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GRAVITY MODELS OF INTRA-EU TRADE: APPLICATION OF THE CCEP-HT ESTIMATION IN HETEROGENEOUS PANELS WITH UNOBSERVED COMMON TIME-SPECIFIC FACTORS

LAURA SERLENGA[a] AND YONGCHEOL SHIN[b]*

[a] *Department of Economics, University of Bari, Bari, Italy*
[b] *LUBS, University of Leeds, Leeds, UK*

SUMMARY

We follow recent developments of panel data studies and allow for the existence of both observed and unobserved common factors where their individual responses are allowed to be heterogeneous. We then develop a generalized Hausman–Taylor estimation methodology, and apply our proposed estimation technique to an analysis of the gravity equation of bilateral trade flows among 15 European countries over 1960–2001. Empirical results demonstrate that our proposed approach provides more sensible results than the conventional approach based on fixed time dummies. These findings may highlight the importance of allowing for a certain degree of cross-section dependence through unobserved heterogeneous time-specific effects; the resulting estimates would otherwise be severely biased. Copyright © 2007 John Wiley & Sons, Ltd.

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1. INTRODUCTION

The gravity model of international trade flows is widely used as a baseline model for estimating the impact of a variety of policy issues such as regional trading groups, currency unions and trade distortions (e.g., Bougheas *et al.*, 1999; Frankel and Rose, 2002; Glick and Rose, 2002; De Sousa J and Disdier A, unpublished 2002; Martinez-Zaroso and Nowak-Lehmann, 2003). Further, since the seminal paper by Anderson (1979), attempts have been made to derive the prediction of the gravity model from different theoretical models. Thus, as Davis (2000) suggests, the gravity model has gone in two decades from theoretical orphan to having several competing claims to maternity.

Empirically, the use of conventional cross-section estimation is criticized since it is not able to deal with bilateral (exporter and/or importer) heterogeneity. In this regard a panel-based approach will be more desirable because such heterogeneity can be modelled by including country-pair individual effects. Although a number of panel estimation techniques are used, the assumption that individual effects are uncorrelated with all the regressors is convincingly rejected in almost all studies, so the fixed-effects estimator is the preferred method. The problem with a fixed-effects approach is that it is not able to estimate the impacts on trade flows of time-invariant variables such as distance and, in the case of the gravity model, consistent estimations of the time-invariant effects are also important. To obtain estimates of these time-invariant effects Cheng and Wall (2005) estimate the regression of the (estimated) individual effects on individual-specific variables by ordinary least squares (OLS). This approach ignores the potential correlation between

* Correspondence to: Yongcheol Shin, LUBS, University of Leeds, Leeds LS2 9JT, UK. E-mail: Y.Shin@leeds.ac.uk

individual specific variables and individual effects, and thus the resulting estimates are likely to be severely biased. In order to properly address this issue we should employ the Hausman and Taylor (1981; hereafter HT) instrumental variable estimation technique. This paper aims to develop an econometric procedure to consistently estimate a gravity model in panel data that allows both time-varying and time-invariant effects.

Further, recent empirical studies emphasize the importance of explicitly allowing for the presence of time-specific effects in order to capture business cycle effects or deal with globalization issues. These studies have adopted the simple approach of augmenting the model with the fixed time dummies in the panel regression (Matyas, 1997). However, this paper follows recent developments in panel data studies by accommodating the presence of (heterogeneous) unobserved common time effects (e.g., Ahn *et al.*, 2001; Bai and Ng, 2002; Phillips and Sul, 2003). We do this by explicitly allowing for observed and/or unobserved common time-specific factors together with the individual effects across country pairs. Due to a certain degree of cross-section dependence introduced by unobserved (heterogeneous) time-specific factors the conventional estimators would be seriously biased. In this paper we follow the correlated common effect pooled (CCEP) estimation approach recently advanced by Pesaran (2006), and develop the associated CCEP-HT estimation theory.

We apply our proposed estimation technique along with the conventional panel data approaches to an analysis of the gravity equation of bilateral trade flows amongst 15 EU member countries over the period 1960–2001. Impacts of core explanatory variables such as GDP, population, distance, common language, common border, free-trade area and currency union membership dummies are examined. Following recent theoretical developments (e.g., Helpman, 1987; Egger, 2002) we also include variables measuring both similarity in relative size of trading countries and differences in relative factor endowments. Our main empirical findings using the generalized panel data set-up are fourfold. First, the impact of the total GDP is significantly positive, whereas the impact of population is mostly insignificant. Second, the impacts of custom union membership are positively significant, while the results are mixed for European Monetary Union (EMU) membership. Third, the impact of similarity in relative size of trading countries is mostly significant and positive, while the impact of differences in relative factor endowments (RLF) is ambiguous. Finally, for individual-specific variables, we find that the impacts of distance, common language dummy and common border dummy are mostly significantly negative, positive and positive, respectively.

Our econometric conclusion is that when using the conventional approach based on (homogeneous) fixed time-specific effects, the estimated impact of the total GDP is too large, whereas the associated CCEP-HT estimates of the impacts of distance and common border dummy are no longer significant. Furthermore, we find that the estimation results obtained using the CCEP-HT estimation procedure produce more sensible predictions on the impacts of differences in factor endowments (RLF) and of the common currency dummy on EU trade flows. Our findings show that the impacts of these variables become insignificant, which is plausible for two reasons. First, considering that the total trade flows are the sum of inter- and intra-industry trades, and RLF is positively correlated only with inter-industry trade, 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 mixed; see Rose and van Wincoop (2001), Rose (AK, unpublished 2002), Engel and Rose (2002), Frankel and Rose (2002) and Glick and Rose (2002) for a large positive effect of currency union on trade, and Persson (2001), Pakko and Wall (2002) and De Nardis and Vicarelli (2003) for negative or insignificant effects. As argued by de Souza (2002), the (evaluation) periods are too short after an introduction of the euro in 1999 to use the EMU dummy as an adequate proxy for monetary union membership. Therefore, we expect the timeframe to be too short for the impacts

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of EMU to be materialized. This result may indicate the importance of properly accommodating a certain degree of cross-section dependence through unobserved heterogeneous time-specific effects. Finally, it is worth noting that once the correlation between the common language dummy and individual effect is accommodated by the CCEP-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 compensating each other, whereas the role of cultural affinities proxied by common language dummy becomes more significant. This is strong evidence of the value of our proposed econometric framework for estimating gravity models.

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

2. OVERVIEW ON GRAVITY MODELS OF INTERNATIONAL TRADE

The gravity model has been successfully applied to explain the determinants of varying types of flows, such as migration, flows of buyers to shopping centres, 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. The early empirical use of the gravity model is criticized because of its weak theoretical foundation; however, that is not true now. Since the seminal paper by Anderson (1979) it is recognized that the prediction of the gravity model can be derived from different structural models such as Ricardian models, Heckscher–Olin (HO) models and increasing returns to scale (IRS) models of the New Trade Theory (e.g., Bergstrand, 1990; Leamer, 1992; Deardorff, 1998; Eaton and Kortum, 2002).[1]

Although the gravity model per se cannot be used to test the validity of any of these trade theories against each other, its empirical success is due to its ability to incorporate most of empirical phenomena typically 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 model generates gravity-like trade predictions. The HO 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 they find robust evidence that an IRS-based trade theory provides an important reason why the gravity equation fits trade flows data.

Most of earlier empirical studies relied upon the use of cross-section estimation techniques. However, it is well known that cross-section OLS estimation ignores heterogeneous characteristics related to the bilateral trade relationship. For instance, a country would export different amounts of the same product to two different countries, even if their GDPs are identical and they are equidistant from the exporter. The cross-section estimates fail to account for these heterogeneous factors and are likely to suffer from a substantial heterogeneity bias. A panel data approach will

[1] These models differ by the way product specialization is obtained in equilibrium: technology differences across countries in the Ricardian model, factor proportion differences in the HO model, and increasing returns at the firm level in the IRS model.

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be more desirable because the effects of such heterogeneity can be modelled by including country-pair 'individual' effects. In this regard Cheng and Wall (2005) propose the panel data model with two-way fixed effects:[2]

$$y_{hft} = \alpha_{hf} + \theta_t + \boldsymbol{\beta}_1'\mathbf{x}_{hft} + \boldsymbol{\beta}_2'\mathbf{x}_{ht} + \boldsymbol{\beta}_3'\mathbf{x}_{ft} + \boldsymbol{\beta}_4'\mathbf{z}_{hf} + u_{hft} \quad (1)$$

for $h, f = 1, \ldots, N$, $h \neq f$, $t = 1, \ldots, T$, 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), $\mathbf{x}_{ht}$ and $\mathbf{x}_{ft}$ 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), α_{hf} is a (country-pair-specific) individual effect that might be correlated with some or all of the explanatory variables, θ_ts are time-specific effects common to all cross-section units that are meant to correct for the impact of all the individual invariant determinants such as potential trend or business cycle, and the disturbance terms u_{hft} are assumed to be i.i.d. with zero mean and constant variance across all h, f, t. In general, the bilateral (fixed) effects, α_{hf}, account for any time-invariant geographical, political, cultural and other bilateral influences which will lead to deviations from a country pair's 'normal' propensity to trade. Since most are unobserved, including bilateral interaction fixed effects is the natural way of controlling them. Although a number of panel estimation techniques such as the pooled OLS, the fixed effects model (FEM) and the random effects model (REM) have been applied, the assumption that individual effects, α_{hf}, are uncorrelated with all the regressors is convincingly rejected in almost all studies (e.g., Egger, 2002). Therefore, FEM estimation has been mostly preferred in the literature in order to avoid potentially biased estimation.

It is worth noting that the FEM is not able to estimate the coefficients on time-invariant variables such as distance, common border or language dummies, since those variables are eliminated by the within transformation. Although it is difficult to find an appropriate measure of economic distance and control for contiguity (e.g., considering Canada and the USA, 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 (2005) suggest estimating the additional regression of the (estimated) individual effects on individual-specific variables by OLS. This approach clearly suffers from the potential bias stemming from the correlation between individual specific variables and individual effects. In order to properly address the issue of such a correlation we should employ the Hausman and Taylor (1981) instrumental variable estimation, which provides consistent estimation of the coefficients on time-invariant variables. For example, Brun *et al.* (2005) 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.

The triple index model as given in (2) is not the only way of representing the panel data-based gravity model of international trade. Thus we now consider the following more conventional double index panel data model:

$$y_{it} = \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\gamma}'\mathbf{z}_i + \alpha_i + \theta_t + u_{it}, i = 1, \ldots, N, t = 1, \ldots, N \quad (2)$$

[2] Matyas (1997) argues that the proper econometric specification of the gravity model should be a 'triple-way model', where time, exporter and importer effects are specified as fixed and unobservable; namely, the bilateral trade interaction effects, α_{hf} in (1) are decomposed as export and import country-specific effects, α_h and α_f, respectively. However, Egger and Pfaffermayr (2003) demonstrate that when Matyas' model is extended to include bilateral trade interaction (dummy) effects, then the three-way specification is identical to (1) with time and bilateral effects only (see also Baltagi *et al.*, 2003).

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where an index i represents each country-pair hf such that $\alpha_i = \alpha_{hf}$ and $u_{it} = u_{hft}$. Notice that variables in $\mathbf{x}_{it}$ are defined as a combination of features of the countries in each pair, but importantly embrace variables, $\mathbf{x}_{hft}$, $\mathbf{x}_{ht}$ and $\mathbf{x}_{ft}$, respectively. Time-invariant regressors are now included in $\mathbf{z}_i$ that coincide with $\mathbf{z}_{hf}$. For instance, De Sousa and Disdier (2002) use (2) to investigate the role of consumers' 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, but also apply the HT estimation to consistently estimate the impacts of trading countries' characteristics (see also Glick and Rose, 2002; Egger, 2004).

3. THE HAUSMAN–TAYLOR ESTIMATION IN HETEROGENEOUS PANELS WITH TIME-SPECIFIC COMMON FACTORS

We begin with the double-indexed panel-data model (2), which can be rewritten as

$$y_{it} = \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\gamma}'\mathbf{z}_i + \varepsilon_{it},\ i = 1, \ldots, N,\ t = 1, \ldots, T \tag{3}$$

with the two-way error components structure

$$\varepsilon_{it} = \alpha_i + \theta_t + u_{it} \tag{4}$$

where $\mathbf{x}_{it} = (x_{1,it}, \ldots, x_{k,it})'$ is a $k \times 1$ vector of variables that vary over individuals and time periods, $\mathbf{z}_i = (z_{1,i}, \ldots, z_{g,i})'$ is a $g \times 1$ vector of individual-specific variables, $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_k)'$ and $\boldsymbol{\gamma} = (\gamma_1, \ldots, \gamma_g)'$ are conformably defined column vectors of parameters, α_i is an individual effect that might be correlated with explanatory variables $\mathbf{x}_{it}$ and $\mathbf{z}_i$, θ_t is the time-specific effects common to all cross-section units, and u_{it} is a zero mean idiosyncratic random disturbance uncorrelated across cross-section units and over time periods. It is then easily seen that various econometric specifications proposed in the literature can be expressed as a variation of (3) and (4).

Recent empirical studies (e.g., De Sousa and Disdier, 2002; Egger, 2002) emphasize the importance of explicitly allowing for the presence of time-specific effects in order to capture globalization issues, but adopt the approach given by (4), where such effects are captured simply by the fixed time dummies, θ_t. Considering that θ_t is usually assumed to measure the common macro shocks or policies, it is too restrictive to impose that an individual's responses with respect to θ_t are homogeneous. Recently, there have been a growing number of panel studies which aim to generalize the homogeneous factor structure given by (4) (e.g., Ahn *et al.*, 2001; Bai and Ng, 2002; Phillips and Sul, 2003; Pesaran, 2006). We thus consider the following generalized panel data model:

$$y_{it} = \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\gamma}'\mathbf{z}_i + \boldsymbol{\pi}_i'\mathbf{s}_t + \varepsilon_{it},\ i = 1, \ldots, N,\ t = 1, \ldots, T \tag{5}$$

$$\varepsilon_{it} = \alpha_i + \varphi_i\theta_t + u_{it} \tag{6}$$

where $\mathbf{s}_t = (s_{1,t}, \ldots, s_{s,t})'$ is an $s \times 1$ vector of observed time-specific factors with conformable parameter vector, $\boldsymbol{\pi}_i = (\pi_{1,i}, \ldots, \pi_{s,i})'$, and φ_is capture heterogeneous individual responses with respect to unobserved common time-specific effects, θ_t. The distinguishing feature of this model

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is that it allows us to accommodate certain degrees of cross section dependence of ε_{it} in (6) via a heterogeneous factor loading coefficient, φ_i.

In this section we will develop the associated HT instrumental variable estimation theory in the context of the panel data model, (5) and (6). We rewrite (5) as

$$y_{it} = \boldsymbol{\beta}_1'\mathbf{x}_{1it} + \boldsymbol{\beta}_2'\mathbf{x}_{2it} + \boldsymbol{\gamma}_1'\mathbf{z}_{1i} + \boldsymbol{\gamma}_2'\mathbf{z}_{2i} + \boldsymbol{\pi}_i'\mathbf{s}_t + \varepsilon_{it} \tag{7}$$

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 $k_1 \times 1$ and $k_2 \times 1$ vectors, $\mathbf{z}_{1i}$, $\mathbf{z}_{2i}$ are $g_1 \times 1$ and $g_2 \times 1$ vectors, and $\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_2$, $\boldsymbol{\gamma}_1$, $\boldsymbol{\gamma}_2$ are conformably defined column vectors of parameters, and make the following assumptions:

Assumption 1 (i) $u_{it} \sim \text{i.i.d.}(0, \sigma_u^2)$. (ii) $\alpha_i \sim \text{i.i.d.}(\alpha, \sigma_\alpha^2)$. (iii) $E(\alpha_i u_{jt}) = 0$ and $E(\theta_t u_{it}) = 0$ for all i, j, t. (iv) $E(\mathbf{x}_{it} u_{js}) = \mathbf{0}$, $E(\mathbf{s}_t u_{is}) = \mathbf{0}$ 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) $\mathbf{x}_{1it}$ and $\mathbf{z}_{1i}$ 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 (see Hausman and Taylor, 1981). In particular, Assumption 1(vi) is necessary to consistently estimate any (nuisance) heterogenous parameters.

It is easily seen that the conventional panel data estimators of $\boldsymbol{\beta}$ and/or $\boldsymbol{\gamma}$ obtained from (5) would be seriously biased and thus misleading without properly accommodating the error component structure given by (6).[3] Hence, we follow the correlated common effect pooled (CCEP) estimation approach advanced by Pesaran (2006), and then develop the (consistent) HT estimation theory by using the following augmented specification of (5):[4]

$$y_{it} = \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\gamma}'\mathbf{z}_i + \boldsymbol{\lambda}_i'\mathbf{f}_t + \alpha_i^* + u_{it}^*, i = 1, \ldots, N, t = 1, \ldots, T \tag{8}$$

where $\mathbf{f}_t = (\mathbf{s}_t', \overline{y}_t, \overline{\mathbf{x}}_t')'$ is the $\ell \times 1$ vector of augmented time-specific factors with $\ell = s + 1 + k$, $\overline{y}_t = N^{-1}\sum_{i=1}^N y_{it}$ and $\overline{\mathbf{x}}_t = N^{-1}\sum_{i=1}^N \mathbf{x}_{it}$, $\boldsymbol{\lambda}_i' = (\boldsymbol{\pi}_i' - (\varphi_i/\overline{\varphi})\overline{\boldsymbol{\pi}}', (\varphi_i/\overline{\varphi}), -(\varphi_i/\overline{\varphi})\boldsymbol{\beta}')'$ with $\overline{\varphi} = N^{-1}\sum_{i=1}^N \varphi_i$ and $\overline{\boldsymbol{\pi}} = N^{-1}\sum_{i=1}^N \boldsymbol{\pi}_i$, $\alpha_i^* = \alpha_i - (\varphi_i/\overline{\varphi})\overline{\alpha} - (\varphi_i/\overline{\varphi})\boldsymbol{\gamma}'\overline{\mathbf{z}}$ with $\overline{\alpha} = N^{-1}\sum_{i=1}^N \alpha_i$ and $\overline{\mathbf{z}} = N^{-1}\sum_{i=1}^N \mathbf{z}_i$, and $u_{it}^* = u_{it} - (\varphi_i/\overline{\varphi})\overline{u}_t$ with $\overline{u}_t = N^{-1}\sum_{i=1}^N u_{it}$.

Setting the pooling weight equal to N^{-1}, the CCEP estimator of $\boldsymbol{\beta}$ is given by

$$\hat{\boldsymbol{\beta}}_C = \left(\sum_{i=1}^N \mathbf{x}_i'\mathbf{M}_T\mathbf{x}_i\right)^{-1}\left(\sum_{i=1}^N \mathbf{x}_i'\mathbf{M}_T\mathbf{y}_i\right) \tag{9}$$

where $\mathbf{y}_i = (y_{i1}, \ldots, y_{iT})'$, $\mathbf{x}_i = (\mathbf{x}_{i1}, \ldots, \mathbf{x}_{iT})'$, $\mathbf{M}_T = \mathbf{I}_T - \mathbf{H}_T(\mathbf{H}_T'\mathbf{H}_T)^{-1}\mathbf{H}_T'$, $\mathbf{H}_T = (\mathbf{1}_T, \mathbf{f})$, $\mathbf{1}_T = (1, \ldots, 1)'$ and $\mathbf{f} = (\mathbf{f}_1, \ldots, \mathbf{f}_T)'$. Under fairly standard regularity conditions and assuming that

[3] Pesaran (2006) shows via Monte Carlo experiments that there is substantial estimation bias for $\boldsymbol{\beta}$ if cross-section dependence of the errors in (6) is ignored. Kapetanios and Pesaran (2005) find that the small sample property of the CCEP estimator of $\boldsymbol{\beta}$ works well even in the multiple factor models, whereas the principal component-based factor augmented estimation suffers from substantial bias in small samples.

[4] The CCEP estimator is obtained as the generalized within estimator being applied to the panel data regression augmented with cross-sectional averages of y_{it} and $\mathbf{x}_{it}$ that consistently replace unobserved common time-specific effects. As $N \to \infty$, $u_{it}^* \to_p u_{it}$, so the approximation error will be asymptotically negligible. Pesaran (2006) considers a more general multi-factor error structure but also proposes the correlated common effect mean group estimator, which is likely to be more robust to slope heterogeneity.

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all the variables are (covariance) stationary, Pesaran (2006, Theorems 3 and 4) shows that as $(N, T) \to \infty$ jointly, the CCEP estimator, denoted $\hat{\boldsymbol{\beta}}_C$, is consistent and follows the asymptotic normal distribution:

$$\sqrt{NT}(\hat{\boldsymbol{\beta}}_C - \boldsymbol{\beta}) \overset{a}{\sim} N(\mathbf{0}, \boldsymbol{\Sigma}_\beta) \tag{10}$$

where the robust consistent estimator of $\boldsymbol{\Sigma}_\beta$ is given by[5]

$$\hat{\boldsymbol{\Sigma}}_\beta = \frac{1}{N}\boldsymbol{\Psi}^{-1}\mathbf{R}\boldsymbol{\Psi}^{-1} \tag{11}$$

$$\mathbf{R} = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{\mathbf{x}_i'\mathbf{M}_T\mathbf{x}_i}{T}\right)(\hat{\boldsymbol{\beta}}_{C,i} - \hat{\boldsymbol{\beta}}_{MG})(\hat{\boldsymbol{\beta}}_{C,i} - \hat{\boldsymbol{\beta}}_{MG})'\left(\frac{\mathbf{x}_i'\mathbf{M}_T\mathbf{x}_i}{T}\right)$$

$$\boldsymbol{\Psi} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\mathbf{x}_i'\mathbf{M}_T\mathbf{x}_i}{T}\right), \hat{\boldsymbol{\beta}}_{MG} = \frac{1}{N}\sum_{i=1}^{N}\hat{\boldsymbol{\beta}}_{C,i}$$

where $\hat{\boldsymbol{\beta}}_{C,i}$ is the OLS estimator of $\boldsymbol{\beta}$ obtained from the individual regression of y_i on $(1, \mathbf{x}_{it}, \mathbf{f}_t)$ for $i = 1, \ldots, N$.

The CCEP estimation will wipe out any individual specific variables in $\mathbf{Z}_i$ from (7). We now describe how to consistently estimate $\boldsymbol{\gamma}_1$ and $\boldsymbol{\gamma}_2$. We rewrite (8) as

$$d_{it} = \boldsymbol{\gamma}_1'\mathbf{z}_{1i} + \boldsymbol{\gamma}_2'\mathbf{z}_{2i} + \alpha_i^* + u_{it}^* = \mu + \boldsymbol{\gamma}'\mathbf{z}_i + \varepsilon_{it}^*, i = 1, \ldots, N, t = 1, \ldots, T \tag{12}$$

where $d_{it} = y_{it} - \boldsymbol{\beta}'\mathbf{x}_{it} - \boldsymbol{\lambda}_i'\mathbf{f}_t$, $\mu = E(\alpha_i^*)$ and $\varepsilon_{it}^* = (\alpha_i^* - \mu) + u_{it}^*$ is a zero mean process by construction, and in matrix notation

$$\mathbf{d} = \mu\mathbf{1}_{NT} + \mathbf{Z}_1\boldsymbol{\gamma}_1 + \mathbf{Z}_2\boldsymbol{\gamma}_2 + \boldsymbol{\varepsilon}^* \tag{13}$$

where $\mathbf{d} = (\mathbf{d}_1', \ldots, \mathbf{d}_N')'$, $\mathbf{d}_i = (d_{i1}, \ldots, d_{iT})'$, $\mathbf{Z}_j = ((\mathbf{z}_{j1}' \otimes \mathbf{1}_T)', \ldots, (\mathbf{z}_{jN}' \otimes \mathbf{1}_T)')'$, $j = 1, 2$, $\mathbf{1}_{NT} = (\mathbf{1}_T', \ldots, \mathbf{1}_T')'$, $\mathbf{1}_T = (1, \ldots, 1)'$, and $\boldsymbol{\varepsilon}^* = (\boldsymbol{\varepsilon}_1^{*'}, \ldots, \boldsymbol{\varepsilon}_N^{*'})'$, and $\boldsymbol{\varepsilon}_i^* = (\varepsilon_{i1}^*, \ldots, \varepsilon_{iT}^*)'$. Replacing $\mathbf{d}$ by its consistent estimate, $\hat{\mathbf{d}} = \{\hat{d}_{it}, i = 1, \ldots, N, t = 1, \ldots, T, \}$, where $\hat{d}_{it} = y_{it} - \hat{\boldsymbol{\beta}}_C'\mathbf{x}_{it} - \hat{\boldsymbol{\lambda}}_i'\mathbf{f}_t$ and $\hat{\boldsymbol{\lambda}}_i$ are the OLS estimators of $\boldsymbol{\lambda}_i$ consistently estimated from the regression of $(y_{it} - \hat{\boldsymbol{\beta}}_C'\mathbf{x}_{it})$ on $(1, \mathbf{f}_t)$ for $i = 1, \ldots, N$, we now have[6]

$$\hat{\mathbf{d}} = \mu\mathbf{1}_{NT} + \mathbf{Z}_1\boldsymbol{\gamma}_1 + \mathbf{Z}_2\boldsymbol{\gamma}_2 + \tilde{\boldsymbol{\varepsilon}} = \mathbf{C}\boldsymbol{\delta} + \boldsymbol{\varepsilon}^+ \tag{14}$$

where $\boldsymbol{\varepsilon}^+ = \boldsymbol{\varepsilon}^* + (\hat{\mathbf{d}} - \mathbf{d})$, $\mathbf{C} = (\mathbf{1}_{NT}, \mathbf{Z}_1, \mathbf{Z}_2)$ and $\boldsymbol{\delta} = (\mu, \boldsymbol{\gamma}_1', \boldsymbol{\gamma}_2')'$.

To deal with non-zero correlation between $\mathbf{Z}_2$ and $\boldsymbol{\alpha}$, we need to find the following $NT \times (1 + g_1 + h)$ matrix of instrument variables:

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

[5] Monte Carlo studies by Pesaran (2006) demonstrate that the robust heterogeneous estimator given by (11) performs well in small samples even for the CCEP estimator. In practice, when u_{it}s are likely to be subject to possible heterogeneity and serial correlation, then the conventional variance estimate given by $\left(N^{-1}\sum_{i=1}^{N}T^{-1}\mathbf{x}_i'\mathbf{M}_T\mathbf{x}_i\right)^{-1}\hat{\sigma}_u^2$ could be inconsistent, where $\hat{\sigma}_u^2 = \sum_{i=1}^{N}\hat{\mathbf{u}}_i'\hat{\mathbf{u}}_i/(N(T - \ell - 1) - k)$, and $\hat{\mathbf{u}}_i = (\hat{u}_{i1}, \ldots, \hat{u}_{iT})'$ is a $T \times 1$ vector of the within residuals.

[6] As $(N, T) \to \infty$, $\hat{\mathbf{d}} = \mathbf{d} + o_p(1)$, so the approximation errors stemming from the use of $\hat{\mathbf{d}}$ in (14) are (asymptotically) negligible (see also Section 2.3 in Hausman and Taylor, 1981).

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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 thus we may use $\mathbf{PX}_1$ as the instruments for $\mathbf{Z}_2$, where $\mathbf{P} = \mathbf{D}(\mathbf{D}'\mathbf{D})^{-1}\mathbf{D}'$ is the $NT \times NT$ idempotent matrix with $\mathbf{D} = \mathbf{I}_N \otimes \mathbf{1}_T$ and $\mathbf{I}_N$ being an $N \times N$ identity matrix (see also Amemiya and MaCurdy, 1986; Breusch *et al.*, 1989).

We suggest using an alternative source of instruments and thus rewrite (8) as

$$y_{it} = b_i + \boldsymbol{\beta}'\mathbf{x}_{it} + \lambda_{\ell,i} f_{1t} + \lambda_{2,i} f_{2,t} + \cdots + \lambda_{\ell,i} f_{\ell,t} + u_{it} \tag{15}$$

where $b_i = \alpha_i^* + \boldsymbol{\gamma}'\mathbf{z}_i$, $\boldsymbol{\lambda}_i = (\lambda_{1,i}, \ldots, \lambda_{\ell,i})'$ and $\mathbf{f}_t = (f_{1,t}, \ldots, f_{\ell,t})'$. Define $\hat{\xi}_{j,it} = \hat{\lambda}_{j,i} f_{j,t}$ for $j = 1, \ldots, \ell$, $i = 1, \ldots, N$ and $t = 1, \ldots, T$, where $\hat{\lambda}_{j,i}$ are consistent estimates of heterogeneous factor loadings $\lambda_{j,i}$ and similarly define the $NT \times 1$ vector, $\hat{\boldsymbol{\xi}}_j = (\hat{\lambda}_{j,1}\mathbf{f}_j', \hat{\lambda}_{j,2}\mathbf{f}_j', \ldots, \hat{\lambda}_{j,N}\mathbf{f}_j')'$, $j = 1, \ldots, \ell$, where $\mathbf{f}_j = (f_{j,1}, \ldots, f_{j,T})'$. We assume:

Assumption 2 $\hat{\boldsymbol{\xi}}_j$, $j = 1, \ldots, \ell_1$, are correlated with $\mathbf{z}_{2i}$, but not correlated with α_i, while $\hat{\boldsymbol{\xi}}_j$, $j = \ell_1 + 1, \ldots, \ell$, are correlated with both $\mathbf{z}_{2i}$ and α_i.

Assumption 2 implies that the subset of $\hat{\boldsymbol{\xi}} = (\hat{\boldsymbol{\xi}}_1, \ldots, \hat{\boldsymbol{\xi}}_\ell)$ may be correlated with individual-specific variables in $\mathbf{Z}_2$, but not with individual effects. The implication of this assumption is basically similar to Assumption 1(v), under which the cross-section averages of $\mathbf{x}_{1it}$ are correlated with $\mathbf{z}_{2i}$, but not with α_i, so that they could also be used as valid instruments for $\mathbf{z}_{2i}$.

Under Assumptions 1(v) and 2 we obtain the following augmented instrument matrix for $\mathbf{Z}_2$:

$$\mathbf{W}_2 = (\mathbf{PX}_1, \mathbf{P}\hat{\boldsymbol{\xi}}_1, \mathbf{P}\hat{\boldsymbol{\xi}}_2, \ldots, \mathbf{P}\hat{\boldsymbol{\xi}}_{\ell_1})$$

where the dimension of $\mathbf{W}_2$ is $NT \times h$ with $h = k_1 + \ell_1$ Then, the consistent estimator of $\boldsymbol{\delta}$ is obtained as follows: Pre-multiplying $\mathbf{W}'$ by (3.12), we have

$$\mathbf{W}'\hat{\mathbf{d}} = \mathbf{W}'\mathbf{C}\boldsymbol{\delta} + \mathbf{W}'\boldsymbol{\varepsilon}^+ \tag{16}$$

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

$$\hat{\boldsymbol{\delta}}_{GLS} = [\mathbf{C}'\mathbf{W}\mathbf{V}^{-1}\mathbf{W}'\mathbf{C}]^{-1}\mathbf{C}'\mathbf{W}\mathbf{V}^{-1}\mathbf{W}'\hat{\mathbf{d}} \tag{17}$$

where $\mathbf{V} = \text{var}(\mathbf{W}'\boldsymbol{\varepsilon}^+)$. 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 (14) and construct a consistent estimate of $\boldsymbol{\varepsilon}^+$ by $\hat{\boldsymbol{\varepsilon}}_{OLS} = \hat{\mathbf{d}} - \mathbf{C}\hat{\boldsymbol{\delta}}_{OLS}$, where $\hat{\boldsymbol{\varepsilon}}_{OLS} = (\hat{\boldsymbol{\varepsilon}}'_{OLS,1}, \ldots, \hat{\boldsymbol{\varepsilon}}'_{OLS,N})'$. Then, we estimate the initial consistent estimate of $\mathbf{V}$ and the feasible GLS (FGLS) estimator of $\boldsymbol{\delta}$ by

$$\hat{\mathbf{V}}_{(1)} = \sum_{i=1}^{N} \mathbf{w}_i'\hat{\boldsymbol{\varepsilon}}_{OLS,i}\hat{\boldsymbol{\varepsilon}}'_{OLS,i}\mathbf{w}_i; \hat{\boldsymbol{\delta}}^{(1)}_{FGLS} = [\mathbf{C}'\mathbf{W}\hat{\mathbf{V}}_{(1)}^{-1}\mathbf{W}'\mathbf{C}]^{-1}\mathbf{C}'\mathbf{W}\hat{\mathbf{V}}_{(1)}^{-1}\mathbf{W}'\hat{\mathbf{d}} \tag{18}$$

where $\mathbf{w}_i$ is the $T \times (1 + g_1 + h)$ instrument matrix for individual i and $\mathbf{W} = (\mathbf{w}_1', \ldots, \mathbf{w}_N')'$. Next, we construct 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

$$\hat{\mathbf{V}}_{(2)} = \sum_{i=1}^{N} \mathbf{w}_i'\hat{\boldsymbol{\varepsilon}}_{GLS,i}\hat{\boldsymbol{\varepsilon}}'_{GLS,i}\mathbf{w}_i; \hat{\boldsymbol{\delta}}^{(2)}_{FGLS} = [\mathbf{C}'\mathbf{W}\hat{\mathbf{V}}_{(2)}^{-1}\mathbf{W}'\mathbf{C}]^{-1}\mathbf{C}'\mathbf{W}\hat{\mathbf{V}}_{(2)}^{-1}\mathbf{W}'\hat{\mathbf{d}} \tag{19}$$

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This iteration will be repeated until the convergence occurs, e.g. $|\hat{\boldsymbol{\delta}}^{(j)}_{FGLS} - \hat{\boldsymbol{\delta}}^{(j-1)}_{FGLS}| < 0.0001$, $j = 1, 2, \ldots$. Once we have obtained the final FGLS estimator, its covariance matrix will be computed by $\mathrm{var}(\hat{\boldsymbol{\delta}}_{FGLS}) = \{[\mathbf{C}'\mathbf{W}\hat{\mathbf{V}}^{-1}_{FGLS}\mathbf{W}'\mathbf{C}]^{-1}\}$. Under fairly standard conditions the consistency and the asymptotic normality of the FGLS estimator of $\boldsymbol{\delta}$ can be easily established; as $(N, T) \to \infty$ jointly, we have

$$\sqrt{NT}(\hat{\boldsymbol{\delta}}_{FGLS} - \boldsymbol{\delta}) \overset{a}{\sim} N(\mathbf{0}, \boldsymbol{\Sigma}_{\delta}) \tag{20}$$

where the consistent estimator of $\boldsymbol{\Sigma}_{\delta}$ is given by $\hat{\boldsymbol{\Sigma}}_{\delta} = \left[\frac{\mathbf{C}'\mathbf{W}}{NT}\left(\frac{\hat{\mathbf{V}}_{FGLS}}{NT}\right)^{-1}\frac{\mathbf{W}'\mathbf{C}}{NT}\right]^{-1}$.

Finally, a small Monte Carlo study on the finite sample performance of the CCEP-HT estimator of $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ has been reported separately as an online supplement in Serlenga and Shin (2006). It is demonstrated that the small sample performance of the CCEP-HT estimator is indeed much superior to that of the two-way FE-HT estimator in the presence of unobserved heterogeneous common factor in panels. This finding confirms that an inappropriate treatment of heterogeneous common unobserved factors will result in severely biased estimates and thus misleading inference.

4. EMPIRICAL APPLICATION TO INTRA-EU TRADE

In this section we will provide a comprehensive analysis of the determinants of bilateral trade flows amongst 15 EU member countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxemburg, Netherlands, Portugal, Spain, Sweden, United Kingdom),[7] using the double indexed gravity equation (2),[8] where the logarithm of real total trade is the dependent variable and there are 91 country pairs. The annual data used cover a period of 42 years (1960–2001).[9]

We consider two different specifications. First, we consider the basic model where bilateral trade flows only depend on the mass of the countries (measured by GDPs and populations) and barrier to trade (measured by distance). The variable *TGDP* is the sum of the logged GDPs and *TPOP* the sum of the logged populations of trading partners to proxy for their overall economic mass. This allows us to focus on total bilateral trade flows rather than on the direction of the trade flow from each country. We expect the positive impacts of *TGDP* on trade flows, whereas the effect of *TPOP* is not expected to be 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 labour (capital)-intensive goods, while 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 (*DIS*) is certainly expected to be negative on trade flows.

Second, we consider the full model 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

[7] Here Belgium and Luxemburg are treated as a single country.
[8] We have also considered the triple indexed version of the gravity equation, (1), where the logarithm of real export is the dependent variable, and obtained qualitatively similar results in what follows. See the previous version of the paper which is available from the authors upon request.
[9] See the Appendix for detailed definitions of all the variables.

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 De Sousa and Disdier (2002), Martinez-Zaroso and Nowak-Lehmann (2003) and Cheng and Wall (2005) for an analysis of the effects of regional trading blocks. The dummy variable *EMU* is equal to one when both trading partners adopt the same currency. The issue on the benefits of joining the 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. Frankel and Rose (2002) and Glick 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., Brada and Mendez, 1988; Frankel *et al.*, 1995). See also a number of recent studies that find negative or insignificant effects on trade of a monetary union (e.g., Persson, 2001; Pakko and Wall, 2002). In particular, de Souza (2002) and De Nardis and Vicarelli (2003) investigate the effect of *EMU* in the euro area over the last two decades and find no significant evidence. 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. Obviously, both effects on bilateral trade flows are expected to be positive. We also consider the impact of (logarithm of) bilateral real exchange rates (*RER*), which is defined as the price of the foreign currency per the home currency unit and 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 if the export component of the total trade is significantly larger than the import component, and vice versa (e.g., De Grauwe and Skudelny, 2000; Egger and Pfaffermayr, 2003).

We also follow recent developments of the New Trade Theory advanced by Krugman (1979) and Helpman (1987), and thus add two more variables in the full specification. The variable *RLF* is defined as the logarithm of the absolute value of the difference between per capita GDPs of trading countries, and measures the difference in terms of relative factor endowments. The higher is *RLF*, the larger is the difference between their factor endowments, resulting in a higher volume of inter-industry trade and a lower share of intra-industry trade. Therefore, the total impact of *RLF* on the total trade flows (sum of inter- and intra-industry trades) might not be unambiguous. The variable *SIM* is defined as the logarithm of an index that captures the relative size of two countries in terms of GDP, where this index is bounded between zero (absolute divergence in size) and 0.5 (equal country size). Helpman (1987) conducts the cross-section OLS estimation for 14 countries for every year from 1970 to 1981, and finds that there is a negative correlation between the share of intra-industry trade and *SIM*, but a positive correlation between the share of intra-industry trade and *RLF*, which is interpreted as supporting evidence of the theory of IRS and imperfect competition in international trade flows. See also Hummels and Levinsohn (1995) and Egger (2002) for a panel data extension of Helpman's analysis.

Finally, we drop the population variable from the full specification in order to avoid collinearity as *RLF* is a linear combination of GDP and population.

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4.1. Exploratory Data Analysis

Table I 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 the EU's total trade (currently about two-thirds). In general, intra-EU trade volumes have been positively affected by the enlargement of the European Community, e.g., the accession of new member states (Greece in 1981, Portugal and Spain in 1986), the German unification at the beginning of the 1990s, and the enlargement of the EU in 1995 with Austria, Sweden and Finland. Table I shows that the trade volume between EU countries grows faster than GDP, which 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, through the abolition of non-tariff barriers, border formalities, a liberalization of public procurement practices and the mutual recognition of technical standards. These liberalizations would tend to lower prices through increased competition and foster a concentration of resources in a more efficient use. Table I also shows that the share of exports is generally higher than the share of imports within EU trades. In light of this we 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* further reports that the removal of barriers to the mobility of goods leads to an increase in trade flows (mostly of the intra-industry type) within the Community, boosted by similarity of the trading nations. Figure 1 shows the evolution of intra-EU trade between 1980 and 1994. 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 Evenett and Keller, 2002).

Table I. Descriptive and summary statistics

Panel A	1960[a]	1970[b]	1980[c]	1990[d]	2000[e]
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	

[a] EU6 (Belgium, France, Germany, Italy, Luxemburg, Netherlands) from 1960 to 1969.
[b] EU6 from 1970 to 1973 and EU9 (EU6 plus Denmark, Ireland and UK) from 1973 to 1979.
[c] EU9 in 1980, EU10 (EU9 plus Greece) from 1981 to 1985, and EU12 (EU10 plus Portugal and Spain) from 1986 to 1989.
[d] EU12 from 1990 to 1994 and EU15 (EU12 plus Austria, Finland and Sweden) from 1995 to 1999.
[e] EU15 from 2000 to 2001.
Sources: Eurostat (1997) and WTO (2002).

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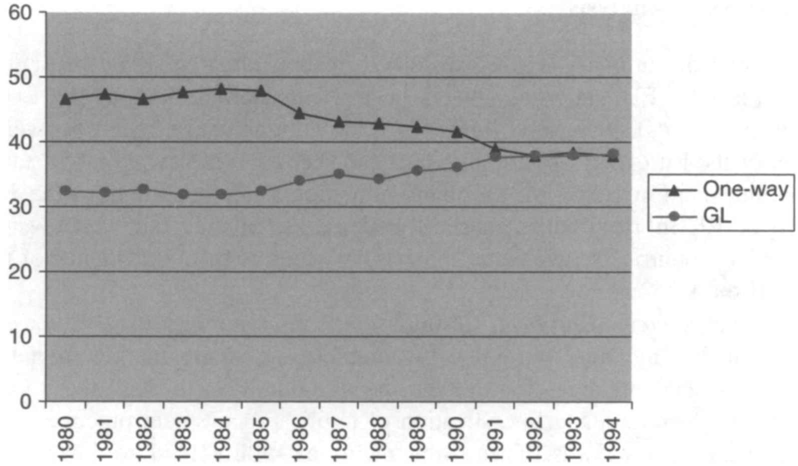

Figure 1. Evolution of trade in intra-EU trade 1980–1994. The share of intra-industry trade in a particular product group j is measured by the Grubel–Lloyd (1975) index, which is defined as $GL = 1 - \{|X_j - M_j|/(X_j + M_j)\}$. The value ranges from zero to unity, representing a situation of zero and 100% intra-industry trade, respectively. On the other hand, inter-industry trade is represented by the so called 'one-way trade'. Total trade is decomposed into three trade types according to their similarity in price and to overlap in trade: two-way trade in similar products (significant overlap and low price difference); two-way trade in vertically differenced products (significant overlap and high price difference); one-way trade (no price difference and no significant overlap). Source: European Commission (1997, p. 50).

4.2. Estimation Results

We briefly discuss alternative estimation procedures used. The pooled OLS (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 FEM explicitly takes into account the bilateral trade heterogeneity by specifying that all explanatory variables are assumed to be correlated with fixed individual effects, though it wipes out any 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 can be tested by using the Hausman (1978) test, and when this assumption is rejected we should use the HT instrumental variable estimation (in conjunction with FEM) to consistently estimate the impacts of time-invariant variables.

We consider three different cases. First, we estimate (3) and (4), but not including any time-specific effects, θ_t in (4), which we call Case 1. Secondly, we follow recent empirical studies and allow for homogeneous fixed time-specific effects as in (4), which we call Case 2. Finally, we consider the panel data model (5) and (6), which explicitly incorporates both observed and unobserved common time factors with heterogeneous factor loadings, which we call Case 3.[10] In particular, comparison of estimation results for Case 2 and Case 3 would highlight the potential

[10] We have also considered two additional cases: the panels with observed common factors and with unobserved common factors, respectively. The overall estimation results are qualitatively similar, though those obtained from the latter are better than the former. See the previous version of the paper which is available from the authors upon request, for more details.

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importance of an appropriate treatment of unobserved time effects since we analyse the trade data over the longer time span, and these time effects are incorporated to deal with business cycle effects or globalization issues.

Table II presents alternative estimation results for Case 1. Since the validity of the REM assumption that there is no correlation between explanatory variables and individual effects is convincingly rejected in all cases considered, we will mainly discuss the FEM estimation results.[11] For the full model specification, almost all the FEM estimation results are statistically significant and consistent with our a priori expectations. *TGDP*, which is combined GDPs of home and foreign country, has a positive effect on real total trade and a depreciation of the home currency (increase in *RER*) leads to an increase in trade flows. Similarity in size (*SIM*) helps to boost real trade flows, which reflects the fact that the intra-industry trade is the main part of the total EU trade, as described in Section 4.1. The impacts of relative difference, in factor endowments between trading partners (*RLF*) on trade flows are small, but significantly positive. Both trade and currency union

Table II. Alternative panel data estimation results for Case 1

	Basic model			Full model			HT estimation		
	OLS	FE	RE	OLS	FE	RE	OLS	IV1	IV2
Intercept	−7.46*		−16.5*	−10.9*		−13.9*			
	(0.361)		(0.938)	(0.247)		(0.889)			
RER				0.09*	0.06*	0.07*			
				(0.004)	(0.009)	(0.008)			
TGDP	1.68*	2.21*	2.34*	1.57*	1.81*	1.79*			
	(0.030)	(0.031)	(0.023)	(0.012)	(0.019)	(0.018)			
TPOP	−0.52*	0.03	−0.83*						
	(0.039)	(0.164)	(0.099)						
RLF				0.03*	0.03*	0.03*			
				(0.008)	(0.008)	(0.008)			
SIM				0.88*	1.17*	1.14*			
				(0.017)	(0.055)	(0.045)			
CEE				0.32*	0.31*	0.32*			
				(0.022)	(0.016)	(0.016)			
EMU				0.2*	0.08*	0.09*			
				(0.051)	(0.027)	(0.027)			
DIS	−1.18*		−0.97*	−0.64*		−0.59*	−0.59*	−0.38*	−0.37+
	(0.022)		(0.124)	(0.022)		(0.116)	(0.129)	(0.193)	(0.190)
BOR				0.52*		0.44*	0.43*	0.60*	0.61*
				(0.034)		(0.190)	(0.210)	(0.263)	(0.265)
LAN				0.23*		0.41*	0.45*	1.56*	1.63*
				(0.034)		(0.185)	(0.203)	(0.681)	(0.641)

Notes: Using the annual data over 1960–2001 for 91 country pairs, we estimate models (3) and (4) without including time-specific factors, where the dependent variable is the logarithm of real total trade flows and the regressors are $\mathbf{x}'_{it} = \{RER, TGDP, TPOP, RLF, SIM, CEE, EMU\}_{it}$ and $\mathbf{z}_i = \{DIS, BOR, LAN\}_i$. OLS stands for the pooled OLS estimator, FE for fixed effects estimator and RE for random effects estimator, respectively. Figures in $(\cdot)$ indicate the standard error. '*' and '+' denote a significant coefficient at the 5% and the 10% level, respectively. Hausman statistic rejects the null of no correlation between explanatory variables and individual effects in all cases considered. For the Hausman and Taylor estimation results we consider only the full model, and the slope coefficients are already reported as the FE estimates. The set of instrument variables used in the HT estimation are: $\{RER_{it}\}$ for IV1 and $\{RER_{it}, TGDP_{it}, RLF_{it}\}$ for IV2. The Sargan test for the validity of over-identifying restrictions in IV2 is obtained as $\chi^2_2 = 2.66$ with the p-value, 0.265.

[11] For similar empirical evidence see De Sousa and Disdier (2002) and Cheng and Wall (2005).

memberships (*CEE* and *EMU*) appear to boost real trade flows significantly. Although POLS and REM estimation results are likely to be biased because of correlation between regressors and individual effects, both estimation results are relatively consistent with the FEM results. Turning briefly to the basic model specification, we find that the impact of *TPOP* by POLS is significantly negative, which leads us to conclude that the exports within EU countries are likely to be luxury goods, whereas the FEM estimate of the impact of population is generally insignificant. This may imply that the mass effect is likely to be captured mostly by income variables. 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 previous empirical studies.[12]

Both (inconsistent) OLS and (consistent) HT estimation results for the impacts of individual-specific variables are also summarized in Table II. Here we assume a priori that *LAN* is the only time-invariant variable correlated with individual effects (as common language is a proxy for cultural, historical, linguistic proximity, it is highly likely to be correlated with individual effects), and employ two different sets of instrument variables. The first instrument set (IV1) contains only real exchange rates (RER_{it}) and the second set (IV2) adds size-related variables, $TGDP_{it}$ and RLF_{it}.[13] As expected a priori, all estimation results show that distance has a negative effect on trades, while common language and common border have positive effects. It is worth noting that once the correlation between *LAN* and individual effect is accommodated by the HT estimation, then the impacts of distance decrease (in absolute value) as compared to the OLS counterpart, while the impacts of both common language and common border dummies increase, especially the former. Furthermore, when we use the broad set of instruments (IV2), the distance variable loses significance slightly. 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). 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 individual effect is appropriately handled. See also De Sousa and Disdier (2002) for a similar finding.

Table III reports the estimation results for Case 2. Although most estimation results follow similar patterns as obtained for Case 1, there are a few notable discrepancies (mainly in the context of the FEM estimation results). First, the impact of *TGDP* seems to be too large. Second, the impacts of both *EMU* and *SIM* are now significantly larger. Third, the HT estimate of the impact of distance is surprisingly positive but insignificant, and common border dummy loses its statistical significance. Only the impacts of common language dummy are significant, but seem too large. Finally, the validity of the over-identifying restriction for IV2 is strongly rejected. Therefore, estimation results obtained using panel regression with fixed time dummies are much less sensible than those obtained using panel regression even without considering any time-specific factors.

Table I shows that the share of EU trade with the USA has 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 WTO (2002) that the percentage of export (import) from Europe to the USA increases from around

[12] For example, Matyas *et al.* (2004) argue that allowing for heterogeneous bilateral effects is likely to increase the impact of *GDP*. Also most empirical studies (e.g., Matyas, 1997; Cheng and Wall, 2005; Martinez-Zaroso and Nowak-Lehmann, 2003) find that estimates of the income coefficient are well over unity.

[13] The instrument set, IV1, implicitly assumes that $\mathbf{x}_{1,it} = \{RER\}$ and $\mathbf{x}_{2,it} = \{TGDP, RLF, SIM, CEE, EMU\}$. IV1 is just-identified since there is one instrument, $\mathbf{x}_{1,it} = \{RER\}$ for $z_{2i} = \{LAN\}$. The over-identified instrument set, IV2, assumes that $\mathbf{x}_{1,it} = \{RER, TGDP, RLF\}$ and $\mathbf{x}_{2,it} = \{SIM, CEE, EMU\}$. The Sargan test, reported in Table II, confirms the validity of over-identifying restrictions for IV2.

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Table III. Alternative panel data estimation results for Case 2

	Basic Model			Full Model			HT Estimation		
	OLS	FE	RE	OLS	FE	RE	OLS	IV1	IV2
Intercept	−1.3*		−15.3*	−10.2*		−20.2*			
	(0.418)		(1.28)	(0.257)		(1.21)			
RER				0.09*	0.09*	0.06*			
				(0.003)	(0.010)	(0.009)			
TGDP	1.03*	2.58*	2.31*	1.53*	3.05*	2.22*			
	(0.038)	(0.084)	(0.078)	(0.013)	(0.078)	(0.053)			
TPOP	0.18*	−0.49*	−0.96*						
	(0.045)	(0.154)	(0.111)						
RLF				0.02*	0.02*	0.02*			
				(0.008)	(0.007)	(0.007)			
SIM				0.84*	1.42*	1.27*			
				(0.017)	(0.055)	(0.049)			
CEE				0.17*	0.32*	0.31*			
				(0.026)	(0.017)	(0.017)			
EMU				0.21*	0.22*	0.28*			
				(0.070)	(0.034)	(0.035)			
DIS	−1.28*		−1.01*	−0.69*		−0.44*	−0.07	0.38	0.71
	(0.021)		(0.125)	(0.022)		(0.123)	(0.297)	(0.437)	(0.510)
BOR				0.54*		0.28	0.03	0.39	0.66
				(0.033)		(0.195)	(0.486)	(0.595)	(0.710)
LAN				0.26*		0.65*	0.94*	3.27*	5.02*
				(0.034)		(0.189)	(0.468)	(1.54)	(1.717)

Notes: Using the annual data over 1960–2001 for 91 country pairs we estimate models (3) and (4) with homogeneous fixed time-specific effects. Figures in $(\cdot)$ indicate the standard error. *denotes a significant coefficient at the 5% level. Hausman statistic rejects the null of no correlation between regressors and individual effects in all cases considered. The Sargan test for the validity of over-identifying restrictions in IV2 is obtained as $\chi^2_2 = 31.5$ with the p-value, 0.000. See also notes to Table II.

10% (10%) in 1960 to around 25% (20%) in 2000. Hence, we expect that certain characteristics of the USA would help in explaining the pattern of intra-EU total trades. This suggests that the US reference variables may be used as observed common time factors. Here we choose $s_t = \{RERT_t\}$ in (5), where $RERT_t$ is the (logarithm of) real exchange rates ($RERT_t$) that would capture any of the relative price effects between the European currencies and the US dollar.[14] We expect that a depreciation of the European currency with respect to the US dollar (an increase in $RERT_t$) would result in more extra-EU exports to and less extra-imports from the USA, though its impact on the intra-EU trade will be ambiguous. Since the choice of observed common factors might be arbitrary and there is always a possibility of missing factors, we also allow for the presence of unobserved common factors with their heterogeneous factor loadings, see (6).

We thus consider the factor-augmented panel data model (8) with $\mathbf{f}_t = \{RERT_t, \overline{TGDP}_t, \overline{SIM}_t, \overline{RLF}_t, \overline{RER}_t, \bar{y}_t\}'$, where the bar over the variables indicates their cross-sectional average,[15] and focus on the CCEP-HT estimation procedure developed in Section 3 for consistent estimation

[14] The home currency is the European currency, i.e., ECU until 1998 and euro from 1999 to 2001, and the foreign currency is the US dollar. See Appendix. We have also tried different US reference variables such as the US GDP, and found qualitatively similar results to what follows.

[15] We do not include cross-sectional average of the *CEE* and *EMU* dummies, to avoid the potential multicollinearity problem.

of $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ using the full model specification. In particular, the consistent estimator of $\boldsymbol{\gamma}$ is obtained under the maintained assumption that the common language dummy (*LAN*) is only correlated with individual effects. We now consider the same two IV sets, IV1 and IV2, together with the two additional instrument sets; namely, IV1A = $\{IV1, \hat{\lambda}_{5i}\overline{RER}_t\}$, and IV2A = $\{IV2, \hat{\lambda}_{2i}\overline{TGDP}_t, \hat{\lambda}_{4i}\overline{RLF}_t, \hat{\lambda}_{5i}\overline{RER}_t, \}$, respectively.[16]

The estimation results for Case 3 summarized in Table IV are similar to those in Table II, but with the following main differences: the coefficients on *EMU* and *RLF* are insignificant while the impact of *CEE* is significantly smaller. The CCEP-HT estimates of the impacts of distance, common language and common border dummies are significantly negative, positive and positive, respectively, a finding mostly consistent with the previous results in Table II. Therefore, in light of our a priori expectations, we may conclude that the CCEP-HT estimation results for Case 3 are more sensible than those obtained using the conventional panel data approach based on the (homogeneous) fixed time dummies as in Case 2.

We summarize our main findings, focusing on the estimation results obtained for Cases 1 and 3. The impacts of *TGDP* are all significant and positive, whereas the impacts of population are insignificant. The impacts of both *SIM* and *CEE* are significant and positive. The impacts of *RLF* and *EMU* are significantly positive in Table II, but insignificant in Table IV. The impacts of

Table IV. The CCEP-HT estimation results for Case 3

	CCEP	OLS	IV1	IV1A	IV2	IV2A
RER	0.04*					
	(0.007)					
TGDP	1.72*					
	(0.032)					
RLF	−0.01					
	(0.007)					
SIM	1.12*					
	(0.044)					
CEE	0.05*					
	(0.003)					
EMU	−0.0003					
	(0.004)					
DIS		−0.67*	−0.44*	−0.42*	−0.43*	−0.41*
		(0.123)	(0.211)	(0.215)	(0.207)	(0.213)
BOR		0.45*	0.64*	0.66*	0.65*	0.67*
		(0.201)	(0.248)	(0.253)	(0.242)	(0.248)
LAN		0.48*	1.70*	1.81*	1.73*	1.85*
		(0.194)	(0.625)	(0.637)	(0.646)	(0.654)
Sargan				$\chi_1^2 = 1.60$	$\chi_2^2 = 0.06$	$\chi_5^2 = 2.20$
				[0.206]	[0.968]	[0.821]

Notes: Using the annual data over 1960–2001 for 91 country pairs, we estimate models (3) and (4) with the factor-augmented regressor set, $\mathbf{f}_t = \{RERT_t, \overline{TGDP}_t, \overline{SIM}_t, \overline{RLF}_t, \overline{RER}_t, \overline{y}_t\}$. The CCEP estimator is obtained by (9) and the associated robust standard errors are estimated by (11). For the HT estimation we consider the following sets of instrument variables: IV1 = $\{RER_{it}\}$, IV1A = $\{IV1, \hat{\lambda}_{5i}\overline{RER}_t\}$, IV2 = $\{RER_{it}, TGDP_{it}, RLF_{it}\}$ and IV2A = $\{IV2, \hat{\lambda}_{2i}\overline{TGDP}_t, \hat{\lambda}_{4i}\overline{RLF}_t, \hat{\lambda}_{5i}\overline{RER}_t\}$. Figures in $(\cdot)$ indicate the standard error. *denotes a significant coefficient at the 5% level. Sargan denotes the Sargan statistic testing for the validity of over-identifying restrictions and figures in $[\cdot]$ indicate the p-values. See also notes to Table II.

[16] The Sargan test, reported in Table IV, confirms the validity of over-identifying restrictions for all IV1A, IV2 and IV2A.

distance, common language and common border are significantly negative, positive and positive, respectively. Overall, these results are more or less consistent with our a priori expectations, though there are conflicting findings on the role of *RLF* and *EMU* variables. First, 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. Second, we have discussed earlier 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 EMU membership. In this regard we expect that the impacts of *EMU* are yet to be significant. Along this line of logics we therefore conclude that the CCEP-HT estimation results obtained for Case 3 are mostly sensible.

5. CONCLUSIONS

In this paper we follow recent developments of panel data studies surrounding the use of unobserved heterogeneous common factors, and develop the generalized panel data estimation methodology by combining the CCEP estimation advanced by Pesaran (2006) and the HT instrument variable estimation. We apply this approach to an analysis of the gravity equation of bilateral trade amongst 15 EU member countries over 1960–2001. Empirical results demonstrate that our proposed approach fits the data reasonably well. In particular, the CCEP-HT estimation results provide more sensible predictions than the conventional approach using the 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 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 such an augmented trade-barrier function (e.g., Brun *et al.*, 2005). Secondly, it would be interesting to reinvestigate the role of explanatory variables such as *RLF* and *EMU* in the gravity models of international trade over different time periods. Of particular importance will be to re-examine 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.

APPENDIX

We describe here how the variables are constructed. All variables are converted into constant dollar prices with 1995 as the base year. Bilateral exports and imports are defined as logarithms of real export, $X_{hft}^R = (X_{hft}^N / XPI_{US}) \times 100$, and real imports $M_{hft}^R = (M_{hft}^N / MPI_{US}) \times 100$, where X_{hft}^N and M_{hft}^N are bilateral export and import measured in millions of current US dollars, and XPI_{US}

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and MPI_{US} are the US export and import price indices. Then, the (log of) total volume of trade is given by $Trade = \ln(X^R_{hft} + M^R_{hft})$.

The explanatory variables used in this analysis can be divided into two categories: time-varying and time-invariant variables. Among the time-varying variables we consider:

- *TGDP*: the (log of) total GDP defined as $TGDP_{hft} = \ln(GDP^R_{ht} + GDP^R_{ft})$. *GDP*s 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 home and foreign countries, respectively. GDPs are originally expressed in millions of euros for the 12 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 the UK (GDP^N). For the former 12 countries the European GDP deflator has been used, while for the latter three countries the original nominal values of GDP have been deflated by the GDP deflator (*GDPD*, 1995 = 100) of the respective countries. We also convert GDPs into US dollars at the exchange rate of 1995 (mean over period) in order to exclude the effect of a dollar depreciation or appreciation as $GDP^R_{hft} = (GPD^N_{hft}/GDPD_{ht}) \times (US\$/NC_h)_{1995} \times 100$, where NC_h stands for national currency of the home country.
- *TPOP*: the (log of) total population defined as $TPOP_{hft} = \ln(POP_{ht} + POP_{ft})$. Populations of home and foreign countries are defined as logarithms of POP_{ht} and POP_{ft}, where POP_{ht} and POP_{ft} are the populations of countrys h and f measured in millions of inhabitants.
- *SIM*: a measure of countries' similarity in size constructed as

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

- *RLF*: a measure of countries' difference in relative factor endowment calculated as

$$RLF_{hft} = \ln|PGDP^R_{ft} - PGDP^R_{ht}|$$

  where *PGDP* is per capita GDP.
- *RER*: the real exchange rate. Real exchange rates in constant dollars at 1995 are defined as $RER_{hft} = NER_{hft} \times XPI_{US}$, where NER_{hft} is nominal exchange rate between currencies h and f in year t in terms of US dollars.
- *CEE*: a dummy for the European Community which is equal to one when both countries belong to the European Community.
- *EMU*: a dummy for the European Monetary Union which is equal to one when both trading partners adopt the same currency.

On the other hand, the time-invariant variables are:

- *LAN*: a dummy for common language which is equal to one when both countries speak the same official language.
- *BOR*: a dummy for common border which is equal to one when the trading partners share a border.

- *DIS*: the (log of) distance, where the distance (DIS_{hf}) between countries is measured as the (log) of great circle distance between national capitals in kilometres.

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

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