade from home country h to target country f at time t), $\mathbf{x}_{hft}$ are explanatory variables with variation in all the three dimensions (say, exchange rates between local currencies), $\mathbf{x}_{ht}$, $\mathbf{x}_{ft}$ are explanatory variables with variation in h or f and t (say, GDP or population), $\mathbf{z}_{hf}$ are explanatory variables that do not vary over time but vary in h and f (say, distance), and the disturbance terms u_{hft} are assumed to be *iid* with zero mean and constant variance across all h, f, t. Then, (2.1) is estimated by the cross-section OLS for each year, where α_0 and θ_t cannot be separately identified. However, it is well-known that this cross-section OLS estimation will ignore any of heterogeneous characteristics related to bilateral trade relationship. For instance, a country would export different amounts of the same product to the two different countries, even if their GDPs are identical and they are equidistant from the exporter. Since the cross-section OLS estimates clearly fail to account for these heterogeneous factors, they are likely to suffer from substantial heterogeneity bias.

A panel-based approach will be more desirable in order to deal with heterogeneity issues because the effects of such determinants can be modelled by including country-pair "individual" effects. Imposing $\boldsymbol{\beta}_{jt} = \boldsymbol{\beta}$ for all t and $j = 1, ...4$, and $\theta_t = 0$ in (2.1), we obtain the following pooled panel data model:

$$y_{hft} = \alpha_0 + \boldsymbol{\beta}'_1\mathbf{x}_{hft} + \boldsymbol{\beta}'_2\mathbf{x}_{ht} + \boldsymbol{\beta}'_3\mathbf{x}_{ft} + \boldsymbol{\beta}'_4\mathbf{z}_{hf} + u_{hft}. \tag{2.2}$$

The pooled OLS estimator obtained from (2.2) does not still deal with the issue of heterogeneity bias.

Matyas (1997) claims that the gravity model based on the pooled specification (2.2) is misspecified, and proposes that the proper econometric specification of the gravity model should be a three-way model:

$$y_{hft} = \alpha_0 + \alpha_h + \gamma_f + \theta_t + \boldsymbol{\beta}_1'\mathbf{x}_{hft} + \boldsymbol{\beta}_2'\mathbf{x}_{ht} + \boldsymbol{\beta}_3'\mathbf{x}_{ft} + \boldsymbol{\beta}_4'\mathbf{z}_{hf} + u_{hft}. \tag{2.3}$$

where one dimension is time-specific effect (θ_t), and the other two are time invariant export and import country-specific effects (α_h and γ_f), and it is assumed that these effects are unobservable and thus specified as fixed effects. Clearly, the unduly strict restrictions $\alpha_h = \gamma_f = \theta_t = 0$ for all h, f, and t are imposed in (2.2). Estimating both models (2.2) and (2.3), he finds a statistically significant evidence against restrictions, $\alpha_h = \gamma_f = \theta_t = 0$.

Egger and Pfaffermayr (2002) demonstrates that when the Matays' model (2.3) is extended to include bilateral trade interaction effects such as

$$y_{hft} = \alpha_0 + \alpha_h + \gamma_f + \theta_t + \alpha_{hf} + \boldsymbol{\beta}_1'\mathbf{x}_{hft} + \boldsymbol{\beta}_2'\mathbf{x}_{ht} + \boldsymbol{\beta}_3'\mathbf{x}_{ft} + \boldsymbol{\beta}_4'\mathbf{z}_{hf} + u_{hft}, \tag{2.4}$$

then this generalized three way specification is in fact identical to a two way model with time and bilateral effects only. This implies that the Matyas' model (2.3) is also likely to be mis-specified, since it does not span the whole vector space of possible treatments of explaining variations in bilateral trade and ignoring such bilateral trade interactions may lead to biased estimation. In general, the bilateral effect accounts for any time invariant historical, geographical, political, cultural and other bilateral influences which will lead to deviations from country pair's 'normal' propensity to trade. Since most of these influence usually remain unobserved, including bilateral interaction effects is the natural way of controlling them.

Cheng and Wall (2002) also focus on the issue of heterogeneity bias and propose the following fixed effects model (FEM):

$$y_{hft} = \alpha_0 + \alpha_{hf} + \theta_t + \boldsymbol{\beta}_1'\mathbf{x}_{hft} + \boldsymbol{\beta}_2'\mathbf{x}_{ht} + \boldsymbol{\beta}_3'\mathbf{x}_{ft} + \boldsymbol{\beta}_4'\mathbf{z}_{hf} + u_{hft}. \tag{2.5}$$

It is argued that the fixed effects are a result of ignorance because we do not know which variables are responsible for heterogeneity bias in practice. Indeed, those cultural, historical and political factors are difficult to observe and measure. Thus, they suggest to allow each pair of countries to have its own dummy variable that may be correlated with both the bilateral trade and explanatory variables. The main feature that distinguishes it from Matyas' model is the inclusion of country-pair effects which are allowed to differ accordingly with the direction of trade, *i.e.* $\alpha_{hf} \neq \alpha_{fh}$. In this regard, (2.3) can be seen as a special case of (2.5), where arbitrary cross-country restrictions on the country-pair effect are imposed, *i.e.* $\alpha_{hf} = \alpha_h + \gamma_f$. Cheng and Wall also consider the two other models: the symmetric fixed effect (SFE) and the difference fixed effect model (DFE). The former specification imposes the restriction that country-pair effects are symmetric, *i.e.* $\alpha_{hf} = \alpha_{fh}$, whilst the latter model applies first differencing to (2.5) so as to eliminate the fixed effects. Based on the statistical finding that the restrictions imposed in (2.2), the symmetry restriction on the country-pair effects and those needed to obtain the DFE specification are all significantly rejected, they conclude that the FEM (2.5) will be the most robust econometric specification of the gravity model of international trade.

However, it is worth noting that the fixed effects approach does not allow for estimating coefficients on time invariant variables such as distance, common border or language dummies. Although it is difficult to find an appropriate measure of economic distance and of controlling for contiguity (*e.g.*, considering Canada and the US, China and Russia, and Argentina and Chile are all equivalently contiguous pairs), it is still important to find relatively precise effects on trade flows of those variables. Cheng and Wall (2002) simply suggest to estimate the additional regression of the (estimated) individual effects on individual-specific variables by the OLS. See also Martinez-Zaroso and Nowak-Lehmann (2003) for a similar two-step approach to an analysis of determinants of bilateral trade flows between European Union and Mercosur countries. However, this approach clearly ignores the potential correlation between individual specific variables and (unobserved) individual effects and therefore, the resulting estimated impacts are likely to be biased. In order to properly address the issue of correlation between regressors (including both time-varying and time-invariant) and unobserved individual effects we need to employ the Hausman and Taylor (1981, hereafter HT) instrumental variable estimation technique, which allows us to obtain consistent estimation of the coefficients on time invariant variables as well. In this context, Brun *et al.* (2002) attempt to apply the HT estimation by using infrastructure and population as instruments for standard trade-barrier function such as distance, common language and common border dummies, assuming that they are not correlated with individual effects.

The triple index model as given in (2.5) is not the only way of representing the panel data-based gravity model of international trade. A more conventional double index-based panel data specification have also been applied in which case explanatory variables are expressed as a combination of characteristics of trading partners, *e.g.* Egger (2001) and Glink and Rose (2002). Thus we now consider the following double index panel data model:

$$y_{it} = \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\gamma}'\mathbf{z}_i + \alpha_i + \theta_t + \varepsilon_{it},\ i = 1, ..., N,\ t = 1, ..., N, \tag{2.6}$$

where an index i represents each country-pair hf such that $\alpha_i = \alpha_{hf} = \alpha_h + \gamma_f$ as in Cheng and Wall (2002). Notice that variables in $\mathbf{x}_{it}$ are defined as a combination of features of the countries in each pair, but importantly embrace variables, $\mathbf{x}_{hft}$ that vary in all the three dimensions, and variables, $\mathbf{x}_{ht}$ and $\mathbf{x}_{ft}$ that vary only with one partner of trade and time, respectively. Time invariant regressors such as distance, common language and common borders dummies are now included in $\mathbf{z}_i$ that coincide with $\mathbf{z}_{hf}$. For instance, De Sousa and Disdier (2002) use (2.6) to investigate the role of consumer's preferences as well as tariff and non-tariff barriers in explaining border effects on trade flows among Hungary, Romania and Slovenia, European Union (EU) and Central European Free Trade Agreement (CEFTA) countries, and apply the HT estimation to consistently estimate the impacts of individual country's characteristics like distance, common border or language. In particular, they find that once the correlations between regressors and unobserved individual effects are properly accommodated, the significance of the distance is strongly reduced and the coefficient of on common border becomes insignificant.

Motivated by the New Trade Theory initiated by Krugman (1979), who attempts to explain trade patterns under monopolistic competition and increasing returns, Helpman

(1987) suggests that the share of intra-industry trade in bilateral trade flows should be larger for countries with similar incomes per capita or similar characteristics in general. Helpman estimates (2.1) by the cross-section OLS estimation for 14 countries for every year from 1970 to 1981, where the share of intra-industry trade is used as the dependent variable and some combined measures of trading partners' incomes and relative country size are suggested as the regressors that are meant to proxy for size, similarity in size and difference in relative factor endowments of trading partners, and finds that there is a positive correlation between the share of intra-industry trade and similarity in income per capita. Hummels and Levinsohn (1995) extend Helpman's analysis into a panel data framework. In similar veins, Egger (2002) attempts to explain the total volume of export (the sum of inter- and intra-industry volumes) in terms of the geographical distance between two trading partners, the relative factor endowments, the relative size of two countries (GDP) and their overall economic space. His empirical findings generally confirm the importance of allowing for both heterogeneity and correlation between explanatory variables and individual effects.

In summary, we may conclude that the FEM along with the HT is the most preferred estimation technique in the analysis of gravity model of international trade, because we need to deal with unobserved heterogeneous individual effects and its correlation with both time-varying and time invariant regressors to avoid any potential biases. In next section we will generalize the HT estimation in presence of both observed and unobserved common time-specific factors.

3 The Hausman-Taylor Estimation in Heterogeneous Panels with Time-specific Factors

Noticing that both triple and double index versions of the gravity model of trade, (2.5) and (2.6), can be expressed as a conventional double index panel-data model, we begin with

$$y_{it} = \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\gamma}'\mathbf{z}_i + \varepsilon_{it},\ i = 1, ..., N,\ t = 1, ..., T, \tag{3.1}$$

$$\varepsilon_{it} = \alpha_i + \theta_t + u_{it}, \tag{3.2}$$

where the error term ε_{it} is composed of three parts; namely, α_i is an individual effect that accounts for the effect of all possible time invariant determinants and might be correlated with some of the explanatory variables $\mathbf{x}_{it}$ and $\mathbf{z}_i$, θ_t is the time-specific effects common to all cross section units that is meant to correct for the impact of all the individual invariant determinants such as potential trend or business cycle, and u_{it} is a zero mean idiosyncratic random disturbance uncorrelated across cross section units and over time periods. The conventional assumptions are that these three components are independent of each other.

We now generalize (3.2) such that the individual responses to variations of the common time-specific effects are heterogeneous. This suggests that we extend (3.2) to

$$\varepsilon_{it} = \alpha_i + \lambda_i f_t + u_{it}, \tag{3.3}$$

where λ_i capture heterogeneous responses that trade flows between trading countries might have with respect to the time-specific common factors, f_t. It is clearly seen that the pooled or fixed effects estimation of $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ in (3.1) will be less efficient without properly accommodating the error component structure given by (3.3). More importantly, in the case where some or all of the regressors in $\mathbf{x}_{it}$ are likely to be correlated with f_t, the uncorrected estimator will be severely biased. There is now a growing number of panel studies using (3.3) explicitly, *e.g.*, Ahn, Lee and Schmidt (2001), Bai and Ng (2002), Pesaran (2002) and Phillips and Sul (2002). Additional advantage of this approach is to allow for certain degrees of cross section dependence via heterogeneous time-specific effects.

To accommodate this potentially important issue, we now combine (3.1) and (3.3). Here we consider the two cases. *First*, we simply assume that all of the time-specific common effects are observable in which case we have

$$y_{it} = \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\gamma}'\mathbf{z}_i + \boldsymbol{\lambda}_i'\mathbf{f}_t^* + \varepsilon_{it},\ i = 1, ..., N,\ t = 1, ..., T, \tag{3.4}$$

$$\varepsilon_{it} = \alpha_i + u_{it}, \tag{3.5}$$

where $\mathbf{f}_t^*$ are observed multiple time-specific factors. The distinguishing features of the above model are: (i) it considers explicitly the impacts of time-specific factors $\mathbf{f}_t^*$ instead of the conventional fixed time effects to investigate the business cycle or the globalization issues, and (ii) it does not impose the homogeneous restriction on the coefficients on $\mathbf{f}_t^*$. Considering that $\mathbf{f}_t^*$ usually measure the common macro shocks or policies, it is natural to expect that individual's responses will be different from each other. *Secondly*, in the case where we have both observed and unobserved common time-specific effects, we follow the pooled correlated common effect (PCCE) estimation approach advanced by Pesaran (2002), and extend the model (3.4) to

$$y_{it} = \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\gamma}'\mathbf{z}_i + \boldsymbol{\lambda}_i'\mathbf{f}_t + \alpha_i + u_{it},\ i = 1, ..., N,\ t = 1, ..., T, \tag{3.6}$$

where we assume that there is a single unobserved time-specific common effect in ε_{it} and then $\mathbf{f}_t$ is the augmented set including $\mathbf{f}_t^*$ and the cross sectional averages of y_{it} and $\mathbf{x}_{it}$, namely $\overline{y}_t = N^{-1}\sum_{i=1}^N y_{it}$ and $\overline{\mathbf{x}}_t = N^{-1}\sum_{i=1}^N \mathbf{x}_{it}$. Pesaran (2002) shows that the PCCE estimation (also called the generalised within estimator) will provide the consistent estimator of $\boldsymbol{\beta}$, though it does not provide a consistent estimator of $\boldsymbol{\gamma}$.

In what follows we will work on (3.6) without loss of generality. Here notations are: $\mathbf{x}_{it} = (x_{1,it}, x_{2,it}, ..., x_{k,it})'$ is a $k \times 1$ vector of variables that vary over individuals and time periods, $\mathbf{z}_i = (z_{1,i}, z_{2,i}, ..., z_{g,i})'$ is a $g \times 1$ vector of individual-specific variables, $\mathbf{f}_t = (f_{1,t}, f_{2,t}, ..., f_{l,t})'$ is an $l \times 1$-vector of time-specific variables, and $\boldsymbol{\beta} = (\beta_1, \beta_2, ..., \beta_k)'$, $\boldsymbol{\gamma} = (\gamma_1, \gamma_2, ..., \gamma_g)'$, $\boldsymbol{\lambda}_i = (\lambda_{1,i}, \lambda_{2,i}..., \lambda_{l,i})'$ are conformably defined column vectors of parameters, respectively. Finally, we follow Hausman and Taylor and rewrite (3.6) by

$$y_{it} = \boldsymbol{\beta}_1'\mathbf{x}_{1it} + \boldsymbol{\beta}_2'\mathbf{x}_{2it} + \boldsymbol{\gamma}_1'\mathbf{z}_{1i} + \boldsymbol{\gamma}_2'\mathbf{z}_{2i} + \boldsymbol{\lambda}_i'\mathbf{f}_t + \alpha_i + u_{it}, \tag{3.7}$$

where $\mathbf{x}_{it} = (\mathbf{x}_{1it}', \mathbf{x}_{2it}')'$, $\mathbf{z}_i = (\mathbf{z}_{1i}', \mathbf{z}_{2i}')'$, $\mathbf{x}_{1it}$, $\mathbf{x}_{2it}$ are k_1- and k_2-vectors, $\mathbf{z}_{1i}$, $\mathbf{z}_{2i}$ are g_1- and g_2-vectors, and $\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_2$, $\boldsymbol{\gamma}_1$, $\boldsymbol{\gamma}_2$ are conformably defined column vectors.

We now make the following assumptions:

Assumption 1. (i) $u_{it} \sim iid\,(0, \sigma_u^2)$. (ii) $\alpha_i \sim iid\,(\alpha, \sigma_\alpha^2)$. (iii) $E\,(\alpha_i u_{jt}) = 0$ for all i, j, t. (iv) $E\,(\mathbf{x}_{it} u_{js}) = \mathbf{0}$, $E\,(\mathbf{f}_t u_{is}) = \mathbf{0}$ and $E\,(\mathbf{z}_i u_{jt}) = \mathbf{0}$ for all i, j, s, t, so all the regressors are exogenous with respect to the idiosyncratic errors, u_{it}. (v) $\mathbf{x}_{1it}$, $\mathbf{z}_{1i}$ and f_t are uncorrelated with α_i for all i, t, whereas $\mathbf{x}_{2it}$ and $\mathbf{z}_{2i}$ are correlated with α_i. (vi) Both N and T are sufficiently large.

Assumption 1 is standard in the panel data literature. In particular, we need to use prior information to distinguish columns of $\mathbf{x}$ and $\mathbf{z}$ which are correlated with the individual unobservable effect, α_i and those which are not. Assumption (vi) is necessary to consistently estimate (nuisance) heterogenous parameters, $\boldsymbol{\lambda}_i$.

We now develop the estimation theory for all the parameters in (3.7), which involves the two steps. First, we rewrite (3.4) as

$$y_{it} = \alpha_i + \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\gamma}'\mathbf{z}_i + \boldsymbol{\lambda}_i'\mathbf{f}_t + u_{it},\ i = 1, ..., N,\ t = 1, ..., T, \tag{3.8}$$

and obtain the consistent estimator of $\boldsymbol{\beta}$ by

$$\hat{\boldsymbol{\beta}}_{FE} = \left(\sum_{i=1}^{N} \mathbf{x}_i'\mathbf{M}_T\mathbf{x}_i\right)^{-1} \left(\sum_{i=1}^{N} \mathbf{x}_i'\mathbf{M}_T\mathbf{y}_i\right), \tag{3.9}$$

where

$$\underset{(T\times 1)}{\mathbf{y}_i} = \begin{pmatrix} y_{i1} \\ y_{i2} \\ \vdots \\ y_{iT} \end{pmatrix};\ \underset{(T\times 1)}{\mathbf{1}_T} = \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{pmatrix},\ \underset{(T\times l)}{\mathbf{f}} = \begin{pmatrix} \mathbf{f}_1' \\ \mathbf{f}_2' \\ \vdots \\ \mathbf{f}_T' \end{pmatrix},\ \underset{(T\times k)}{\mathbf{x}_i} = \begin{pmatrix} \mathbf{x}_{i1}' \\ \mathbf{x}_{i2}' \\ \vdots \\ \mathbf{x}_{iT}' \end{pmatrix},$$

$\mathbf{H}_T = (\mathbf{1}_T, \mathbf{f})$ is a $T \times (l+1)$ matrix and $\mathbf{M}_T = \mathbf{I}_T - \mathbf{H}_T\left(\mathbf{H}_T'\mathbf{H}_T\right)^{-1}\mathbf{H}_T'$. Next, the consistent estimators of $\boldsymbol{\lambda}_i$ can be obtained from the following regression:

$$\tilde{y}_{it} = b_i + \boldsymbol{\lambda}_i'\mathbf{f}_t + \tilde{u}_{it},\ i = 1, ..., N,\ t = 1, ..., T, \tag{3.10}$$

where $\tilde{y}_{it} = y_{it} - \hat{\boldsymbol{\beta}}_{FE}'\mathbf{x}_{it}$ and $b_i = \alpha_i + \boldsymbol{\gamma}'\mathbf{z}_i$.

Assuming that all the underlying variables are stationary, in which case under fairly standard conditions, the consistency and the asymptotic normality of the FE estimator of $\boldsymbol{\beta}$ can be easily established. In the current context, as $(N, T) \to \infty$ jointly, we have

$$\sqrt{NT}\left(\hat{\boldsymbol{\beta}}_{FE} - \boldsymbol{\beta}\right) \overset{a}{\sim} N\left(\mathbf{0}, \Sigma_{\beta_{FE}}\right), \tag{3.11}$$

where the consistent estimator of $\Sigma_{\beta_{FE}}$ is given by

$$\hat{\Sigma}_{\beta_{FE}} = \left(\frac{1}{N}\sum_{i=1}^{N}\frac{\mathbf{x}_i'\mathbf{M}_T\mathbf{x}_i}{T}\right)^{-1}\hat{\sigma}_u^2, \tag{3.12}$$

where $\hat{\sigma}_u^2$ is a consistent estimator of σ_u^2 provided by

$$\hat{\sigma}_u^2 = \frac{\sum_{i=1}^{N}\hat{\mathbf{u}}_i'\hat{\mathbf{u}}_i}{N(T-1-l)-k}, \tag{3.13}$$

$\hat{\mathbf{u}}_i = (\hat{u}_{i1}, ..., \hat{u}_{iT})'$ with $\hat{u}_{it} = \tilde{y}_{it} - \hat{b}_i - \hat{\boldsymbol{\lambda}}_i'\mathbf{f}_t = y_{it} - \hat{\boldsymbol{\beta}}_{FE}'\mathbf{x}_{it} - \hat{b}_i - \hat{\boldsymbol{\lambda}}_i'\mathbf{f}_t$ for $i = 1, ..., N,\ t = 1, ..., T$, and $\hat{b}_i$, $\hat{\boldsymbol{\lambda}}_i$ are the OLS estimators of b_i, $\boldsymbol{\lambda}_i$ obtained from (3.10).

However, the above FE estimation will wipe out any individual specific variables in $\mathbf{Z}_i$ from (3.7). In order to consistently estimate $\boldsymbol{\gamma}_1$ and $\boldsymbol{\gamma}_2$ on individual specific variables, we notice that (3.8) can be written as

$$d_{it} = \alpha_i + \boldsymbol{\gamma}_1'\mathbf{z}_{1i} + \boldsymbol{\gamma}_2'\mathbf{z}_{2i} + u_{it},\ i = 1, ..., N,\ t = 1, ..., T, \tag{3.14}$$

where $d_{it} = y_{it} - \boldsymbol{\beta}'\mathbf{x}_{it} - \boldsymbol{\lambda}_i'\mathbf{f}_t$ for $i = 1, ..., N$ and $t = 1, ..., T$. Using Assumption 1(ii), we rewrite (3.14) as

$$d_{it} = \alpha + \boldsymbol{\gamma}_1'\mathbf{z}_{1i} + \boldsymbol{\gamma}_2'\mathbf{z}_{2i} + \alpha_i^* + u_{it} = \alpha + \boldsymbol{\gamma}'\mathbf{z}_i + \varepsilon_{it}^*,\ i = 1, ..., N,\ t = 1, ..., T, \tag{3.15}$$

where $\alpha_i^* \sim (0, \sigma_\alpha^2)$ and $\varepsilon_{it}^* = \alpha_i^* + u_{it}$ is a zero mean process by construction. Rewriting (3.15) in matrix notation we have

$$\mathbf{d}_i = \alpha\mathbf{1}_T + \mathbf{z}_{1i}\mathbf{1}_T\boldsymbol{\gamma}_1 + \mathbf{z}_{2i}\mathbf{1}_T\boldsymbol{\gamma}_2 + \boldsymbol{\varepsilon}_i^*,\ i = 1, ..., N, \tag{3.16}$$

$$\mathbf{d} = \alpha\mathbf{1}_{NT} + \mathbf{Z}_1\boldsymbol{\gamma}_1 + \mathbf{Z}_2\boldsymbol{\gamma}_2 + \boldsymbol{\varepsilon}^*, \tag{3.17}$$

where

$$\underset{(NT\times 1)}{\mathbf{d}} = \begin{pmatrix} \mathbf{d}_1 \\ \mathbf{d}_2 \\ \vdots \\ \mathbf{d}_N \end{pmatrix};\ \underset{(NT\times 1)}{\mathbf{1}_{NT}} = \begin{pmatrix} \mathbf{1}_T \\ \mathbf{1}_T \\ \vdots \\ \mathbf{1}_T \end{pmatrix},\ \underset{(T\times g)}{\mathbf{Z}_j} = \begin{pmatrix} \mathbf{z}_{j1}\mathbf{1}_T \\ \mathbf{z}_{j2}\mathbf{1}_T \\ \vdots \\ \mathbf{z}_{jN}\mathbf{1}_T \end{pmatrix},\ j = 1, 2,\ \underset{(NT\times 1)}{\boldsymbol{\varepsilon}^*} = \begin{pmatrix} \boldsymbol{\varepsilon}_1^* \\ \boldsymbol{\varepsilon}_2^* \\ \vdots \\ \boldsymbol{\varepsilon}_N^* \end{pmatrix}.$$

Replacing $\mathbf{d}$ by its consistent estimate, $\hat{\mathbf{d}} = \left\{\hat{d}_{it}, i = 1, ..., N,\ t = 1, ..., T,\right\}$, where $\hat{d}_{it} = y_{it} - \hat{\boldsymbol{\beta}}'\mathbf{x}_{it} - \hat{\boldsymbol{\lambda}}_i'\mathbf{f}_t$ for $i = 1, ..., N,\ t = 1, ..., T$, we now have

$$\hat{\mathbf{d}} = \alpha\mathbf{1}_{NT} + \mathbf{Z}_1\boldsymbol{\gamma}_1 + \mathbf{Z}_2\boldsymbol{\gamma}_2 + \boldsymbol{\varepsilon} = \mathbf{C}\boldsymbol{\delta} + \boldsymbol{\varepsilon}^*, \tag{3.18}$$

where $\mathbf{C} = (\mathbf{1}_{NT}, \mathbf{Z}_1, \mathbf{Z}_2)$ and $\boldsymbol{\delta} = (\alpha, \boldsymbol{\gamma}_1', \boldsymbol{\gamma}_2')'$. Here we notice that approximation errors stemming from the use of $\hat{\mathbf{d}}$ in (3.18) are (asymptotically) negligible. To deal with the nonzero correlation between $\mathbf{Z}_2$ and $\boldsymbol{\alpha}$ or $\boldsymbol{\alpha}^*$, we need to find the following $NT \times (1 + g_1 + h)$ matrix of instrument variables:

$$\mathbf{W} = (\mathbf{1}_{NT}, \mathbf{Z}_1, \mathbf{W}_2),$$

where $\mathbf{W}_2$ is an $NT \times h$ matrix of instrument variables for $\mathbf{Z}_2$ with $h \geq g_2$ for identification. The advantage of the HT estimation is that the instrument variables for $\mathbf{Z}_2$ can be obtained internally, and they suggest to use $\mathbf{QX}_1$ as the instruments for $\mathbf{Z}_2$. See also Amemiya and MaCurdy (1986) and Breusch, Mizon and Schmidt (1989) for additional source of instruments.

We now suggest to use an alternative source of instruments as follow: For this we rewrite (3.8) as

$$y_{it} = b_i + \boldsymbol{\beta}'\mathbf{x}_{it} + \lambda_{1i}f_{1t} + \lambda_{2i}f_{2t} + \cdots + \lambda_{li}f_{lt} + u_{it}, \tag{3.19}$$

where $b_i = \alpha_i + \boldsymbol{\gamma}'\mathbf{z}_i$. Define $\hat{\theta}_{jit} = \hat{\lambda}_{ji} f_{jt}$ for $j = 1, ..., l$, $i = 1, ..., N$ and $t = 1, ..., T$, where $\hat{\lambda}_{ji}$ are consistent estimates of heterogenous factor loadings λ_{ji}, and similarly define the $NT \times 1$ matrix,

$$\hat{\Theta}_j = \begin{pmatrix} \mathbf{f}_j \hat{\lambda}_{j1} \\ \mathbf{f}_j \hat{\lambda}_{j2} \\ \vdots \\ \mathbf{f}_j \hat{\lambda}_{jN} \end{pmatrix}, \quad \underset{(T\times 1)}{\mathbf{f}_j} = \begin{pmatrix} f_{j,1} \\ f_{j,2} \\ \vdots \\ f_{j,T} \end{pmatrix}, \; j = 1, ..., l.$$

We now make the following assumption:

Assumption 2. λ_{ji}, $j = 1, ..., l_1$, are correlated with $\mathbf{z}_{2i}$, but not correlated with α_i, whilst λ_{ji}, $j = l_1 + 1, ..., l$, are correlated with both $\mathbf{z}_{2i}$ and α_i.

Assumption 2 implies that some of individuals' heterogeneous responses with respect to common factors $\mathbf{f}_t$ are correlated with $\mathbf{Z}_2$, but not with individual effects. In fact, the nature and implication of this assumption is basically the same as those of Assumption 1(v). Under Assumption 1(v) and Assumption 2, we now obtain the following instrument matrix for $\mathbf{Z}_2$,

$$\mathbf{W}_2 = \left(\mathbf{Q}\mathbf{X}_1, \hat{\Theta}_1, \hat{\Theta}_2, ..., \hat{\Theta}_{l_1}\right),$$

where the dimension of $\mathbf{W}_2$ is $NT \times h$ with $h = k_1 + l_1$. Then, the consistent estimator of $\boldsymbol{\delta}$ is obtained by the GLS-IV estimation. Premultiplying $\mathbf{W}'$ by (3.18), we have

$$\mathbf{W}'\hat{\mathbf{d}} = \mathbf{W}'\mathbf{C}\boldsymbol{\delta} + \mathbf{W}'\boldsymbol{\varepsilon}^*. \tag{3.20}$$

and therefore we obtain the GLS estimator of $\boldsymbol{\delta}$ by

$$\hat{\boldsymbol{\delta}}_{GLS} = \left[\mathbf{C}'\mathbf{W}\mathbf{V}^{-1}\mathbf{W}'\mathbf{C}\right]^{-1} \mathbf{C}'\mathbf{W}\mathbf{V}^{-1}\mathbf{W}'\hat{\mathbf{d}}, \tag{3.21}$$

where $\mathbf{V} = Var\left(\mathbf{W}'\boldsymbol{\varepsilon}^*\right)$. The feasible GLS estimator is obtained by replacing $\mathbf{V}$ by its consistent estimator. We first obtain an initial consistent estimation of $\hat{\boldsymbol{\delta}}$ by the OLS estimator from (3.18) and construct a consistent estimate of $\boldsymbol{\varepsilon}^*$ by $\hat{\boldsymbol{\varepsilon}}^*_{OLS} = \hat{\mathbf{d}} - \mathbf{C}\hat{\boldsymbol{\delta}}_{OLS}$, where $\hat{\boldsymbol{\varepsilon}}^*_{OLS} = \left(\hat{\boldsymbol{\varepsilon}}^{*\prime}_{OLS,1}, ..., \hat{\boldsymbol{\varepsilon}}^{*\prime}_{OLS,N}\right)'$. Then, we estimate the initial consistent estimate of $\mathbf{V}$ by

$$\hat{\mathbf{V}}_{(1)} = \sum_{i=1}^{N} \mathbf{w}_i' \hat{\boldsymbol{\varepsilon}}^*_{OLS,i} \hat{\boldsymbol{\varepsilon}}^{*\prime}_{OLS,i} \mathbf{w}_i, \tag{3.22}$$

where $\mathbf{w}_i$ is the $T \times (1 + g_1 + h)$ instrument matrix for individual i, defined in $\mathbf{W} = (\mathbf{w}_1', ..., \mathbf{w}_N')'$, and estimate the feasible GLS (FGLS) estimator of $\boldsymbol{\delta}$ by

$$\hat{\boldsymbol{\delta}}^{(1)}_{FGLS} = \left[\mathbf{C}'\mathbf{W}\hat{\mathbf{V}}^{-1}_{(1)}\mathbf{W}'\mathbf{C}\right]^{-1} \mathbf{C}'\mathbf{W}\hat{\mathbf{V}}^{-1}_{(\mathbf{1})}\mathbf{W}'\hat{\mathbf{d}}. \tag{3.23}$$

Next, we construct the GLS residuals by $\hat{\boldsymbol{\varepsilon}}_{GLS} = \hat{\mathbf{d}} - \mathbf{C}\hat{\boldsymbol{\delta}}^{(1)}_{FGLS}$, and estimate $\mathbf{V}$ and $\boldsymbol{\delta}$ further by

$$\hat{\mathbf{V}}_{(2)} = \sum_{i=1}^{N} \mathbf{w}_i' \hat{\boldsymbol{\varepsilon}}^*_{GLS,i} \hat{\boldsymbol{\varepsilon}}^{*\prime}_{GLS,i} \mathbf{w}_i.$$

$$\hat{\boldsymbol{\delta}}_{FGLS}^{(2)} = \left[\mathbf{C}'\mathbf{W}\hat{\mathbf{V}}_{(2)}^{-1}\mathbf{W}'\mathbf{C}\right]^{-1}\mathbf{C}'\mathbf{W}\hat{\mathbf{V}}_{(2)}^{-1}\mathbf{W}'\hat{\mathbf{d}}. \tag{3.24}$$

This iteration will be repeated until the convergence occurs, *e.g.* $\left|\hat{\boldsymbol{\delta}}_{FGLS}^{(j)} - \hat{\boldsymbol{\delta}}_{FGLS}^{(j-1)}\right| < 0.0001$, $j = 1, 2, ...$ Once we have obtained the final converged FGLS estimator, its covariance matrix will be computed by

$$Var\left(\hat{\boldsymbol{\delta}}_{FGLS}\right) = \left\{\left[\mathbf{C}'\mathbf{W}\hat{\mathbf{V}}_{FGLS}^{-1}\mathbf{W}'\mathbf{C}\right]^{-1}\right\}. \tag{3.25}$$

Under fairly standard conditions the consistency and the asymptotic normality of the FGLS estimator of $\boldsymbol{\delta}$ can also be easily established. As $(N, T) \to \infty$ jointly, we have

$$\sqrt{NT}\left(\hat{\boldsymbol{\delta}}_{FGLS} - \boldsymbol{\delta}\right) \overset{a}{\sim} N\left(\mathbf{0}, \Sigma_{\delta_{FGLS}}\right), \tag{3.26}$$

where the consistent estimator of $\Sigma_{\delta_{FGLS}}$ is given by

$$\hat{\Sigma}_{\delta_{FGLS}} = \left[\frac{\mathbf{C}'\mathbf{W}}{NT}\left(\frac{\hat{\mathbf{V}}_{FGLS}}{NT}\right)^{-1}\frac{\mathbf{W}'\mathbf{C}}{NT}\right]^{-1}. \tag{3.27}$$

4 Empirical Application to the Intra-EU Trade

In this section we will provide a comprehensive analysis of the determinants of bilateral trade flows amongst the fifteen European countries using both triple and double indexed versions of the gravity equation, (2.5) and (2.6), where we consider as the dependent variable the logarithm of real export in (2.5) and the logarithm of total trade in (2.6). (For detailed definition of all the variables see the Data Appendix.)

In each case we consider the three different specifications. *First*, the basic model specifies that bilateral export or trade only depends on the mass of the countries (measured by GDP and population) and barrier to trade (measured by distance). A high level of income in the exporting country indicates a high level of production, which increase availability of goods for exports, whereas a high level of income in importing country suggest higher imports. Therefore, we expect the positive impacts of those variables on trade flows. The effect of population is not unambiguous as disputed in the literature. Here we follow Bergstrand (1989) and interpret that a positive (negative) impact of exporter population indicates that the exports tend to be labor (capital) intensive goods, whilst a positive (negative) impact of importer population indicates that the exports tend to be necessity (luxury) goods. As noted by Baldwin (1994), however, both impacts might be negative as larger countries are sometimes regarded as self-efficient. On the other hand, the effect of transportation costs proxied by geographical distance between capital cities is certainly expected to be negative on trade flows. Notice that in the double indexed version both GDP and population are expressed as a combined measure of trading partners.

Second, we consider the augmented specification, where trade flows are also allowed to depend on variables that take into account free trade agreements and common currency union as well as time invariant dummies for common language and common border. The variable CEE is a dummy that is equal to one when both countries belong to the European Community and is expected to exert a positive impact. See also De Grauwe and Skudelny (2000), Martinez-Zaroso and Lehmann (2001), Cheng and Wall (2002) and De Sousa and Disdier (2002) for an analysis of the effects of regional trading blocks. We also consider the time-varying dummy variable EMU which is equal to one when both trading partners adopt the same currency. The issue on the benefits of joining a common currency union has recently been getting more attention since the introduction of the Euro in 1999. Since an official motivation behind the EMU project (European Commission, 1990) is that a single currency will reduce the transaction costs of trade within member countries, the impact of EMU on trade flows is expected to be positive. But, the empirical evidence is mixed. Rose (2002) and Glink and Rose (2002) have analysed the trade data for almost all countries in the world and found evidence of a rather large positive effect of currency union on trade. Interestingly, this finding is not consistent with the earlier studies that fail to find a significant link between exchange rate stability and trade, *e.g.* Branda and Mendez (1988) and Frankel and Wei (1993). See also a number of recent studies that find negative or insignificant effects on trade of a monetary union, *e.g.* Persson (2001) and Pakko and Wall (2002). In particular, de Souza (2002), and De Nardis and Vicarelli (2003) investigate the effect of the EMU in the euro area over the last two decades and find no significant evidence of a robust relationship between EMU and trade. The common language dummy (Lan) has a value equal to one when both countries speak the same official language and is meant to capture similarity in cultural and historical backgrounds between trading countries. The shared border dummy (Bor) is equal to one when the trading partners share a border, which is a proxy for geographical proximity. Obviously, both effects on bilateral trade flows are expected to be positive.

Finally in the full specification version of the gravity equation, we also aim to follow recent developments of the New Trade Theory advanced by Helpman (1987), Hummels and Levinsohn (1995) and Egger (2001, 2002) and thus add variables such as RLF and SIM. The variable RLF measures the difference in terms of relative factor endowments (proxied by per capita GDPs) between two countries and takes a minimum value of zero when there is equality in relative factor endowments. The larger is this difference, the higher is the volume of inter-industry (and the total) trade will be, and the lower the share of the intra-industry trade. The variable SIM captures the relative size of two countries in terms of GDP. This index is bounded between zero (absolute divergence in size) and 0.5 (equal country size). The larger this measure is (meaning that the more similar two countries are), the higher the share of the intra-industry trade will be. We note in passing that these variables have been considered to mainly explain trends of the intra-industry trade share. For example, Helpman (1987) finds a negative correlation between the intra-industry trade share and RLF, and a positive correlation between the intra-industry trade share and SIM, which is interpreted as supporting evidence of the theory of IRS and imperfect competition in international trades. Since our analysis aims to explain the patterns of both intra-industry trades and the total trade flows (sum of inter- and intra-industry trades), the impact of RLF might not be unambiguous on total trade flows. We also consider the impact of (logarithm of) real exchange rates (RER) between two countries, which is defined as the price of the foreign currency per the home currency unit and which is meant to capture the relative price effects. A depreciation of the home currency relative to the foreign currency (an increase in RER) should lead to more export and less import for the home country. The effect of real exchange rates on total trade flow will be positive (negative) if the export component of the total trade is significantly larger than the import component. For similar lines of studies see De Grauwe and Skudelny (2000) and Egger and Pfaffermayr (2002). Here we drop the population variables from the full specification in order to avoid collinearity as RLF is a linear combination of GDP and population.

4.1 Explanatory Data Analysis

The data used cover a period of 42 years (1960-2001) whereas the country sample contains all of the 15 EU member countries, namely Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxemburg, Netherlands, Portugal, Spain, Sweden, United Kingdom where Belgium and Luxemburg are treated as a single country, counting 182 country-pairs in the triple index version of the gravity model (2.5) and 91 country-pairs in the double index version (2.6).

Table 1 reports some of summary figures presented in the *Statistical Yearbook* (Eurostat, 1997) and shows that the intra-EU trade has always been a considerable part of EU' s total trade (currently it is almost two-thirds). Since 1960, there have been only three time periods during which an intra-EU trade share declined as a percentage of the total EU trade. During the periods 1973-1975 and 1979-1981, the relative importance of the intra-EU trade fell sharply due to price increases in primary goods. As a result, the total value of the extra-EU imports went up, raising total value of extra-EU trade. Even when the internal market was introduced in 1993, the relative importance of intra-EU trade has declined. But this may be a purely statistical phenomena due to the fact that the collection of the intra-EU data has been reorganized since 1993.

In general, the intra-EU trade volumes were positively affected by the enlargement of the European Community, *e.g.* with the accession of new member states (Greece, Portugal and Spain) in the 1980s and with the German unification at the beginning of the 1990s, see *Single Market Review* (European Commission, 1997). Also, the enlargement of the EU in 1995 with Austria, Sweden and Finland has significantly increased the intra-EU trade volume: for example, the intra-EU share of total EU trade before the three new member states joined the EU was 58% in 1994, whereas it reached around 64% in 1995, see *External and intra-European Union trade: Statistical Yearbook* (Eurostat, 1996). This clearly suggests that one of main factors behind the increasing importance of intra-EU trade within the total EU trade is clearly the stronger link among member states over the last few decades.

Table 1 about here

Table 1 also shows that an intra-EU trade trends along with the total EU GDP. But, the fact that the trade volume between EU countries grows faster than GDP is further evidence of the increasing integration of EU market. The *Single Market Review* (European Commission, 1997) summarizes that the growth of the Intra-EU trade, initiated by the programme to complete the single market implemented in the mid-1980s, leads to major changes for the European economies. The measures taken consist mainly of a liberalization of trade in products and services through the abolition of non-tariff barriers, border formalities, a liberalization of public procurement practices and the mutual recognition of technical standards. Also included are the liberalization of factors movements and deregulation of sectors formerly subject to tight national regulation. The anticipation by economic agents of the completion of the single market caused a drive towards strong industrial restructuring at the microeconomic level, notably through merges and acquisitions by both European and non-European companies. Liberalization would also tend to lower prices through increased competition and foster a concentration of resources in more efficient use. These effect would translate into sizable welfare gains, increases in GDP, and increase competitiveness *vis-a-vis* non-member states. On the other hand, as Jacquemin and Sapir (1990) notice, the concentration of European industries might also create or foster dominant position which lead to higher domestic prices. This lowers trade barriers against imports from the rest of the world, meaning more extra-EU and less inter-EU import. Table 1 actually shows that in our sample the share of exports is generally higher than the share of imports within EU trades. In light of these figures we therefore expect that positive effects of an increase in real exchange rates on exports will dominate negative impacts on imports. As a result its influence on total trades is expected to be positive.

The *Single Market Review* (European Commission, 1997) further reports that the removal of barriers to the mobility of goods leads to an increase in trade flows within the Community, and most increases are of the intra-industry type. Intra-industry, boosted by similarity of the trading nations, may lead to cost-free adjustments, increased efficiency and welfare gains associated with variety. In contrast, inter-industry trade, traditionally associated with comparative advantages of nations, may lead to more costly adjustments, as trade and specialization move factors from contested, export-oriented industries. Figure 1 shows the evolution of trade in intra-EU trade between 1980 and 1994.[1] At the beginning of the 1980s the most important trade was the inter-industry type (share of 45%), but it started to decline from the mid-1980s onwards. The resulting increase in the share of intra-industry is essentially due to a trade boost in vertically differentiated products that are predominant in the largest European countries, *e.g.*, Germany and France since 1986 and the UK since 1989. This is consistent with evidence that intra-industry trade accounts for a substantial fraction of total trade among industrialized countries, see Deardorff (1984) and Evenett and Keller (2002). Molle (1997) states that contrary to what some had expected, both EU and EFTA has not produced specialization among countries along lines of traditional trade theory predicting that one country will be specialized in one good and the other in the other

[1] The share of intra-industry trade is measured by the traditional Grubel-Lloyd (1975) index, whereas inter-indusrty trade is represented by the so called 'one way trade'. The Grubel-Lloyd index is defined as $GL = 1 - \frac{X_j - M_j}{X_j + M_j}$ and measures the amount of intra-industry trade in a particular product group j. The value ranges from zero to unity representing a situation of zero and 100 percent intra-industry trade, respectively. When X_j or M_j equal to zero, there is no overlap of export or import so no intra-industry trade will take place. On the other hand if $X_j = M_j$, matching will be completed and $GL = 1$. Total trade is decomposed in three trade types according to their similarity in price (proxy for quality) and to overlap in trade: two-way trade in similar products (significant overlap and low price differences); two-way trade in vertically differenced products (significant overlap and high price differences); one-way trade (no or no significant overlap).

good on the basis of comparative advantages. In fact, at the beginning of the 1960s, it became clear that specialization occurred within sectors and consumers have benefited from the resulting increased range of products available. The more similar the demand structures of two countries are, the more intensive are the potential trade between them, see Linder (1961).

Figure 1 about here

4.2 Estimation results

We now briefly discuss alternative estimation procedures used to estimate (2.5) and (2.6): namely, the pooled OLS (POLS), the between estimation (BTW), the fixed effect model (FEM), the random effect model (REM) and Hausman and Taylor (HT) instrumental variable estimation. The POLS estimation is likely to gain in efficiency due to the increased number of observations but estimation results would be biased due to neglected (individual) heterogeneity. The between estimator runs an OLS regression on the time averages of cross section pairs, but is also likely to subject to the potential heterogeneity bias. The FEM explicitly takes into account the bilateral trade heterogeneity by specifying that all explanatory variables are assumed to be correlated with unobserved fixed individual effects, though it also wipes out any of time invariant variables. On the other hand, under the stronger assumption that unobserved individual effects are randomly distributed but uncorrelated with all regressors, the REM allows us to estimate the parameters on both time-varying and time-invariant variables, simultaneously. The validity of this assumption should be tested by using the Hausman (1978) test , and when this assumption is rejected, we will use the HT estimator to consistently estimate the impacts of time-invariant variables.

We consider the two different scenarios: *First*, we estimate both (2.5) and (2.6) without including any time-specific effects, which we call the benchmark case. *Secondly*, we follow most recent empirical studies that also emphasise the importance of explicitly allowing for the time specific effects in (2.5) and (2.6), *e.g.,* Matyas (1997) and Egger (2002). Since we analyse the trade data over the longer time span, this issue should be addressed properly in order to capture business cycle effects or deal with the generic globalization issues. We consider the three extensions: we extend the benchmark model by incorporating the conventional fixed time-specific dummies in the regressions. We will also use our proposed approach described in Section 3, namely by incorporating observed and unobserved common time factors, respectively.

Tables 2 present alternative estimation results for triple and double index gravity models of bilateral trades amongst the 15 EU countries. Since the validity of the REM assumption that there is no correlation between explanatory variables and unobserved individual effects is convincingly rejected in all cases considered, we will discuss estimation results mainly with the FEM results. For overwhelmingly similar empirical evidence see Egger (2001), Cheng and Wall (2002) and De Sousa and Disdier (2002) and Glink and Rose (2002)

Starting from the full specification of the triple index version (see Table 2(a)), almost all the FEM estimation results are statistically significant and consistent with our *a priori* expatiations. Both GDPs of home and foreign country have a positive effect on real exports and a depreciation of the home currency leads to an increase in export flows. Similarity in size and relative difference in factor endowments between trading partners help to boost real exports although the impact of RLF is much smaller than that of SIM. This finding clearly reflects the fact that the intra-industry trade is the main part of the total EU trade as described in subsection 4.1. A trade union membership also boosts real exports significantly, though the effect of EMU appears negative but insignificant. Although both REM and the POLS estimation results are likely to be biased because of correlation between regressors and unobserved individual effects, both estimation results are relatively consistent with the corresponding FEM results. Only the coefficient on EMU is positive but insignificant. Next, the BTW estimates appear to be mostly insignificant (SIM, RLF, CEE, EMU). This may be a clear indication of severe bias problem expected over the relatively long time span considered in our estimation, though we might expect to obtain different results over different time periods since the between estimator is based on a regression on time averages of cross section pairs. Turning briefly to the basic and augmented specifications, we find that only the impact of importer population is significant and negative, which leads us to conclude that the exports within EU countries are most likely to be luxury goods.

Table 2(b) reports the estimation results for the double index version, (2.6). Though they are mostly consistent with those of the triple index model, there are two notable differences. First, the impact of EMU on the total trade is now positive and significant. Hence, EMU seems to have a more positive impact on imports than on exports contrary to the evidence observed after the completion of the single market. Secondly, the impact of SIM on the total trade (mostly via the impact on the intra-industry trade) is much higher (1.17 versus 0.35). Once again the effect of income variable is highly significant, whereas the impact of population is insignificant. This reinforces the previous finding in the triple index version, but may also imply that the mass effect is likely to be captured mostly by income variable rather than population. (Considering that both GDP and population are proxies for the economic size of trading partners and they are highly correlated, this might indicate a certain degree of collinearity.) We also note that the magnitude of the FEM coefficient on the total GDP is somewhat larger than its OLS counterpart, a consistent finding with the previous empirical study by Matyas, Konya and Harris (2000) who argue that allowing for heterogeneous bilateral effects is likely to increase the magnitude of the impact of GDP.[2]

One of our main purposes of the current study is an investigation of consistent estimation (and thus precise evaluation) of the impacts of individual specific variables. We consider both (inconsistent) OLS and (consistent) HT estimations and summarise such estimation results in Table 2(c). Here we assume *a priori* that Lan is the only time invariant variable correlated with unobserved individual effects (as common language is a proxy for cultural, historical, linguistic proximity, it is highly likely to be correlated with unobserved individual effects). We employ two different sets of instrument variables. The first instrument set (HT1) contains only real exchange rates (RER), the second set (HT2) adds size related variables such as $GDPs$, SIM and RLF. Following de Sousa and Disdier (2002) we do not consider time-varying dummy variables as valid instruments. As expected *a priori*, all estimation results show that distance has a negative effect on exports and trades, while

[2]Most empirical studies find that estimates of the income coefficient are well over unity, *e.g.*, Matyas (1997), Cheng and Wall (2002) and Martinez-Zaroso and Nowak-Lehmann (2003).

common language and common border have positive effects on them. Here a notable finding is that once the correlation between Lan and unobserved individual effect is accommodated by the HT estimation, then the impacts of distance decrease (in absolute value) as compared to the OLS counterpart, whilst the impacts of both common language and common border dummies increase, especially the former. Furthermore, when we use the broad set of instruments (HT2), the distance variable loses significance. This result might be plausible given the fact that both distance and common border proxy geographical distance, the effects of which might compensate each other (the correlation coefficient between them is about 0.6). Overall, this result suggests that the role of cultural affinities will become more important in explaining the pattern of bilateral trade flows once the correlation between Lan and unobserved individual effect is appropriately handled.

Table 2 about here

Next, we consider an extended model in order to capture business cycle effects or deal with globalization issues. We first follow the conventional approach and include the $T-1$ fixed dummy variables (not T dummies to avoid multicollinearity) in (2.5) and (2.6), that are common to all country pairs. Notice that the impacts of fixed time dummies are assumed to be homogeneous. Table 3 reports the related estimation results. Although most estimation results for both triple and double index specifications follow similar patterns as obtained in Table 2, there are a few notable discrepancies (mainly in the context of the FEM estimation results). First, the impact of EMU is now mostly significantly positive. Second, the impact of the GDPs seem to be somewhat too large. Third, the impact of SIM on exports is no longer significant (see Table 3(a)), whereas the impact of SIM on total trades is still significant and larger (see Table 3(b)). Finally, turning to the HT estimation of the impacts of individual specific variables, we find that the estimates of the impact of distance are surprisingly positive but insignificant, the impact of common language dummy are much larger than in Table 2(c), but common border dummy loses its statistical significance.

Table 3 about here

We move to address an alternative approach of allowing for common time factors; namely we consider our proposed extended HT approach as developed in Section 3. We find from Table 1 that the share of EU trade with the US has always been a consistent part of the extra-EU trade. For example, it is reported in *Trade policy review of the European Union: A Report by the Secretariat of the WTO* (2002) that the percentage of export (import) from Europe to the US increases from around the 10% (10%) of the total volume of EU export in 1960 to around the 25% (20%) in 2000. Hence, we expect that certain characteristics of the US will also help in further explaining the pattern of the intra-EU exports and/or total trades. In this regard, we consider the EU and the US as two main trade blocks and then augment the model with the US reference variables, which we regard as observed common time factors. Here we simply choose the (logarithm of) real exchange rates ($RERT_t$) that will capture any of the relative price effects between the European currencies and the US dollar.[3] We expect that a depreciation of the European currency with respect to the US

[3]Here the home currency is the European currency, *i.e.* ECU till 1998 and Euro from 1999 to 2001, and

dollar (an increase in $RERT_t$) should result in more extra-EU exports to and less extra-imports from the US, though its impact on the intra-EU trade will be ambiguous. We thus consider the model (3.7) for both triple and double index versions, where $f_t = RERT_t$, and focus only on the FEM combined with the HT estimation results. Under our maintained assumption that common language dummy is only correlated with unobserved individual effects, we consider the four different instrument sets, denoted HT1, HT2, HT3 and HT4, respectively, where HT1 and HT2 are exactly the same as before, namely $HT1 = \{RER\}$ and $HT2 = \{RER, GDPs, SIM, RLF\}$, whilst HT3 and HT4 are the sets combining HT1 and HT2 respectively with $\hat{\lambda}_i RERT_t$. Remind that we follow our theoretical discussion in Section 3 and use $\hat{\lambda}_i RERT_t$ as an additional source of instrument in HT3 and HT4.

Table 4 summarizes there results. First, looking at the results for the triple index model (Table 4(a)), we find that signs and significances of coefficients are preserved, though the magnitudes of the coefficients are somewhat different from the previous estimates reported in Table 2(a). But, the coefficient on EMU is surprisingly negative and significant. The HT estimates of coefficients on individual specific variables all show the expected signs, but the language dummy loses its statistical significance. Next turning to the double index model (Table 4(b)), most FEM estimates are similar to those shown in Table 2(b) with the following main difference: the coefficients on EMU and RLF are both insignificant. The HT estimates of the impacts of individual specific variables show more or less the similar patterns to Table 2(c), namely, the distance variable becomes insignificant whilst the language variable becomes more important in explaining the pattern of trade flows.

Table 4 about here

We notice in passing that the choice of observed common factors might be somewhat arbitrary in general and that there is always a possibility of missing factors. In this regard, there is still a room for further improving previous estimation results, and we now take an alternative approach based on the assumption that the common time factors are unobserved and their impacts are heterogeneous. This approach has two advantages: First, we may avoid inevitable arbitrariness and difficulty in selecting observed common factors. Secondly and more importantly, this approach is also able to accommodate certain degrees of cross section dependence via heterogeneous time-specific effects, and thus to avoid the potential bias of uncorrected estimates as described earlier. Here we follow the PCCE estimation methodology advanced by Pesaran (2002) to deal with this issue and thus consider the model (3.7), where $f_t = \left\{\overline{y}_t, \overline{TGDP}_t, \overline{SIM}_t, \overline{RLF}_t, \overline{RER}_t\right\}$ and the bar over the variable indicates the cross sectional average of the variable of interest, namely $\overline{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$ and so on.[4] As before, we focus only on the FEM combined with the HT estimation results and maintain the assumption that common language dummy is only correlated with unobserved individual effects. We now consider the following four different instrument sets: $HT1 = \{RER\}$ and $HT2 = \{RER, GDPs, SIM, RLF\}$, whilst HT3 and HT4 are the sets combining HT1 and

the foreign currency is the US Dollar. See also Data Appendix. We have also tried different US reference variables such as the US GDP, and found the qualitatively similar results.

[4]We do not include cross sectional average of the CEE and EMU dummies to avoid the potential multicollinearity problem. We also notice that $\overline{TGDP}_t = \overline{GDP}_{ht} = \overline{GDP}_{ft}$.

HT2 respectively with $\left\{\hat{\lambda}_{1i}\overline{y}_t, \hat{\lambda}_{2i}\overline{TGDP}_t, \hat{\lambda}_{3i}\overline{SIM}_t, \hat{\lambda}_{4i}\overline{RLF}_t, \hat{\lambda}_{5i}\overline{RER}_t\right\}$.[5]

We provide these estimation results in Table 5. From Table 5(a) for the triple index model, we find that the impacts of foreign GDP, RLF and EMU are all insignificant, while the impact of CEE is smaller than reported in Table 2(a). The HT estimation results show that the distance is significantly more negative while both common language and border dummies become insignificant. Turning to Table 5(b) for the double index model, most FEM estimates are quite similar to those reported in Table 2(b). Main differences are: the coefficients on EMU and RLF are both insignificant while the impact of CEE is now much smaller. The HT estimates of the impacts of individual specific variables confirms similar findings to those reported in Table 2(c). Interestingly, once the instrument set is augmented with $\left\{\hat{\lambda}_{1i}\overline{y}_t, \hat{\lambda}_{2i}\overline{TGDP}_t, \hat{\lambda}_{3i}\overline{SIM}_t, \hat{\lambda}_{4i}\overline{RLF}_t, \hat{\lambda}_{5i}\overline{RER}_t\right\}$, we find that all individual specific variables (distance, common language and border) become strongly significant with expected signs. This may indicate the potential importance of using additional source of instruments.

Table 5 about here

Comparing and evaluating the above three extended estimation results in light of our *a priori* expectations, we may reach to the following conclusion: *First*, the results obtained using the conventional $T-1$ fixed dummies (with their homogeneous impacts) are least satisfactory, which might indicate that the conventional approach may be too limited to accommodate the time effects. *Second*, the estimation results with an observed time factor are somewhat mixed in the sense that most estimation results are relatively sensible for the double index model, but not quite for the triple index model. *Finally*, the estimation results with unobserved time factor (in conjunction with the PCCE estimation) are similar to but more sensible than those obtained using the observed common time factor. In particular, the results of Table 5(b) for the double index model for explaining the patterns of bilateral total trade flows are mostly sensible. Therefore, this overall observation may suggest the potential advantage of our proposed approach over the conventional one based on the fixed time dummies.

We now summarise our main findings in a broad context combining all of the above estimation results together but mainly focussing on estimation results in Tables 2 and 5. We begin with the triple index model in explaining the pattern of bilateral real exports. The impact of the GDP variables is mostly significant and positive with the total impact being just under 2. Only the impacts of foreign population are found to be significant but negative. The impact of similarity in relative size of trading countries are mostly significant and positive, ranging between 0.16 and 0.35. The impact of differences in relative factor endowments are mostly significant and positive, ranging between 0.01 and 0.03. The impacts of CEE are all positive and significant, mostly around 0.3. The results are mixed for the impacts of EMU, but mostly insignificant in both Tables 2(a) and 5(a). The impacts of distance are mixed in Table 2(c), but become significantly negative in Table 5(a). The impacts of common

[5] In practice, the subset of $\left\{\hat{\lambda}_{1i}\overline{y}_t, \hat{\lambda}_{2i}\overline{TGDP}_t, \hat{\lambda}_{3i}\overline{SIM}_t, \hat{\lambda}_{4i}\overline{RLF}_t, \hat{\lambda}_{5i}\overline{RER}_t\right\}$ can be parsimoniously used as instruments.

language are mixed in Table 2(c) but become insignificant in Table 5(a). The impacts of common border are mostly significant and range between 0.49 and 0.76.

Next, we move on to the double index model in explaining the pattern of bilateral real total trades. The impacts of GDP are all significant and positive, ranging between 1.63 and 2.02. The impacts of population are insignificant. The impacts of SIM are all significant and positive, ranging between 1.11 and 1.4, which are significantly larger than its impacts on exports only. The impacts of RLF are significantly positive in Table 2(b), but insignificant in Table 5(b). The impacts of CEE are all significantly positive. The impact of EMU is significantly positive in Table 2(b), but becomes insignificant in Table 5(b). The impacts of distance, common language and common border are mostly significantly negative, positive and positive, respectively.

Though the above estimation results and their interpretations are more or less consistent with our *a priori* expectations, we notice that there are two conflicting findings between the benchmark estimation results in Table 2 and the extended HT estimation results in Table 5; namely, the role of the RFL and EMU variables. The impacts of RLF are found to be significant and positive in Table 2, but become insignificant in Table 5, whilst the impacts of EMU are found to be mostly insignificant, but only become significantly positive in Table 2(b). As mentioned earlier, the impact of RLF on total trade flows might not be unambiguous since the total trade flows are the sum of inter- and intra-industry trades. Next, we earlier discussed that empirical evidence on the impact of EMU on trade flows is mixed. In particular, de Souza (2002) argues that either the periods are too short after an introduction of the Euro to use the EMU dummy as an adequate proxy for monetary union membership, or forward looking agents anticipate and thus discount the increase of trade associated with the EMU membership. In this regard we also expect that the impacts of EMU are yet to be significant. Along this line of logics we may conclude that the estimation results obtained using our proposed HT methodology seem to be much more sensible.

5 Conclusions

In this paper we follow recent developments of panel data studies surrounding the use of common time effects, and advance an alternative estimation framework in which we explicitly allow for the existence of observed and/or unobserved common time-specific factors and individual responses to those common factors are heterogeneous across country pairs. We then generalize the HT estimation methodology in the context of the extended panel data model and develop the underlying econometric theory.

We apply our proposed HT estimation technique along with the conventional approaches to a comprehensive analysis of the gravity equation of bilateral trade amongst the 15 European countries over 1960-2001. Empirical results clearly demonstrate that our proposed approach fits the data reasonably well and its estimations results are sensible in a number of different dimensions. In particular, our proposed (extended) HT estimation provides much more sensible results than the conventional approach based on the fixed time dummies, especially in terms of the impacts of individual sepcific variablse such as distance, common border and langauage dummies. We further notice that our proposed HT estimation results produce more sensible predictions on the impacts of differences in factor endowments and of the common currency dummy on intra-EU trade flows than the conventional approach with and without fixed time dummies. This observation may indicate the importance of properly accommodating a certain degree of cross section dependence through unobserved heterogeneous time effects, otherwise the resulting estimates would be severely biased.

A couple of extensions will be desirable. *First*, it would be worth investigating the effect of globalization on transport costs more explicitly. For instance, transport and communication revolutions should lead to a dispersion of economic activity. Although this dispersion did not occur with the reduction in transportation costs during the first wave of the globalization in the 20th century, the second wave of globalization associated with recent information and communication technologies revolution should lead to an integrated equilibrium view of the 'death of the distance'. Hence, it would be interesting to study the effect of an 'augmented' trade-barrier function which make transport costs both dependent on and independent of distance in addition to the standard trade-barrier function that only comprehend variables like distance, common language and common border dummies as employed in the current paper, see for example Brun *et al.* (2002). *Secondly*, it would be interesting to analyse the gravity models of international trade over different time periods. For instance, the impacts of intra- and inter-industry trades will be different over different time periods, and thus we might expect that the role of certain explanatory variables such as RLF and EMU changes accordingly. Of the particular importance will be to reexamine the issue concerning the impacts of the Euro on the bilateral intra-EU trade once the data over the longer time periods will be available, as we argue that the insignificantly estimated impact of the EMU dummy might be due to the shortage of observations.

Data Appendix

We now describe how the variables are constructed. All variables are converted in constant dollar prices with 1995 as the base year. Bilateral exports and imports are defined as logarithms of real export $\left(X^R_{hft}\right)$ and real imports $\left(M^R_{hft}\right)$, X^R_{hft} and M^R_{hft} are obtained by $X^R_{hft} = X^N_{hft} \times \frac{100}{XPI_{US}}$, $M^R_{hft} = M^N_{hft} \times \frac{100}{MPI_{US}}$, where X^N_{hft} and M^N_{hft} are bilateral export and import measured in millions of current US dollars, and XPI_{US} and MPI_{US} are the US export and import price indices. Then, the total volume of trade is given by $Trade = \ln\left(X^R_{hft} + M^R_{hft}\right)$. GDP of home and foreign country are defined as logarithms of GDP^R_{ht} and GDP^R_{ft}, where GDP^R_{ht} and GDP^R_{ft} are gross domestic products at constant dollar of country h and f, respectively, and the total GDP is defined as $TGDP_{it} = \ln\left(GDP^R_{ht} + GDP^R_{ft}\right)$. GDP's are originally expressed in million Euro for the twelve countries that joined the European Monetary Union (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxemburg, Netherlands, Portugal, Spain) and in millions of current national currency for Denmark, Sweden and UK (GDP^N). In the last three cases the original nominal values of GDP have been deflated by the GDP deflator ($GDPD$, 1995 = 100) of the respective countries whereas for the remaining countries the European GDP deflator has been used. We also convert GDPs in US dollar at the exchange rate of 1995 (mean over period) in order to exclude the effect of a dollar depreciation or appreciation as follow:

$$GDP^R_{hft} = GPD^N_{hft} \times \frac{100}{GDPD_{ht}} \times \left(\frac{US\$}{NC_h}\right)_{1995},$$

where NC_h stands for national currency of the home country. Population of home and foreign countries are defined as logarithms of POP_{ht} and POP_{ft}, where POP_{ht} and POP_{ft} are the population of country h and f measured in million of inhabitants and the total population is defined as $TPOP_{it} = \ln\left(POP_{ht} + POP_{ft}\right)$. Next, we construct SIM_{it} and RLF_{it} respectively by

$$SIM_{it} = \ln\left[1 - \left(\frac{GDP^R_{ht}}{GDP^R_{ht} + GDP^R_{ft}}\right)^2 - \left(\frac{GDP^R_{ft}}{GDP^R_{ft} + GDP^R_{ht}}\right)^2\right],$$

$$RLF_{it} = \ln\left|PGDP^R_{ft} - PGDP^R_{ht}\right|,$$

where $PGDP$ is per capita GDP. Real exchange rates in constant dollars at 1995 are defined as $RER_{it} = NER_{it} \times XPI_{US}$, where NER_{it} is nominal exchange rate between currencies h and f in year t in terms of dollars. Lastly, the distance between countries is measured as the great circle distance between national capitals in kilometers.

The data sources are as follows: Export and import price indices are collected from OECD *Economic Outlook*, GDP deflators from World Bank *World Development Indicators*, and bilateral nominal export and import data (X^N and M^N) from OECD, *Statistical Compendium*, Main Economic Indicator, Yearly Statistic of Foreign Trade in current dollars, GDP from IMF *International Financial Statistics*, Economic Concept View, National Accounts, per capita GDP (already converted in constant dollars) from the World Bank *World Development Indicators*, population from the World Bank *World Development Indicators*, and NER from OECD, *National Accounts*, Volume I.

Table Appendix

Table 1 Descriptive and Summary Statistics

Panel A	1960	1970	1980	1990	2000
Share of US on Extra-EU trade	16.5*	26.3*	33.8**	19**	21.9***
Share of Intra-EU on EU trade	37.2*	49.8*	50.5**	59.7**	61.7***
Share of Export on Intra-EU trade	52.4*	51.6*	51.1**	49.7**	51.2***
Panel B	60/70	70/80	80/90	90/00	
Average Growth of GDP	8.9	16.4	7.8	3.5	
Average Growth of Intra-EU trade	11.5	17.3	9.3	5.8	
Average Growth of Total EU trade	10.3	20.1	7.2	3.9	
Average Growth of Bilateral Exchange Rate	0.12	7.9	-1.4	-3.7	

Notes: Source: *Trade Policy Review of the European Union: a Report by the Secretariat of the WTO*, WTO (2002) and *Statistical Yearbook*, Eurostat *(1997)*. '*' denotes values for EU9 (Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxemburg, Netherlands), '**' for EU12 (EU9 plus Greece, Portugal and Spain) and '***' for EU15 (EU12 plus Denmark, Sweden and United Kingdom) countries, respectively.

Table 2(a). Alternative Panel Data Estimation Results for Triple Index Models

	Basic Model				Augmented Model				Full Model			
	OLS	BTW	FEM	REM	OLS	BTW	FEM	REM	OLS	BTW	FEM	REM
Con	−11.8* (.241)[2]	−6.1* (1.89)		−16.5* (.59)	−12.7* (.266)	−8.4* (1.94)		−16* (.745)	−10* (.211)	−10* (1.24)		−15.3* (.73)
GDP_h	0.73* (.015)	.49* (.106)	.64* (.035)	.78* (.03)	.68* (.015)	.51* (.101)	.55* (.034)	.67* (.029)	.76* (.007)	.73* (.041)	.49* (.03)	.73* (.021)
GDP_f	1.25* (.015)	.99* (.106)	1.5* (.035)	1.55* (.03)	1.21* (.015)	1.03* (.101)	1.4* (.034)	1.4* (.029)	.87* (.007)	.85* (.041)	1.43* (.03)	1.18* (.021)
POP_h	.01 (.019)	.27* (.124)	.06 (.127)	−.01 (.058)	.04* (.019)	.25* (.121)	−.02 (.124)	.07 (.057)				
POP_f	−.52* (.019)	−.25* (.124)	.72* (.127)	−.61* (.058)	−.48* (.019)	−.26* (.121)	.64* (.124)	−.54* (.057)				
SIM									.11* (.013)	.04 (.071)	.35* (.051)	.30* (.041)
RLF									.03* (.007)	.02 (.05)	.03* (.007)	.03* (.007)
RER									.1* (.003)	.09* (.019)	.08* (.007)	.09* (.007)
CEE					.28* (.019)	−.12 (.202)	.28* (.013)	.29* (.014)	.33* (.019)	−.08 (.19)	.31* (.014)	.32* (.013)
EMU					.07 (.044)	−2.21 (1.44)	−.01 (.023)	−.01 (.023)	.17* (.043)	−1.1 (1.49)	−.01 (.023)	.01 (.024)
Dist	−1.05* (.015)	−1.2* (.086)		−.92* (.079)	−.79* (.018)	−.92* (.109)		−.71* (.097)	−.68* (.019)	−.77* (.11)		−.57* (.096)
Lan					.51* (.028)	.48* (.16)		.59* (.155)	.25* (.029)	.27** (.163)		.41* (.152)
Bor					.45* (.029)	.52* (.167)		.41* (.161)	.51* (.028)	.60* (.163)		.44* (.156)

Notes: Here the dependent variable is logarithm of real export. OLS stands for the pooled OLS estimator, BTW the between estimator; FEM fixed effects estimator and REM random effects estimator, respectively. Figures in (.) indicate the standard error. '*' denotes coefficient significant at the 5% level of significance. '**'denotes coefficient significant at the 1% level of significance. Hausman statistic rejects the null hypothesis of no correlation between explanatory variables and unobserved individual effects in all cases considered.

Table 2(b). Alternative Panel Data Estimation Results for Double Index Models

	Basic Model				Augmented Model				Full Model			
	OLS	BTW	FEM	REM	OLS	BTW	FEM	REM	OLS	BTW	FEM	REM
Con	-7.5^{*} (.361)	.02 (2.64)		-16.5^{*} (.94)	-7.9^{*} (.39)	-2.3 (2.78)		-15.4^{*} (1.18)	-10.9^{*} (.247)	-9.7^{*} (1.55)		-13.9^{*} (.88)
GDP	1.7^{*} (.03)	$.98^{*}$ (.234)	2.2^{*} (.031)	2.3^{*} (.023)	1.5^{*} (.032)	1.08^{*} (.231)	1.9^{*} (.031)	2.1^{*} (.025)	1.57^{*} (.012)	1.5^{*} (.08)	1.81^{*} (.019)	1.79^{*} (.018)
POP	$-.52^{*}$ (.039)	.24 (.281)	.03 (.164)	$-.83^{*}$ (.099)	$-.38^{*}$ (.039)	.12 (.279)	.01 (.154)	$-.74^{*}$ (.095)				
SIM									$.88^{*}$ (.017)	$.81^{*}$ (.104)	1.17^{*} (.055)	1.14^{*} (.045)
RLF									$.03^{*}$ (.008)	.01 (.06)	$.03^{*}$ (.008)	$.03^{*}$ (.008)
RER									$.09^{*}$ (.004)	$.09^{*}$ (.023)	$.06^{*}$ (.009)	$.07^{*}$ (.008)
CEE					$.47^{*}$ (.03)	.14 (.321)	$.14^{*}$ (.028)	$.36^{*}$ (.016)	$.32^{*}$ (.022)	$-.03$ (.244)	$.31^{*}$ (.016)	$.32^{*}$ (.016)
EMU					$.22^{*}$ (.069)	.89 (.778)	$.31^{*}$ (.016)	$.14^{*}$ (.028)	0.2^{*} (.051)	-1.4 (1.84)	$.08^{*}$ (.027)	$.09^{*}$ (.027)
Dist	-1.2^{*} (.022)	-1.3^{*} (.129)		$-.97^{*}$ (.124)	$-.93^{*}$ (.028)	-1.03^{*} (.169)		$-.77^{*}$ (.156)	$-.64^{*}$ (.022)	$-.71^{*}$ (.13)		$-.6^{*}$ (.116)
Lan					$.36^{*}$ (.043)	.24 (.255)		$.51^{*}$ (.247)	$.23^{*}$ (.034)	.24 (.201)		$.41^{*}$ (.185)
Bor					$.42^{*}$ (.045)	$.58^{*}$ (.269)		.39 (.258)	$.52^{*}$ (.034)	$.61^{*}$ (.201)		$.44^{*}$ (.19)

Notes: Here the dependent variable is logarithm of real export; Hausman statistic rejects the null hypothesis of no correlation between explanatory variables and unobserved individual effects in all cases considered. See also notes to Table 2(a).

Table 2(c). Hausman and Taylor Estimation Results

	Triple index model			Double index model		
	OLS	HT1	HT2	OLS	HT1	HT2
Dist	$-.57^{*}$ $(.026)^{2}$	$-.43^{*}$ (.208)	$-.34$ (.208)	$-.6^{*}$ (.021)	$-.38^{*}$ (.192)	$-.34^{**}$ (.199)
Lan	0.45^{*} (.041)	1.05 (.755)	1.57^{*} (.72)	0.45^{*} (.034)	1.56^{*} (.707)	1.8^{*} (.695)
Bor	0.43^{*} (.042)	0.53^{**} (.282)	0.61^{*} (.289)	0.43^{*} (.035)	0.6^{*} (.258)	0.64^{*} (.275)

Notes: Here we consider only the full specifications, and those slope coefficients are already reported as FEM estimates in Tables 2(a) and 2(b). The set of instrument variables used in the HT estimation are as follows: $\{RER\}$ for HT1 and $\{RER, GDP, SIM, RLF\}$ for HT2. See also notes to Tables 2(a) and 2(b).

Table 3(a). Alternative Panel Data Estimation Results for Triple Index Models with Time Dummies

	Basic Model			Augmented Model			Full Model		
	OLS	FEM	REM	OLS	FEM	REM	OLS	FEM	REM
Con	-7.15^* (.314)		-19.3^* (.859)	-9.64^* (.323)		-20.2^* (.996)	-10.6^* (.215)		-18.7^* (.997)
GDP_h	0.51^* (.018)	0.97^* (.044)	0.91^* (.041)	0.54^* (.017)	0.91^* (.043)	0.86^* (.041)	0.73^* (.007)	1.04^* (.045)	0.84^* (.029)
GDP_f	1.03^* (.018)	1.82^* (.044)	1.68^* (.041)	1.06^* (.017)	1.76^* (.043)	1.62^* (.041)	0.84^* (.007)	1.97^* (.045)	1.32^* (.029)
POP_h	0.24^* (.021)	0.03 (.123)	$-.14^*$ (.063)	0.21^* (.021)	$-.007$ (.12)	$-.11^{**}$ (.062)			
POP_f	$-.28^*$ (.021)	0.69^* (.123)	$-.73^*$ (.063)	$-.32^*$ (.021)	0.65^* (.12)	$-.7^*$ (.062)			
SIM							0.07^* (.012)	0.02 (.052)	0.25^* (.041)
RLF							0.02^* (.007)	0.02^* (.007)	0.02^* (.006)
RER							0.09^* (.003)	0.08^* (.009)	0.06^* (.008)
CEE				0.11^* (.022)	0.29^* (.014)	0.29^* (.015)	0.15^* (.022)	0.33^* (.015)	0.31^* (.015)
EMU				0.13^* (.061)	0.19^* (.031)	0.23^* (.032)	0.18^* (.059)	0.17^* (.032)	0.23^* (.032)
Dist	-1.15^* (.015)		$-.86^*$ (.081)	$-.89^*$ (.018)		$-.61^*$ (.099)	$-.75^*$ (.019)		$-.52^*$ (.1)
Lan				0.51^* (.027)		0.64^* (.156)	0.28^* (.028)		0.62^* (.154)
Bor				0.44^* (.028)		0.41^* (.162)	0.53^* (.028)		0.31^* (.157)

Notes: Here we augment the models in 2(a) by adding the time-specific fixed effects. Hausman statistic rejects the null hypothesis of no correlation between explanatory variables and unobserved individual effects in all cases considered. See also notes to Table 2(a).

Table 3(b). Alternative Panel Data Estimation Results for Double Index Models with Time Dummies

	Basic Model			Augmented Model			Full Model		
	OLS	FEM	REM	OLS	FEM	REM	OLS	FEM	REM
Con	-1.75^* (.12)		-15.5^* (.75)	-3.37^* (.44)		-16.5^* (1.45)	-10.2^* (.257)		-20.2^* (1.2)
GDP	1.03^* (.038)	2.5^* (.084)	2.3^* (.077)	1.07^* (.037)	2.48^* (.081)	2.23^* (.074)	1.53^* (.013)	3.05^* (.078)	2.22^* (.053)
POP	0.18^* (.045)	$-.49^*$ (.154)	$-.96^*$ (.111)	0.11^* (.045)	$-.44^*$ (.147)	$-.9^*$ (.108)			
SIM							0.84^* (.017)	1.42^* (.055)	1.27^* (.049)
RLF							0.02^* (.008)	0.02^* (.007)	0.02^* (.007)
RER							0.09^* (.003)	0.09^* (.01)	0.06^* (.009)
CEE				0.17^* (.034)	0.35^* (.036)	0.31^* (.017)	0.17^* (.026)	0.32^* (.017)	0.31^* (.017)
EMU				0.11 (.091)	0.32^* (.017)	0.37^* (.036)	0.21^* (.07)	0.22^* (.034)	0.28^* (.035)
Dist	-1.3^* (.021)		-1.01^* (.125)	-1.05^* (.027)		$-.76^*$ (.158)	$-.69^*$ (.022)		$-.44^*$ (.123)
Lan				0.35^* (.041)		0.52^* (.248)	0.26^* (.034)		0.65^* (.189)
Bor				0.43^* (.043)		0.41 (.258)	0.54^* (.033)		0.28 (.195)

Notes: Here we augment the models in 2(b) by adding time-specific fixed effects; Hausman statistic rejects the null hypothesis of no correlation between explanatory variables and unobserved individual effects in all cases considered. See also notes to Tables 2(a) and 2(b).

Table 3(c). Hausman and Taylor Estimation Results with Time Dummies

	Triple index model			Double index model		
	OLS	HT1	HT2	OLS	HT1	HT2
Dist	$-.14^*$ (.036)	0.27 (.331)	0.52 (.388)	$-.07$ (.045)	0.38 (.43)	0.67 (.529)
Lan	0.92^* (.057)	3.1^* (1.17)	4.71^* (1.31)	0.94^* (.072)	3.27^* (1.52)	5.06^* (1.78)
Bor	.06 (.059)	0.4 (0.44)	0.7 (.54)	0.03 (.074)	0.39 (.583)	0.71 (.734)

Notes: See notes to Tables 2(c), 3(a) and 3(b).

Table 4. FEM and HT Estimation Results with an Observed Time Factor

Table 4(a). Triple index model

	FEM[1]	OLS	HT1	HT2	HT3	HT4
GDP_h	1.09^* (.035)[2]					
GDP_f	0.88^* (.035)					
SIM	0.21^* (.055)					
RLF	0.01^* (.005)					
RER	0.16^* (0.01)					
CEE	0.33^* (.011)					
EMU	$-.06^*$ (.018)					
Dist		$-.43^*$ (.02)	$-.23$ (.344)	$-.43^*$ (.161)	$-.13$ (.367)	$-.43^*$ (.161)
Lan		0.25^* (.032)	1.26 (1.68)	0.25 (.472)	1.85 (1.81)	0.24 (.473)
Bor		0.49^* (.033)	0.65^* (.312)	0.49^* (.222)	0.74^* (.319)	0.49^* (.222)

Notes: Here we augment the models in 2(a) by adding $RERT$. See also notes to Table 2(a). The set of instrument variables used in the HT estimation are as follows: $\{RER\}$ for HT1, $\{RER, GDP, SIM, RLF\}$ for HT2, and HT3 and HT4 are HT1 and HT2 respectively combined with $\left\{\hat{\lambda}_i RERT_t\right\}$.

Table 4(b). Double index model

	FEM[1]	OLS	HT1	HT2	HT3	HT4
GDP	2.02^* (.03)[2]					
SIM	1.4^* (.062)					
RLF	0.009 (.006)					
RER	0.11^* (.011)					
CEE	0.31^* (.012)					
EMU	$-.008$ (.019)					
Dist		$-.4^*$ (.024)	$-.38^{**}$ (.208)	$-.19$ (.227)	$-.35^{**}$ (.211)	$-.17$ (.227)
Lan		0.39^* (.038)	0.44 (.641)	1.45^* (.671)	0.64 (.627)	1.6^* (.081)
Bor		0.43^* (.041)	0.45 (.317)	0.61^* (.309)	0.48 (.312)	0.63^* (.311)

Notes: Here we augment the models in 2(b) by adding the single observed time-specific factor, $RERT$. See also notes to Table 4(a).

Table 5 FEM and HT Estimation Results with an Unobserved Time Factor

Table 5(a). Triple index model

	FEM[1]	OLS	HT1	HT2	HT3	HT4
GDP_h	1.26* (.075)[2]					
GDP_f	−.03 (.075)					
SIM	0.16* (.081)					
RLF	−.0001 (.005)					
RER	0.03* (.011)					
CEE	0.12* (.013)					
EMU	−.001 (.018)					
Dist		−.97* (.039)	−.72* (.299)	−.92* (.268)	−.6* (.302)	−.94* (.254)
Lan		0.31* (.062)	1.57 (1.26)	0.5 (1.12)	2.25** (1.21)	0.46 (1.01)
Bor		0.56* (.064)	0.76* (.385)	0.59 (.371)	0.87* (.396)	0.59 (.364)

Notes: Here we follow Pesaran (2002) and augment the model in 2(a) by adding multiple factors, $\{\overline{y}_t, \overline{TGDP}_t, \overline{SIM}_t, \overline{RLF}_t, \overline{RER}_t\}$, where the bar over the variable indicates its cross-section average. See also notes to Table 2(a). The set of instrument variables used in the HT estimation are: $\{RER\}$ for HT1, $\{RER, GDP, SIM, RLF\}$ for HT2, and HT3 and HT4 are HT1 and HT2 respectively combined with $\left\{\hat{\lambda}_{1i}\overline{y}_t, \hat{\lambda}_{2i}\overline{TGDP}_t, \hat{\lambda}_{3i}\overline{SIM}_t, \hat{\lambda}_{4i}\overline{RLF}_t, \hat{\lambda}_{5i}\overline{RER}_t\right\}$.

Table 5(b). Double index model

	FEM	OLS	HT1	HT2	HT3	HT4
GDP	1.63* (.115)					
SIM	1.11* (.093)					
RLF	−.001 (.005)					
RER	0.03* (.014)					
CEE	0.14* (.013)					
EMU	−.01 (.017)					
Dist		−.73* (.023)	−.38** (.23)	−.41** (.233)	−.46* (.218)	−.48* (.209)
Lan		0.51* (.037)	2.33* (0.78)	2.17* (.76)	1.89* (.638)	1.82* (.628)
Bor		0.44* (.038)	0.72* (0.28)	0.7* (.266)	0.65* (.255)	0.65* (.245)

Notes: Here we follow Pesaran (2002) and augment the model in 2(b) by adding $\{\overline{y}_t, \overline{TGDP}_t, \overline{SIM}_t, \overline{RLF}_t, \overline{RER}_t\}$. See also notes to Table 5(a).

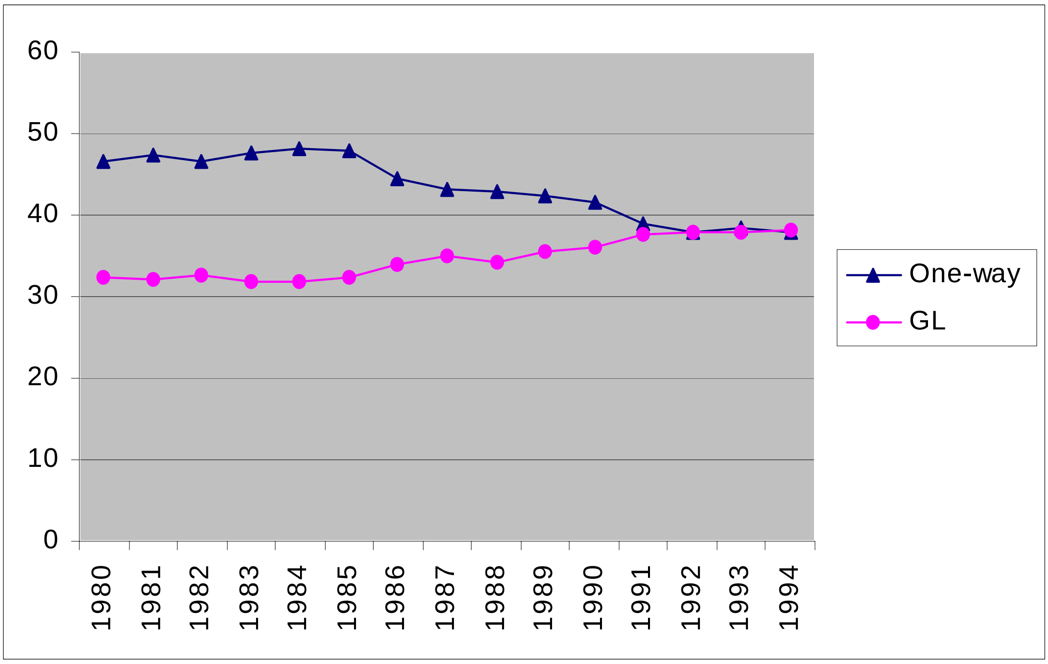

Figure 1 Evolution of trade in intra-EU trade 1980-1994

Notes: The Grubel-Lloyd indicator measures the share of intra-industry trade and one-way trade represents inter-industry trade. See also the footnote 1. Source: *Single Market Review,* European Commission *(1997):* Trade Patterns inside the Single Market, page 50.

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