

On Bayesian Estimation of the Eurozone Currency Union Effect

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Web Appendix

1 Gravity Models and Data

Two main choices for dependent variable have been considered by researchers in estimating the gravity equation: trade levels and ratios. The level dependent variable can be the log of bilateral (unidirectional) imports/exports, or the average/sum of imports and exports between countries, whereas the latter one suffers from the silver medal error proposed by Baldwin and Taglioni (2007). These trade flow data can be measured by current dollar or deflated by price index (US CPI). However, estimations with deflated trade values suffer from the bronze medal error shown in Baldwin and Taglioni (2007). The model with log of bilateral import levels is shown as below,

$$lim_t^{ik} = cons + lyy + \beta_{EZ}EZ + \beta_{EU}EU + \delta^{ik} + \theta_t^i + \phi_t^k + \sum_{j=1}^J \gamma_{jt} g_{jt}^{ik} + \varepsilon_t^{ik}. \quad (1)$$

The dependent variable, lim_t^{ik} , is the log of bilateral import levels, $\log(IM_t^{ik})$, which is determined by heterogeneous preferences ($\delta^{ik} \equiv \log(\alpha^{ik})$), the product of importers'

expenditures and exporters' outputs ($lyy \equiv \log(EXP_t^i * OUT_t^k)$), trade costs ($g_{jt}^{ik} \equiv \log(\tau_t^{ik})$) and fixed effects. The trade costs g_{jt}^{ik} include log of distance, dummies for border, common language, land-lock, Eurozone and European Union. With symmetric conditions, $\tau_t^{ik} = \tau_t^{ki}$ and $\alpha^i(k) = \alpha^k(i)$, trade balance for each country is zero and total output is equal to total expenditure, $EXP_t^i = OUT_t^i$, so that $lyy = \log(OUT_t^i * OUT_t^k)$ if replacing expenditure EXP_t^i using output OUT_t^i .

This type of estimation has a potential endogeneity problem because the economic mass data “ lyy ” are included in the explanatory variables. Therefore, researchers use the second choice: the log of the bilateral import ratio— imports divided by the product of the importer’s expenditure and exporter’s output as in Anderson and Van Wincoop (2003) with cross-section data. This estimation restricts the unit effect of economic mass variables on bilateral trade. The model using bilateral import ratios in Anderson and Van Wincoop (2003) and Aviat and Coeurdacier (2007) is given below,

$$limr_t^{ik} = cons + \beta_{EZ}EZ + \beta_{EU}EU + \delta^{ik} + \theta_t^i + \phi_t^k + \sum_{j=1}^J \gamma_{jt} g_{jt}^{ik} + \varepsilon_t^{ik}, \quad (2)$$

where the dependent variable is defined as

$$limr_t^{ik} = \log\left(\frac{IM_t^{ik}}{OUT_t^i * OUT_t^k}\right) \text{ or } \log\left(\frac{IM_t^{ik}}{EXP_t^i * OUT_t^k}\right).$$

The version of bilateral import ratios may be non-stationary with long panel data. Hence, as in section 3 of Guo (2015), this paper uses the import ratios in equation (??) of section ??

$$limr_t^{ik} = \log\left(\frac{IM_t^{ik} * WOUT_t}{OUT_t^i * OUT_t^k}\right).$$

The data contain 22 OECD countries. There are fourteen countries in EU by 1995—AUT, BEL-LUX, DEU, DNK, ESP, FIN, FRA, GBR, GRC, IRL, ITA, NLD, PRT, and

SWE, among which four countries did not join in the EZ in 2000—DNK, GBR, GRC, and SWE. Another eight countries—AUS, CAN, CHE, JPN, USA, ISL, NOR, and NZL— do not belong to EU. The data source is listed as below,

- 1) Current dollar value of bilateral import/export data: IMF’s Direction of Trade Statistics (DOTS).
- 2) Current dollar value of GDP: WDI and IMF DOTS (robustness check).
- 3) Current dollar value of private consumption expenditure: World Bank’s World Development Indicators (WDI).
- 4) Bilateral trade costs variables: distance, dummies for border connection, land-lock, and common language are taken from CEPII. Geodesic (great circle) distances are measured as kilometers between capital cities.¹
- 5) EU and EZ dummies: constructed by author following the dates of countries’ participation in the European Union and Eurozone respectively.

Compared with the above LS results, Table 1 provides results estimated by MLE, assuming i.i.d. normally distributed country pair random effects. The MLE results provide a robustness check on the variation of EZ and EU effects due to different choices of fixed effects. On average, the MLE results show the EZ effect on increasing the import ratio is 7.9%, compared with 25.4% using the LS in Table ???. The magnitude of the EZ effect depends on the choice of time-varying or time-invariant country fixed effects. Estimations with time-varying fixed effects in columns of “Baseline”, “YIMYEXPair”, “YIMYEX”, “YNAPair”, and “YNA”, do not provide evidence to support a significant EZ effect, but show a significant effect for EU membership (15% more). The model with year and pair dummies (“PairYear”) used by Micco et al. (2003) show a 12% increase

¹<http://www.cepii.fr/anglaisgraph/bdd/distances.htm>

in import ratio due to the currency union. In contrast, models with time-invariant country fixed effects in columns of “NA”, “NAYear”, “IMEX” and “IMEXYear”, shows that both EZ and EU variables significantly affect imports, around 21% and 25 % more respectively. If we use the simple difference-in-difference method (DID) and take year 1999 as the breaking point, estimations with time-invariant country fixed effects show that using euros can increase 24% import ratios. After controlling for the time-varying country fixed effect, however, the EZ effect from DID drops to 9%.

2 Monte Carlo Simulations

2.1 Type I Error under Homoscedastic Errors

All models with different groups of dummy variables are nested in the baseline model. We use the baseline model (the alternative) and the model “IMEX” (the null) as an example to illustrate the Monte Carlo simulations for size distortion presented in table 4 in the paper,

$$w_t^{ik} = cons + \beta_{EZ}EZ + \beta_{EU}EU + \delta^{ik} + (\tilde{\theta}_t^i + \tilde{\theta}^i) + (\tilde{\phi}_t^k + \tilde{\phi}^k) + \sum_{j=1}^3 \gamma_{jt}g_j^{ik} + \varepsilon_t^{ik},$$

where $\theta_t^i = \tilde{\theta}_t^i + \tilde{\theta}^i$ and $\phi_t^k = \tilde{\phi}_t^k + \tilde{\phi}^k$. In order to obtain the model “IMEX”, we need to impose the following 1448 restrictions on the baseline model: $\delta^{ik} = 0$, $\tilde{\theta}_t^i = 0$, and $\tilde{\phi}_t^k = 0$. All simulations are performed 1000 times.

- 1) Obtain the coefficients B_0 ($\tilde{\theta}^i$, $\tilde{\phi}^k$, β_{EZ} , β_{EU} , γ_{jt} and the constant intercept) and variance σ_0^2 ($=var(\epsilon_0)$) based on the model $y = XB_0 + \epsilon_0$. We estimate the coefficients from the model “IMEX” using the real data. The dependent variable is import ratio $\log \left(\frac{(1+IM_t^{ik}) * WOUT_t}{EXP_t^i * OUT_t^k} \right)$. The coefficients on trade costs γ_{jt} are based

on the OLS regressions and listed in table 1 of the paper. The variance is the mean of the squared residual.

2) Simulate the dependent variables \hat{y} for 1000 times given B_0 , σ_0^2 , and the covariates X from the model “IMEX”. The random sample comes from the random draws of the error term.

3) Fit the simulated \hat{y} using both the null and alternative models ($y = XB_m + \epsilon_j$ and $m \in \{n, a\}$, the subscript “ n ” and “ a ” is represented the the null and alternative models respectively.) and obtain the estimated coefficients (\hat{B}_n and \hat{B}_a) and variance ($\hat{\sigma}_n^2$ and $\hat{\sigma}_a^2$) for 1000 times assuming i.i.d.

4) Calculate the statistics for the LR test and rejection rate (size). We use the formula

$$LR1 = N * \left[\log(\hat{\sigma}_n^2) - \log(\hat{\sigma}_a^2) \right]$$

to calculate the statistic for the LR test, “LR1”, where $\hat{\sigma}_j^2 = RSS_j/N$ and RSS_j is the residual sum of squares of model m . Following Italianer (1985), the “LR2” adjusts the dimensions of the models; that is

$$LR2 = LR1 * (N - r - K_n/2) = LR1 * (11550 - 1448 - 0.5 * 48)/11550.$$

The statistic is chi-squared distributed with 1448 degrees of freedom and the critical value at 5% significant level is 1537.639. The size is the percentage of rejecting the null model “IMEX” with 1000 simulations when the null model “IMEX” is true.

5) The power curve. The difference between model “IMEX” and the baseline model includes the $\sigma_{\hat{\theta}}$ and $\sigma_{\tilde{\theta}}$, and σ_{δ} . For example, $\tilde{\theta}_t^i = \theta_t^i - \hat{\theta}^i$ with zero mean

and $var(\tilde{\theta}_t^i) = \sigma_{\tilde{\theta}}^2$. The standard deviation $\sigma_{\tilde{\theta}}$ is equal to zero in model “IMEX”; so do $\sigma_{\tilde{\phi}}$ and $\sigma_{\tilde{\delta}}$. By increasing the $\sigma_{\tilde{\theta}}^2$, $\sigma_{\tilde{\phi}}^2$, and $\sigma_{\tilde{\delta}}^2$ by the same scale, i.e. 0.01, the rejection rate of the null model “IMEX” goes up. The power curve plots the rejection rate along with the increasing variance.

6) Calculate the statistic for the F test. The F test can be used to compare models with homoscedastic error terms. The F test statistic for null and alternative models is calculated as

$$F = \frac{(RSS_n - RSS_a)/(K_a - K_n)}{RSS_a/(N - K_a)},$$

where RSS is the residual sum of squares and K is the number of estimated coefficients. The F statistic has the degrees of freedom ($K_a - K_n = 1496 - 48 = 1448$ and $N - K_a = 11550 - 1496 = 10054$) and the critical value for the significant level 5% is 1.067.

7) Calculate the statistic for the $Wald$ test. The constraint matrix R_n can be constructed using the conditions $\delta^{ik} = 0$, $\tilde{\theta}_t^i = 0$, and $\tilde{\phi}_t^k = 0$. The Wald statistic is calculated as follows

$$Wald = (R_n \hat{B}_a)' * [R_n var(\hat{B}_a) R_n']^{-1} * (R_n \hat{B}_a),$$

where $var(\hat{B}_a) = \hat{\sigma}_a^2 * (X_a' * X_a)^{-1}$. We use the consistent and biased estimate $\hat{\sigma}_a^2 = RSS_a/N$ to calculate the Wald1 statistics, and use consistent and unbiased estimate $\hat{\sigma}_a^2 = RSS_a/(N - K_a)$ to calculate (dimension adjusted) Wald2 statistics. The statistic is chi-squared distributed with degrees of freedom 1448 and the critical value at 5% significant level is 1537.639. The size is the percentage to reject the null model “IMEX” with 1000 simulations when the null model “IMEX”

is true.

Two figures provide direct evidence for the biased distributions of the hypothesis tests due to the high dimensionality. We take the Comb. (1) as an example to illustrate the mechanism. Figure 1 provides the chi-square densities with DF 1469 for three cases: 1) the solid red line is the ideal theoretical kernel density, drawing 1000 observations from the Chi-square distribution directly; 2) the dashed black line plots the empirical LR kernel density (LR1) based on the null model “NA” and the baseline model using 1000 simulations ; 3) the blue dash-dot line plots dimension adjusted LR kernel density (LR2) based on Italianer (1985). The vertical red line is equal to 1559.3, the theoretical critical value (CV) at the 5% significant level. Similarly, figure 2 portrays the densities for the Wald tests.

With DF 1469, the empirical Chi-squared distribution for the LR and Wald tests (the dash black lines) in Figure 1 and Figure 2 are biased compared to the ideal theoretical distribution (the red solid line). These biased asymptotical chi-square distributions occur because of the high dimensions in these models and a large number of constraints associated with the hypothesis tests. Using the conventional CV at the 5% significant level (1559.3), the empirical LR1 and Wald1 tests both have a large size distortion. In Figure 1, the dash black LR1 line has a 62.1 % rejection rate on the null model “NA”. A small adjustment proposed by Italianer (1985) (the weight is equal to $0.872 = \frac{11550-1469-0.5*27}{11550}$) shown in the dash-dot blue LR2 line reduces this large size to zero. A value, such as 1560, is changed into 1360.32 with the adjustment (the weight is equal to 0.872), which is no longer significant compared with the CV 1559.3. This simple adjustment does not work well for the LR test. Similarly in Figure 2 for the Wald tests, the size is 97.6% for the Wald1 test, and decreases to 6.9% for the Wald2 test after the dimension adjustment (the weight is equal to $0.873 = \frac{11550-1469}{11550}$).

2.2 Errors with Heteroskedasticity and Autocorrelations

In table 3 of the paper, we calculate the Wald statistics using Newey-West standard errors with 2 lags, robust to the heteroskedasticity and autocorrelation (HAC). The Monte Carlo simulations assume HAC error terms for a specific importer i and exporter k pair (462 pairs) and specify three parametric forms for the HAC. The conclusions on three hypothesis tests and size distortions (with misspecification or not) are robust to the choices on HAC.

The first HAC, ‘‘HAC1’’, in tables 2-5 takes the form as below,

$$\epsilon_t^{ik} = g^{ik} + \nu_t^{ik} \quad \nu_t^{ik} = b_\nu \nu_{t-1}^{ik} + \mu_t^{ik} \quad \text{var}(g^{ik}) = \sigma_{g^{ik}}^2 \quad \text{var}(\mu_t^{ik}) = \sigma_\mu^2$$

There is no contemporaneous correlation across country pairs. This parametric assumption considers the role of fixed effect in the variance covariance matrix $\Xi (= \text{var}(\epsilon))$. The matrix $\Xi (= \text{var}(\epsilon))$ is a block diagonal matrix with Ω^{ik} (462 pairs) for one specific importer i and exporter k pair and Ω^{ik} has the following form,

$$\Omega^{ik} = \sigma_{g^{ik}}^2 \begin{bmatrix} 1 & 1 & \cdots & 1 \\ 1 & 1 & \vdots & \vdots \\ \vdots & \vdots & 1 & 1 \\ 1 & \cdots & 1 & 1 \end{bmatrix} + \frac{\sigma_\mu^2}{1 - b_\nu^2} \begin{bmatrix} 1 & b_\nu & \cdots & b_\nu^{T-1} \\ b_\nu & 1 & \vdots & \vdots \\ \vdots & \vdots & 1 & b_\nu \\ b_\nu^{T-1} & \cdots & b_\nu & 1 \end{bmatrix}.$$

The second HAC, ‘‘HAC2’’, does not take the fixed affect into account and takes the form,

$$\epsilon_t^{ik} = b\epsilon_{t-1}^{ik} + v_t^{ik}, \text{ and } \text{var}(v_t^{ik}) = \sigma_{v^{ik}}^2$$

The variance Ξ is a block diagonal matrix with Ω^{ik} , where

$$\Omega^{ik} = \frac{\sigma_{\nu_t^{ik}}^2}{1 - b^2} \begin{bmatrix} 1 & b & \dots & b^{T-1} \\ b & 1 & \vdots & \vdots \\ \vdots & \vdots & 1 & b \\ b^{T-1} & \dots & b & 1 \end{bmatrix}.$$

Considering both cases in HAC1 and HAC2 leads to the third HAC form, ‘‘HAC3’’, which takes the form,

$$\epsilon_t^{ik} = g^{ik} + \nu_t^{ik} \quad \nu_t^{ik} = b_\nu \nu_{t-1}^{ik} + \mu_t^{ik} \quad \text{var}(g^{ik}) = \sigma_{g^{ik}}^2 \quad \text{var}(\mu_t^{ik}) = \sigma_{\mu^{ik}}^2$$

The variance Ξ is a block diagonal matrix with Ω^{ik} , where

$$\Omega^{ik} = \sigma_{g^{ik}}^2 \begin{bmatrix} 1 & 1 & \dots & 1 \\ 1 & 1 & \vdots & \vdots \\ \vdots & \vdots & 1 & 1 \\ 1 & \dots & 1 & 1 \end{bmatrix} + \frac{\sigma_{\mu^{ik}}^2}{1 - b_\nu^2} \begin{bmatrix} 1 & b_\nu & \dots & b_\nu^{T-1} \\ b_\nu & 1 & \vdots & \vdots \\ \vdots & \vdots & 1 & b_\nu \\ b_\nu^{T-1} & \dots & b_\nu & 1 \end{bmatrix}.$$

With HAC2, the size distortions are larger than those with HAC1 and conclusions remain. With HAC3, the size distortions are close to either HAC1 or HAC2 depending on the null hypothesis models. Simulations with only heteroskedastic errors without serial correlation gives similar results too. The results with HAC1 only are reported in the paper to save space.

The last HAC, ‘‘HAC4’’, in tables 2-5 is White-type heteroscedastic. The variance Ξ_0 is diagonal matrix with $(\sigma^{ik})^2 (= \varepsilon_t^{ik})$ for a specific importer-exporter group. Zeros are for all non-diagonal elements. This is assumed in the Bayesian model specification.

2.3 Monte Carlo Simulations for the Misspecified Case

We consider four HAC forms. The first three HACs obtain qualitatively similar results and we mainly focus on ‘‘HAC1’’. The HAC1 takes the form as below,

$$\epsilon_t^{ik} = g^{ik} + \nu_t^{ik} \quad \nu_t^{ik} = b_\nu \nu_{t-1}^{ik} + \mu_t^{ik} \quad \text{var}(g^{ik}) = \sigma_{g^{ik}}^2 \quad \text{var}(\mu_t^{ik}) = \sigma_\mu^2$$

There is no contemporaneous correlation across county pairs.² This parametric assumption considers the heterogeneous fixed effect in the variance covariance matrix $\Xi (= \text{var}(\epsilon))$, which is a block diagonal matrix with Ω^{ik} (462 pairs) for one specific country pair (importer i and exporter k) and Ω^{ik} has the following form,

$$\Omega^{ik} = \sigma_{g^{ik}}^2 \begin{bmatrix} 1 & 1 & \cdots & 1 \\ 1 & 1 & \vdots & \vdots \\ \vdots & \vdots & 1 & 1 \\ 1 & \cdots & 1 & 1 \end{bmatrix} + \frac{\sigma_\mu^2}{1 - b_\nu^2} \begin{bmatrix} 1 & b_\nu & \cdots & b_\nu^{T-1} \\ b_\nu & 1 & \vdots & \vdots \\ \vdots & \vdots & 1 & b_\nu \\ b_\nu^{T-1} & \cdots & b_\nu & 1 \end{bmatrix}.$$

The HAC4 is White-type heteroscedastic. The variance Ξ_0 is diagonal matrix with $(\sigma^{ik})^2 (= \epsilon_t^{ik})$ for a specific importer-exporter group. Zeros are for all non-diagonal elements. This is assumed in the Bayesian model specification.

In simulations, we consider the case of misspecifications on the error structure, which the true errors have HAC but the estimations do not control for HAC (assuming spherical errors), noted as HAC(M). In table 2, compared with the case of ‘‘HOMO’’, the case of misspecification HAC1(M) has overwhelmingly higher rejection rates for both the null and alternative models; most of the values are 100%. Because of the misspecification, both the null and alternative models cannot estimate consistent coefficients and are rejected easily by the Wald test. Surprisingly, some of the rejection rates are

²Models with contemporaneous correlation across county pairs can be estimated by spacial regression.

very small, and several are even less than 5% for the case of misspecification HAC4(M). Particularly, for the last five combinations the rates in rejecting the true null model are higher than those in rejecting the alternative model though on average the former one is smaller than the later one. In sum, the country-pair specific variance structure remarkably influences the estimations of the coefficients. Without controlling for the true HAC, both the null and alternative models cannot obtain consistent coefficients except few specifications in HAC4(M).

We continue to use the combination of the null model “IMEX” and the alternative baseline model as an example to illustrate the Monte Carlo simulations on the misspecified case (HAC1(M)) in tables 2-5. The misspecification refers (no controlling for HAC) to the fact that the simulated data have HAC in the error term, but the regressions ignore the HAC and assume homoscedastic error terms to estimate the variance-covariance matrix of the coefficients.

- 1) Obtain the coefficients B_0 and variance $\Xi_0 (= var(\epsilon_0))$ based on $(y = X B_0 + \epsilon_0)$. The (estimated) variance covariance matrix Ω^{ik} has the form either HAC1 or HAC2 or HAC3.
- 2) Simulate the dependent variables \hat{y} for 1000 times given B_0 , Ξ_0 , and covariates in the null model “IMEX”. The random sample comes from the random draws of the error term.
- 3) Fit the simulated data into models, same as in the section 2.1 assuming homoscedasticity.
- 4) Calculate the statistics for three tests, including “LR1” and “LR2” for the LR test, “F” for the F test and “Wald1” and “Wald2” for the Wald test. Then obtain the rejection rates (size) for each test, which follows the section 2.1 assuming homoscedasticity.

2.4 Monte Carlo Simulations for the Wald Test on B_0

Tables 2, 3, 4 and 5 show the Wald hypothesis tests (Wald2) on the estimated coefficients from both the null (n) and alternative (a) with respect to the artificial B_0 . The ‘‘HAC1(M)’’ refers to the misspecification case discussed in section 2.3 without controlling for the HAC1. Particularly, tables 3 and 5 provide details for EZ and EU effects, a subset of the B_0 . We continue using the same example to illustrate the simulation.

- 1) Obtain the coefficients B_0 and variance, either homoscedasticity σ_0^2 or heteroskedasticity Ξ_0 based on $(y = XB_0 + \epsilon_0)$ as in append 2.1 and 2.3.
- 2) Simulate the dependent variables \hat{y} for 1000 times given B_0 , σ_0^2 or Ξ_0 , and covariates in the null model (n). The random sample comes from the random draws of the error term.
- 3) Fit the simulated data into models, same as in the section 2.1 if with homoscedasticity. With HAC, we transform the \hat{y} by multiply the cholesky decomposition of the variance matrix Ξ_0 , which has no misspecification. The case with HAC and misspecification is the fact that the simulated data have HAC in the error term, but the regressions assume homoscedastic error terms.
- 4) Calculate the statistic for the Wald test for both null and alternative models. The null hypothesis in the Wald test is $H0 : \hat{B}_m = B_0$ for $m \in \{a, n\}$, and Wald statistic (Wald2) is calculated by following formula

$$Wald = (\hat{B}_m - B_0) * \left[\widehat{var}(\hat{B}_m) \right]^{-1} * (\hat{B}_m - B_0),$$

where $\widehat{var}(\hat{B}_m) = \hat{\sigma}_m^2 * (X'_m X_m)^{-1}$ and $\hat{\sigma}_m^2 = RSS_m / (N - K_m)$. Then obtain the rejection rates (size) for the test under different assumptions of the error terms.

5) Obtain the rejection rates (size) in table 3 for both null and alternative models based on the choice of the subset of the coefficients B_0 .

6) Calculate the Wald statistics in table 4. The null hypothesis is $H_0 : \bar{\hat{B}}_m = B_0$ for $m \in \{a, c\}$, the statistic is calculated as

$$Wald = (\bar{\hat{B}}_m - B_0) * \left[\widehat{var(\bar{\hat{B}}_m)} \right]^{-1} * (\bar{\hat{B}}_m - B_0),$$

where the variance covariance matrix is

$$\widehat{var(\bar{\hat{B}}_m)} = \hat{\sigma}_m^2 * (X_m' X_m)^{-1} / 1000.$$

with mean of the estimated variance $\hat{\sigma}_m^2 = \overline{RSS}_m / (N - K_m)$ and mean of the sum of squared residual \overline{RSS}_m . The Wald statistic follows chi-squared distribution given degrees of freedom $K = 48$ and the critical value for the significant level 5% are 65.17.

3 Steps of MCMC via Gibbs

Markov Chain Monte Carlo Simulation via Gibbs Sampler has the following five steps:

Step 1. Give initial values for the variances, $\Sigma_{1,2} ((\sigma^{ik})^2, \sigma_p^2, \sigma_{\theta t}^2, \sigma_{\phi t}^2)$, and the second level parameters $\mathbf{B}_2 (p, \theta^i, \phi^k)$;

Step 2. (update the first level parameters) Draw values from the posterior distributions for the first level parameters $\mathbf{B}_1 (cons, \beta_{EZ}, \beta_{EU}, \theta_t^i, \phi_t^k, \text{ and } \delta^{ik})$, given $\Sigma_{1,2}$ and \mathbf{B}_2 ;

Step 3. (update all the variance) Draw values from the posterior distributions for the variances $\Sigma_{1,2}$ ($(\sigma^{ik})^2$, σ_p^2 , $\sigma_{\theta t}^2$, and $\sigma_{\phi t}^2$), given \mathbf{B}_1 in Step 2 and \mathbf{B}_2 in Step 1.

Step 4. (update the second level parameters) Draw values from the posterior distributions for the parameters \mathbf{B}_2 , given \mathbf{B}_1 in Step 2 and $\Sigma_{1,2}$ in Step 3.

Step 5. Repeat from the second step until the chain converges.

4 Graphs and Tables

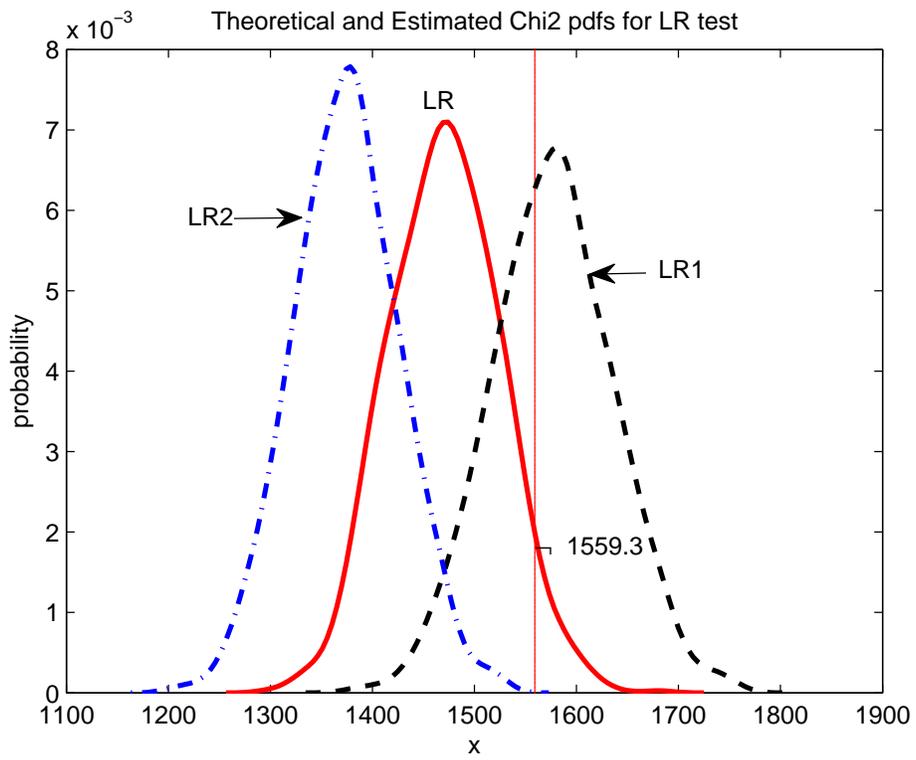


Figure 1: Theoretical and empirical Chi-squared distributions with DF 1469

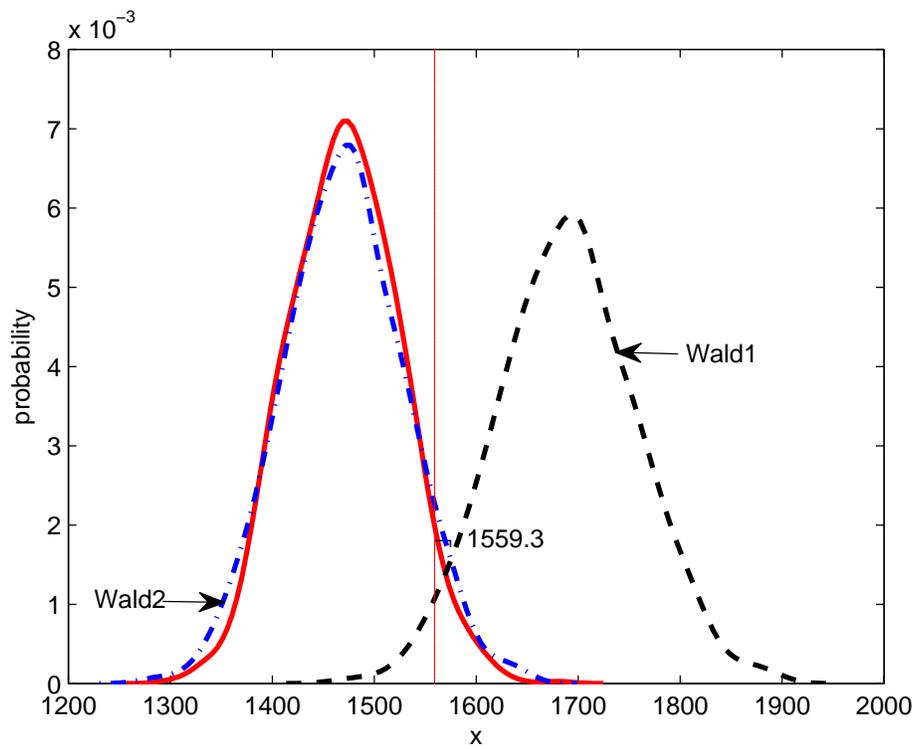


Figure 2: Kernel densities for Wald1 and Wald2: NA vs Baseline

Table 1: Eurozone effect and European Union effect on the log of bilateral import ratio by MLE: 1980-2004

Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dummies	Baseline	NA	NAYear	YNA	YNAPair	IMEX	IMEXYear	YIMYEX	YIMYEXPair	PairYear
Time-varying	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No
Imp. & Exp.	Yes	No	No	No	No	Yes	Yes	Yes	Yes	No
Nation	No	Yes	Yes	Yes	Yes	No	No	No	No	No
Year	No	No	No	Yes	No	No	Yes	No	No	Yes
Pair	Asym.	No	No	No	Sym.	No	No	No	sym.	Sym.
EZ	-0.004	0.158***	0.141***	0.001	-0.004	0.158***	0.142***	0.002	-0.004	0.139***
	0.023	0.016	0.017	0.025	0.025	0.016	0.017	0.023	0.023	0.017
EU	0.227***	0.191***	0.163***	0.227***	0.227***	0.191***	0.163***	0.226***	0.227***	0.163***
	0.018	0.014	0.014	0.020	0.020	0.014	0.014	0.018	0.018	0.015
log(dist)		-0.892***	-0.897***	-0.890***		-0.892***	-0.897***	-0.890***		
		0.052	0.052	0.053		0.047	0.047	0.047		
contig.		0.211*	0.212*	0.210*		0.211*	0.212*	0.210*		
		0.122	0.122	0.123		0.109	0.109	0.109		
comlang.		0.426***	0.422***	0.430***		0.426***	0.422***	0.430***		
		0.104	0.104	0.104		0.092	0.092	0.092		
locked_EX										-1.236***
										0.372
locked_IM										-1.409***
										0.372
Obs	11,550	11,550	11,550	11,550	11,550	11,550	11,550	11,550	11,550	11,550
R2-p	0.968	0.115	0.188	0.409	0.445	0.126	0.199	0.629	0.682	0.224
sigma_u	0.002	0.542	0.543	0.545	0.367	0.481	0.481	0.484	0.268	0.364
sigma_e	0.255	0.328	0.317	0.286	0.286	0.328	0.317	0.260	0.260	0.317
rho	0.008	0.733	0.746	0.784	0.621	0.683	0.697	0.776	0.515	0.569

See table note in Table ?? . MLE assumes the random effects, i.e. $\epsilon_t^{ik} = u^{ik} + e_t^{ik}$, $var(u^{ik}) = \sigma_u^2$ and $var(e_t^{ik}) = \sigma_e^2$.

Table 2: Size of the Wald test (Wald2), $H_0: \hat{\mathbf{B}}_m = \mathbf{B}_0$, where $m \in \{n, a\}$

Comb.	Null (n)	Alternative (a)	DF	n			a		
				HOMO	HAC1(M)	HAC4(M)	HOMO	HAC1(M)	HAC4(M)
(1)	NA	Baseline	27	4.5	100	5.1	4	100	21.4
(2)	NAYear	Baseline	51	4.8	100	3.7	4.3	100	4.4
(3)	YNA	Baseline	555	4.7	48.7	8	6	100	11.3
(4)	YNAPair	Baseline	761	6	100	14.9	5.9	100	17.3
(5)	IMEX	Baseline	48	4.5	100	6.9	5.3	100	29.8
(6)	IMEXYear	Baseline	72	4.7	100	7.3	4.1	100	13.2
(7)	YIMYEX	Baseline	1080	5.7	45.3	10.4	6.2	100	22.1
(8)	YIMYEXPair	Baseline	1286	7.2	100	15.7	7.3	100	24.1
(9)	PairYear	Baseline	258	5	100	14.7	4.2	100	7.1
(10)	IMEX	YIMYEX	48	4.5	100	6.9	4.9	89.4	7.7
(11)	IMEXyear	YIMYEX	72	4.7	100	7.3	5	77.9	2.7
(12)	YNA	YIMYEX	555	4.7	48.7	8	6.2	44.7	6.2
(13)	YNAPair	YIMYEXPair	761	6	100	14.9	6.3	100	9.1

Section 2.4 provides the calculations on the size distortions. The subscripts n and a represents the null and alternative models respectively. See section 2.1 for the Monte Carlo simulations for the homoscedasticity case (the ‘‘HOMO’’ columns); see Sections 2.2 and 2.3 for ‘‘HAC1(M)’’ and ‘‘HAC4(M)’’ columns.

Table 3: Actual size of the Wald test (Wald2), $H_0: \bar{\beta}_{EZ}^m = \beta_{EZ}^0$ and $\bar{\beta}_{EU}^m = \beta_{EU}^0$, where $m \in \{n, a\}$

Comb.	Null (n)	Alternative (a)	n			a		
			HOMO	HAC1(M)	HAC4(M)	HOMO	HAC1(M)	HAC4(M)
(1)	NA	Baseline	4.1	58.2	1.9	4.7	48.6	2.6
(2)	NAYear	Baseline	4.2	60	2.5	4.7	49.3	2.7
(3)	YNA	Baseline	5.3	74.2	4.9	4.7	48.6	2.7
(4)	YNAPair	Baseline	4.7	13.5	3.2	4.7	46.9	3.2
(5)	IMEX	Baseline	4.1	58.8	1.8	4.7	48	3.3
(6)	IMEXYear	Baseline	4.2	62.6	2.7	4.7	48.9	3.1
(7)	YIMYEX	Baseline	5.3	73.2	6.1	4.7	47.4	3
(8)	YIMYEXPair	Baseline	4.7	19.2	3.3	4.7	44.8	3.3
(9)	PairYear	Baseline	4.5	19.2	1.5	4.7	48.2	3.3
(10)	IMEX	YIMYEX	4.1	58.8	1.8	5.3	73.6	5.9
(11)	IMEXyear	YIMYEX	4.2	62.6	2.7	5.3	74.1	5.7
(12)	YNA	YIMYEX	5.3	74.2	4.9	5.3	74.1	4.8
(13)	YNAPair	YIMYEXPair	4.7	13.5	3.2	4.7	14.5	3.2

This table focuses on the EZ and EU coefficients particularly. See table notes in table 2.

Table 4: Wald statistics (Wald2), $H_0: \bar{\mathbf{B}}_m = \mathbf{B}_0$, where $m \in \{n, a\}$

Comb.	Null (n)	Alternative (a)	DF	CV(Chi2)	n			a		
					HOMO	HAC1(M)	HAC4(M)	HOMO	HAC1(M)	HAC4(M)
(1)	NA	Baseline	27	40.1	25.5	280.8	18.1	17.9	2356.4	14.4
(2)	NAYear	Baseline	51	68.7	55.9	290.7	51.6	35.7	2671.8	25.1
(3)	YNA	Baseline	555	610.9	507.6	377.7	513.3	518.1	5349.2	503.3
(4)	YNAPair	Baseline	761	826.3	706.4	7412.1	691.7	744.5	22973.4	730.4
(5)	IMEX	Baseline	48	65.2	43.1	618.6	41.7	54.1	2626.1	43.7
(6)	IMEXYear	Baseline	72	92.8	73.6	637.2	74.2	74.5	2682.9	58.3
(7)	YIMYEX	Baseline	1080	1157.6	1016.4	800.9	1021.3	1017	9141.7	1011.4
(8)	YIMYEXPair	Baseline	1286	1370.5	1215.2	7054.1	1182.2	1244.1	18610.6	1239
(9)	PairYear	Baseline	258	296.5	256.8	7093.3	221.4	268.3	14530.8	270.8
(10)	IMEX	YIMYEX	48	65.2	43.1	618.6	41.7	51.7	38.1	75.3
(11)	IMEXyear	YIMYEX	72	92.8	73.6	637.2	74.2	69.9	45.1	89.4
(12)	YNA	YIMYEX	555	610.9	507.6	377.7	513.3	516.1	465.4	499
(13)	YNAPair	YIMYEXPair	761	826.3	706.4	7412.1	691.7	714.9	7631.6	675.8

This table focuses on the mean of the estimated coefficients. See table notes in table 2.

Table 5: Wald statistics (Wald2), H0: $\bar{\beta}_{EZ}^m = \beta_{EZ}^0$ and $\bar{\beta}_{EU}^m = \beta_{EU}^0$, where $m \in \{n, a\}$

Comb.	Null (n)	Alternative (a)	CV(chi2)	n			a		
				HOMO	HAC1(M)	HAC4(M)	HOMO	HAC1(M)	HAC4(M)
(1)	NA	Baseline	6.0	5.7	4.0	2.2	1.1	7.4	0.2
(2)	NAYear	Baseline	6.0	5.0	6.4	1.1	1.1	8.1	0.2
(3)	YNA	Baseline	6.0	7.8	13.9	3.1	1.1	7.1	0.2
(4)	YNAPair	Baseline	6.0	1.1	3.0	1.0	1.1	8.3	1.0
(5)	IMEX	Baseline	6.0	5.7	2.2	4.0	1.1	6.9	0.2
(6)	IMEXYear	Baseline	6.0	5.0	4.0	2.5	1.1	7.3	0.1
(7)	YIMYEX	Baseline	6.0	7.8	11.6	4.8	1.1	8.2	0.1
(8)	YIMYEXPair	Baseline	6.0	1.1	2.8	1.1	1.1	6.1	1.1
(9)	PairYear	Baseline	6.0	0.4	1.0	1.1	1.1	9.1	0.7
(10)	IMEX	YIMYEX	6.0	5.7	2.2	4.0	7.8	4.8	4.7
(11)	IMEXyear	YIMYEX	6.0	5.0	4.0	2.5	7.8	5.9	4.7
(12)	YNA	YIMYEX	6.0	7.8	13.9	3.1	7.8	13.9	3.1
(13)	YNAPair	YIMYEXPair	6.0	1.1	3.0	1.0	1.1	3.1	1.0

This table focuses on the mean of the estimated EZ and EU coefficients, β_{EZ} and β_{EU} , particularly. See table notes in table 2.

Table 6: Posterior means and standard deviations of \mathbf{B}_2

Var.		mean	std	Var.		mean	std
p		1.669	0.098	σ_p^2		2.292	0.175
θ_i	AUS	1.110	0.052	ϕ_k	AUS	0.400	0.069
	AUT	-1.172	0.074		AUT	-0.123	0.071
	BEL	0.968	0.055		BEL	0.324	0.049
	CAN	0.679	0.060		CAN	0.190	0.049
	CHE	-0.560	0.046		CHE	0.640	0.051
	DEU	-0.049	0.043		DEU	0.309	0.048
	DNK	-0.151	0.091		DNK	0.277	0.056
	ESP	-0.092	0.061		ESP	-0.877	0.067
	FIN	0.375	0.146		FIN	0.840	0.064
	FRA	0.040	0.062		FRA	-0.262	0.055
	GBR	0.908	0.049		GBR	0.848	0.056
	GRC	-0.770	0.141		GRC	-0.926	0.092
	IRL	-0.279	0.143		IRL	1.383	0.070
	ISL	2.080	0.105		ISL	-1.348	0.152
	ITA	0.374	0.037		ITA	0.103	0.053
	JPN	1.710	0.042		JPN	0.682	0.062
	NLD	0.688	0.065		NLD	0.301	0.061
	NOR	0.073	0.079		NOR	-0.341	0.094
	NZL	0.332	0.428		NZL	0.299	0.414
	PRT	-0.071	0.120		PRT	-0.543	0.067
	SWE	-0.099	0.065		SWE	1.051	0.055
	USA	omitted	omitted		USA	0.218	0.047

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