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"Measurement of uncertainty shocks: a Global-VAR model"

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"Ogni opinione ha due tempi:
uno al passato su ciò che è giusto,
uno al presente su ciò che è più adatto"
(Francis Bacon)

Abstract

This work analyses the effects of uncertainty shocks (policy and financial uncertainty) originated in Usa and Euroarea on output, equity and foreign exchange markets from a global perspective, by considering a pool of 34 countries (about 85% of world GDP) and existing interlinkages among them. In doing so, a Global-Vector of AutoRegressive (GVAR) model is estimated using monthly data for the period January 1999 – December 2013. Once estimated the specified GVAR, the effect of uncertainty shocks originated in Us and in the Euro area are analysed.

Estimated results show significant differences both in size and airtime of uncertainty shocks. Effects of Us-uncertainty are usually doubly larger if compared with the same shocks originated in Europe. In particular, Usa and Euro area output reduce by 0.6% and 1.2% respectively in case of an uncertainty shock in Usa; whereas they decrease by 0.2% and 0.6% respectively in case of uncertainty shocks within the Euro area. Similar effects on equity indexes of Usa and Euro area: they decrease by 3% and 7% respectively in case of shock in Us, by 1% and 4% in case of European uncertainty shocks. In spite of some degree of heterogeneity across individual-model responses, similar spillover effects are also confirmed at global level. Thus, empirical results are in line with theoretical predictions concerning of uncertainty shocks.

The size of the spillover effects due to uncertainty shocks seem to be positively correlated with trade openness. It confirm the idea that a relatively high intensity in trade relations reflects in a relatively high degree of vulnerability to external shocks. This vulnerability to foreign uncertainty is also confirmed by responses in the foreign exchange markets, where currencies of developing and emerging markets (i.e. those of Central and Latin America, South-East Asia, Central Europe) devaluate around 1.5% while currencies of advanced economies (Usa, Euro area, Japan) appreciate.

Sommario

Questo lavoro analizza gli effetti di shock di incertezza (sia di politica economica che finanziaria)originatisi negli Usa e nell'eurozona in termini di prodotto aggregato e sul mercati azionari e valutari da una prospettiva globale, considerando un insieme di 34 Paesi (circa l'85% del PIL mondiale) ed i collegamenti esistenti tra loro. Nel far ciò, viene stimato un modello Global-VAR (GVAR) usando dati mensili per il periodo Gennaio 1999 - Dicembre 2013. Una volta stimato, vengono analizzati gli effetti degli shock di incertezza originatisi negli Stati Uniti e nell'eurozona.

I risultati delle stime mostrano differenze significative sia in livello che in tempo di trasmissione degli shocks di incertezza. Gli effetti di shock di incertezza americana sono doppiamente più grandi se comparati con quelli europei. In particolare, il prodotto di Usa e dell'eurozona diminuiscono rispettivamente dello 0.6% e dell'1.2% nel caso di shock di incertezza americana, mentre si riducono rispettivamente dello 0.2% e dello 0.6% nel caso di shock di incertezza nell'eurozona. Effetti simili sui mercati azionari, statunitensi ed europei: essi decrescono rispettivamente del 3% e del 7% nel caso di shock americano, rispettivamente dell'1% e del 4% in caso di shock di incertezza europea. Malgrado qualche grado di eterogeneità delle risposte dei singoli modelli. Simili effetti spillover vengono confermati a livello globale. Così, i risultati empirici sono in linea con le predizioni teoriche relative agli shock di incertezza.

L'entità degli effetti spillover dovuti a shock di incertezza sembrano essere positivamente correlati con l'apertura commerciale. Ciò conferma l'idea che una relativamente alta intensità nelle relazioni commerciali si riflettano in un relativamente alto grado di vulnerabilità a shock esterni. Questa vulnerabilità nei confronti dell'incertezza straniera viene anche confermata nelle risposte dei mercati delle valute straniere, dove le monete dei mercati in via di sviluppo ed emergenti (cioè quelli dell'America Centrale e Latina, del Sud-est asiatico, dell'Europa centrale) si svalutano intorno all'1.5% mentre le valute dei paesi avanzati (Usa, Eurozona, Giappone) si apprezzano.

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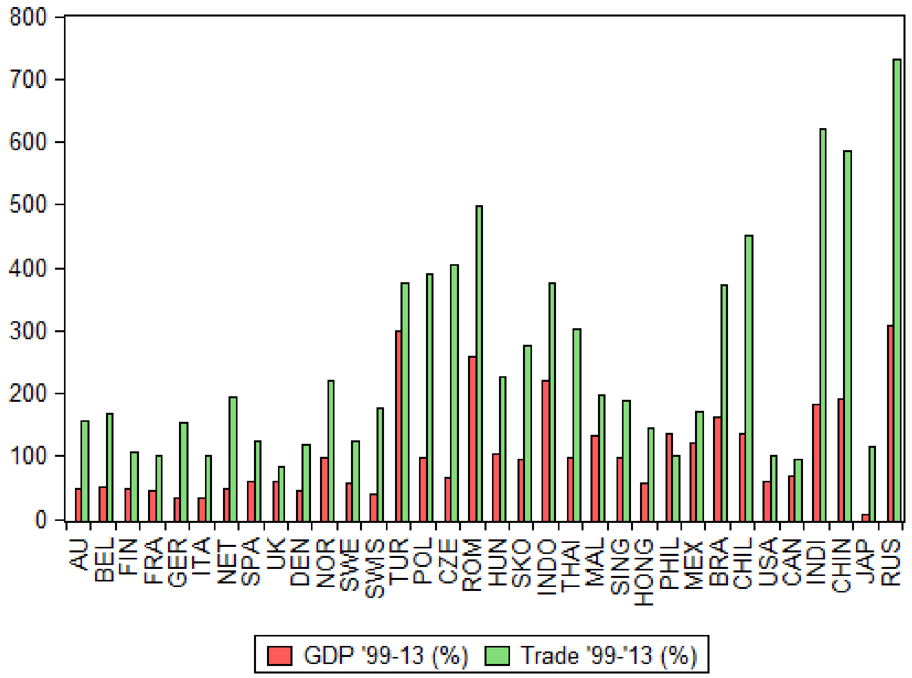
1 Introduction

1.1 A global interconnected perspective

Since its outset, globalization has shown its irreversible effect of a sharp increase in the economic interlinkages among majority of developed, developing and emerging countries. Not surprisingly, in the last 15 years world economy has become increasingly interconnected.

Fig.1: Evolution of foreign trade over 1999-2013



How we can see in Fig.1, all countries have notably increased their international trade (intensity[1]) in the last 15 ears. While the most of the developed countries have had an increment of about 200%, all other countries have more-than-tripled their foreign trade intensity in foreign trade relations. In more details, looking at the table in Appendix D.1, 20% of foreign trade intensity among countries has increased more than 5 times. There are also countries which, in some cases, have decreased (e.g. Usa and Uk with Philippines) their trade volume in the last fifteen years; whereas some others remain constant (especially those of Uk and Japan). All these considerations clearly indicates new consolidated trade relations within the world countries, empirically showing that the majority of world economy have experienced a considerable degree of integration in the last 15 years. Although it has surely been positive for economic growth, such an increased interdependence of different economies has also implied that economies have become more vulnerable to external

[1] Intensity of trade between 2 countries, i and j, is measured as sum of imports from country i/j to country j/i.

shocks than it was in the past. In particular, US 2007-2008 financial crisis demonstrated how external shocks can quickly propagate in the globalized world[2]. Another, more recent, empirical evidence of outwards transmission (i.e. propagation) of shocks is the sovereign debt crisis, firstly originated in Greece and then propagated to Portugal, Spain, Italy, France and the Eurozone as whole.

Transmission channels through which shocks to a foreign country can spill over its effect on are many and complex. Mainly, they are due to presence of economic, financial and political interlinkages.

In particular, trade interdependences comes up as direct consequences of international trade flows of goods and services among world countries. Even thou different countries can have different degree of openness to external trade (see Appendix D.1), and therefore can be more or less vulnerable to external trade shocks, variation in the determinants of exchange flows[3] of one country can likely affect the trade relation with other partner.

About financial interdependences, they mainly consist in cross-borders financial flow realized under different forms, e.g. foreign direct investments[4], banks' external claims and international financial markets transactions. Flow liberalization of '90s and the information technology innovations largely contributed to such an increase in financial interdependences among countries. In particular, allowing institutional investors to trade more easily on (integrated) global financial markets, this has contributed to reduce the airtime of idiosyncratic financial shocks, so that financial conditions of one country have repercussions on other connected countries.

Finally, political interdependences, consisting in cause-effect relations influencing the market sentiment of a country because of political events due in other country she is joint to, also contribute to the characterisation of (structural) patterns involving that particular country.

[2] The corresponding 2007-2009 economic downturn is paradigmatic in this respect: starting as idiosyncratic in the US sub-prime financial market and then spread over other financial markets and the real world economy.

[3] E.g. volumes and prices of imports and exports, foreign exchange rates.

[4] Represented by operations of mergers and acquisitions among foreign firms.

1.2 Macroeconomic shocks and economic uncertainty

The recent financial and sovereign debt crisis have been, *mutatis mutandis*, relevant not only for their capacity of affecting other countries, but also because they shed light on an important determinant of an economic downturn, i.e. uncertainty[5].

In studying the dynamics of an economic system, majority of empirical macroeconomic models have been concentrated on the following shocks[6]:

-*growth surprise*, consisting in a exogenous variation in a country's GDP spreading over other countries via trade and financial linkages;

-*financial shocks*, consisting in exogenous variation in banking and financial sector risk indicator[7] and in asset returns of banking sector, firms and other financial institutions;

-*monetary shocks*, consisting in exogenous variation in policy interest rate;

-*fiscal shocks*, consisting in exogenous variation in tax and public expenditure level.

After the global financial crisis, interests of economic researchers and policy makers focused not only on the aforementioned first-moment shocks[8], but especially on second-moment (i.e. variance-related) shocks due to exogenous variation in uncertainty (i.e. volatility) referring to the general climate of confidence perceived at macro level. This attention has led to the consideration of a further transmission channel of externally originated disturbances: economic uncertainty.

Economic uncertainty refers to an environment where little or nothing is known about the future state of the economy. Interests in this topic firstly arose in Bernanke (1983) and then in Dixit (1994), who find that an increase in uncertainty causes a temporary fall in the economic activity of productive firms. By households' viewpoint, an increased uncertainty about future streams of income and dividends feeds a (herding) tendency to increase precautionary savings by reducing consumption. An increase in uncertainty affects also the risk-aversion of financial agents, who raise their risk premium which, on its turn, affect the financial system.

After the US financial crisis of 2007, the analysis of interrelation between uncertainty and economic activity has become an hot topic. Not surprisingly, unlike other post-World War II global financial recessions[9], that of 2009 has been the deepest and the most synchronized across other world countries (Kose-Loungani-Terrones, 2012). Firstly, Bloom (2009) show an increase in uncertainty

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[5] For sake of technicism, I should refer to risk and not uncertainty, rather. More precisely, the term (Kightian)-uncertainty refer to risks which are not measurable. On the contrary, risk refers to a measurable uncertainty.

[6] The following categorization of shocks is based on the one proposed by IMF (2013). For each of them, empirical evidence show that US idiosyncratic shocks tend to have important effects on economic activity in other countries.

[7] Tipically a Credit Default Swap spread is used as proxy for sectorial risk.

[8] I.e. a shock in the mean of the probability distribution of the random variable to be shocked.

[9] I.e. those of 1975, 1982, 1991. The term 'global recession' refer to a period (usually 2 consecutive quarters) in which world real GDP per capita and in other measures of economic activity (e.g. industrial production, industrial orders, employment).

(i.e. volatility) generate a quick drop and rebound in industrial production. Carrière-Swallow-Céspedes (2013) estimated a battery of small open economies VARs in which the uncertainty is exogenously determined, finding that emerging markets suffer a deeper and more prolonged impacts from uncertainty shocks[10]. Bachmann-Elstner-Sims (2013), using survey business data, show that uncertainty shocks have a protracted negative effects on the level of economic activity, with no evidence of the drop-and-rebound dynamics documented by Bloom (2009). Thus, uncertainty seems to be countercyclical as it is lower during expansionary times and relatively higher during recessions.

Despite this empirical evidence on link between uncertainty and economic activity, it is difficult to establish a clear direction of causality between uncertainty and business cycle. Indeed, uncertainty seems to be a symptom, rather than a cause, of economic instability (Cesa-Bianchi-Pesaran-Rebucci, 2014).

Another open issue concerning uncertainty is about measurement. Considering uncertainty as a latent variables (i.e. not directly measurable but it is assumed it can be deduced by other proxies)has led to consideration of the following, alternative, measures (Bloom-Kose-Terrores, 2013):

1) standard deviation of daily stock returns in each advanced economy;

2) Chicago Board Options Exchange Volatility Index (VIX) [11];

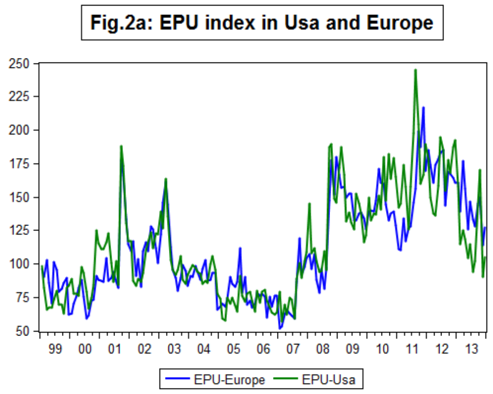
3) uncertainty surrounding economic policy, aka Economic Policy Uncertainty (EPU);

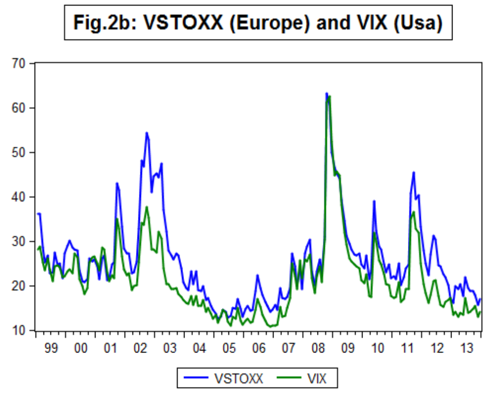
4) uncertainty at global level, defined as aggregate measure of the (N) major economies.

In this application, uncertainty is measured by using either 2) or 3). Fig.2a and Fig.2b show their dynamics under over January 1999 – December 2013.

[10] Results show emerging markets suffer deeper and more prolonged impacts from uncertainty shocks. This is largely due to the presence of more binding credit constraint in the emerging market economies.

[11] Vxo is the new ticker for implied volatility of the S&P500 options (since 2003). Prior to this, the well-known Vix ticker was adopted, instead.





How we can see by Fig.2a and Fig.2b, Usa and Euro area show similar pattern in both uncertainty indexes[12]. Peaks corresponds to sizeable events: 9/11 Twin Towers attack (2001), Iraq War (2003), Northern Rock support (2007), Lehman Brothers' crack (2008), Greek's bailout (2010), Italy's rating cut (2011).

1.3 The GVAR approach

Over the last thirty years, by the work of Sims (1980), Vector of Auto-Regressive processes (VARs) have been considered as principal tool academic economists have used for forecasting, conducting policy analysis and evaluating theories. Despite its flexibility in specification and a statistical diagnostics at hand, their performance has seemed to be reliable only if the variables in each component equation are in a small number[13]. This practical limitation, together with the consideration of a globalized context, brought the focus on single open economy models. It arises the need for a compact macroeconometric global which would have encompassed the drawback represented by the 'curse of dimensionality'[14].

To deal with such a problem, two different approaches have been suggested in the macroeconomic modelling literature:

-*shrinkage of parameter space*, by imposing a set of restrictions directly on parameters. Alternatively, one can impose prior distributions to the parameters to be estimated, e.g. Minnesota prior in Bayesian VAR (Doan-Litterman-Sims, 1984) or other types of prior distributions (Del Negro-Schorfheide, 2004);

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[12] Not surprisingly, correlation coefficients American-European policy and financial uncertainty is relatively high (0.86 and 0.92, respectively). While correlation between policy and financial uncertainty within Usa and the Eurozone are relatively lower (0.46 and 0.51, respectively).

[13] E.g. 7 (Chudick-Pesaran, 2011).

[14] The term 'curse of dimensionality' was coined by Richard Bellman within the context of dynamic optimization. In particular, modelling a VAR(p) of N countries using k endogenous variables would require p(kN-1) parameters.

-*shrinkage of data,* by introducing common (observed and unobserved) factors to the regression equation, e.g. dynamic factor models both in case of cross-sectional independence (Geweke, 1986; Sargent-Sims, 1987) and dependence (Forni-Lippi, 2001). See also Benrnake-Boivin-Eliasz (2005) and Stock-Watson (2005) for Factor-Augmented VAR.

Another approach to deal with the problem of dimensionality in a macroeconomic context is represented by GVAR framework (Pesaran-Shuermann-Wiener, 2004), which explicitly takes into account for proliferation of both parameters and cross-section units considered in the analysis of a global economic context.

Characterized by a two-step procedure, GVAR approach firstly starts with the estimation of single country model and secondly it stakes individual country models into a global VAR and solve them at once. Once solved, GVAR model can be used to generate forecasts (both point and density) and conduct simulated dynamic analysis, explicitly allowing for interdependencies that exist between national and international factors and exploiting the advantages of co-integration theory within VAR-structured models.

1.4 Literature review on GVAR

The GVAR model, firstly introduced in Pesaran-Shuermann-Weiner (2004) and further developed in Dees-Di Mauro-Pesaran-Smith (2007), offers a suitable modelling framework for those want to seek to answer to ‘global-wide’ economic research questions.

By a modelling point of view VARX models, i.e. the single components of a GVAR, can been derived as solution to Dynamic Stochastic General Equilibrium models[15], where over-identifying theoretical restriction can be tested and imposed if statistically acceptable (Pesaran-Smith, 2006). Coherently, Dees-Holy-Pesaran-Smith (2007) implement and test long-run restrictions within the GVAR framework. Furthermore, Dees-Di Mauro-Pesaran-Smith (2007) shows the GVAR as an approximation to a global factor model. Finally, Chudik-Pesaran (2011) establish the condition under which GVAR approach can be derived as an approximation to an Infinite-dimensional VAR[16], both for stationary as well as systems with variables integrated of order 1.

Further extension of the model have been also considered. In particular, Gros (2013) shows how link weights can be estimated jointly with GVAR parameters instead of referring of an external data

[15] See Appendix B.1 for technical details.

[16] I.e. a VAR structured model where all (possibly infinite) variables are assumed to be endogenous.

source. Gros-Kok (2013) introduce a Mixed-Cross-Section[17] GVAR in order to analyze presence of spillovers in credit default swap (CDS) markets showing system of banks and sovereigns has become more densely connected over time[18]. Binder-Gros (2013) accommodate for structural breaks by introducing a Regime-Switching GVAR (RS-GVAR), thus allowing for possible recurring and non-recurring structural changes occurring in individual country model as well as to generate regime-dependent[19] GIRFs. Favero (2013) extends the canonical GVAR features in order to allow for time-varying relation of interdependence[20] among spreads in order to justify the non-linearity in the relation between default premia (spreads) and local fiscal fundamentals.

Despite it has been risk management need for financial institutions that inspired Pesaran-Shuermann-Weiner (2004) to build a global compact macroeconometric model, GVAR framework has also a broad range of applications, both macroeconomic and financial.

Pesaran-Shuermann-Weiner (2004), considering a pool of countries covering about 70% of World GDP using quarterly data (1979-1999), focusing on positive US interest rate and negative US equity price shocks on the rest of the world economies, finding in both cases a negative effect on equity market prices. Dees-Di Mauro-Pesaran-Smith (2007) investigate effects of structural shocks (i.e. innovations) to US country economies (monetary policy,oil price and US equity price variables) to the Euro area, showing financial shocks are transmitted relatively rapidly to the euro area. In this case, they consider countries covering 90% of World GDP using quarterly data over 1979-2003[21]. Similarly, Cesa-Bianchi-Pesaran-Rebucci-Xu (2012) find that the impact of Us on Latin countries has halved, while the impact of growth surprise in China have triples. Bussière-Chudik-Sestiere (2009) investigate factors behind dynamics of global trade flows, showing exports of other countries respond more to an US output shock than a US foreign exchange rate shocks. Cakir-Kabundi (2013) adopt GVAR methodology to assess a significant impacts of output and imports

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[17] I.e. two different, but combined, cross section sets: sovereign and banks. This setup allow to consider endogenous feedbacks between sovereigns and banks.

[18] Findings reveal spillovers in CDS markets were pronounced in 2008 and during 2011-2012. But while in 2008 contagion primarily went from banks to sovereigns, this direction reversed during 2011-2012 sovereign debt crisis.

[19] I.e. IRFs conditioned on a regime-constellation specified across countries.

[20] Notably, patterns became sizeable during 2008-2009 with subsequent separation in co-movements between high- debt countries and low-debt countries. This led to consider weights as relative distance between the fiscal fundamental of each country with the other ones (Favero, 2013).

[21] Same dataset has been used also by Dees-Holy-Pesaran-Smith (2004) to test long run macroeconomic relations. Pesaran-Shuermann-Smith (2009) compare out-of sample forecasts among GVAR model and typical benchmark models (e.g. univariate AR and random walk), while Greenwood-Nimmo-Nguyen-Shin (2012) validate GVAR forecasting performance also during the last financial crisis. Chudik-Smith (2013) compare GVAR benchmark model (i.e. with several small open economies) vis-à-vis its extended version (i.e. with dominant economy, e.g. US). Finally, Dees-Vansteenkiste (2007) focus on the implication of a slowdown of US economy to the other world economy, concluding US business cycle leads that of other world countries but no Asian countries (which seem to having moved independently).

shocks from BRIC[22]s on South Africa. Galesi-Lombardi (2009) analyses the inflationary effects of oil and food price shocks and the inflation linkages among countries[23], finding a direct effect of oil price shock on developing countries and an higher effect of food price shock on emerging economies.

GVAR model can also be evoked for conducting analysis not only of international macroeconomic context, but also within and among different industrial sectors. In particular, Hiebert-Vansteenkiste (2010) focus on US manufacturing labor market considering a group of 12 manufacturing industries over 1977-2003 and investigating the sectorial reaction to exogenous shocks in trade-openness, technology and oil price[24]. Grey-Gros-Paredes-Sydow (2013) exploit the GVAR approach to analyze the interaction between banking sector risk, corporate sector risk, sovereign risk, real economy activity and credit growth using a panel of 53 banks with monthly data ranging over 2002-2012, showing that shocks to Italian and Portuguese sovereign risk are higher than shocks to the corresponding banking sector risks.

Eickmeier-Ng (2007) focuses on credit supply shocks in US, Japan and Euro area, revealing a relatively weaker effects of Japan and Euro area shock with respect to US credit supply shock on GDPs to other world countries. Galesi-Sgherri (2013) finds that asset price is the main channel through which in the short run financial shocks are transmitted.

Another topic covered by GVAR applications concern the housing market. In this context, Vansteenkiste (2007) finds house price spillovers are present in the US at a state level and that a relatively small cost shock causes a long run fall in house prices, thus explaining only part of the driver behind 2005 US house price dynamics. Similarly, Hiebert-Vansteenkiste (2011), show a weak presence of house price spillovers in the Euro area, but a permanent effect (shift) in the house price after 2-3 year due to a shock in the cost of borrowing (long term rates).

GVAR method has also been adopted to investigate recent empirical issues related to the recent financial crisis of 2007-2009 and the sovereign debt crisis 2010-2012. In particular, Chudik-Fratzscher (2011) analyze the effects of tightening liquidity[25] and collapse in risk appetite[26] for global transmission of financial crisis, finding a striking differences also within advanced

[22] BRICs refers to a group of developing countries, namely: Brazil, Russia, India and China. Recently, also South Africa has been included in this group. Thus, acronym now is BRICS.

[23] This has been assessed by disentangling the geographical sources of inflationary pressure for each countries by means of Generalised Forecast Error Variance Decomposition (GFEVD).

[24] They show that a positive unit shock to trade openness negatively affects real compensation but it leads to higher productivity. Effects on employment are negligible. While a positive shock on technology negatively affects the employment level.

[25] Measured as shock in the US-TED spread, i.e. differential between US money market rate and US treasuries (considered as proxy for liquidity pressure).

[26] Measured as shock in Vix, considered as a proxy of financial market risk.

economies[27] before, during and after the crisis[28]. In particular, advanced European countries are the most affected by a fall in risk appetite, while Asiatic emerging countries seem to be the most dependent on foreign direct investments.

About recent sovereign debt crisis, Favero-Missale (2012) focuses on determinants of government yield spreads of 10 European countries and the contagion[29] effect within the Eurozone, using weekly data from June 2006 to June 2011, finding that default risk is the main driver of yield spreads, with small gains from greater liquidity. Chudik-Fratzscher (2012) reveal a fundamental difference in the transmission between 2007-09 financial crisis and 2010-2012 sovereign debt crisis:

-*magnification effects*: effects of liquidity and risk shocks of 2007-09 financial crisis are twice larger with respect to other considered periods;

-*rebalancing effect*: 2007-09 financial crisis cause a massive outflow from emerging to developed countries;

-*flight to safety*: 2007-09 financial crisis led to a shift in financial investments from riskier asset classes (e.g. funds and corporate assets) to less risky one (e.g. bonds).

Recently, Cesa-Bianchi-Pesaran-Rebucci (2014) study the interrelation of financial market volatility and economic activity. Under particular assumptions[30], they find economically sizeable effects of output growth on current volatility but no effect of volatility shock on business cycle: uncertainty is symptomatic rather than causal to economic instability.

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[27] In particular, advanced euro countries result to have been the most affected by fall in risk appetite than other advanced economies (different from Usa). While the most hit by liquidity shocks are especially emerging countries of the Asia continent, as they strongly financially depend on Usa.

[28] Chudik-Fratzscher (2011) split the time span under consideration into two periods: pre-crisis period (from January 2005 to August 2007) and post-crisis period (August 2007 - August 2009).

[29] I.e. a sharp rise in the cross-countries correlations.

[30] Namely, both uncertainty and economic activity are affected by observed and unobserved common factors with a time of lag of at least a quarter.

2 Macroeconometrics of GVAR model

2.1 Introduction

The GVAR approach[31] provides a general modelling framework for the quantitative analysis of an interconnected global economy constituted by individual small open economies. Assuming to deal with integrated variables, GVAR combines individual country vector of error correction models (VECMs[32]) in which a set of domestic variable are related to a set of country-specific foreign variables in a consistent manner. Doing so, existing linkages among countries are explicitly modelled:

-both directly, by the impact of both foreign and global variables used to control for unobserved and observed common components respectively;

-and indirectly, e.g. through non-zero error covariances[33].

Once GVAR model has been solved for the system as whole, similar to all VAR-structured models, it then can be used to generate both point and density forecasts as well as for dynamic analysis, i.e. investigating the time profile of transmissions of shocks to one, or more, variables to the rest of the world economies.

2.2 Structure of a VARX* model and corresponding VECM form

Given a set of $N+1$ countries, consider a general VARX*(p_i, q_i) structure model for the i-th country, for $i = 0, \ldots, N$ and for $t = 1, \ldots, T$:

$$x_{it} = B_i d_t + \sum_{d=1}^{p_i} \Phi_{id}\, x_{i,t-d} + \sum_{f=1}^{q_i} \Lambda_{if}\, x^*_{i,t-f} + u_{it} \qquad (1)$$

Where: $d_t = (1, t, \ldots)'$ is a s×1 vector of deterministics (i.e. intercept and linear trend) and (weakly-exogenous) global variables; B_i is a k_i×s matrix of coefficients for deterministics and global variables; x_{it} represents a k_i×1 vector of k_i domestic (endogenous) domestic variables; x^*_{it} represents a k^*_i×1 vector of k^*_i foreign (weakly exogenous) foreign variables; Φ_{id} is a k_i square matrix of coefficients for domestic variables; Λ_{if} is a k_i×k^*_i matrix of coefficients for foreign

[31] For a book treatment of GVAR model see Di Mauro-Pesaran (2013).

[32] The notion of Vector Error Correction Model and, in general, of cointegration, is treated in 2.4.

[33] This particular structure, with respect to a pure VAR reduced form, will imply conducting dynamic analysis without assuming orthogonality in the residuals.

variables; p_i and q_i are the lag orders for the domestic and foreign part of the i-th country VARX*; u_{it} represents a k_i×1 vector of cross-correlated white noises[34], that is, for $i, j = 0, \dots, N$:

$$u_{it} \sim GWN(0, \Sigma_U) \qquad \text{with} \qquad \Sigma_U = E[u_{it}u'_{jt'}] = \begin{cases} Var[u_{it}] & if\ i = j\ and\ \ t = t' \\ Cov[u_{it}u'_{jt'}] & if\ i \neq j\ and\ t = t' \\ 0 & if\ t \neq t' \end{cases}$$

By assuming that domestic and foreign variables are integrated of order 1, i.e. I(1), and cointegrated, then the corresponding VECM specification is derived[35]:

$$\Delta x_{it} = c_{i0} - \alpha_i \beta'_i [z_{i,t-1} - \gamma_i d_{t-1}] + \Lambda_{i0} \Delta x^*_{it} + \Gamma_i \Delta z_{i,t-1} + u_{it} \qquad (2)$$

Where: $c_{i0} = \alpha_i \beta'_i \gamma_i \Delta d_t$; $z_{it} = (x'_{it}, x^{*\prime}_{it})'$ is a $(k_i + k^*_i)$×1 partition vector of both domestic and foreign variables; α_i is a $k_i \times r_i$ matrix of factor loading[36]; r_i is the resulting cointegrating rank for the i-th country; β_i is a $(k_i + k^*_i) \times r_i$ matrix of cointegration coefficients; γ_i is a $(k_i + k^*_i) \times s$ matrix of coefficients for d_{t-1}. Equivalently, VECMs can be expressed as follows:

$$\Delta x_{it} = c_{i0} - \alpha_i ECM_{i,t-1} + \Lambda_{i0} \Delta x^*_{it} + \Gamma_i \Delta z_{i,t-1} + u_{it} \qquad (3)$$

Where $ECM_{i,t-1}$ is a r_i×1 vector expressed by:

$$ECM_{it} = \beta'_i (z_{it} - \gamma_i d_t) = \beta'_i x_{it} + \beta'_i x^*_{it} - \beta'_i \gamma_i d_t \qquad (4).$$

Let us note equation (4) represents a particular form of the error correction term of individual VECMs, which allows for cointegration both within x_{it} and between x_{it} and x^*_{it} and across countries (i.e. across x_{it} and x_{jt}, for $i \neq j$). Once x^*_{it} and β_i are given, VARX* models are estimated by means of reduced rank regression technique[37].

[34] For detailed statistics about VECM residuals, see Appendix C.8.

[35] See A.3 for an analytical derivation of VECM from a general VARX*(p_i, q_i).

[36] They represents the speed of adjustments towards long-run equilibrium relations.

[37] This regression technique, introduced by Johansen (1991) for endogenous and I(1) variables and then modified by Pesaran-Shin-Smith (2000) to allow for (weakly) exogenous I(1) variables, like OLS technique has as objective the minimization of sum of squared residuals subject to a redued rank condition.

2.3 Solution of a GVAR model

Although estimation is done on a country by country basis, the GVAR model is solved for the system as whole, that is considering all $k = \sum_{i=0}^{N} k_i$ variables as endogenous to the system.

First of all, rewrite (1) in terms of the partition vector $z_{it} = (x_{it}', x_{it}^{*\prime})'$:

$$A_{i0} z_{it} = B_i d_t + \sum_{j=1}^{p_i} A_{ij} z_{i,t-j} + u_{it} \qquad (5)$$

Where: $A_{i0} = \left(I_{k_i}, -\Lambda_{i0}\right)$ and $A_{ij} = \left(\Phi_{ij}, \Lambda_{ij}\right)$ are $k \times (k_i + k_i^*)$ matrices of coefficients.

Introducing the $(k_i + k_i^*) \times k$ matrix of (international) links[38] W_i, we get:

$$z_{it} = W_i x_t \qquad (6)$$

Where: $x_t = (x_{0t}', \dots, x_{Nt}')'$ is a $k \times 1$ vector of all endogenous variables in the system. Substituting (6) into (5), it follows:

$$A_{i0} W_i x_t = B_i d_t + \sum_{j=1}^{p_i} A_{ij} W_i x_{t-j} + u_{it} \qquad (7)$$

Stacking individual models (7), for $i = 0, \dots, N$, yields the global model for x_t:

$$G_0 x_t = B d_t + \sum_{j=1}^{p_i} G_j x_{t-j} + u_t \qquad (8)$$

Where:

$$G_i = \begin{pmatrix} A_{0a} W_0 \\ \vdots \\ A_{Na} W_N \end{pmatrix} \quad \text{for } a = 0, \dots, p_i; \; u_t = \begin{pmatrix} u_{0t} \\ \vdots \\ u_{Nt} \end{pmatrix}$$

Now, since G_0 is non-singular, as it depends on positive link weights and parameter estimates, pre-multiplying (8) by G_0^{-1} it results:

$$x_t = B^G d_t + \sum_{j=1}^{p_i} F_j x_{t-j} + \varepsilon_t \qquad (9)$$

Where: $B^G = G_0^{-1} B$; $F_j = G_0^{-1} G_j$; $\varepsilon_t = G_0^{-1} u_t$.

Equation (9) can be then used for solving the GVAR model, analyze the eigenvalues of the model, computing persistence profiles, conducting dynamic analysis and forecasting activity.

[38] For a detailed procedure of construction of trade weights w_{ij} and corresponding matrix W_i see 3.4.

3 GVAR specification: preliminary settings

3.1 Countries, time span and data frequency

In order to setup the GVAR model framework in our analysis, a specified group of countries must be selected as proxy of the global context. In doing so, I mainly focus on OECD countries, including both developed and developing countries, for a total of 34 countries covering about 85% of world economy[39]. I then grouped 28 of those countries into 5 regions, coherently with their commonly sharing feature, which could be sharing the same geographical area (e.g. Latin America countries) or sharing the same currency (e.g. the European Monetary Union countries), for reasons related to their economic history (e.g. South-East Asia and West European countries) *et similia*.

T.1: Country set and regional entities (% World GDP)

European Monetary Union (15,6)	**Central Europe (2,6)**	**Central-Latin America (5,1)**
Austria (0,5)	Turkey (1,1)	Brazile (3,1)
Belgium (0,7)	Poland (0,7)	Mexico (1,6)
Finland (0,3)	Czech Republic (0,3)	Chile (0,4)
France (3,6)	Romania (0,3)	
Germany (4,7)	Hunary (0,2)	
Italy (2,8)		**North America* (24,9)**
Netherlands (1,1)	**South-East Asia (4,8)**	USA (22,4)
Spain (1,8)	South Korea (1,6)	Canada* (2,5)
	Indonesia (1,2)	
Western Europe (6,1)	Thailand (0,5)	**Asia* (24,9)**
United Kingdom (3,4)	Malaysia (0,4)	India (2,5)
Denmark (0,4)	Singapore (0,4)	China (11,4)
Norway (0,7)	Hong Kong (0,4)	Japan (8,2)
Sweden (0,7)	Philippines (0,3)	Russia (2,8)
Switzerland (0,9)		

* North America and Asia are not regional entities.

[39] Corresponding (geographical) coverage of foreign trade is, on average, about 83% at individual-country level.

Another preliminary choice is about the time span, trading off between time proximity and sample size. At the end, I considered the time period ranging from January 1999 to December 2013, which allows to consider Eurozone as whole from its outset and both financial crisis of 2007-2008 and the sovereign debt crisis of 2010-2011.

The third choice regards the data frequency to be used. Unlike most of macroeconomic applications that conduct quarterly frequency analysis, here monthly data are used. This choice is driven not only by the aim of gaining in sample size, but especially as matter of coherence when considering the time profile of uncertainty shocks, for which a lower (i.e quarterly) could be misleading or too smoothed. On the other hand, considering a monthly frequency enables a better description of the dynamics of the model.

3. 2 Domestic, foreign and global variables

Variables entering a VARX* model are distinguished into domestic, foreign and global variables.

Domestic variables

Domestic variables are those variables entering as endogenous any individual country VARX* model. Opting for a macroeconomic GVAR specification, the selected core set of macroeconomic indicators[40] include variables which are widely available and particularly suitable to involve long run relations through cointegration.

Thus, variables chosen for the question at hand are:

$$EPU\ index\colon\ epu_t = \ln(EPU_t)$$

Where: EPU_t indicates the value of the Policy-related uncertainty index at time t.

$$VIX\colon\ vix_t = \ln(VIX_t)$$

Where: VIX_tindicates the value of the financial-related uncertainty at time t.

$$Real\ Output\colon\ \ y_{it} = \ln\left(\frac{IPI_{it}}{CPI_{it}}\right) = \ln(IPI_{it}) - \ln(CPI_{it})$$

Where: ln represents the natural logarithm; IPI_{it} represents the Industrial Production Index for the i-th country at time t; CPI_{it} is the Consumer Price Index of the i-th country at time t.

[40] These variables represents different aspect of an economy, namely: business cycle (real output), money purchasing power (inflation), equity index (equity market), foreign-exchange rate (foreign relative price), bond market (long interest rate) and monetary policy (short interest rate).

$$Inflation\colon\ p_{it} = \ln\left(\frac{CPI_{it}}{CPI_{i,t-1}}\right) = \ln(CPI_{it}) - \ln(CPI_{i,t-1})$$

$$Real\ Equity\colon\ eq_{it} = \ln\left(\frac{MSCI_{it}}{CPI_{it}}\right) = \ln(MSCI_{it}) - \ln(CPI_{it})$$

Where $MSCI_{it}$ indicates the Morgan Stanley Capital International index of the i-th country at time t.

$$Real\ Foreign\ Echange\ (FX)\ rate\colon\ \ln\left(\frac{FX_{it}}{CPI_{it}}\right) = \ln(FX_{it}) - \ln(CPI_{it})$$

Where: FX_{it} represents the FX rate of the i-th country in terms of Us Dollars at time t.

$$Long\ term\ interest\ Rate\ (LR)\colon \frac{1}{12}\ln\left(1 + \frac{LR_{it}}{100}\right)$$

Where: LR_{it} indicates the (yearly) long term interest of country i at time t.

$$Short\ term\ interest\ Rate\ (SR)\colon \frac{1}{12}\ln\left(1 + \frac{SR_{it}}{100}\right)$$

Where: SR_{it} indicates the (annual) short term interest of country i at time t.

Foreign variables

Foreign variables are peculiar in the GVAR framework inasmuch they allow for an explicit influence from the foreign sector into the national dynamics of the individual country models. As such, foreign variables are assumed to enter as I(1)-weakly exogenous any individual country VARX* model, serving as proxy for global unobserved common factors by means of a weighting average. In fact, by definition, foreign variables $x_{it}^{*} = \sum_{j=0}^{N} w_{ij} x_{jt}$ are constructed from the country-specific domestic variables using the following weighted average:

$x_{it}^{*} = \sum_{j=0}^{N} w_{ij} x_{jt}$ with: $w_{ij} > 0$ for i≠j; $w_{ij} = 0$ for i=j; $\sum_{j=0}^{N} w_{ij} = 1$ (10)

Global variables

Global variables enter the model for the reference (i.e. the 0-th) country as endogenous but as (weakly) exogenous any other individual country VARX* model, serving as proxy for global observed common (international) factors.

In this application I use:

$$Oil\ Price:\ poil_t = \ln(POIL_t)$$

Where: $POIL_t$ indicates the price of (crude) oil at time t.

T.2 Individual VARX model specification

	Domestic variables								Foreign variables							Global variables
	unc	**y**	**p**	**eq**	**fx**	**lr**	**sr**	**poil**	**unc***	**y***	**p***	**eq***	**fx***	**lr***	**sr***	**poil**
USA	X	X	X	X		X	X	X		X			X			
EMU	X	X	X	X	X	X	X			X	X	X		X	X	X
WEU		X	X	X	X	X	X			X	X	X		X	X	X
CEU		X	X	X	X	X	X			X	X	X		X	X	X
SEA		X	X	X	X	X	X			X	X	X		X	X	X
CLA		X	X	X	X	X	X			X	X	X		X	X	X
CAN		X	X	X	X	X	X			X	X	X		X	X	X
INDI		X	X	X	X	X	X			X	X	X		X	X	X
CHIN		X	X	X	X	X	X			X	X	X		X	X	X
JAP		X	X	X	X	X	X			X	X	X		X	X	X
RUS		X	X	X	X	X	X			X	X	X		X	X	X

In the specification shown by T.2, we can see that uncertainty enter as endogenous variables in the USA and EMU VARX* models. And this is the unique channel by which uncertainty spread over the other global economies. This setting will allow to consider mere idiosyncratic shocks of uncertainty.

3.3 Data description

Taking the model into data, I do use of the following time series.

Industrial Production Index (IPI) [41]

IPI measures the value of production limitedly to manufacturing[42], mining, construction and utilities (i.e. gas and electricity). IPI time series are extracted from IFS-IMF[43] via Datastream database. Original time series are expressed with 2010 as base years[44] at monthly frequency[45]. All IPI time series have been seasonally adjusted via X-12 Arima procedure within E-Views software package.

Consumer Price Index (CPI)

CPI time series are extracted from OECD database. Original series are expressed with 2010[46] as base years at monthly frequency[47]. All CPI time series have been seasonally adjusted via X-12 Arima procedure within E-Views software package.

Morgan Stanley Capital International Index (MSCI)

MSCI index represent a weighted average of market capitalization designed to measure the equity market performance. MSCI time series are extracted from Datastream database. Original series are expressed in local currency at daily frequency. Thus, all series have been converted to a lower (i.e. monthly) frequency via suitable frequency conversion method. Data for Romania were not available. All MSCI time series have been seasonally adjusted via X-12 Arima procedure within E-Views software package.

Foreign Exchange (FX) rate

Foreign exchange rate (FX) represents the unit price of one currency in terms of another currency.

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[41] Despite GDP is a better proxy than IPI for business cycle, in this application it is not used as it is expressed at quarterly frequency. Similar choice has been made by Favero (2013), Galesi-Lombardi (2009), Grey-Gros-Paredes-Sydow (2013), Galesi-Sgherri (2013).

[42] Only IPI time series for Indonesia, Singapore and Philippines include just the manufacturing sector.

[43] Acronym of International Financial Statistics (issued by) – International Monetary Fund. Only the data source for China was the National Bureau of Statistics.

[44] Only IPI time series for Thailand was expressed in 2000=100 as base year. Accordingly, they have been converted.

[45] Only IPI time series for Switzerland, Hong Kong, Australia and New Zealand were expressed at quarterly frequency. Therefore they have been converted into an higher (i.e. monthly) frequency.

[46] Exceptions are CPIs for Thailand, Singapore, Hong Kong and Philippines, which originally considered as base year 2011, 2009, 2005 and 2006 respectively.

[47] Exceptions are represented by CPI of Romania, Australia and New Zealand which were available only at quarterly level. These CPI series have been converted to monthly frequency using a suitable frequency conversion method.

FX time series are extracted from BI-UIC[48] database at monthly frequency. Original series are expressed in terms of US dollars. All FX time series have been seasonally adjusted via X-12 procedure within E-Views software package.

Long term (LR) interest rate

Long term interest Rate (LR) represents the yield of long-term government securities. LR time series are extracted from International Financial Statistics of IMF. Those for Chile and Russia are from OCSE Database; LR time series for Turkey, Poland, Czech Republic, Romania, Hungary, Hong Kong, Philippines, Brazil, India, China are Oxford Economics. LR time series for Indonesia is not available.

Short term interest Rate

Short term interest rate (SR) are extracted from IFS-IMF[49] under the ticker money market rate or deposit rate (e.g. France, Netherlands, China).

Oil Price

Oil Price time series has been extracted from Thomson Reuters Database under the ticker Crude oil and expresses in US dollar par barrel. Original daily frequency has been converted to monthly frequency via a suitable frequency conversion method within E-View software.

EPU index

EPU index refers to policy-related uncertainty (Baker-Bloom-Davis, 2012) and it is measured as weighted average of the following components:

-frequency of newspaper references to economic policy uncertainty in ten leading newspaper, weighted by ½. For the construction of the European EPU index, this component is based on newspapers of national relevance in Italy, France, Germany, Uk, Spain;

-number of federal tax code provision set to expire in coming years, weighted by 1/6[50];

-forecasters disagreement about future inflation and government purchases, weighted by 1/6[51].

[48] Acronym from Banca d'Italia – Ufficio Italiano Cambi.

[49] SR for Norway, Hungary and Chile are extracted from the OECD database. SR for Austria, Belgium and India are taken from Oxford Economics.

[50] This components is not taken into account when constructing European EPU index. Thus newspapers and forecasters disagreement component are re-scaled to be 0.5 each.

[51] For the US case, these are based on Survey of Professional Forecasters issued by Federal Reserve Bank of Philadelphia. While for European EPU index, the corresponding entity is the Consensus Economics Forecasters. Anyway, as of April 2014, European EPU index is solely based on first components (i.e. newspapers)

VIX and VSTOXX indices

VIX and VSTOXX indexes reflect the expected[52] annualized volatility of the S&P100[53] and STOXX50[54] respectively. Both are measured as square root of implied volatility of European call and put options over the last 30 days[55]. Original time series has been extracted from the CBOE[56] and VSTOXX official websites[57], respectively. Original data have been converted from daily to monthly frequency via a suitable conversion method within E-Views software.

Trade Weights

Trade weight are computed based on yearly data on imports from 1999 to 2012. Data on imports are extracted from IMF-DOTS[58], expressed in US dollars. Trade Weights are computed as share of total trade[59] between countries pairwise considered. Afterward, trade weights are obtained as (simple) average over 1999-2012.

PPP-GDPs

Power Purchasing Parity (PPP)-valuation of individual country GDPs refer to country's GDP converted to international dollars[60] PPP rates. Corresponding time series are extracted from WB-WDI[61] at yearly frequency. Final values are obtained as simple average of 2009-2012 corresponding values.

3.4 Link matrices

Within GVAR framework, link matrices are used to explicitly consider the individual contributions of each country into other economies. In particular:

-*trade weights*, used to construct foreign variables; -

PPP GDP weights, to regional aggregation of variables, shocks and responses.

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52 In fact, for this reason, VIX and VSSTOXX are considered forward-looking indicators.

53 S&P100 represents the benchmark of the US derivative financial market, as it is expressed by a weighted average of the 100 most relevant option contracts.

54 STOXX50 represents the benchmark of the European financial market considered as whole, as it is expressed by a weighted average of the 50 selected companies quoted in European equity markets (France 19, Germany, 13, Spain 5, Italy 6, Netherlands 5, Finland and Luxembourg 1).

55 This means that if today VXO index quotes 10, it implies markets expect next month annualized volatility of S&P500 index will show a volatility of 10% with respect to its actual value.

56 Acronym of Chicago Board Option Exchanges, it is the largest US (and the first in the world) options exchange market.

57 In particular, VIX time series has been extracted from http://www.cboe.com/micro/vix/historical.aspx. While VSTOXX time series is taken from http://www.stoxx.com/indices/index_information.html?symbol=V2TX.

58 Acronym of Direction of Trade Statistics. This is a statistical periodical release of the IMF.

59 I.e. sum of imports of country j from country I plus imports of country I from country j, for all countries.

60 By definition, one international dollar has the same power purchasing parity as one Us dollar in United States.

61 Acronym of World Development Indicator.

Construction of foreign variables

One of the main feature of the GVAR is the explicit allowance for individual-country influence, via introduction of weakly exogenous foreign variables, expressed as weighted average of the same variable in the other countries. Same weights are then used to solve the GVAR as whole[62].

Recalling the $(k_i + k_i^*) \times k$ matrix of links W_i introduced in (6), consider the illustrative case of $i = 3$ countries, $k_i = 2$ domestic variables and $k_i^* = 2$ foreign variables. In this case, we have the following 4×6 matrix W_i defined as:

$$W_1 = \begin{bmatrix} I_2 & 0_2 & 0_2 \\ 0_2 & w_{12} I_2 & w_{32} I_2 \end{bmatrix}; W_2 = \begin{bmatrix} 0_2 & I_2 & 0_2 \\ w_{21} I_2 & 0_2 & w_{23} I_2 \end{bmatrix}; W_3 = \begin{bmatrix} 0_2 & 0_2 & I_2 \\ w_{31} I_2 & w_{32} I_2 & 0_2 \end{bmatrix} \quad (27)$$

Where: w_{ij} is the intensity of the j-th country into i-th country's economy.

The choice of the particular type (fixed or time-varying) and source (external source of endogenously estimated) of weights strictly depends on the application of the GVAR model, pursuing that weighting scheme that better mimic the intensity of linkages among units (e.g. single or group of countries, firms, banks, investors).

Within macroeconomic applications, Dees-Di Mauro-Pesaran-Smith (2007) adopt trade weights to build the foreign counterpart, while Pesaran-Shuermann-Weiner (2004) and Chudik-Fratzscher (2011) uses weights based of trade and on capital flows to model economic and monetary variables, respectively[63]. Hiebert-Vansteenkiste (2010) adopts a weighting scheme based on Input-Output table of manufacturing industry. While within financial applications, Favero (2013) defines (dynamic) weights by means of the mutual distance of each countries in terms of fiscal fundamentals. Chudik-Fratzscher (2012) constructs weights from portfolio compositions of banks.

A different, more general, weighting scheme has been introduced by Gros (2013), who proposes to estimate weights of link matrix endogenously with respect to the other model parameters, instead of being computed from an external data source[64]. In details, Gros (2013) proposes to derive weights for constructing foreign variables as solution to a constrained optimization problem, e.g.. by minimizing the sum of squared residual from VARX* models subject to the constraints of non-negativity and normality (i.e. they sum to unity) of weights.

Besides the source, one needs also to specify the type of link-weights, choosing between:

-fixed (i.e. state-specific) weights, based either on a specific year as in Binder-Gros (2013) or on an average of years as in Dees-Di Mauro-Pesaran-Smith (2007), Cakir-Kabundi (2013), Galesi-

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[62] See 2.3 for solving procedure of GVAR model.

[63] Pesaran-Shuermann-Weiner (2004) uses trade weights to build foreign product, foreign inflation and foreign rate. While they use capital flow-based weights to construct foreign equity index and foreign interest rate.

[64] As pointed out in Pesaran-Shuermann-Smith (2009), trade weights could also be considered as endogenous if trade flows are determined by economic conditions. Gros (2013), Gros-Kok (2013), Grey-Gros-Paredes-Sydow (2013), such a weights differ about 50-80% from trade-based ones.

Lombardi (2009), Bussière-Chudik-Sestiere (2009), Dees-Vansteenkiste (2007).
-or time-varying (i.e. time and state specific)[65], allowing for non-constant composition of foreign variables as in Dees-Di Mauro-Pesaran-Smith (2007)[66] and Favero (2013).
The choice of the right weights one should employ is still an open question, despite it seems to be of secondary importance if certain conditions are satisfied (Dees-Di Mauro-Pesaran-Smith, 2007), namely small open economies and granularity of weights.
Recall that time-varying weights are particularly important to model the case of rapidly emerging economies with the rest of the world, it is worth noting that this characterization of inter-linkages may add an undesirable degree of volatility in the GVAR model (Pesaran-Shuermann-Smith, 2009).
Keeping all these consideration in mind, being aware of many tradeoffs for the case at hand, the final choice for this work concerns a fixed weighting scheme with trade weight represented by average of (import) weights over the whole time span 1999-2012.
At the end, the adopted trade weight matrix is based on trade weights w_{ij} defined as the sum be total sum of imports[67] from the j-th country to the i-th country share (i.e. IMP_{ij}), and viceversa (i.e. IMP_{ji}), divided by the overall sum of the i-th country to the rest of the world countries (i.e. IMP_{iw}) and the other way round (i.e. IMP_{wi}). In symbols:

$$w_{ij} = \frac{(IMP_{ij} + IMP_{ji})}{(IMP_{iw} + IMP_{wi})} \qquad with\ i \neq j\ and\ for\ i, j = 0, 1, \dots, N \tag{11}$$

[65] In this case, weight matrices are defined as $W_{ij,t}\ for\ t = 0, \dots, T$.
[66] Dees-Di Mauro-Pesaran-Smith (2007) comparing results of GVAR using fixed and time-varying weights they conclude that, as changes in trade weights are gradual, estimations of GVAR model based on one or other type of weights are very close in case number of countries is large enough.
[67] The reason underlying this choice is supported by empirical regularity of strong co-movements between imports and exports across countries. According to Bussière-Chudik-Sestiere (2009), these strong co-movements may be explained as:
-demand shocks can affect both exports and imports;
-intertemporal budget constraints imposes stationarity of the current balance, which implies imports and exports are cointegrated with each other;
-fragmentation of production across countries, which implies an higher import content of exports.

T.3: Trade weight matrix

	USA	EMU	WEU	CEU	SEA	CLA	CAN	INDI	CHIN	JAP	RUS
USA	0,00	0,13	0,10	0,04	0,18	0,29	0,68	0,16	0,21	0,20	0,08
EMU	0,14	0,00	0,60	0,64	0,13	0,26	0,06	0,19	0,15	0,10	0,42
WEU	0,06	0,32	0,00	0,11	0,05	0,05	0,05	0,12	0,05	0,04	0,08
CEU	0,01	0,16	0,06	0,00	0,01	0,02	0,01	0,02	0,02	0,01	0,15
SEA	0,11	0,07	0,06	0,03	0,00	0,08	0,03	0,23	0,30	0,28	0,06
CLA	0,18	0,04	0,02	0,01	0,03	0,00	0,05	0,04	0,06	0,04	0,02
CAN	0,20	0,02	0,02	0,01	0,01	0,03	0,00	0,02	0,03	0,02	0,01
INDI	0,02	0,02	0,02	0,01	0,04	0,02	0,01	0,00	0,02	0,01	0,01
CHIN	0,17	0,10	0,07	0,06	0,34	0,16	0,08	0,15	0,00	0,27	0,13
JAP	0,08	0,04	0,03	0,01	0,19	0,06	0,03	0,05	0,14	0,00	0,05
RUS	0,01	0,09	0,03	0,09	0,01	0,02	0,00	0,02	0,03	0,02	0,00

Comments are left to the reader.

Regional aggregation

Unlike the aforementioned link weights employed to construct foreign variables at individual VARX* level, the choice about aggregation weights is quite standard. In particular, weights used to compose regional variables and to derive both regional responses to shocks and individual country responses to global shocks are based on Power Purchasing Parity (PPP) valuation of country GDP (PPP-GDP).

Similar to foreign variables, regional variables are defined as weighted sum of country specific variables, where weights w_{il}^{0} are derived by dividing the PPP-GDP of the l-th country (i.e. y_l^{PPP}) by the total sum of PPP-GDPs across countries belonging to the same i-th region (i.e. y_i^{PPP}). In symbols:

$$w_{il}^{0} = \frac{(y_l^{PPP})}{(y_i^{PPP})} \qquad (12)$$

Where: $y_i^{PPP} = \sum_{l=1}^{N_i} y_l^{PPP}$. Thus regional variables can be defined as:

$$x_{it}^{0} = \sum_{l=1}^{N_i} w_{il}^{0} x_{ilt} \qquad (13)$$

Where: x_{ilt} denotes the variable of the l-th country belonging to the i-th region are time t; N_i is the number of countries included in the i-th region.

T.4: PPP-GDP weights for regional aggregation

EMU	WEU	CEU	SEA	CLA
Austria (0,3)	United Kingdom (0,63)	Turkey (0,43)	South Korea (0,32)	Mexico (0,42)
Belgium (0,4)	Denmark (0,06)	Poland (0,28)	Indonesia (0,24)	Brazil (0,5)
Finland (0,02)	Norway (0,09)	Czeck Republic (0,1)	Thailand (0,13)	Chile (0,08)
France (0,22)	Sweden (0,11)	Romania (0,12)	Malaysia (0,1)	
Germany (0,3)	Switzerland (0,11)	Hungary (0,07)	Singapore (0,06)	
Italy (0,19)			Hong Kong (0,07)	
Netherlands (0,07)			Philippines (0,08)	
Spain (0,13)				

T.5: PPP-GDP weights for regional aggregations

Region	USA	EMU	WEU	CEU	SEA	CLA	CAN	INDI	CHIN	JAP	RUS
Weight	0,24	0,16	0,05	0,04	0,07	0,07	0,02	0,07	0,16	0,07	0,05

4 Statistical diagnostics in GVAR framework

As any statistical model, once specified and estimated, the statistical assumptions underlying the correct functioning of GVAR model need to be tested. Thus, a number of different statistical tests are conducted to confirm hypothesis of dynamic stability of the model (4.3), serial uncorrelation of residuals (4.4), presence of unit roots (4.5), weak exogeneity of foreign variables (4.6), structural stability of model parameters (4.7).

In what follows, the testing procedure for each performed test in a GVAR context is illustrated together with the provision of test results.

4.1 Lag order selection

In order to select the lag of the individual country VARX* model, typically one uses either Akaike Information Criterion (AIC) or Schwartz-Bayesian information Criterion (SBC).

Given the structure of an individual VARX(p_i, q_i) model for the i-th country, for $i = 0, \dots, N$, the test statistics are computed as follows:

$$AIC_{i,pq} = -\frac{Tk_i}{2}(1 + log2\pi) - \frac{T}{2}\log\left|\hat{\Sigma}_{u_i}\right| - k_i s_i \qquad (14a)$$

$$SBC_{i,pq} = -\frac{Tk_i}{2}(1 + log2\pi) - \frac{T}{2}\log\left|\hat{\Sigma}_{u_i}\right| - \frac{k_i s_i}{2} lnT \qquad (14b)$$

Where: $-\frac{Tk_i}{2}(1 + log2\pi) - \frac{T}{2}\log\left|\Sigma_{u_i}\right|$ is the maximized value of the log-likelihood function of individual-country VARX* residuals under the assumption of multivariate Gaussian White Noise processes; $\hat{\Sigma}_{u_i} = T^{-1}\sum_{t=1}^{T}\hat{u}_{it}\hat{u}'_{it}$ is the estimated sample covariance matrix of residuals $\hat{u}_{it}$ for the i-th country VARX* model; |.| indicates the determinant operator of a matrix;

$s_i = k_i p_i + k^*_i q_i + 2$; k_i, k^*_i are the total number of domestic and foreign variables.

In both cases, the model with the highest AIC or SBC value should be chosen.

In this work, AIC results to be not consistent if compared to SBC, confirming the view of Lutkepohl (2007, pg 326)[68]. Thus, starting from a VARX*(1,1) initially suggested by SBC, lag orders are augmented based on the results of residual autocorrelation test.

[68] Basically, denoted with ord(AIC) and ord(SBC) the lag order selected according to AIC or SBC respectively, it results: $ord(AIC, T) \geq ord(SBC, T) \quad \forall T \geq 16$

T.6: Selected lag orders

Model	P	Q
USA	3	1
EMU	3	1
WEU	1	1
CEU	3	1
SEA	3	1
CLA	2	1
CAN	2	1
INDI	3	1
CHIN	3	2
JAP	1	1
RUS	3	2

4.2 Impact elasticity between domestic and foreign variables

One of the main feature of GVAR model is the inclusion of foreign variables as proxy for common unobserved factors affecting all countries according to their international linkages. Under the assumption of (weakly) exogeneity, foreign variables provides a ‘first layer’ of structuralism if compared to a general VAR model (Pesaran-Shuermann-Smith, 2009).

At this regard, the contemporaneous effects of foreign variables on domestic counterparts are particularly informative. In fact, due to logarithmic transformation of all variables (see 3.2), the estimated coefficients are interpreted as impact elasticity between domestic and foreign variables.

T.7: Impact elasticity of foreign variables to domestic counterparts

Model	y	p	eq	lr	sr
USA	**0,042493**	*	*	*	*
EMU	1,20755	0,413913	0,946076	-0,14953	0,24433
WEU	0,971814	0,558676	0,807853	0,309877	1,604496
CEU	0,856973	1,250966	0,98232	-0,12692	2,235335
SEA	0,475365	0,308954	0,87267	0,804593	0,118734
CLA	0,596703	0,045091	0,961694	2,807156	0,186582
CAN	0,696022	0,949634	0,806962	0,831024	0,935643
INDI	0,177502	-0,50412	0,799142	0,385498	2,32163
CHIN	0,173424	0,359883	1,159142	0,287456	0,361979
JAP	0,638729	0,301449	0,689522	0,302944	0,109917
RUS	0,448141	0,179648	1,20149	**-0,83716**	**0,487737**

As we can see by the T.7, most of coefficients are statistically significant and of positive sign, as expected from the developments of the international linkages among world economies. Bolded estimates are not statistically significant, instead. In particular, those above unity (y for EMU, p for CEU, eq for RUS and for CHIN) indicate an overreaction of domestic variable to the corresponding foreign counterpart. Estimates confirm that relevant channel of transmission are represented by output and equity market.

For a detailed exposition of estimation of corresponding standard errors, see Appendix D.4

4.3 Checking for dynamic stability

The condition of stability of a VAR process implies that the process is uniquely determined by its innovation process, e.g. a multivariate Gaussian White Noise (GWN) process, allowing to retrieve its representation in $MA(\infty)$ form. As results, impulse-response functions should taper off, i.e. converge, relatively quickly.

In order to check for dynamic stability of the whole model, consider the GVAR(p) as in (9):

$$x_t = B^G d_t + \sum_{j=1}^{p_{max}} F_j x_{t-j} + \varepsilon_t$$

From (9), retrieve the GVAR(p) model in the following compact GVAR(1) form:

$$X_t = F X_{t-1} + E_t \quad \text{with:} \quad X_t = \begin{bmatrix} x_t \\ \vdots \\ x_{t-p+1} \end{bmatrix}; \text{ is } F = \begin{bmatrix} F_1 & \dots & F_{p-1} & F_p \\ I_k & 0 & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \dots & I_k & 0 \end{bmatrix}; E_t = \begin{bmatrix} \varepsilon_t \\ 0 \\ \vdots \\ 0 \end{bmatrix} \qquad (15)$$

Where: X_t is the associated $kp \times 1$ vector of random variables; F is the $kp \times kp$ corresponding companion coefficient matrix; E_t is the $kp \times 1$ vector of error terms.

Thus, the eigenvalues of the GVAR(p) model are computed as the eigenvalues λ_{eig} of the companion matrix F by solving the corresponding determinantal equation:

$$\left| I_{kp} \lambda_{eig} - F \right| = 0 \qquad (16)$$

Accordingly, their corresponding moduli are computed as:

$$\lambda_{eig} = a \pm bi \Rightarrow \left| \lambda_{eig} \right| = \sqrt{a^2 + b^2} \qquad (17)$$

The stability condition implies that all of kp roots of the determinantal polynomial should lie inside and at most, in case of I(1) variables, on the unit circle.

Looking at Appendix D.3, 204 eigenvalues respect the stability condition. In details, 48 (23.53%) are equal to 1, while remaining 130 (63.73%) lie inside the unit circle.

4.4 Testing for residual serial correlation

Serial correlation (or autocorrelation[69]) is one of the causes of model misspecification.

In application of regression-like models to the observed data, often assumption of independent residuals may be violated, thus invalidating the adoption of OLS estimation techniques (SURE[70] method used in GVAR applications). Therefore, one needs to test whether the selected order of the model is appropriated and, if serial dependence is still present, raise the number of lags of the single VARX* model. The adopted statistical test is the F-version of Lagrange Multiplier (LM), also known as 'modified' LM.

Given a VARX*(p_i, q_i) model, consider the l-th equation of the estimated i-th VECM:

$$\Delta x_{it,l} = \hat{u}_{il} + \sum_{j=1}^{\hat{r}_i} \hat{\gamma}_{ij,l} \widehat{ECM}_{ij,t-1} + \sum_{n=1}^{\hat{p}_i-1} \hat{\varphi}'_{in,l} \Delta x_{i,t-n} + \sum_{s=0}^{\hat{q}_i-1} \hat{\vartheta}'_{is,l} \Delta x^*_{i,t-s} + \varepsilon_{it,l} \quad (18)$$

More compactly:

$$\Delta x_{it,l} = \hat{\theta}'_{il} z_{it} + e_{it,l} \quad (19)$$

Where: $z_{it} = \left(1, \widehat{ECM}'_{ij,t-1}, \Delta x'_{i,t-n}, \Delta x'^{*}_{i,t-s}\right)'$; $\hat{\theta}_{il} = (\hat{u}_{il}, \hat{\gamma}_{ij,l}, \hat{\varphi}'_{in,l}, \hat{\vartheta}'_{is,l})'$.

The 'modified' LM statistics is given by the following formula:

$$F_{il}(p_{\varepsilon i}) = \left(\frac{T - k_i - p_{\varepsilon i}}{p_{\varepsilon i}}\right)\left[\frac{\chi^2_{il}(p_{\varepsilon i})}{T - \chi^2_{il}(p_{\varepsilon i})}\right] \sim F_{p_{\varepsilon i}, T-k_i-p_{\varepsilon i}} \quad (20)$$

Where: T is the sample size, k_i is the number of regressors for the i-th country model; $p_{\varepsilon i}$ is the selected order[71] of the error process $\varepsilon_{it,l}$; $\chi^2_{il}(p_{\varepsilon i}) \sim \chi^2_{p_{\varepsilon i}}$ is chi-square test statistic defined by:

$$\chi^2_{il}(p_{\varepsilon i}) = T\left[\frac{e'_{il} W_{il} (W'_{il} M_{iz} W_{il})^{-1} W'_{il} e_{il}}{e'_{il} e_{il}}\right] \sim \chi^2_{p_{\varepsilon i}} \quad (21)$$

Where: $e_{il} = \Delta x_{il} - Z_i \hat{\theta}'_{il} = (e_{i1,l}, \dots, e_{iT,l})'$; $\Delta x_{il} = \left(\Delta x_{i1,l}, \dots, \Delta x_{iT,l}\right)'$;

$Z_i = (z_{i1}, \dots, z_{iT})'$; $\hat{\theta}_{il} = \left(\hat{\theta}_{i1,l}, \dots, \hat{\theta}_{iT,l}\right)'$; $M_{iz} = I_T - Z_i (Z'_i Z_i)^{-1} Z'_i$;

[69] Besides over time, serial correlation can also be over space (also known as spatial correlation).

[70] Acronym of Seemingly Unrelated Regression Equations. Introduced by Zollner in 1962, SURE is an OLS-based estimation techniques applied to panel data and assuming correlated error terms over the system of equations.

[71] The selected lag order is 4 for all applications considered.

$$W_{il} = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ e_{i1,l} & 0 & \cdots & 0 \\ \vdots & e_{i1,l} & \cdots & \vdots \\ \vdots & \vdots & \ddots & e_{iT-p_{gi}-1,l} \\ e_{iT-1,l} & e_{iT-2,l} & \cdots & e_{iT-p_{gi},l} \end{bmatrix}$$

Thus, if computed values of the F-statistics are smaller than corresponding critical values, then the serial uncorrelation condition is satisfied for the l-th variable of the i-th country.

T.8: Serial correlation results

Model	5% critical value	unc	y	p	eq	fx	lr	sr	poil
USA	F(4,154)	1,63285	1,400404	1,081475	0,716113		1,092694	0,332843	0,650324
EMU	F(4,149)	0,618852	1,596774	1,74821	0,733563	0,950955	0,306209	0,174308	
WEU	F(4,163)		1,613517	0,547954	1,091067	1,259734	0,035452	0,537645	
CEU	F(4,153)		0,45464	1,458148	1,760417	0,660403	0,207342	0,196305	
SEA	F(4,152)		0,867729	0,384897	2,334216	0,647541	0,075515	0,310312	
CLA	F(4,159)		0,892665	0,962273	1,125502	1,003179	0,268727	0,294566	
CAN	F(4,159)		1,818971	0,654266	2,121807	1,16225	0,133876	0,145687	
INDI	F(4,153)		1,423127	2,215848	0,258325	1,945812	0,111879	0,436911	
CHIN	F(4,146)		2,397993	2,372345	0,878217	2,192107	0,54309	0,551235	
JAP	F(4,164)		1,786251	1,929594	1,57529	1,300716	0,071484	0,069382	
RUS	F(4,146)		**4,453572**	0,884148	1,216443	2,199095	1,694739	1,145251	

How we can see by T.8, the hypothesis of serial uncorrelation is accepted in 67 (98.53%) cases. The unique case of rejection is represented by output variable in Russia model.

4.5 Testing for presence of unit roots

Despite the GVAR model can be applied also to stationary variables, one of the underlying assumptions is the inclusion in all country-specific models of I(1) variables. Thus one needs to test for presence of unit-roots t-statistics for all domestic, foreign and global variables entering the individual VARX* models.

At this aim, the standard Augmented[72] Dickey-Fuller (ADF) and Weighted-Symmetric Dickey-Fuller[73] (WS) tests are applied to the level first and second differences of all variables.

[72] I.e. a standard Dickey-Fuller test whose model of the test is not an AR(1) but an AR(p), with $p > 1$. Inclusion of lagged changes is aimed at clean up serial correlation in the dependent variables.

[73] Introduced by Park-Fuller in 1995, this statistical test exploits the time reversibility of stationary autoregressive process in order to increase their power performance with respect to ADF.

The testing procedure of both ADF and WS-ADF can be illustrated as follow. Given a general AR(p) process:

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + e_t \qquad (22)$$

Where: y_t is one of the domestic, country-specific domestic, foreign or global variable considered in my GVAR specification; $\alpha_0 = \mu(1-\alpha_1)$ with μ be the deterministic trend component; p is lag order selected[74]. The system hypothesis is given by:

$$H_0: \alpha_1 = 1 \text{ vs } H_1: \alpha_1 = 1 \qquad (23)$$

Define the (t-ratio) test statistics:

$$DF = \frac{\hat{\alpha}_1}{SE(\hat{\alpha}_1)} \qquad (24a)$$

In particular:

$$\hat{\alpha}_{1,ADF} = \frac{\sum_{t=2}^{T}(y_{t-1}-\mu)(y_t-\mu)}{\sum_{t=2}^{T}(y_{t-1}-\mu)^2} \qquad (24b)$$

and

$$\hat{\alpha}_{1,WS} = \frac{\sum_{t=2}^{T}(y_{t-1}-\mu)(y_t-\mu)}{\left[\sum_{t=2}^{T}(y_{t-1}-\mu)^2 + (T^{-1})\sum_{t=1}^{T}(y_t-\mu)^2\right]} \qquad (24c)$$

In both tests, the defined hypothesis system is:

$$H_0 : \alpha_1 = 0 \text{ vs } H_1 : \alpha_1 \neq 0 \qquad (25)$$

As usual, if computed values are smaller than corresponding critical values, then H_0 (i.e. presence of unit root) is accepted.

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[74] In this work, lag order p is selected according to the SBC. See 4.1 for technical details.

T.8a: Results from WS-ADF test: domestic variables

	unc	y	p	eq	fx	lr	sr
USA	-3,349901332	-1,385238377	**-9,39886974**	-1,459390294		-2,531955638	-2,124244608
EMU	-3,32302119	-1,738591964	**-7,294557968**	-2,091854637	-1,995693859	-2,501782596	-2,448592308
WEU		-2,206634156	**-7,798429048**	-2,049146629	-2,447781686	-2,181080345	-2,223692357
CEU		-2,118123755	**-4,474587614**	-2,152775442	-2,12185275	-2,770332091	-1,805314019
SEA		-2,452241465	**-7,067465807**	-2,676082132	-2,502047062	-2,164228213	-2,048899328
CLA		-2,71928043	**-5,119204629**	-1,410200502	-2,435934626	-1,804701633	-2,085273589
CAN		-2,116323713	**-10,57821008**	-2,429315717	-1,931080087	-2,462893082	-2,341995723
INDI		1,15775477	**-8,880046586**	-1,538038408	-1,816393015	-0,950196123	-1,732555141
CHIN		-1,173676051	**-8,188487894**	-1,758420728	-0,553127869	-2,97770657	-3,09149663
JAP		-2,374358214	**-8,654602339**	-1,959839237	-1,32474331	-1,947360451	-2,084520241
RUS		-0,948048062	-0,702720913	-1,877165279	-1,908126476	-0,412535722	-1,600011868

By looking at T.8a we can see the hypothesis of unit root is rejected only for the variable inflation, with exclusion of the Russia model. This implies the stationarity of inflation[75] in (almost) all over the world. This recall one of the main effect of the Great moderation period (late '70s), in which targeting inflation low has been become (one of) the main goal of (monetary) policy institutions.

T.8b: Results from WS-ADF test: foreign variables

	y*	p*	eq*	fx*	lr*	sr*	poil
USA	-2,478532662	**-9,351469411**	-1,274284936	-2,28383463	-2,341829863	-1,843460185	-3,000401605
EMU	-2,021301363	**-6,532464849**	-2,090449381		-2,818990772	-1,887115595	-3,000401605
WEU	-2,041522844	**-7,070471538**	-1,967874733		-2,233779453	-2,004985326	-3,000401605
CEU	-2,043178533	**-7,116502952**	-2,056355016		-2,78089339	-2,105897793	-3,000401605
SEA	-2,224232651	**-7,389179752**	-1,847573332		-2,646214831	-2,039652886	-3,000401605
CLA	-2,342189248	**-7,536250774**	-1,919894026		-2,321645413	-1,89053068	-3,000401605
CAN	-2,518084418	**-8,744948976**	-1,722331794		-2,408554474	-1,832044339	-3,000401605
INDI	-2,391024648	**-6,850451364**	-2,074631466		-2,460160876	-2,034521818	-3,000401605
CHIN	-2,716126145	**-7,218953292**	-2,092995986		-2,463985844	-2,063159105	-3,000401605
JAP	-2,33081921	**-6,680981439**	-2,103721133		-2,52150164	-2,048172496	-3,000401605
RUS	-2,019592456	**-6,531915333**	-1,938868486		-2,564058136	-2,170343582	-3,000401605

Not surprisingly, rejection of non-stationarity for inflation is also confirmed if we consider foreign inflation (i.e. a weighted average of individual model inflation) in T.8b.
Detailed results of the ADF and WS-ADF are presented in Appendix D.5.

[75] Accordingly, time series for price levels are integrated of order 1, i.e. I(1).

4.6 Testing for weak exogeneity and pairwise cross-section correlations

Another characteristic assumption underlying individual country VARX* models is the weak exogeneity of foreign variables x^*_{it} with respect to the long run parameters of the conditional model defined by (3). A statistical test (Johansen, 1992) of this assumption is conducted via a test of joint significance of the estimated error correction terms in auxiliary equations for x^*_{it}. In particular, for each l-th element (i.e. variable) of x^*_{it}, the following regression is carried out:

$$\Delta x^*_{it,l} = b_{il} + \sum_{j=1}^{\hat{r}_i} \hat{\zeta}_{ij,l} \widehat{ECM}_{ij,t-1} + \sum_{n=1}^{\hat{p}_i-1} \hat{\varphi}'_{in,l} \Delta x_{i,t-n} + \sum_{s=0}^{\hat{q}_i-1} \hat{\vartheta}'_{is,l} \Delta \tilde{x}^*_{i,t-s} + \varepsilon_{it,l} \qquad (26)$$

Where: $\widehat{ECM}_{ij,t-1}$ are the estimated error correction terms corresponding to the r_i cointegrating relations; $\tilde{x}^*_{it}$ is a vector of (exogenous) foreign and global variables, i.e. $\Delta \tilde{x}^*_{it}$ =.($\Delta x^*_{it,l}$, $\Delta x^G_{it,l}$) with $\Delta x^G_{it,l}$ a vector of global variables. The hypothesis of weak exogeneity of foreign variables, in a context of cointegration, implies that the error correction terms $\widehat{ECM}_{ij,t-1}$ of the individual-country VECM do not enter the marginal model for x^*_{it}. In symbols:

$$H_0: \hat{\zeta}_{ij,l} = 0 \quad \text{vs} \quad H_1: \hat{\zeta}_{ij,l} \neq 0 \ \ for\ j = 1, \dots, r_i \qquad (27)$$

As an F-test, the pivot distribution is an $F_{r_i, T-k_i-r_i}$. Usual decision rule applies.

T.9: Results from weak exogeneity test

Country	Crit-5%	y*	p*	eq*	fx*	lr*	sr*	poil
USA	F(2,143)	1,144183			1,371737			
EMU	F(3,137)	1,954601	1,844751	1,364641		2,140801	1,200644	0,401411
WEU	F(3,159)	**3,274155**	0,379512	2,411736		0,596137	1,683224	1,538662
CEU	F(1,143)	0,453916	**20,7372**	0,257763		0,047373	0,804843	0,250042
SEA	F(1,142)	0,327655	3,821821	0,551276		0,92743	0,495443	2,137792
CLA	F(1,155)	3,39538	0,780123	0,450578		0,05794	1,212043	0,159729
CAN	F(1,155)	0,150006	0,127477	0,114247		1,080504	2,952571	0,088841
INDI	F(1,143)	1,285361	0,000108	**4,350704**		0,000271	0,014736	0,591089
CHIN	F(2,135)	0,699324	1,647854	0,129626		0,41527	1,459877	0,200124
JAP	F(2,160)	0,131085	0,50717	0,126278		1,208442	0,89322	0,622643
RUS	F(2,135)	0,799981	3,005849	1,398269		0,566333	0,435867	1,161438

As we can see by T.9, null hypothesis of weak exogeneity is accepted in 59 (>95%) cases, thus in line with a p-value of 5%. While H_0 is rejected only for foreign output in WEU, foreign inflation in CEU and foreign equity in INDI.

Furthermore, in order to support the assumption of weakly exogenous foreign variables, a test about whether idiosyncratic shocks coming from the individual country VARX model are cross-sectionally weakly correlated, that is $cov(x^*_{it}, u_{it}) \to 0$ for $N \to \infty$, is conducted.

In practice, for each of the k_i domestic variables of the i-th, correlation of that country with (each of the) other country model residuals is firstly computed and then averaged over countries. Thus, by comparing averaged pairwise cross-section correlations of residuals in a VAR (both in level and in first difference form) with no 'foreign counterpart'[76] with corresponding VARX, it is possible to directly supports the idea that inclusion of foreign variables helps in reducing the correlation of domestic variables with error terms.

In particular, by looking at T.10 and the Appendix D.6, we observe that moving from a VAR model to its first difference form helps in reducing cross section correlations by 0.62%, Whereas adopting a VECMX model results in no statistically significant cross-section residual correlations. Thus, results directly support the inclusion that foreign variables as proxy for common unobserved factor do help in alleviating endogeneity problems in this multi-country setting.

T.10: Average pairwise cross-section residual correlations

Variable	VAR level (1)	VAR first diff (2)	VECMX (3)	(1) vs (2)	(2) vs (3)
unc	0,87	0,50	0,37	-0,43	-0,24
y	0,53	0,24	-0,02	-0,45	-1,20
p	0,17	0,10	-0,01	-0,49	0,41
eq	0,51	0,67	-0,02	1,22	-1,03
fx	0,88	0,36	0,26	-0,59	-0,23
lr	0,58	0,30	0,02	-0,42	-1,27
sr	0,38	0,26	0,01	-0,31	-2,78
Mean	0,50	0,33	0,05	-0,62	-1,01

How we can see by T.10, averaged cross-section correlations are in general high for the level of the endogenous variables (0.50) and reduce (0.33) once their first difference form is considered. However, results largely vary across variables and (despite at a less extent) across countries. In any case, inclusion of foreign variables half (on average) the pairwise cross-section correlations between variables and residuals.

For an exposition of estimated results art individual model level, see Appendix D.6.

[76] In particular, VAR specifications (and residuals) are obtained from the exclusion of country-specific foreign variables from the corresponding VARX* model. Global variables are considered, instead.

4.7 Testing for structural stability

Often economic time series display features that are not conform with the assumption of stationarity of the data generating process. Besides trends, cyclical components and time-varying variances[77], there is still an important source of non-stationarity: structural breaks.

Structural breaks represent events causing turbulence in the economic system in particular time period. Econometrically speaking, these changes can affect the regression coefficients (as well as deterministic components) in the extent they become time-varying.

Recall regression (19) and allowing now for parameters changing over time, we have:

$$\Delta x_{it,l} = \hat{\theta}'_{ilt} z_{it} + \varepsilon_{it,l} \tag{28}$$

Where: $\hat{\theta}_{ilt} = \left(u_{it,l}, \gamma_{it,l}, \varphi'_{it,l}, \vartheta'_{it,l}\right)'$. In order to detect for the presence of structural breaks, a group of structural stability tests is performed.

Test based on cumulative sum of OLS residuals[78]

Within this tests, system hypothesis is defined as:

$$H_0: \hat{\theta}_{ilt} = \hat{\theta}_{il} \text{ vs } H_1: \hat{\theta}_{ilt} \neq \hat{\theta}_{ilt'} \quad \text{for } t \neq t' \tag{29}$$

While test statistics for maximal OLS-CUSUM statistics, together with its mean square version, are given by:

$$PK_{MAX} = sup_{\delta \in [0,1]} \left|\mathrm{E}_{iT,l}(\delta)\right| \tag{30a}$$

$$PK_{msq} = \int_0^1 \mathrm{E}_{iT,l}(\delta)^2 d\delta \tag{30b}$$

Where: $\mathrm{E}_{iT}(\delta) = \hat{\sigma}_{il}{}^{-1} T^{-1/2} \sum_{s=1}^{[T\delta]} \varepsilon_{il,s}$; $[.]$ indicates the greatest integer function; $\hat{\sigma}_{il}$ is the standard deviation of the residuals if the l-th variables of the i-th country; $\delta = t/T$.

[77] All these components can, at least in principle, be removed as effect of simple transformation.

[78] Proposed by Ploberger and Kramer in 1992.

Random walk alternative[79]

System hypothesis is defined as:

$$H_0: \hat{\theta}_{ilt} = \hat{\theta}_{il} \text{ vs } H_1: \hat{\theta}_{it,l} = \hat{\theta}_{it-1,l} + \eta_{it,l} \qquad (31)$$

While the corresponding test statistics is given by:

$$R_{il} = T^{-2} \sum_{t=1}^{T} S'_{il,t} \hat{V}_{il}^{-1} S_{il,t} \qquad (32)$$

Where: $\eta_{it,l}$ are i.i.d error terms uncorrelated with $\varepsilon_{it,l}$; $S_{il,t} = \sum_{s=1}^{t} z_{is}\varepsilon_{il,s}$; $\hat{V}_{il} = (T^{-1}\sum_{t=1}^{T} z_{it}z'_{it})\hat{\sigma}_{il}{}^{2}$ or, in its heteroskedasticity-robust version, $\hat{V}_{il} = (T^{-1}\sum_{t=1}^{T} \varepsilon_{il,t}^{2} z_{it}z'_{it})\hat{\sigma}_{il}{}^{2}$.

Sequential Wald tests (one-time change at unknown point in time)

In this case, hypothesis system is expressed as:

$$H_0: \hat{\theta}_{it,l} = \hat{\theta}_{it+1,l} \forall t \in T \text{ vs } H_1: \exists t | \hat{\theta}_{it,l} \neq \hat{\theta}_{it+1,l} \qquad (33)$$

Test statistics are provided in likelihood ratio form[80], mean square form[81] and exponential average form[82] respectively:

$$QLR = sup_{\delta \in [\delta_0, \delta_1]} \mathrm{F}_{ilT}(\delta) \qquad (34a)$$

$$MW = \int_{\delta_0}^{\delta_1} \mathrm{F}_{ilT}(\delta) d\delta \qquad (34b)$$

$$APW = ln\left\{\int_{\delta_0}^{\delta_1} \exp[\mathrm{F}_{ilT}(\delta)/2] d\delta\right\} \qquad (34c)$$

Where: $\delta_1 = 1 - \delta_0$; where δ_0 is the trimming percentage, set as 0.25. In compute the Wald statistics[83], homoscedastic and heteroskedasticity-robust version are provided. Computed values of the test statistics are then compared with critical values obtained by means of (sieve) bootstrapping technique[84].

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[79] Proposed by Nyblom in 1989.
[80] Proposed by Quandt in 1960.
[81] Proposed by Hansen in 1992.
[82] Proposed by Andrews and Ploberger in 1994.
[83] See Galesi-Smith (2013) for a detailed exposition.
[84] See Appendix B.3.4 for technical details about (sieve) bootstrapping procedure.

T.11: Number of acceptance of null hypothesis of no-structural break

TEST	unc	y	p	eq	fx	lr	sr	poil	TOT by TEST (%)
Pksup	2	7	8	9	9	10	10	0	**55 (81)**
PKmsq	2	8	9	8	8	8	11	0	**54 (79)**
Nyblom	2	6	9	7	5	3	3	0	**35 (51)**
Robust Nyblom	2	8	11	8	9	9	10	1	**58 (85)**
QLR	2	4	6	4	3	2	2	0	**23 (34)**
Robust QLR	2	8	8	10	6	10	11	1	**56 (82)**
MW	2	6	7	8	3	2	3	0	**31 (46)**
Robust MW	2	8	10	10	6	11	11	1	**59 (87)**
APW	2	4	5	4	2	1	2	0	**20 (29)**
Robust APW	1	8	8	10	6	10	11	1	**55 (81)**
TOT by variables	2	11	11	11	10	11	11	1	**68 (100)**

How we can see by the table, the null hypothesis of no structural break is accepted (with p-value of 10%) in majority of the tests. In particular, heteroskedastic-robust version of test considered accept the null hypothesis in about 84% of cases. For a detailed illustration of test statistics and critical values for each test see Appendix D.7.

5 Dynamic analysis of GVAR

Once GVAR has been estimated and solved, it can be used to conduct dynamic analysis, assessing the properties of the dynamic system in terms of reactions to exogenous impulses. At this aim, Persistence Profiles (5.1) and Generalized Impulse Response Functions (5.2) are analyzed. How to retrieve structural shocks is also illustrated (5.3) together with the bootstrap procedure adopted to compute empirical distributions of the responses (5.4).

5.1 Persistence Profiles

By definition (Pesaran-Shin, 1996), Persistence Profiles (PPs) refer to the time profiles of the effects of a system or variable-specific shock on the cointegrated variables, providing information about the speed at which cointegrating relationships return to their equilibrium once they have been shocked.

In order to illustrate how PPs work, consider a GVAR(p) as in (9):

$$x_t = B^G d_t + \sum_{j=1}^{p_{max}} F_j x_{t-j} + \varepsilon_t$$

Assumed a stable[85] GVAR, retrieve its infinite Moving Average representation MA(∞):

$$x_t = B^G d_t + \sum_{s=0}^{\infty} A_s \varepsilon_{t-s} \qquad (35)$$

Where: $A_s = \sum_{s=1}^{p} F_j A_{s-j}$ for $s = 1,2,\ldots$; $A_s = I_k$ for $s = 0$; $A_s = 0$ for $s < 0$.

Using identity in (6), i.e. $z_{it} = W_i x_t$, rewrite (35) accordingly:

$$z_{it} = W_i B^G d_t + \sum_{s=0}^{\infty} W_i A_s \varepsilon_{t-s} \qquad (36)$$

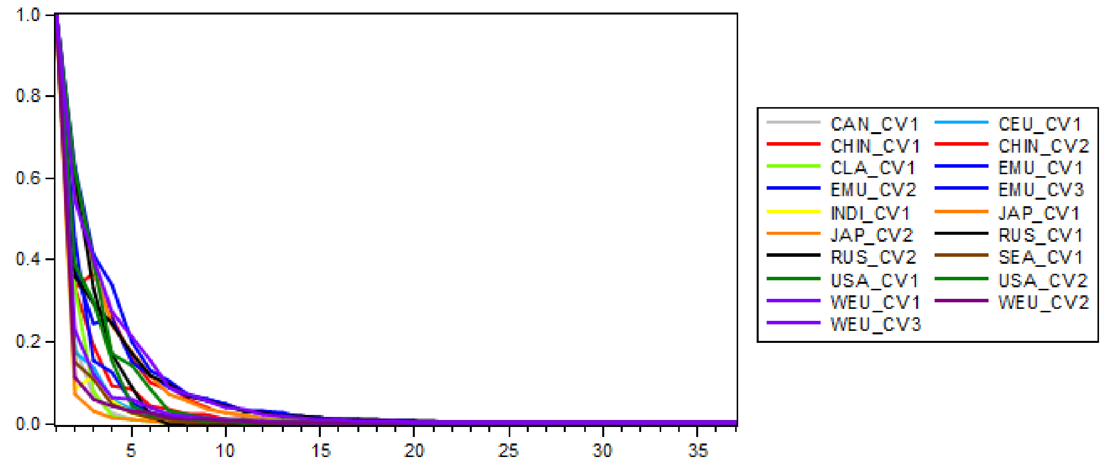
Given a shock to ε_t, the PP of the j-th cointegrating relation in the i-th country is:

$$\mathrm{PP}(\beta_{ji}'; z_{it}; \varepsilon_t; h) = \frac{\beta_{ji}' W_i A_h \Sigma_\varepsilon A_h' W_i \beta_{ji}}{\beta_{ji}' W_i A_0 \Sigma_\varepsilon A_0' W_i \beta_{ji}} \qquad (37)$$

[85] The condition of stability implies the (infinite) sequence of matrices $\mathbf{A_s}$ is absolutely summable. On its turn, it implies the existence in mean square error of the infinite sum (Lutkepohl, 2007, Chapter 2). Stability condition is then ensured once all eigenvalues are (either in absolute values or in corresponding moduli) not greater than 1.

Where: β'_{ji} is the j-th cointegrating relation in the i-th country, for $j = 1, \dots, r_i$; h is the time horizon considered for the length[86] of the impact; Σ_ε is the variance-covariance matrix of residuals $\hat{\Sigma}_\varepsilon = G_0^{-1}\hat{\Sigma}_u G_0^{-1\prime}$, since $\varepsilon_t = G_0^{-1}u_t$; A_s, for $s = 1,2, \dots$ are those defined in (35). Staring from the value of 1 at impact of the shock, if the cointegrating relation is valid for the case at hand, then PPs should rapidly tend to 0 (Pesaran-Shin, 1996).

Fig.3: Persistence Profiles



How we can see by the table, all PPs are well-behaved, supporting the construction of a valid GVAR model. In fact, on average, they converge to 0 (equilibrium level) 15 periods (months) after the shock.

5.2 Generalised Impulse-Response Functions

By definition, Impulse-Response Functions (IRFs) refer to time profile of the effects of the variable-specific shock at a given point in time on the (expected) future states of a dynamical system. Within the GVAR framework, Generalised IRFs (GIRFs), introduced by Koop-Pesaran-Potter (1996) and adapted to VAR models by Pesaran-Shin (1998), are adopted.

One of the main feature of the GIRFs is their invariance property with respect to ordering of the variables entering the VARX* model. Such a property is obtained by firstly shocking one element (e.g. the l-th variable of the i-th country), and then integrate out the effects of other shocks using the assumed (multivariate Normal) or the historical distribution (Pesaran-Shin, 1998). See Appendix B for a exhaustive exposition of differences and similarities between GIRFs and OIRFs.

[86] In this work, a time horizon of 40 periods is considered.

Recall the GVAR(p) model expressed in (8):

$$G_0 x_t = B d_t + \sum_{j=1}^{p_{max}} G_j x_{t-j} + u_t \qquad (38)$$

By definition of GIRF, i.e. time profile of effects of a shock to a system, we have:

$$GIRF(x_t, u_{ilt}, h) = E[x_{t+h} | u_{ilt}, I_{t-1}] - E[x_{t+h} | I_{t-1}] \qquad (39)$$

Where: $E[x_{t+h} | u_{ilt}, I_{t-1}]$ is the response of the shocked system at time $t+h$; $E[x_{t+h} | I_{t-1}]$ is the corresponding base-line profile at the same time; $u_{ilt} = \sqrt{\sigma_{ii,ll}}$, with $\sigma_{ii,ll}$ be the diagonal element of the variance-covariance matrix $\hat{\Sigma}_u = \sum_{t=1}^{T} \hat{u}_t \hat{u}'_t$ corresponding to the l-th equation of the i-th country; h is the time horizon; I_{t-1} is the information set at time $t-1$. Thus, the GIRF of a unit (i.e. one standard error) shock at time t to the l-th equation on the j-th variable at time $t+h$ is given by the j-th element, for $j, l = 1, \ldots, k$, of:

$$GIRF(x_{it}, u_{ilt}, h) = \frac{\xi_j' A_h G_0^{-1} \Sigma_u \xi_l}{\sqrt{\xi_j' \Sigma_u \xi_l}} \qquad (40)$$

Where: $\xi_l = (0,0, \ldots, 0,1,0, \ldots, 0)'$ is a $k \times 1$ selection vector with value of 1 as the l-th element in case of a country-specific shock. For a global shock ξ_l has aggregation weights summing to one, instead. While for a regional shock, ξ_l has aggregation weights only for the countries belonging to the selected region and zeros elsewhere.

As usual, once stability condition of the GVAR model is satisfied (see 4.3), GIRFs should taper off relatively quickly[87].

5.3 Identification of shocks in GVAR framework

In conducting dynamic analysis it is of utmost importance that correlations existing among different shocks is accounted in an appropriate manner. Unlike Orthogonal IRFs (OIRFs), introduced by Sims (1980), GIRFs are invariant to variable ordering[88], thus one needs to be cautious when interpreting the effects of shocks using GIRFs, as they allow for correlation among error term, i.e. the residual covariance matrix is no longer diagonal.

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[87] In general, if all eigenvalues are equal to one (i.e. they lie on the unit circle), shocks permanently affect the level of the variables. If eigenvalues are less that unity (i.e. they lie inside the unit circle), responses return to their equilibrium level 0 depending on their moduli (the higher, the slower the converge). If eigenvalues are above unit (i.e. outside the unit circle), then GIRFs will display a cyclical behavior.

[88] See Appendix B.3 for detailed exposition about dissimilarities between OIRFs and GIRFs

In a typical GVAR context, as shown by Dees-Di Mauro-Pesaran-Smith (2007), in order to consider structural shocks (i.e. innovations), one should:

1) place the dominant country (e.g. USA or EMU) as first within the whole set of countries;

2) orthogonalise the residual covariance matrix, typically via Cholesky decomposition[89];

3) reshuffle the variables of the dominant VARX* according to the selected (causal) order;

So, once condition 1) is satisfied, the Cholesky decomposition is applied to the residual covariance matrix, obtaining the Cholesky factor matrix $\hat{P}$:

$$\hat{\Sigma}_{u_0} = \hat{P}\hat{P}' \qquad (41)$$

Secondly, in order to achieve orthogonality in the residuals pre-multiply them by the matrix $\hat{P}$ of order k_0, thus obtaining i.i.d residuals $\hat{v}_{0t}$:

$$\hat{v}_{0t} = \hat{P}^{-1}\hat{u}_{0t} \qquad (42)$$

Given equation (42), corresponding covariance matrix becomes:

$$\hat{\Sigma}_{v_0} = \hat{P}\hat{\Sigma}_{u_0}\hat{P}' = I_{k_0} \qquad (43)$$

Pre-multiply equation (8) by $\hat{P}^0_{G_0} = \begin{bmatrix} \hat{P} & 0 & \cdots & 0 \\ 0 & I_{k_1} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & I_{k_N} \end{bmatrix}$ we then get:

$$\hat{P}^0_{G_0} G_0 x_t = \hat{P}^0_{G_0} B d_t + \sum_{j=1}^{p_{max}} \hat{P}^0_{G_0} G_j x_{t-j} + v_t \qquad (44)$$

Where: $v_t = (\hat{v}'_{0t}, \hat{u}'_{1t}, \dots, \hat{u}'_{Nt})'$with covariance matrix defined as:

$$\hat{\Sigma}_v = \begin{bmatrix} V(v_{0t}) & Cov(v_{0t}, u_{1t}) & \cdots & Cov(v_{0t}, u_{Nt}) \\ Cov(u_{1t}, v_{0t}) & V(u_{1t}) & \vdots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ Cov(u_{Nt}, v_{0t}) & \cdots & \cdots & V(u_{Nt}) \end{bmatrix} \qquad (45)$$

Where: $V(v_{0t}) = \hat{\Sigma}_{v,00} = \hat{P}\hat{\Sigma}_{u,00}\hat{P}'$; $\mathrm{Cov}(v_{0t}, u_{jt}) = \mathrm{Cov}[\hat{P}\hat{u}_{0t}, \hat{u}_{jt}] = \hat{P}\hat{\Sigma}_{u,0j}$ for $j = 1, \dots, N$.

[89] Cholesky decomposition is a decomposition of a positive-definite matrix into the product of a lower triangular (the so called Cholesky factor) and its conjugate transpose.

Thus, similar to GIRF of (39), in case of Structural GIRFs (SGIRFs) now we have:

$$SGIRF(x_{it}, v_{ilt}, h) = E[x_{t+h} | \xi_{il}' v_{ilt}, I_{t-1}] - E[x_{t+h} | I_{t-1}] \qquad (46)$$

Where: $\xi_{il}' v_{ilt} = \sqrt{\xi_j' \Sigma_v \xi_l}$.

SGIRF of a unit shock at time t to the l-th equation on the j-th variable at time $t + h$ is given by the j-th, for $j, l = 1, \dots, k_i$, element of:

$$SGIRF(x_{it}, v_{ilt}, h) = \frac{\xi_j' A_h \hat{P}_{G_0}^{0} G_0^{-1} \Sigma_v \xi_l}{\sqrt{\xi_j' \Sigma_v \xi_l}} \qquad (47)$$

Despite this would be the right approach to identify a pure, orthogonal, effect, i.e. effects of orthogonal shocks, the sample residual covariance matrix is selected instead.

This choice is coherent with the consideration of a global context within which individual models (representing single economies) act and react according to an interconnected mechanism. This approach seems to be more suitable when modelling the global economies and one focus in the analysis of transmission mechanism rather than the structural interpretation of the shocks in a global, interconnected context (Favero, 2013). Accordingly, residual covariance matrix is not orthogonalised and effects of uncertainty shocks are conditioned on the estimated correlation structure among individual models.

5.4 Empirical findings

Although it is hard to provide a conclusive answer about the impact (and the lengths) of uncertainty shocks, economic theory explains how it can negatively impact on economic activity. On the demand side, firms and households reduce their investments and consumption and thus reducing the aggregate demand. Firms, updating their (expected) valuations, reduce their investments and delay existing projects, as investment is often costly to reverse (Bernanke, 1983; Dixit-Pindyck, 1994). Reductions in investment demands positively affect the level of unemployment and, specularly, negatively affect the demand of workforce. This is the channel by which uncertainty moves from industrial sector to households. Afterwards households reduce their consumption, at least for durable goods, as they prefer to wait for less uncertain time[90].

[90] Furthermore, the impact on savings, as effect of a reduction in consumption, strictly depends on the income level. While at aggregate level, the overall effect will depend on the distribution of income across households.

Fig.4a: Responses of USA and EMU output to a USA-EPU unit shock

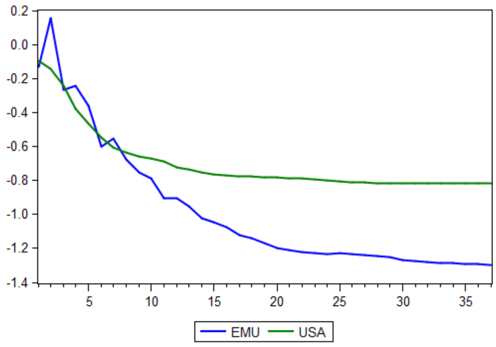
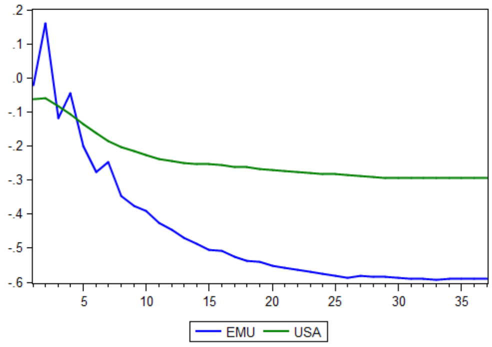


Fig.4b: Responses of USA and EMU output to a EMU-EPU unit shock



How we can see, empirical GIRFs show theoretically coherent findings. In particular we see that EMU and USA suffer a deeper and more prolonged impact from USA uncertainty shock than an EMU uncertainty shock. In fact, in the first case (Fig.4a) output reduces in USA and EMU by 0.6 and 1.2% respectively, whereas it reduces by 0.2 and 0.6 in case of a EMU uncertainty shock (Fig.4b). Responses of USA and EMU stabilise after 10 and 20 periods, respectively. Initial spike in EMU responses can be due to aggregation of heterogeneous countries equipped with an inner compensation mechanism[91]. A similar, negative, reaction also characterizes the responses of other model economies. Fig.5a and Fig.5b show EMU and WEU result to be the most hit by USA and EMU uncertainty shocks, but impact of the shock of is halved in the latter case. JAP results to be the most damaged by spillover effects of uncertainty shocks[92].

The transmission mechanism of uncertainty shocks obviously includes also the financial side of the economy, with a relevant negative impact on equity market indexes. This negative impact on equity market feed(-back) the negative impact on growth.

[91] In this case, this could be explained by the presence of Germany (i.e. the soundest country) within the Euro area. Recent dynamics support this consideration.

[92] Even thou this differences cannot be exhaustively explained within the model, historical and actual considerations help to explain such a heterogeneity across world countries.

Fig.5a: Responses of GVAR output to a USA-EPU unit shock

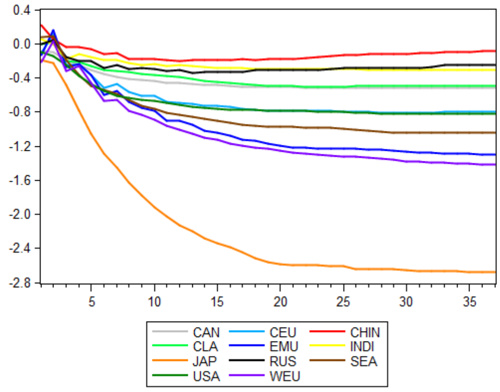
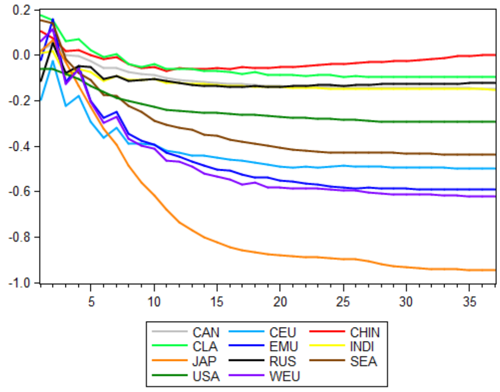


Fig.5b: Responses of GVAR output to a EMU-EPU unit shock



Looking at Fig.6a and Fig.6b, we see that uncertainty shock instantaneously affects USA and EMU equity indexes, with a negative impact of 1% in both cases. Persistent effects to USA and EMU are about -3% and -7% (Fig.6a) and -1% and -4% (Fig.6b), respectively. As in the former case, responses of USA and EMU differ also with respect to the speed of convergence towards a new (lower) equilibrium level. In fact, whereas USA equity responses stabilise after 5 months in both cases (Fig. 6a and Fig.6b, respectively), EMU equity responses stabilise after 30 and 20 periods (Fig.6a and Fig.6b, respectively).

Fig.6a: Responses of USA and EMU equity to a USA-EPU unit shock

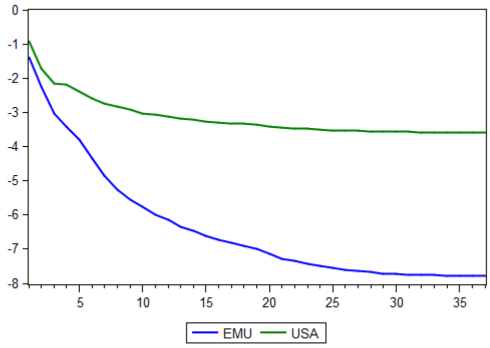
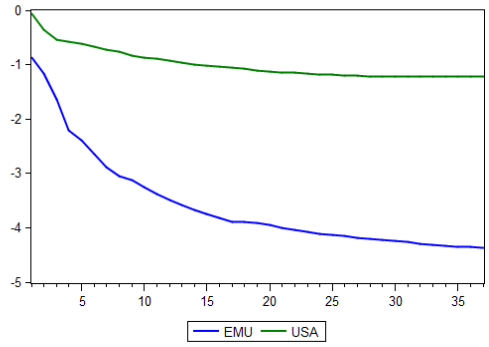


Fig.6b: Responses of USA and EMU equity to a EMU-EPU unit shock



By a global perspective, responses of other models result to be theoretically coherent with previous considerations. In both Fig.6a and Fig .6b USA equity results to be the most resistant to uncertainty shocks if compared to other economic areas (E.g. EMU, WEU, RUS).

Fig.7a: Responses of GVAR equity to a USA-EPU unit shock

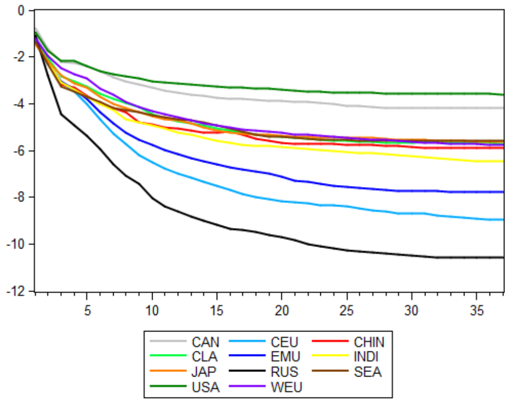
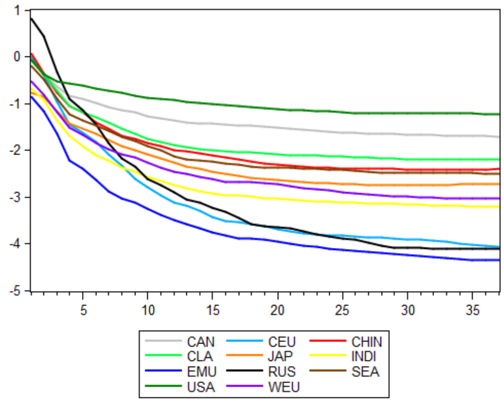


Fig.7b: Responses to GVAR equity to a EMU-EPU unit shock



Once uncertainty shocks have been internalized, creditors charge higher interest rates and shrink the intensity of their lending activities. Firms, especially if credit-constrained, will then shut down their growth opportunities together with their productivity.

A sizeable increase in uncertainty in a country (e.g. Usa and Euro area) is captured by international investors and speculators, which operate[93] and speculate across countries.

This reflects on the international currency market by means of the so-called ‘flight to safety’ phenomenon (Chudick-Fratzcher, 2012), consisting in locating and dislocating financial and non-financial investments away from uncertain environments[94]. International investors liquidate their foreign investments thus increasing the supply of foreign currency against the domestic currency of international investors. They repatriate their funds to compensate losses due to uncertainty shocks on output (and investments) and equity.

Fig.8a: Responses of GVAR fx rate to a USA-EPU unit shock

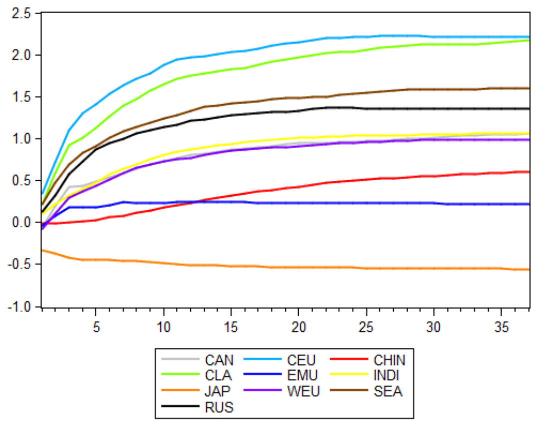
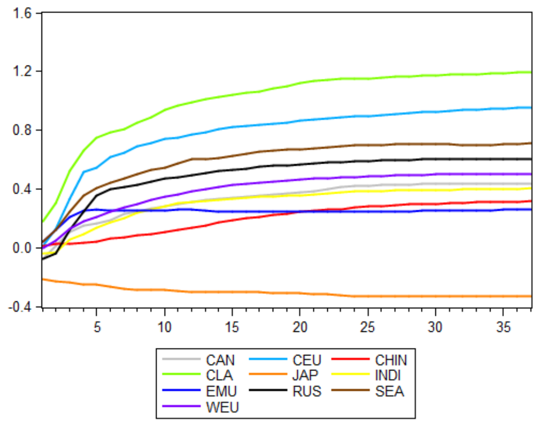


Fig.8b: Responses of GVAR fx rate to a EMU-EPU unit shock



[93] E.g. cross- border operations of merger, acquisition, delocalization.

[94] It can be considered as a substitution effect on a currency markets which infects other currencies in a domino-fashion.

How we can see by Fig.8a and Fig.8b, the ‘flight to safety’ is largely displayed by an appreciation especially of the US$ and of the JAPY(-0.4%) and EMU€ (0.2%) and in a less extent. In particular (Fig.8a), all other currencies, especially those of developing countries, show a persistent appreciation between 0.5 (e.g. WEU, CAN, INDI) and 1.5% (e.g. CEU, SEA, CLA; RUS). In case of impact of EMU uncertainty shocks (Fig.8b), responses result to be lower for all model economies.

6 Conclusions and further research

6.1 Conclusive remarks

The aim of this work was to show the transmission mechanism of uncertainty shocks by a global perspective, thus enlighten similarities and differences among different word countries.
Similar to Favero-Giavazzi (2008) [95] and Colombo (2013)[96], results confirm the dominant role of the Us in the World economy (read: the Us-dependence of the World economy), also in terms of magnitude of uncertainty shocks on output, equity and currency. Effects on these respects seem to be halved depending whether shocks are originated in Usa or Eurozone.
In particular, shocks to USA (EMU) uncertainty result in a negative effect on output of 0.6% (0.3%) for USA, 1.2% (0.6%) for EMU and 0.8% (0.5%) at a globally-aggregate level. Effects of uncertainty shocks in Usa (Euro area) with respect to equity also strongly support the depressing role of uncertainty, as it is associated with a reduction of 3% (1%) of USA equity index, -7% (-4%) of EMU equity index and a -5% (-3%) at a global level. Results are in line with previous researches on the topic of effects of uncertainty shocks.
The most interesting result regard the effects of uncertainty shocks on foreign currencies, where we assist to a ‘flight to safety’ on FX market, realized as an appreciation of world-wide currencies like Us dollar, euro and yen with respect to currencies of developing economies like those of Central America, south-East Asia, India, Central Europe.
Undoubtedly there is a feedback effect between uncertainty, output and equity. While effects on currencies seem to be a direct consequence of the triple uncertainty-output-equity.
All these patterns confirm the view by which idiosyncratic shocks in the 2 most advanced economies of the World, namely Usa and Euro area are extremely dangerous for the other world economies, globally considered. Individual model-responses to uncertainty shocks show how an exogenous, dramatic, systemic shock hitting either Us or the Euro Area (which the global economy has recently experienced) will have a significant effect on other economies both on real (e.g. output) and financial sectors (equity index). The size of the of the effect directly depends on the degree of intensity (read: economic importance) that economy has with the ‘uncertainty-shocked’ country (read: Us and Euro area).

[95] In particular, as noted by Favero-Giavazzi (2008), US variables are more relevant than local variables for the decision undertaken by the European monetary authorities.
[96] Unlike this work, Favero-Giavazzi (2008) and Colombo (2013) use a double-country Structural VAR embodying US and the Euro Area in one vector controlling for 3 variables par country, namely industrial production, inflation and long term rate or inflation respectively.

6.2 Further research

Further research can be carried on in assessing the proper role of uncertainty within the economic system. In spite of the presence of a feedback system, no clear (empirical) evidence has been made about causality relation between uncertainty and reduction in output: does the first cause the latter? Further aspects on the propagation of both economic uncertainty shocks can be investigated. For example, none is still know whether uncertainty affects wealth distribution or not.

Theoretical refinement of the model can also be considered. Namely:

-*imposing over-identifying restrictions*, which could provide a better interpretation of model dynamics; -*regime switching specification*, taking into account for structural breaks affecting model parameters.

Unconsidered GVAR specification can also be considered within the same constructed dataset[97].

In particular:

-*different domestic specification*, including aggregate investment indicators, labor market indicators, wealth distribution indexes, monetary aggregates, fiscal variables;

-*different weighting scheme*, including financial weights for financial variables; cross-country migration weights for research questions concerning international labor market issues;

-different time span, either changing the data frequency[98].

[97] Dataset I constructed include: monthly time series for 34 countries and 6 variables over 1999M01-2013M12. I also constructed yearly cross-country import flows in order to determine trade weights over 1999-2012. All included, it result in an overall set (read: a tensor) containing more than 50,000 data.

[98] As largely suggested, quarterly for macroeconomic applications, monthly for monetary and banking issues, weekly for issue related to financial issues.

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APPENDIX A: Cointegration analysis

A.1 The notion of cointegration[99]

A stochastic process is said to be (weakly) stationary if its first and second moments (i.e. mean and variance) are time-invariant. Clearly, stationary processes cannot capture some main features if the economic time series show having a simple linear trend *vel* time-variant variance (a common features in macroeconomic time series). We also know that integrated variables of order d, i.e. I(d), need to be differentiated d-times before entering linear regression models[100]. But differencing I(d) variables is not always innocent, as it may distort some important feature of the time series. Empirically, it happens that some of the economic variables share a common stochastic trend[101] in the extent they move together. This is the reason why they are called cointegrated[102]. In case of cointegration, VECMs offer a suitable way to describe their dynamics in terms of deviation from some equilibrium relation.

Formally[103], given a k-dimensional vector y_t, the k variables are said to be cointegrated of order (d,b), i.e. $y_t \sim CI(d, b)$, if all components are I(d) and there exists a linear combination $z_t = \beta' y_t$, with $\beta = (\beta_1, \ldots, \beta_k)' \neq 0$ be the cointegrating vector, such that $z_t \sim I(d - b)$. In case of I(1) variables, the cointegrating (linear) relations becomes stationary.

A.2 VECM

VECMs, firstly introduced by Engle-Granger (1981) within the Granger Representation Theorem, characterize the speed at which a dynamical (cointegrated) system returns to the equilibrium relation after a change in an independent variable.

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[99] The idea of cointegration goes back to Granger (1981) and then was popularised by Engle-Granger (1987) with the introduction of VECMs. Stock (1987) derived the asymptotic properties of OLS in case of cointegration. Lastly, Johansen (1988) considered statistical validating procedure for detecting the presence (and the number) of cointegrating relations.

[100] As originally suggested by some of the 'fathers' (i.e. Box and Jeckins), who indicate to differentiate time series until their correlograms do not indicate non-stationarity.

[101] As effect of presence of stochastic trend, variance of data-generating process increases over time.

[102] Usually, behavior of unit-root stochastic processes (e.g. random walks) are introduced by the example of a drunkard's walk. To have a humorous, but still useful, example on the notion of cointegration (a drunkard and her dog) between two stochastic processes, see Murray (1984). The multivariate extension of the humorous example (a drunkard, her god and her boyfriend) is treated in Harrison-Smith (1995).

[103] See Lutkepohl (2007), Chapter 6, for a book treatment on the topic of cointegration.

To derive a VECM representation model, recall the VARX*(p_i, q_i) structure as in (1):

$$x_{it} = B_i d_t + \sum_{d=1}^{p_i} \Phi_{id}\, x_{i,t-d} + \sum_{f=1}^{q_i} \Lambda_{if}\, x^*_{i,t-f} + u_{it}$$

Add and subtract from left hand side (LHS) of (1) $\pm x_{i,t-1}$. After some algebra, it results:

$$x_{it} - x_{i,t-1} = B_i d_t + (\Phi_{i1} - I_{k_i}) x_{i,t-1} + \sum_{d=2}^{p_i} \Phi_{id}\, x_{i,t-d} + \sum_{f=0}^{q_i} \Lambda_{if}\, x^*_{i,t-f} + u_{it} \qquad (A.1)$$

Adding and subtracting from LHS of (A.1) $\pm\Phi_{id}\, x_{i,t-1}$ for $d = 1, \dots, p_i$ and $\pm\Lambda_{if}\, x^*_{i,t-1}$ for $f = 1, \dots, q_i$ we get:

$$\begin{aligned}\Delta\, x_{it} = B_i d_t &+ \left[\left(\sum_{d=1}^{p_i} \Phi_{id}\right) - I_{k_i}\right] x_{i,t-1} - \left(\sum_{j=2}^{p_i-1} \Phi_{id}\ \Delta\, x_{it-j}\right) + \Lambda_{i0}\ \Delta\, x^*_{it} \\ &+ \left(\sum_{f=1}^{q_i} \Lambda_{if}\right) x^*_{i,t-1} - \left(\sum_{f=2}^{q_i-1} \Lambda_{if}\ \Delta\, x^*_{i,t-f}\right) + u_{it} \qquad (A.2)\end{aligned}$$

Rewriting equation (A.2) more compactly, it results:

$$\Delta\, x_{it} = B_i d_t - \Pi_i z_{i,t-1} + \sum_{j=0}^{p_{i,max}-1} \Gamma_i\ \Delta\, z_{i,t-j} + \Lambda_{i0}\ \Delta\, x^*_{it} + u_{it} \qquad (A.3)$$

Where: $\Pi_i = \left(I_{k_i} - \sum_{d=1}^{p_i-1} \Phi_{id}\, , -\sum_{f=1}^{q_i-1} \Lambda_{if}\right)$; $\Gamma_i = \left(-\sum_{d=2}^{p_i-1} \Phi_{id}\, , -\sum_{f=2}^{q_i-1} \Lambda_{if}\right)$

Now, factorize B_i matrix as:

$$B_i = \Pi_i \gamma_i \qquad (A.4)$$

Where: γ_i is a $(k_i + k_i^*)\times s$ unrestricted matrix of coefficients.

In order to accommodate for cointegration, it is assumed that Π_i is not full rank[104]. Thus, given rank(Π_i) = $r_i < k_i$, matrix Π_i is (not uniquely[105]) factorable as:

$$\Pi_i = \alpha_i \beta_i' \qquad (A.5)$$

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[104] See A.3 for the estimation procedure of the number of cointegrating rank.

[105] This decomposition is not unique, which implies the non-uniqueness of the cointegration relations. In fact, for each square matrix H of order r_i, it results: $\Pi_i = \alpha_i \beta_i' = \alpha_i H H^{-1} \beta_i' = (\alpha_i H)[\beta_i'(H^{-1})']' = \alpha_i^* \beta_i^*$

However, it is possible to impose restriction on α *vel* β to get unique relations. There restrictions can come from normalization procedure or from some economic theory.

Where: α_i is a $k_i \times r_i$ full column rank matrix of factor loading; β_i is a $(k_i + k_i^*) \times r_i$ full columns rank matrix of cointegration coefficients. By replacing (A.4) and (A.5) into (A.3):

$$\Delta x_{it} = \alpha_i \beta_i' \gamma_i d_t - \alpha_i \beta_i' z_{i,t-1} + \sum_{j=0}^{p_{i,max}} \Gamma_i \Delta z_{i,t-j} + \Lambda_{i0} \Delta x_{it}^* + u_{it} \quad (A.6)$$

Finally, adding and subtracting from LHS of (A.6) $\pm\alpha_i \beta_i' \gamma_i d_{t-1}$ leads to the VECM representation of a general VARX*(p_i, q_i) as in (2):

$$\Delta x_{it} = c_{i0} - \alpha_i \beta_i' (z_{i,t-1} - \gamma_i d_{t-1}) + \sum_{j=0}^{p_{i,max}} \Gamma_i \Delta z_{i,t-j} + \Lambda_{i0} \Delta x_{it}^* + u_{it}$$

Where: $c_{i0} = \alpha_i \beta_i' \gamma_i \Delta d_t$ and $\Delta d_t = d_t - d_{t-1}$.

A.3 Testing for the number of cointegrating rank

Cointegrating rank indicates the number of linearly independent relations of cointegration.

In fact, if $rank(\Pi_i) = 0$, then there are no cointegrating relations and a VAR in differences would be more appropriate; while if $rank(\Pi_i) = k_i$, i.e. full-rank, it implies all variables are stationary and disturbing the system has no long-run impact on the variables of the system. In order to test for the number of cointegrating relations at individual-country level, the Johansen's two-step procedure (Johansen, 1988) is implemented.

Firstly, recalling equation (2), short run dynamics are eliminated from Δx_{it} and $\tilde{x}_{i,t-1} = (x_{i,t-1}, t)'$ by regressing them on lagged differences $\Delta x_{it-1}, \dots, \Delta x_{i,t-p+1}$ in order to get residuals R_{0t} and R_{1t}:

$$\mathrm{R}_{0t} = \Delta x_{it} - E[\Delta x_{it} \mid \Delta x_{it-1}, \dots, \Delta x_{i,t-p+1}] \quad (A.7a)$$

$$\mathrm{R}_{1t} = \tilde{x}_{i,t-1} - E[\tilde{x}_{i,t-1} \mid \Delta x_{it-1}, \dots, \Delta x_{i,t-p+1}] \quad (A.7b)$$

Secondly, the following matrix is defined:

$$S = S_{11}^{-1} S_{10} S_{00} S_{01}^{-1} \quad (A.8)$$

Where: $S_{ij} = T^{-1} \sum_{t=1}^{T} R_{it} R_{jt}'$ for $i, j = 0,1$.

Now, the k_i eigenvalues of the matrix S, i.e. $\lambda_1, \dots, \lambda_{k_i}$ are computed and ordered. The number of eigenvalues greater than zero determine the cointegrating rank r_i.

Finally, in order to test the null hypothesis of r_i cointegrating relations[106], one can follow:

Trace statistics[107]

Under the null of having at most r_i cointegrating relations, system hypothesis is given by:

$$H_0: r_i \leq \overline{r_i} \quad vs \quad H_1: r_i > \overline{r_i} \qquad \text{(A.9)}$$

While the corresponding test statistics is expressed as:

$$Tr(r) = -T \sum_{i=r+1}^{k_i} (1 - \lambda_i) \qquad \text{(A.10)}$$

*Maximal Eigenvalue statistic*s

Under the null of having exactly r_i cointegrating relations, system hypothesis becomes:

$$H_0: r_i = \overline{r_i} \quad vs \quad H_1: r_i = \overline{r_i} + 1 \qquad \text{(A.11)}$$

Now, the test statistics is given by:

$$\lambda_{MAX}(r) = -T(1 - \lambda_{r_i+1}) \qquad \text{(A.12)}$$

Starting with $H_0: r_i = 0$, both tests are recursively conducted until H_0 is accepted. Values of test statistics are then compared with critical values obtained from Mac-Kinnon-Haug-Michelis 1999). See Appendix C.2 for details about results of both statistical tests.

In the application at hand, cointegrating rank for each model result to be the following:

T.A.1: Cointegrating ranks

Model	USA	EMU	WEU	CEU	SEA	CLA	CAN	INDI	CHIN	JAP	RUS
Coint. Rel	2	3	3	1	1	1	1	1	2	2	2

[106] This statement is equivalent of assumption of having r_i positive eigenvalues.

[107] Trace statistics results to be more powerful test with respect to Maximal Eigenvalues statistics, especially if the sample is relatively small (Lutkepohl-Saikonnen-Treckler, 2007).

A.4 Testing for co-trending restrictions

Within cointegration analysis, testing for the presence of the deterministic component c_{i0} is relevant both for estimation of VECM coefficients and for determining the number of cointegrating relations.

Recalling $c_{i0} = \alpha_i \beta_i' \gamma_i \Delta d_t$ from (2), following Garrat-Lee-Pesaran-Shin (2012), there are five possible cases:

I case) Nor intercept or trend, i.e. $c_{i0} = 0$;

II case) Restricted intercept and no trend, i.e. $c_{i0} = \alpha_i \beta_i' \gamma_i \neq 0$;

III case) Unrestricted intercept and no trend, i.e. $c_{i0} = \gamma_i \neq 0$;

IV case) Unrestricted intercept and restricted trend, i.e. $c_{i0} = \alpha_i \beta_i' \gamma_i \Delta d_t \neq 0$;

V case) Unrestricted intercept and unrestricted trend, i.e. $c_{i0} = \gamma_i \Delta d_t \neq 0$.

In particular, following Galesi-Sgherri (2013), only the case III versus case IV is tested.

A test of whether cointegrating relations are trended or not can be carried out stating the following hypothesis system, which implies r_i linear restrictions:

$$\mathrm{H}_0\colon \alpha_i \beta_i' = 0 \quad vs \quad \mathrm{H}_1\colon \alpha_i \beta_i' \neq 0 \qquad \text{(A.13)}$$

Corresponding test statistics (together with its pivot distribution) is given by:

$$2\left[l\left(\hat{\theta}_i; r_i\right) - l\left(\tilde{\theta}_i; r_i\right)\right] \sim \chi^2_{r_i} \qquad \text{(A.14)}$$

Where: $\theta_i = vec(\beta_i)$; $\beta_i = (\beta_{i1}, \dots, \beta_{ir_i})$; $l\left(\hat{\theta}_i; r_i\right)$ is the maximized value of log-likelihood function when cointegrating relations are just identified[108]; $l\left(\tilde{\theta}_i; r_i\right)$ is the maximized value of log-likelihood function when cointegrating relations are over identified[109]. Under H_0, the test statistics is asymptotically distributed as a chi-square with r_i degrees of freedom. Thus, if computed values of the likelihood ratio test statistics are lower than corresponding $\chi^2_{r_i}$ critical values, then H_0 is accepted and case III is imposed. On the contrary, if null hypothesis is rejected, then case IV is set up for that individual-country model. The following table shows empirical values of the test statistics together with the resulting case of co-trending restriction opportunely selected.

[108] If not specified, the r_i^2 exact identifying restrictions imposed by the program are based on the identity matrix

[109] I.e. when r_i co-trending restrictions are specified in addition to the just-identified r_i^2 constraints, for a total of $m_i r_i - r_i^2$ over-restrictions. In this case, $m_i r_i$ represents the total number of restrictions, with m_i indicating the total number of both domestic and foreign variables.

T.A.1: Co-trending restrictions: III vs IV

COUNTRY	$l(\tilde{\theta}_i; r_i)$	$l(\tilde{\theta}_i; r_i)$	Test Stat	Crit value_95%	Case
USA	4838,856796	4836,72022	4,27314397	5,991	3
EMU	5755,098692	5753,50142	3,19455419	7,815	3
WEU	5165,728478	5161,31373	8,82949716	7,815	4
CEU	4335,214567	4334,50662	1,41589819	3,841	3
SEA	4926,419686	4924,16525	4,50888277	3,841	4
CLA	4627,063436	4625,52661	3,07364668	3,841	3
CAN	5259,029568	5258,95037	0,15838884	3,841	3
INDI	4641,840538	4641,52662	0,62784407	3,841	3
CHIN	5080,046459	5078,74647	2,59997478	5,991	3
JAP	5243,762341	5243,18381	1,1570606	5,991	3
RUS	4003,049777	4001,97285	2,15386217	5,991	3

As we can see by the table, case IV is accepted only in 2 cases (e.g. WEU and SEA). For all other models, case III is imposed.

A.5 Testing for over-identifying restrictions

Here it is shown how over-identifying cointegrating restrictions can be tested and, if accepted, imposed to the individual-country VECMs.

Given r_i cointegrating relations for the i-th country, they are of following form:

$$\beta_i' z_{it} \sim I(0) \qquad \text{(A.15)}$$

Where: $\beta_i = (\beta'_{i1}, \dots, \beta'_{ir_i})'$; $z_{it} = (x'_{it}, x^{*\prime}_{it})'$.

Hence, if we want to test the validity of some cointegrating relations suggested by economic theory, we need to specify them by means of the cointegrating vectors β_{ij} (for $j = 1, \dots, r_i$) by imposing the coefficient that those variables have in that theoretical relation.

Under the null hypothesis that $m_i r_i - r_i^2$ over-identifying restrictions are valid, the log-likelihood ratio test statistics is defined as:

$$2\left[l(\tilde{\theta}_i; r_i) - l(\tilde{\theta}_i; r_i)\right] \sim \chi^2_{m_i r_i - r_i^2} \qquad (A.16)$$

Where: $\theta_i = vec(\beta_i)$; $\beta_i = (\beta_{i1}, \dots, \beta_{ir_i})$; $l(\tilde{\theta}_i; r_i)$ is the maximized value of log-likelihood function when cointegrating relations are just identified; $l(\tilde{\theta}_i; r_i)$ is the maximized value of log-likelihood under the total number of restrictions, i.e. $m_i r_i$. Under H_0, the test statistics is asymptotically distributed as a chi-square with degrees of freedom equal to the number of over-identifying restrictions.

Also in this case, if computed values of the likelihood ratio test statistics are lower than corresponding $\chi^2_{m_i r_i - r_i^2}$ critical values, then H_0 is accepted and those cointegrating relations can be imposed to the otherwise unrestricted individual-country model[110].

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[110] Due to limited number of observations considered in this work, no cointegrating relation has been specified and imposed. However, for an application of GVAR model with imposed cointegrating relations, see Dees-Di Mauro-Pesaran-Smith (2007) and Dees-Holy-Pesaran-Smith (2007) where a number of cointegrating relations are statistically tested and, in some case, accepted. If left unrestricted, by default the exact identification is assumed, with $\beta'_{ix} = (I_{r_i} : Q_i)$ where Q_i is a $r_i \times (k_i - r_i)$ matrix of parameters to be estimated freely.

APPENDIX B: theoretical results

B.1 GVAR as solution to a standard DSGE model

Here it is shown that a standard theoretical DSGE macro-model has a VARX* structure.

A standard DSGE system is composed by a system of three equation coming from the optimizing decisions of representative agents[111]. In particular, the canonical three-equation system is defined by:

1) New Keynesian Phillips curve, explaining inflation π_{it} by deviation of log-output y_{it} from its natural level $\bar{y}_i$, i.e. $\tilde{y}_{it} = (y_{it} - \bar{y}_i)$. In symbols:

$$\pi_{\mathrm{it}} = a_{i\pi} + \lambda_{i\pi}\pi_{\mathrm{it-1}} + (1-\lambda_{i\pi})E_t[\pi_{\mathrm{it+1}}] + \gamma_{i\pi}\tilde{y}_{it} + \varepsilon_{i\pi t} \qquad (\mathrm{B.1.1})$$

Where: $a_{i\pi}$ is the deterministic component; $\varepsilon_{i\pi t}$ is a general cost shock. With no loss of generality, it is possible to use an alternative measure of output gap, namely $\tilde{y}_{it} = (y_{it} - y^*_{it})$, where y^*_{it} represents the foreign[112] level of output (averaged across countries) at time t.

2) Optimising IS curve, explaining the output gap $\tilde{y}_{it}$ by the real interest rate $\tilde{r}_{it}$, where $\tilde{r}_{it} = (r_{it} - E_t[\pi_{\mathrm{it+1}}])$. In symbols:

$$\tilde{y}_{\mathrm{it}} = a_{i\tilde{y}} + \lambda_{i\tilde{y}}\tilde{y}_{\mathrm{it-1}} + (1-\lambda_{i\tilde{y}})E_t[\tilde{y}_{\mathrm{it+1}}] + \gamma_{i\tilde{y}}\tilde{r}_{it} + \varepsilon_{i\tilde{y}t} \qquad (\mathrm{B.1.2})$$

Where: $a_{i\tilde{y}}$ is the deterministic component; $\varepsilon_{i\tilde{y}t}$ is a general preference or technological shock.

3) Taylor rule, describing the determination of the short interest rate r_{it} in response to inflation π_{it}, output gap $\tilde{y}_{it}$ and expected foreign inflation $E_t[\pi^*{}_{\mathrm{it+1}}]$. In symbols:

$$r_{\mathrm{it}} = a_{ir} + \rho_{ir}r_{\mathrm{it-1}} + \rho_{i\pi}\pi_{\mathrm{it}} + \rho_{i\tilde{y}}\tilde{y}_{\mathrm{it}} + \lambda_{ir}E_t[\pi^*{}_{\mathrm{it+1}}] + \varepsilon_{irt} \qquad (\mathrm{B.1.3})$$

Where: a_{ir} is the deterministic component; ε_{irt} is a monetary policy shock.

More compactly, system of equations B.1.1)- B.1.3) may be written as:

[111] Economic agents are assumed to be both backward and forward looking, i.e. past and future values of dependent variable enter the corresponding equation.

[112] This formulation is more coherent in a context of international dissemination of technology.

$$A_{i0}x_{it} = a_i + A_{i1}x_{it-1} + A_{i2}E_t[x_{it+1}] + A_{i3}x_{it}^* + A_{i4}x_{it-1}^* + A_{i5}E_t[x_{it+1}^*] + \varepsilon_{it} \qquad (B.1.4)$$

Where: $a_i = (a_{i\pi}, a_{i\tilde{y}}, a_{ir})'$; $\varepsilon_{it} = (\varepsilon_{i\pi t}, \varepsilon_{i\tilde{y}t}, \varepsilon_{irt})'$; $x_{it} = (\pi_{it}, \tilde{y}_{it}, r_{it})$; $x_{it}^* = (y_{it}^*, \pi_{it}^*)$;

$$A_{i0} = \begin{bmatrix} 1 & -\gamma_{i\pi} & 0 \\ 0 & 1 & \gamma_{i\tilde{y}} \\ -\rho_{i\pi} & -\rho_{i\tilde{y}} & 1 \end{bmatrix}; \quad A_{i1} = \begin{bmatrix} \lambda_{i\pi} & 0 & 0 \\ 0 & \lambda_{i\tilde{y}} & 0 \\ 0 & 0 & \rho_{ir} \end{bmatrix}; \quad A_{i2} = \begin{bmatrix} 1-\lambda_{i\pi} & 0 & 0 \\ \gamma_{i\tilde{y}} & 1-\lambda_{i\tilde{y}} & 0 \\ 0 & 0 & 0 \end{bmatrix};$$

$$A_{i3} = \begin{bmatrix} -\gamma_{i\pi} & 0 \\ 1 & 0 \\ -\rho_{i\tilde{y}} & 1 \end{bmatrix}; \quad A_{i4} = \begin{bmatrix} 0 & 0 \\ -\lambda_{i\tilde{y}} & 0 \\ 0 & 0 \end{bmatrix}; \quad A_{i5} = \begin{bmatrix} 0 & 0 \\ -(1-\lambda_{i\tilde{y}}) & 0 \\ 0 & \lambda_{ir} \end{bmatrix};$$

In standard DSGE framework, x_{it}^*, excluding any feedback (i.e. a mutual Granger-causation[113]) from lagged values of x_{it}^*. But assuming x_{it}^* does not Granger-cause x_{it} would be restrictive, especially if we consider that in a global context both quantities are jointly determined. Accordingly, it would be more realistic assuming that x_{it}^* Granger-causes x_{it} only in the long-run, thus allowing for short-run feedbacks from x_{it} to x_{it}^*.

Assuming a stable VAR structure[114] for x_{it}^*:

$$x_{it}^* = a_i^* + A_i^* x_{it-1}^* + \varepsilon_{it}^* \qquad (B.1.5)$$

Where: a_i^* is the deterministic component; A_i^* is the coefficient matrix of order k_i^*, with k_i^* is the number of foreign variables; ε_{it}^* is a foreign shock. Combining (B.1.4) and (B.1.5), the rational expectation solution[115] of this standard DSGE can be obtained as:

$$A_{iz_0} z_{it} = a_{iz} + A_{iz_1} z_{it-1} + A_{iz_2} E_t[z_{it+1}] + \varepsilon_{iz_t} \qquad (B.1.6)$$

Where: $z_{it} = (x'_{it}, x_{it}^{*\prime})'$; $a_{iz} = (a_i, a_i^*)$; $\varepsilon_{iz_t} = (\varepsilon'_{it}, \varepsilon_{it}^{*\prime})'$; $\varepsilon_{it}, \varepsilon_{it}^*$ are serially uncorrelated i.i.d residuals, i.e. $\varepsilon_{it} \perp \varepsilon_{it}^*$ as $\varepsilon_{it} \sim N(0, \sigma^2_{\varepsilon_{it}})$ and $\varepsilon_{it} \sim N\left(0, \sigma^2_{\varepsilon_{it}^*}\right)$; $A_{iz_0} = \begin{bmatrix} A_{i0} & -A_{i3} \\ 0 & I_{k_i^*} \end{bmatrix}$;

$A_{iz_1} = \begin{bmatrix} A_{i1} & -A_{i4} \\ 0 & A_i^* \end{bmatrix}$; $A_{iz_2} = \begin{bmatrix} A_{i2} & -A_{i5} \\ 0 & 0 \end{bmatrix}$.

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[113] Granger-causality implies an improvement in forecasting performance, measured as reduction of RMSE (Lutkepohl, 2007).

[114] Although a specification of a model for x_{it}^* is not needed for the purpose of parameter estimation as it is exogenous in this respect, one need to provide a model for forecasting, dynamic analysis or model solution.

[115] DSGE is solved via log-linearisation around the (presumably correct) steady state, assumed to be constant or estimated via a statistical filtering (e.g. Hedrick-Prescott filter).

Consider the corresponding quadratic matrix equation in B_{iz}:

$$A_{iz_2}B_{iz}^2 + A_{iz_1}B_{\mathrm{iz}} + A_{iz_0} = 0 \qquad \text{(B.1.7)}$$

Suppose there exists a real matrix solution to above equation (B. 1.7) such that all eigenvalues of B_{iz} and $(I_{k_i+k_i^*} - A_{iz_2}B_{\mathrm{iz}})^{-1}A_{iz_2}$ all lie inside or on the unit circle. The multivariate rational expectation has a unique and stable solution given by:

$$z_{\mathrm{it}} = b_{iz} + B_{iz}z_{\mathrm{it-1}} + v_{it} \quad \text{(B.1.8)}$$

Where: $b_{iz} = \left(A_{iz_0} - A_{iz_2}B_{\mathrm{iz}} - A_{iz_2}\right)^{-1}a_{iz}$; $v_{it} = \left(A_{iz_0} - A_{iz_2}B_{\mathrm{iz}}\right)^{-1}\varepsilon_{izt}$.

Conditioning on x_{it}^* yields the following VARX*(1,1) structure:

$$x_{\mathrm{it}} = b_i + B_{i1}x_{\mathrm{it-1}} + B_{i0}^*x_{it}^* + B_{i1}^*x_{it-1}^* + u_{it} \qquad \text{(B.1.9)}$$

Where: $corr(x_{it}^*, u_{it})$; $B_{i1}, B_{i0}^*, B_{i1}^*$(are reduced form) matrix of coefficients.

Despite the above rational expectation solution maybe a reasonable approximation, it need not to be consistent across countries, as different marginal models of x_{it}^* can be assumed for each of the i-th individual country DSGE model. Accordingly, the global version of (B. 1.6) becomes:

$$A_{iz_0}W_{\mathrm{i}}x_{\mathrm{it}} = a_{iz} + A_{iz_1}W_{\mathrm{i}}x_{\mathrm{it-1}} + A_{iz_1}W_{\mathrm{i}}E_t[x_{\mathrm{it+1}}] + \varepsilon_{iz_t} \qquad \text{(B.1.10)}$$

Where: $W_{\mathrm{i}}x_{\mathrm{it}} = z_{\mathrm{it}}$; W_{i} is the link matrix, supposed to be fixed[116].

Grouping these models all together in a compact way, it yields:

$$A_0x_{\mathrm{t}} = a_x + A_1x_{\mathrm{t-1}} + A_2E_t[x_{\mathrm{t+1}}] + \varepsilon_t \qquad \text{(B.1.11)}$$

Where: $A_j = \begin{bmatrix} A_{0z_j}W_0 \\ \vdots \\ A_{Nz_j}W_{\mathrm{N}} \end{bmatrix}$ for $j = 0,1,2$; $a_x = \begin{bmatrix} a_{0\mathrm{z}} \\ \vdots \\ a_{\mathrm{Nz}} \end{bmatrix}$; $\varepsilon_t = \begin{bmatrix} \varepsilon_{0\mathrm{t}} \\ \vdots \\ \varepsilon_{\mathrm{Nt}} \end{bmatrix}$.

[116] Link weights can be also time-varying, i.e W_{it}. In this case one needs to provide a model for the corresponding evolution.

B.2 GVAR model as approximation to a global factor model

Here it is shown how a GVAR model can be derived as approximation of a factor model. Starting from a general, yet static[117], factor model for the i-th country, with $i = 0, \ldots, N$:

$$x_{it} = \delta_{i0} + \delta_{i1} t + \Gamma_{id} \mathrm{d}_t + \Gamma_{if} \mathrm{f}_t + \varepsilon_{it} \qquad \text{(B.2.1)}$$

Where: x_{it} is a set of country-specific macroeconomic variables at time t; $\Gamma_i = (\Gamma_{id}, \Gamma_{if})$ is the $k_i \times m$ matrix of factor loadings, with $m = m_d + m_f$; $h_t = (\mathrm{d}'_t, \mathrm{f}'_t)'$ is a $(m_d + m_f) \times 1$ vector of observed and unobserved global factors, respectively; δ_{i0} and δ_{i1} represents country-specific intercept and coefficient of linear trend t; ε_{it} are residuals.

Accommodating for cointegrating properties of x_{it}, let h_t and ε_{it} have unit roots:

$$\Delta h_t = \Lambda(L)\eta_t \qquad \eta_t \sim IID(0, I_m) \qquad (\mathrm{B}.2.2a)$$

$$\Delta \varepsilon_{it} = \Psi_i(L) v_{it} \qquad v_{it} \sim IID(0, I_{k_i}) \qquad (\mathrm{B}.2.2b)$$

Where: L is the lag operator; $\eta_t \sim IID(0, I_m)$ and $v_{it} \sim IID(0, I_{k_i})$ are residuals of $MA(\infty)$ form; $\Lambda(L) = \sum_{l=0}^{\infty} \Lambda_l L^l$ and $\Psi_i(L) = \sum_{l=0}^{\infty} \Psi_{il} L^l$ are absolute summable square matrices of coefficients of order m and k_i, respectively. Differencing (B.2.1) and using (B.2.2.b), it results:

$$[\Psi_i(L)]^{-1}(1-L)\left(x_{it} - \delta_{i0} - \delta_{i1} t - \Gamma_{id}\mathrm{d}_t - \Gamma_{if}\mathrm{f}_t\right) = \mathrm{v}_{it} \qquad \text{(B.2.3)}$$

Where the existence of $[\Psi_i(L)]^{-1}$ is ensured by the absolute summability of matrix $\Psi_i(L)$, which implies that $var(\Delta\varepsilon_{it})$ its boundedness and positive definitiveness of matrix $\Delta\varepsilon_t$:

$$var(\Delta\varepsilon_{it}) = \sum_{l=0}^{\infty} \Psi_{il} \Psi'_{il} \leq K < \infty \qquad \text{(B.2.4)}$$

Where: K is a fixed and bounded matrix. Exploiting the following approximation:

$$(1-L)[\Psi_i(L)]^{-1} \approx \sum_{l=0}^{p_i} \Phi_{il} L^l = \Phi_i(L, p_i) \qquad \text{(B.2.5)}$$

Replacing (B.2.5) into (B.2.3), we obtain the following approximated VAR(p_i) model:

$$\Phi_i(L, p_i)\left(x_{it} - \delta_{i0} - \delta_{i1} t - \Gamma_{id}\mathrm{d}_t - \Gamma_{if}\mathrm{f}_t\right) \approx \mathrm{v}_{it} \qquad \text{(B.2.6)}$$

[117] Dynamic factor models (Geweke, 1976) can also be accommodated by including, via matrix-extension, lagged values of d_t and f_t.

Now, following Pesaran (2004)[118], d_t and f_t are 'proxied' by cross-section averages of country-specific variables x_{it}. Using general weights w_{ij}, for $j = 0, \dots, N$, to aggregate the country specific relations defined by (B.2.1) in the model for the i-th country, it yields:

$$x_{it}^* = \delta_{i0}^* + \delta_{i1}^* t + \Gamma_{id}^* \mathrm{d}_t + \Gamma_{if}^* \mathrm{f}_t + \varepsilon_{it}^* \qquad \text{(B.2.7)}$$

Where: $x_{it}^* = \sum_{j=0}^{N} w_{ij}\, x_{ij,t}$; $\delta_{i0}^* = \sum_{j=0}^{N} w_{ij}\, \delta_{ij0}$; $\delta_{i1}^* = \sum_{j=0}^{N} w_{ij}\, \delta_{ij1}$; $\Gamma_{id}^* = \sum_{j=0}^{N} w_{ij}\, \Gamma_{ijd}$; $\Gamma_{if}^* = \sum_{j=0}^{N} w_{ij}\, \Gamma_{ijf}$; $\varepsilon_{it}^* = \sum_{j=0}^{N} w_{ij}\, \varepsilon_{ijt}$. Moreover, considering (B2.2b), it results:

$$\Delta\varepsilon_{it}^* = \sum_{j=0}^{N} w_{ij}\, \Psi_{ij}(L) v_{it} \qquad \text{(B.2.8)}$$

Assuming that link weights w_{ij} are granular $\forall i, j$ ($\mathrm{w}_{ij} = 0$ for $i = j$) and normalized, i.e. $\sum_{j=0}^{N} w_{ij}$ $\forall i$, using Lemma A.1 in Pesaran (2006), equation (B.2.8) converge zero in quadratic mean:

$$\Delta\varepsilon_{it}^* = \varepsilon_{it}^* - \varepsilon_{it-1}^* \xrightarrow{q.m} 0 \quad \Longrightarrow \quad \varepsilon_{it}^* \xrightarrow{q.m} \varepsilon^* \qquad \text{(B.2.9)}$$

Where: ε^* is a time-invariant random variable of error terms. Recall equation (B.2.9), we obtain:

$$f_{it} \xrightarrow{q.m} \left(\Gamma_{if}^{*'} \Gamma_{if}^*\right)^{-1} \Gamma_{if}^* (x_{it}^* - \delta_{i0}^* - \delta_{i1}^* t - \Gamma_{id}^* \mathrm{d}_t - \varepsilon^*) \qquad \text{(B.2.10)}$$

Condition (B.2.10) justifies the use of the observable vector $\{1, t, \mathrm{d}_t, x_{it}^*\}$ as proxies for the unobserved common factors. Substituting (B.2.10) into (B.2.6) it yields:

$$\Phi_i(L, p_i)\left(x_{it} - \tilde{\delta}_{i0} - \tilde{\delta}_{i1} t - \tilde{\Gamma}_{id} \mathrm{d}_t - \tilde{\Gamma}_{if} x_{it}^*\right) \approx \mathrm{v}_{it} \qquad \text{(B.2.11)}$$

Where: $\tilde{\delta}_{i0} = [\delta_{i0} - \tilde{\Gamma}_{if}(\delta_{i0}^* + \varepsilon_{it}^*)]$; $\tilde{\delta}_{i0} = [\delta_{i1} - \tilde{\Gamma}_{if}\delta_{i1}^*]$; $\tilde{\Gamma}_{id} = \Gamma_{id} - \tilde{\Gamma}_{if}\Gamma_{id}^*$; $\tilde{\Gamma}_{if} = \Gamma_{if}'(\Gamma_{if}'\Gamma_{if}^*)^{-1}\Gamma_{if}^*$.

Finally, the VARX*(p_i, q_i) counterpart of (B.2.11) can be written as:

$$\Phi_i(L, p_i)\, x_{it} = a_{i0} + a_{i1} t + \Upsilon_i(L, p_i)\mathrm{d}_t + \Lambda_i(L, q_i) x_{it}^* + \mathrm{u}_{it} \qquad \text{(B.2.12)}$$

[118] Basically, given a panel data model with a multifactor error structure, it consists in adding weighted cross-section aggregates such that, as cross section dimension N goes to infinity, differential effects of unobserved common factors are eliminated (Pesaran, 2011).

B.3 OIRFs vs GIRFs

Here it is described the technical details underlying the invariance property of GIRFs (Pesaran-Shin, 1998) with respect to the ordering of the variables typically used in conducting dynamic analysis[119]. It is also shown the cases on which OIRFs and GIRFs coincide. Formal derivation of the GIRFs in the context of cointegrating VAR is also provided.

B.3.1 OIRFs and GIRFs: differences

To show the differences between OIRFs and GIRFs, consider an augmented VAR(p) model:

$$x_t = \sum_{i=1}^{p} \phi_i x_{t-i} + \psi w_t + \varepsilon_t \qquad \text{(B.3.1)}$$

Where: x_t is a $k \times 1$ vector of k (endogenously) dependent variables; w_t is $q \times 1$ vector of deterministics and exogenous variables; ϕ_is, ψ are $k \times k$ and $k \times q$ matrices of coefficients, respectively; ε_t is a $k \times 1$ vector of residuals. Given (1), assume the following:

1) i.i.d serially uncorrelated residuals: $E[\varepsilon_t] = 0;\ E[\varepsilon_t \varepsilon_t'] = \Sigma_\varepsilon;\ E[\varepsilon_t \varepsilon_{t'}] = 0$

2) stability: all roots of determinantal polynomial $|I_k - \sum_{i=1}^{p} \phi_i z^i| = 0$ fall out of the unit circle;

3) non perfect (pairwise) collinearity between $x_{t-1}, x_{t-2}, \dots, x_{t-p}, w_t$ for $t=1,\dots,T$.

Under the assumption of stability, (B.3.1) is covariance-stationary and, thus, admit an MA(∞) form:

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} + \sum_{i=0}^{\infty} G_i w_{t-i} \qquad \text{(B.3.2)}$$

Where: $G_i = A_i \psi$; $A_i = \begin{cases} I_k \ if\ i = 0 \\ \sum_{j=1}^{p} \phi_j A_{i-j} \ \ if\ i > 0 \\ 0\ if\ i < 0 \end{cases}$ are $k \times k$ coefficient matrices.

Introducing a $k \times 1$ vector of shocks $\delta = (\delta_1, \dots, \delta_k)'$ and a non-decreasing information set at time $t-1$, i.e. I_{t-1}, we have:

$$IRF(x_t, \delta, h, \mathrm{I}_{t-1}) = E[x_{t+h} | \varepsilon_t = \delta, \mathrm{I}_{t-1}] - E[x_{t+h} | \mathrm{I}_{t-1}] = A_h \delta \qquad \text{(B.3.3)}$$

[119] Such a invariance property does not hold in case of nonlinear models (Pesaran-Shin, 1998).

How we can see by (B.3.3) the choice of δ is relevant for the behavior of the IRFs.

Traditional approach, suggested by Sims (1980), imply to choose δ according to a Choleski decomposition of Σ_ε, i.e. $\Sigma_\varepsilon = PP'$ with P being the Choleski factor[120], orthogonal residuals (i.e. innovations) are obtained as $\mu_t = P^{-1}\varepsilon_t$. At this point, is then possible give a causal interpretation to the shocks by setting an (assumed) appropriate order of the variables[121]. which will affect the responses of the system. It then results:

$$\Sigma_\mu = E[\,\mu_t, \mu_t'] = I_k \qquad \text{(B.3.4)}$$

Replacing $\mu_t = P^{-1}\varepsilon_t$ into (B.3.2) we obtain:

$$x_t = \sum_{i=0}^{\infty} (A_i P)(P^{-1}\varepsilon_{t-i}) + \sum_{i=0}^{\infty} G_i w_{t-1} \qquad \text{(B.3.5)}$$

The orthogonalized-IRF (OIRF) of a unit shock to the j-th equation of x_t is given by:

$$\phi_j^O(h) = A_h P \epsilon_j \qquad \text{(B.3.6)}$$

Where: ϵ_j is a $k \times 1$ selection vector with 1 as the j-th element and zero elsewhere.

Pesaran-Shin (1998) proposes firstly to shock the j-th element of ε_t, i.e. ε_{jt} (instead of all elements). Secondly, they integrate out the effects of other shocks using an assumed (or historically observed) distribution of the errors. In particular, assuming a multivariate Normal:

$$E\left[\varepsilon_t | \varepsilon_{jt} = \delta_j\right] = \left(\sigma_{1j}, \dots, \sigma_{kj}\right)' \sigma_{jj}^{-1}\delta_j = \Sigma_\varepsilon \epsilon_j \sigma_{jj}^{-1}\delta_j \qquad \text{(B.3.7)}$$

Recalling (B.3.3), the $k \times 1$ vector of (unscaled) $GIRF$ of a unit shock hitting at time $t + h$ the j-th equation of x_t is given by:

$$GIRF\left(x_t, \delta_j, h, \mathrm{I}_{t-1}\right) = E\left[x_{t+h} | \varepsilon_{jt} = \delta_j, \mathrm{I}_{t-1}\right] - E[x_{t+h} | \mathrm{I}_{t-1}] = \frac{A_h \Sigma_\varepsilon \epsilon_j}{\sqrt{\sigma_{jj}}} \frac{\delta_j}{\sqrt{\sigma_{jj}}} \qquad \text{(B.3.8)}$$

Setting $\delta_j = \sqrt{\sigma_{jj}}$, the (scaled) GIRFs of a unit shock hitting are obtained:

$$\phi_j^G(h) = \frac{A_h \Sigma_\varepsilon \epsilon_j}{\sqrt{\sigma_{jj}}} \qquad \text{(B.3.9)}$$

[120] I.e. a lower triangular matrix.

[121] Moreover, due to the non-uniqueness of Choleski decomposition, the responses of the system will be order-specific.

B.3.2 Relations between OIRFs and GIRFs

By comparing (B.3.6) and (B.3.9), we can see that OIRFs and GIRFs are variant and invariant with respect to the ordering of the variables within the VAR structure, respectively.

But by looking at (B.3.6) and (B.3.9) together, we can see that OIRFs and GIRFs coincide if:

1) Σ_ε is diagonal;

2) $j = 1$ (if Σ_ε is not diagonal).

Proof of 1): rewrite (B.3.6) and (B.3.9), for $j = 1, \dots, k$, as:

$$\phi_j^O(h) = A_h \varphi_j^o \qquad \text{(B.3.10)}$$

$$\phi_j^G(h) = A_h \varphi_j^G \qquad \text{(B.3.11)}$$

With:

$$\varphi_j^o = P\epsilon_j = (p_{1j}, \dots, p_{kj})' \qquad \text{(B.3.12)}$$

$$\varphi_j^G = \Sigma_\varepsilon \epsilon_j \sigma_{jj}^{-1} = (\sigma_{1j}, \dots, \sigma_{kj})' \qquad \text{(B.3.13)}$$

Where: $p_{ij} = 0$ for $i < j$; $\sigma_{ij} \neq 0 \ \forall i, j = 1, \dots, k$. Thus:

$$\varphi_j^G = \varphi_j^O \Rightarrow p_{ij} = 0 \text{ for } i < j$$

Proof of 2): recall (B.3.12) and (B.3.13), for $k = 1$, assuming Σ_ε is not diagonal, it results:

$$\varphi_1^o = P\epsilon_1 = (p_{11}, \dots, p_{k1})' \qquad \text{(B.3.14)}$$

$$\varphi_1^G = \Sigma_\varepsilon \epsilon_1 \sigma_{11}^{-1/2} = \sigma_{11}^{-1/2}(\sigma_{11}, \dots, \sigma_{k1})' \qquad \text{(B.3.15)}$$

Using the equality $PP' = \Sigma_\varepsilon$, noting that $p_{11}^2 = \sigma_{11}$, it results:

$$(\sigma_{11}, \dots, \sigma_{k1})' = (p_{11}^2, \dots, p_{11}p_{k1})' \qquad \text{(B.3.16)}$$

Plugging (B.3.16) into (B.3.15), we now see:

$$\varphi_1^o = \varphi_1^G = (p_{11}^2)^{-1/2}(p_{11}^2, \dots, p_{11}p_{k1})' = \sigma_{11}^{-1/2}(\sigma_{11}, \dots, \sigma_{k1})' \quad \text{(B.3.17)}$$

B.3.3 GIRFs in cointegrated VARs

Here the notion of GIRFs is extended to cointegrated VAR model.

To accommodate for cointegrated variables, condition 3) of B.3.1 is satisfied for |z|>1 or z=1. Accordingly, (B.3.1) can be expressed as a Vector of Error Correction (VEC) model:

$$\Delta x_t = -\Pi x_{t-1} + \sum_{i=1}^{p} \Gamma_i \Delta x_{t-1} + \Pi \Lambda w_t + \varepsilon_t \qquad (B.3.18)$$

Where: $\Pi = \mathrm{I}_k - \sum_{i=1}^{p} \Phi_i$; $\Gamma_i = -\sum_{j=i+1}^{p} \Gamma_j$ for $i = 1, \dots, p-1$; Λ is a k$\times$ q matrix of parameters to be estimated; $\Phi_i = \begin{cases} I_k - \Pi + \Gamma_1 \; if \; i = 0 \\ \Gamma_i - \Gamma_{i-1} \; if \; 0 < i < p-1 \\ -\Gamma_{p-1} \; if \; i = p \end{cases}$.

Assuming cointegration matrix Π is not full rank[122], i.e. $rank(\Pi) = r < k$, it can be decomposed as:

$$\Pi = \alpha\beta' \qquad (\mathrm{B.3.19})$$

Where: α, β are $k \times r$ matrices of full column rank and r is the number of cointegrating relations. In order to ensure variables included in x_t are at most $I(1)$, so that $z_t = \beta' x_t \sim I(0)$, assume that

$$rank(\alpha'_{\perp} \Gamma \beta_{\perp}) = full \qquad (\mathrm{B.3.20})$$

Where: $\alpha_{\perp}, \beta_{\perp}$ are k$\times$ $(k-r)$ matrices of full column rank such that $\alpha'\alpha_{\perp} = 0$ and $\beta'\beta_{\perp} = 0$; $\Gamma = \mathrm{I}_k - \sum_{i=1}^{p-1} \Gamma_i$. Now, under assumptions 3), (B.3.19) and (B.3.20), (B.3.18) admit the following $MA(\infty)$ form:

$$\Delta x_t = \sum_{i}^{\infty} C_i \varepsilon_{t-i} + \sum_{i}^{\infty} C_i \Pi \Lambda w_{t-i} \qquad (\mathrm{B.3.21})$$

Given (B.3.21), (B.3.11) can now be expressed as:

$$\phi^{G}_{\Delta x_t, j}(h) = \frac{\beta' B_h \Sigma_\varepsilon \epsilon_j}{\sqrt{\sigma_{jj}}} \qquad (\mathrm{B.3.22})$$

[122] This parametric restriction of rank deficiency implies that the effects of shocks of the individual (integrated) variables are persistent.

Where: $B_h = \sum_{j=0}^{h} C_j$ is the matrix of cumulative effects, with $B_0 = C_0 = I_k$. While the cointegrated version of (B.3.6) becomes:

$$\phi^{O}_{\Delta x_t, j}(h) = \beta' B_h P \epsilon_j \qquad (B.3.23)$$

B.3.4 Bootstrapping procedure

Within the conducted analysis, the empirical distribution of the PPs, and GIRFs with associated lower and upper bounds are obtained by bootstrapping the GVAR model[123].

Given the sample variance-covariance matrix of residuals Σ_u of the GVAR model as given in (8), in order to get a bootstrap sample from the k endogenous variables of the GVAR model:

1) residuals u_t are orthogonalised (i.e. i.i.d) by means of Cholesky decomposition of Σ_u:

$$\Sigma_u = PP' \Rightarrow v_t = P^{-1} u_t \Rightarrow \Sigma_v = \mathrm{I}_{k_i} \qquad (B.3.24)$$

2) resampling with replacement from the kT elements of matrix Σ_v from stacking the $k \times 1$ vectors v_t, for $t = 1, \dots, T$;

3) bootstrapped errors corresponding to the b-th replication, for $b = 1, \dots B$[124], are obtained as:

$$u_t^{(b)} = P v_t^{(b)} \qquad (B.3.25)$$

4) a bootstrap sample is then constructed as:

$$x_t^{(b)} = \hat{b}_0 + \hat{b}_1 t + \sum_{j=1}^{p} F_j x_{t-j} + G_0^{-1} u_t \qquad (B.3.26)$$

For each bootstrap replication, GVAR model is recursively reconstructed and solved.

[123] Bootstrapping procedure is also adopted in order to compute empirical distribution for PPs (5.1) and critical values for structural stability tests (4.7) and for testing over-identifying cointegrating restrictions (A.5).

[124] In this empirical exercise, number of bootstrap replications were set as 1000.

APPENDIX C: Empirical results

Here the GIRFs are depicted for each of the 11 regional models with respect to output, equity and foreign-exchange variables. Results are robust to: -

different periods: non critical (Jan 1999-Jun 2006) and a critical (Jul 2006-Dec 2013);

-*different uncertainty measures*: i.e. financial (Vxo and VStoxx);

-*different trade weight matrix specification*, i.e baseline scenario (averaged 1999-2012-based) and 'alternative' scenario (exponentially smoothed 2013-based).

C.1 Usa model-responses

Impulse-Responses of ***output*** *to a unit shock of uncertainty (EPU) in Usa (Fig. 1a) and Emu (Fig. 1b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

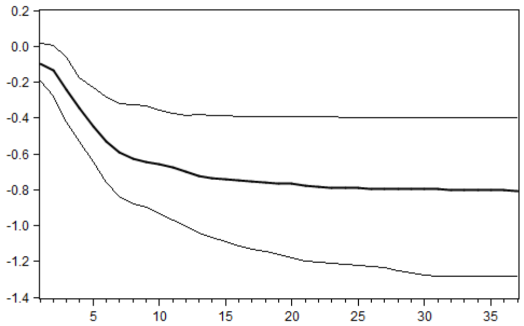


Fig. 1a

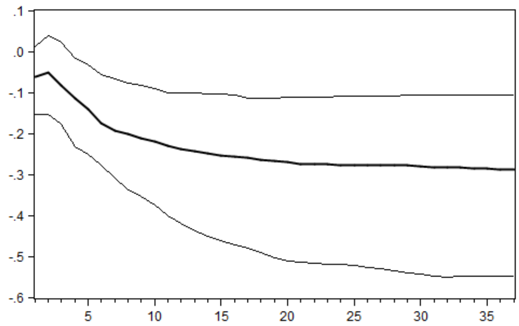


Fig. 1b

Impulse-Responses of ***equity index*** *to a unit shock of uncertainty (EPU) in Usa (Fig. 2a) and Emu (Fig. 2b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

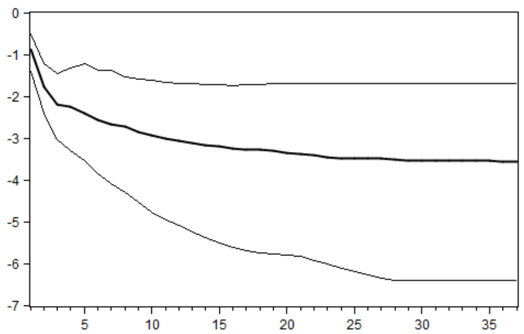


Fig. 2a

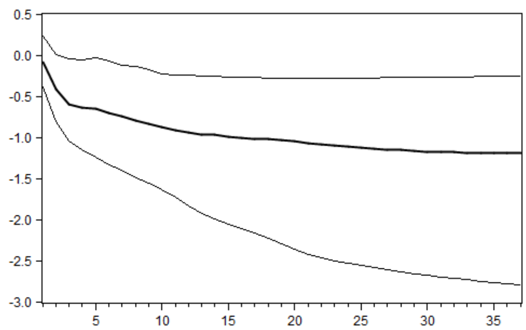


Fig. 2b

C.2 Euro Area model-responses

Responses of European Monetary Union output to an uncertainty (EPU) shock in Usa (Fig. 1a) and Emu (Fig. 1b).

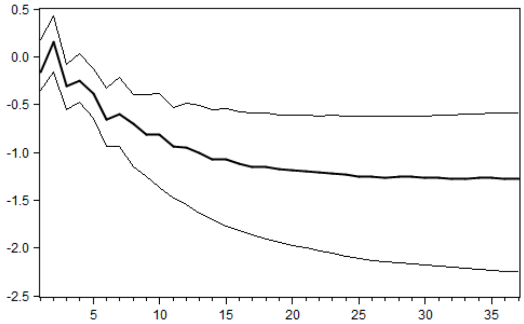


Fig. 1a

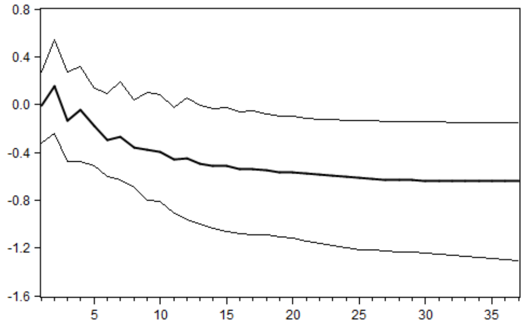
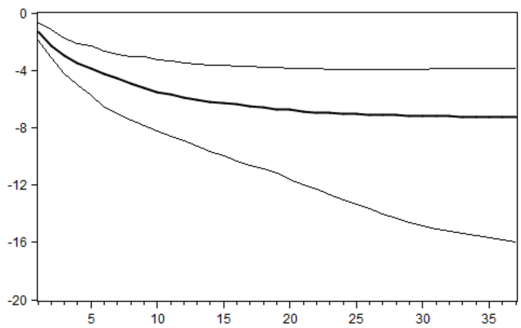


Fig.1b

Impulse-Responses of ***equity index*** *to a unit shock of uncertainty (EPU) in Usa (Fig. 2a) and Emu (Fig. 2b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds*



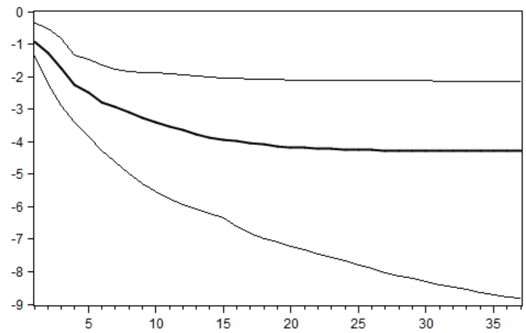


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Fig. 2a

Fig.2b

Impulse-Responses of ***fx rate*** *to a unit shock of uncertainty (EPU) in Usa (Fig. 3a) and Emu (Fig. 3b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

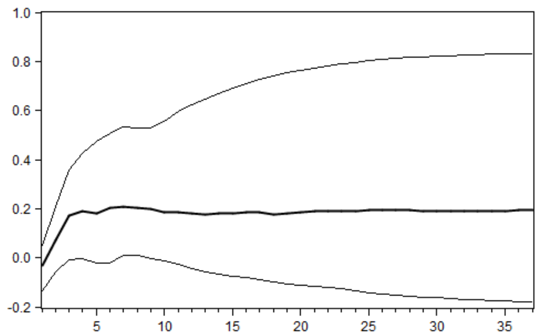


Fig. 3a

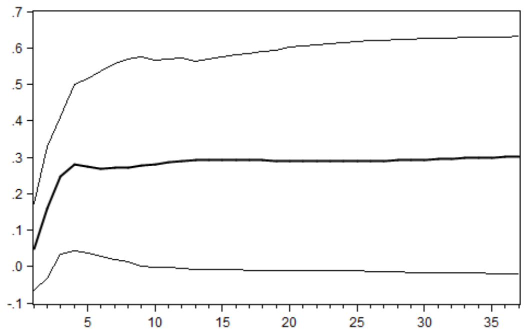


Fig.3b

C.3 Western Europe model-responses

Responses of Western Europe ***output*** *to an uncertainty (EPU) shock in Usa (Fig. 1a) and Emu (Fig. 1b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

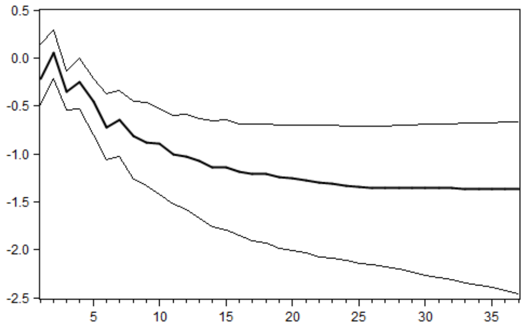


Fig. 1a

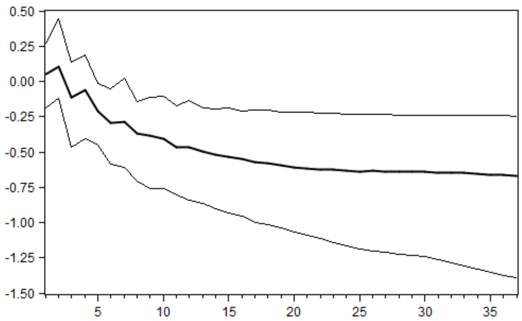


Fig.1b

Responses of Western Europe ***equity index*** *to an uncertainty (EPU) shock in Usa (Fig. 2a) and Emu (Fig. 2b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

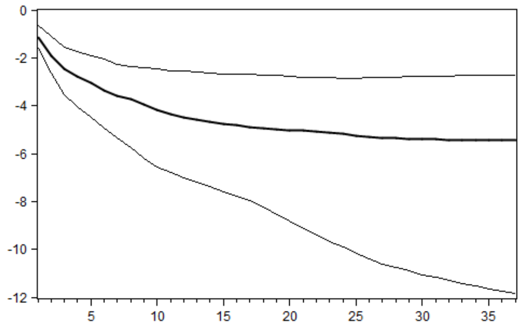


Fig. 2a

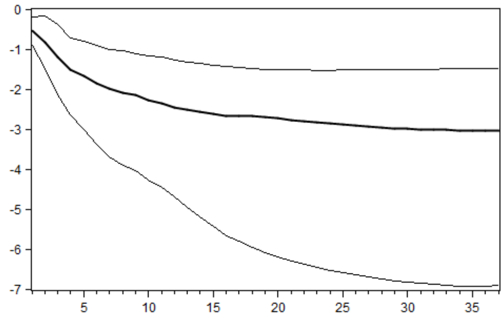


Fig.2b

Responses of Western Europe ***equity index*** *to an uncertainty (EPU) shock in Usa (Fig. 3a) and Emu (Fig. 3b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

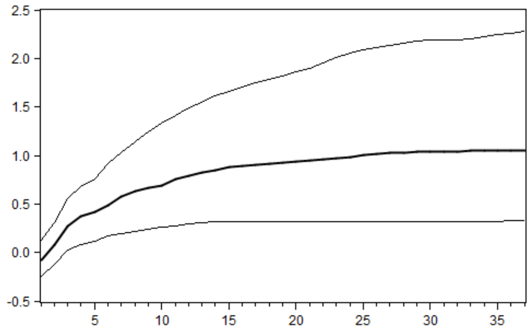


Fig. 3a

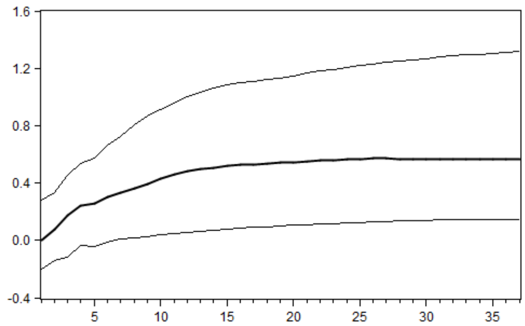


Fig.3b

C.4 Central Europe model-responses

Responses of Central Europe ***output*** *to an uncertainty (EPU) shock in Usa (Fig. 1a) and Emu (Fig. 1b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

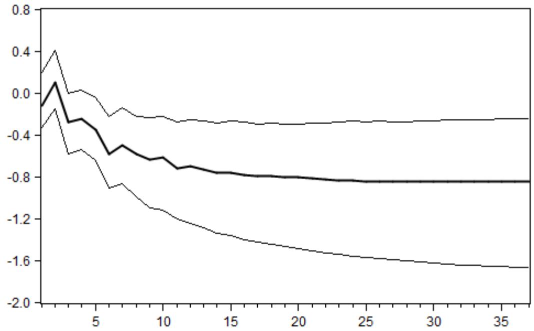


Fig. 1a

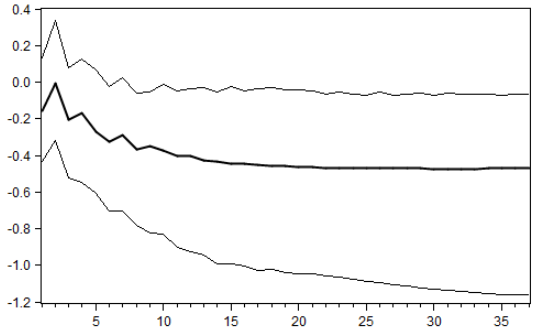


Fig. 1b

Responses of Central Europe ***equity index*** *to an uncertainty (EPU) shock in Usa (Fig. 2a) and Emu (Fig. 2b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

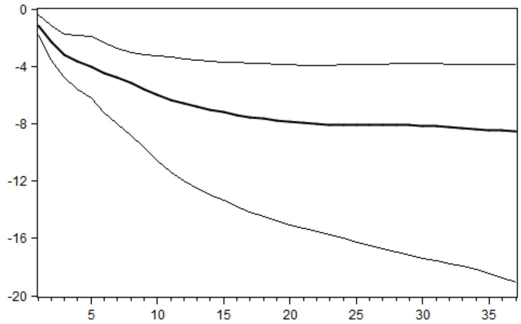


Fig. 2a

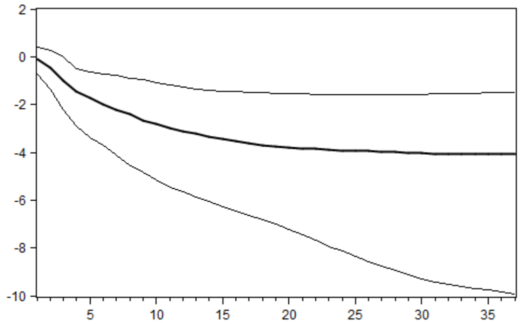


Fig. 2b

Responses of Central Europe ***fx rate*** *to an uncertainty (EPU) shock in Usa (Fig. 3a) and Emu (Fig. 3b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

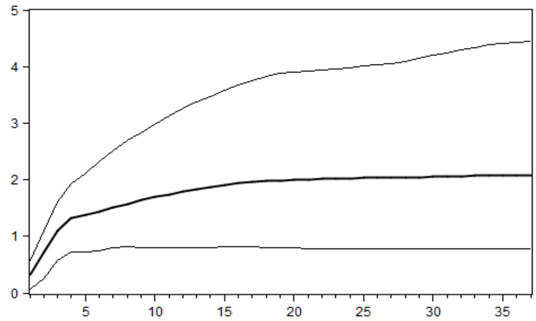


Fig. 3a

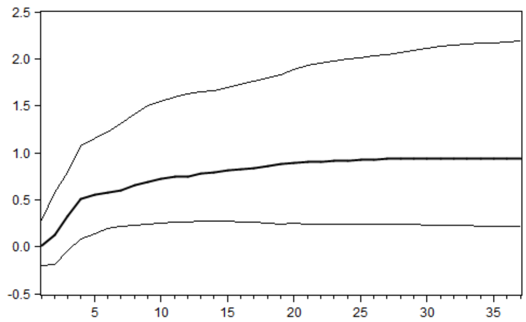


Fig. 3b

C.5 South-East Asia model-responses

*Responses of South-East Asia **output** to an uncertainty (EPU) shock in Usa (Fig. 1a) and Emu (Fig. 1b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

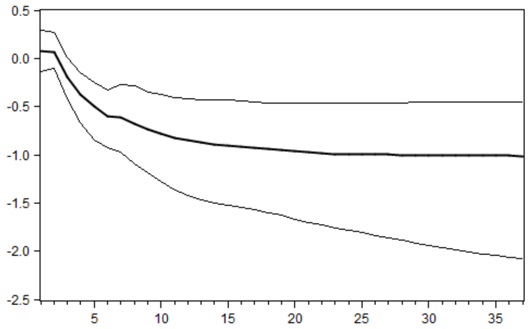


Fig. 1a

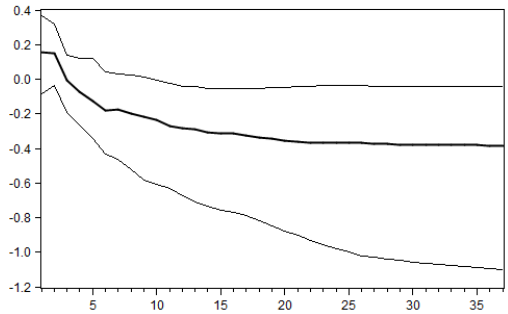


Fig. 1b

*Responses of South-East Asia **equity index** to an uncertainty (EPU) shock in Usa (Fig. 2a) and Emu (Fig. 2b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

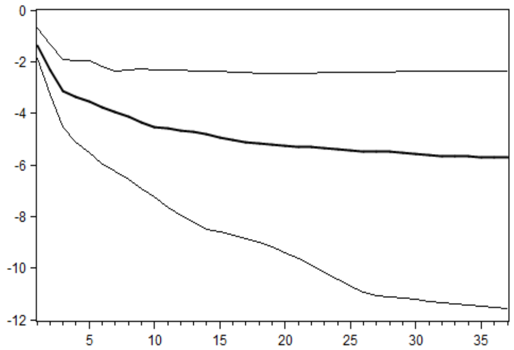


Fig. 2a

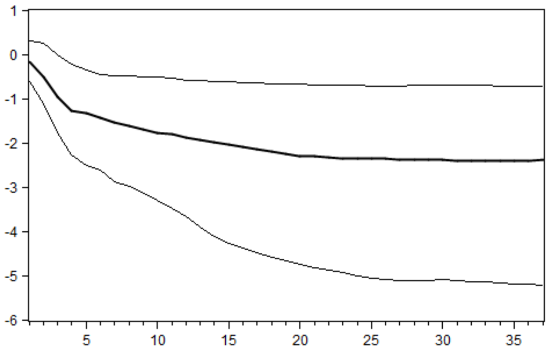
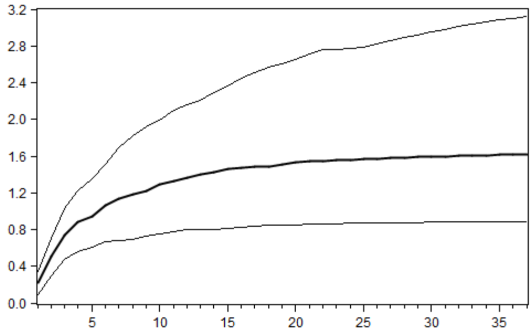


Fig. 2b

*Responses of South-East Asia **fx rate** to an uncertainty (EPU) shock in Usa (Fig. 3a) and Emu (Fig. 3b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds*



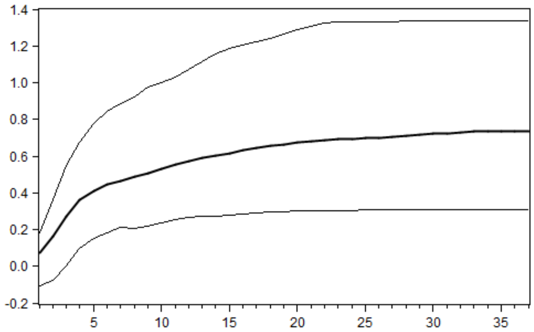


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Fig. 3a

Fig. 3b

C.6 Central and Latin America model-responses

Responses of Central-Latin America ***output*** *to an uncertainty (EPU) shock in Usa (Fig. 1a) and Emu (Fig. 1b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

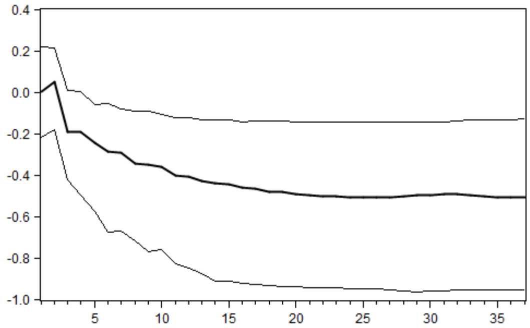

Fig. 1a

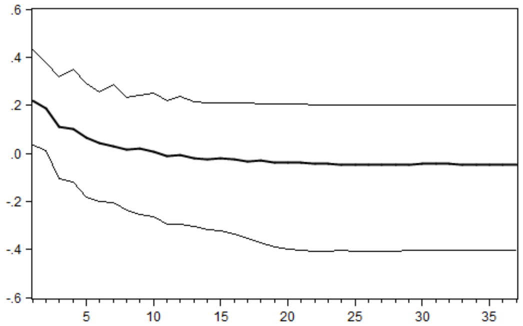

Fig. 1b

Responses of Central-Latin America ***equity index*** *to an uncertainty (EPU) shock in Usa (Fig. 2a) and Emu (Fig. 2b). Bootstrap median estimate (bolded line) and 90% bounds.*

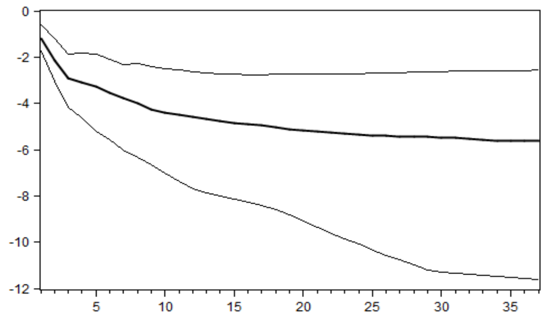

Fig. 2a

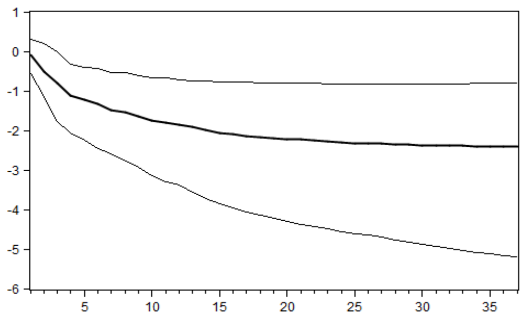

Fig. 2b

Responses of Central-Latin America ***fx rate*** *to an uncertainty (EPU) shock in Usa (Fig. 3a) and Emu (Fig. 3b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

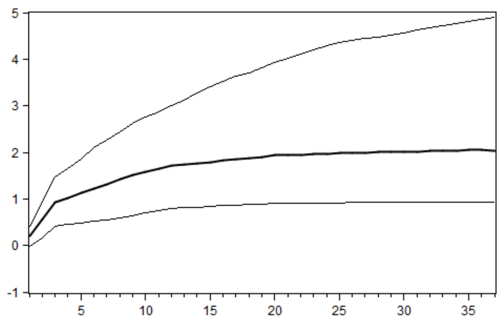

Fig. 3a

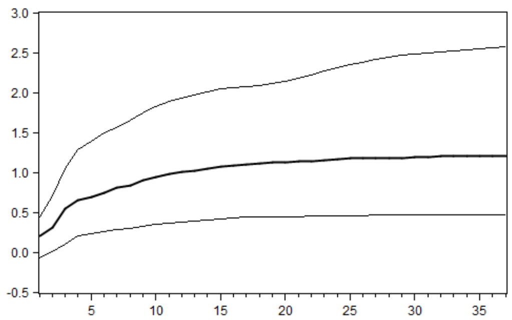

Fig. 3b

C.7 Canada model-responses

*Responses of Canada **output** to an uncertainty (EPU) shock in Usa (Fig. 1a) and Emu (Fig. 1b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

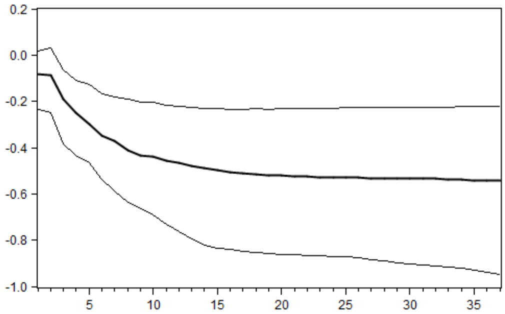

Fig. 1a

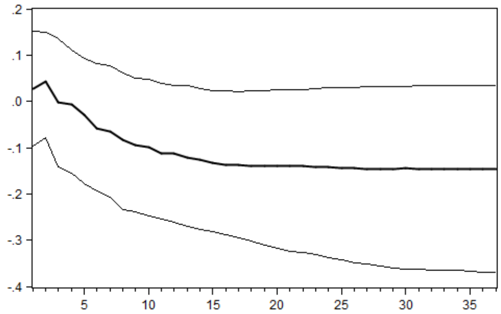

Fig. 1b

*Responses of Canada **equity index** to an uncertainty (EPU) shock in Usa (Fig. 2a) and Emu (Fig. 2b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

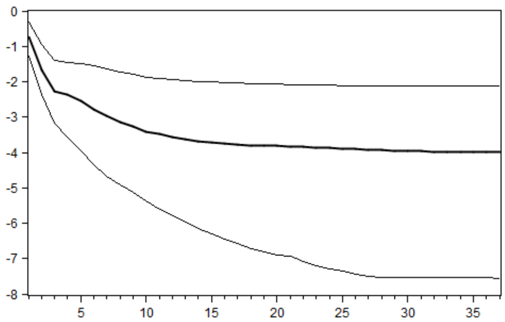

Fig. 2a

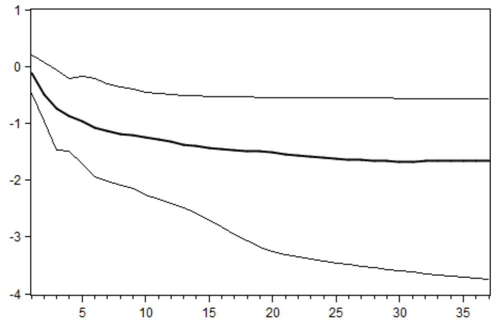

Fig. 2b

*Responses of Canada **fx rate** to an uncertainty (EPU) shock in Usa (Fig. 3a) and Emu (Fig. 3b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

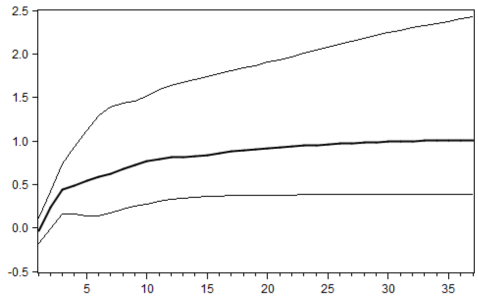

Fig. 3a

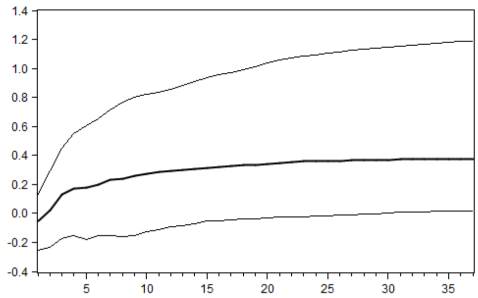

Fig. 3b

C.8 India model-responses

*Responses of India **output** to an uncertainty (EPU) shock in Usa (Fig. 1a) and Emu (Fig. 1b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

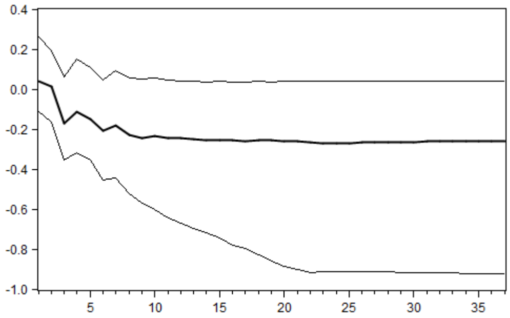

Fig. 1a

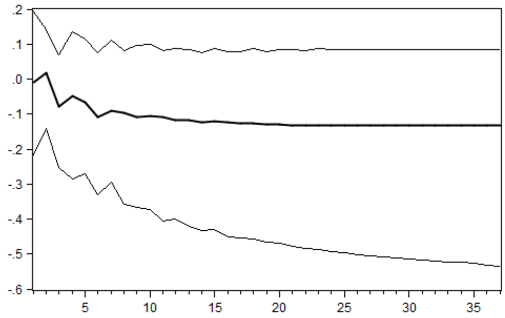

Fig. 1b

*Responses of India **equity** to an uncertainty (EPU) shock in Usa (Fig. 2a) and Emu (Fig. 2b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

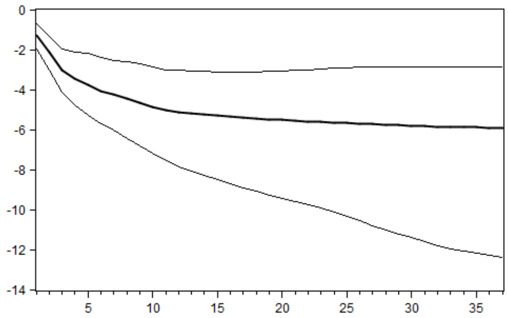

Fig. 2a

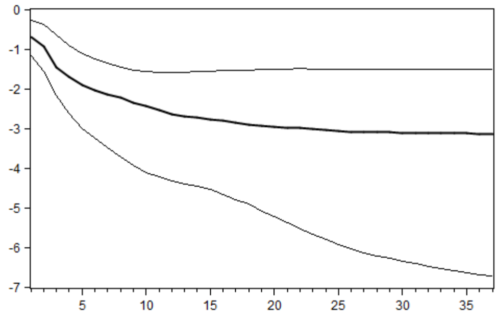

Fig. 2b

*Responses of India **fx rate** to an uncertainty (EPU) shock in Usa (Fig. 3a) and Emu (Fig. 3b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

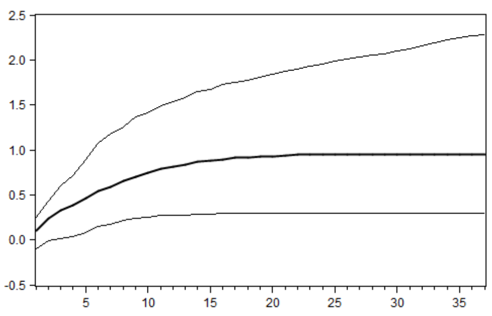

Fig. 3a

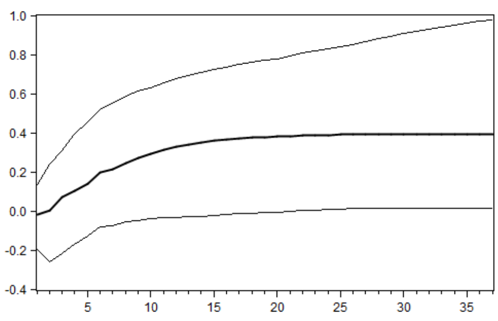

Fig. 3b

C.9 China model-responses

*Responses of China **output** to an uncertainty (EPU) shock in Usa (Fig. 1a) and Emu (Fig. 1b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

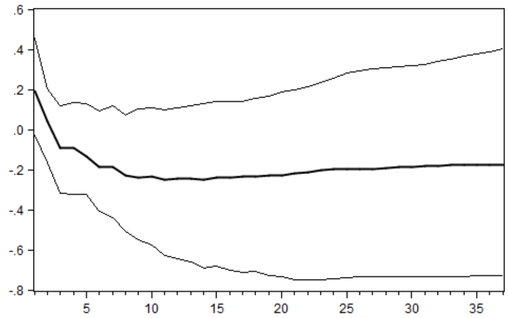

Fig. 1a

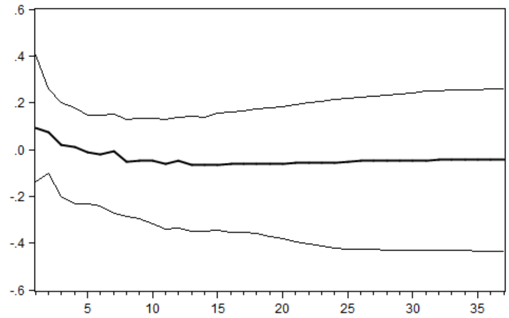

Fig. 1b

*Responses of China **equity index** to an uncertainty (EPU) shock in Usa (Fig. 1a) and Emu (Fig. 1b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

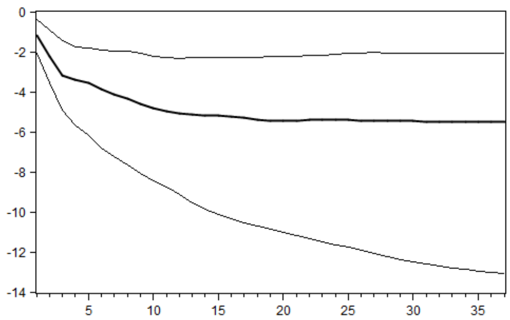

Fig. 2a

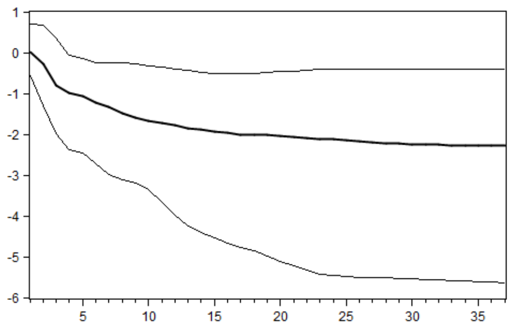

Fig. 2b

*Responses of China **fx rate** to an uncertainty (EPU) shock in Usa (Fig. 1a) and Emu (Fig. 1b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

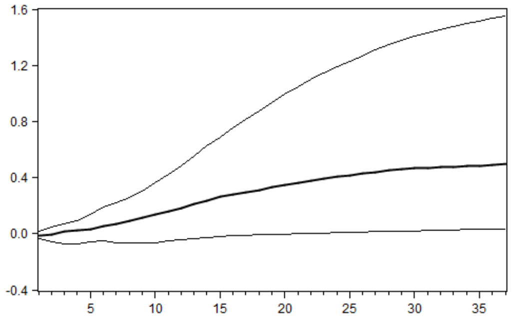

Fig. 3a

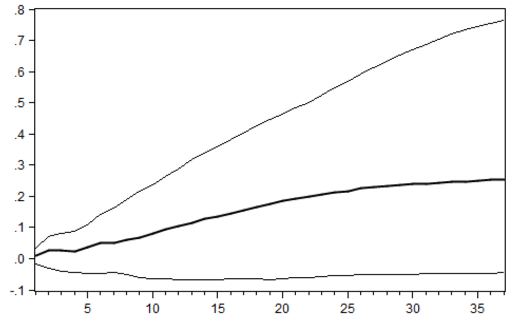

Fig. 3b

C.10 Japan model-responses

*Responses of Japan **output** to an uncertainty (EPU) shock in Usa (Fig. 1a) and Emu (Fig. 1b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

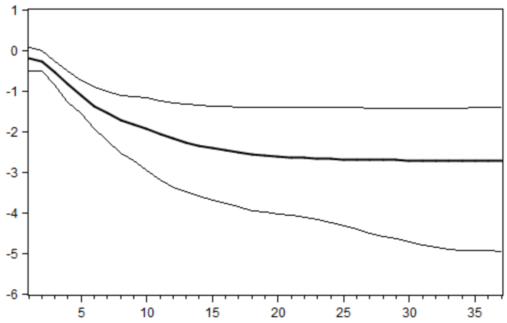

Fig. 1a

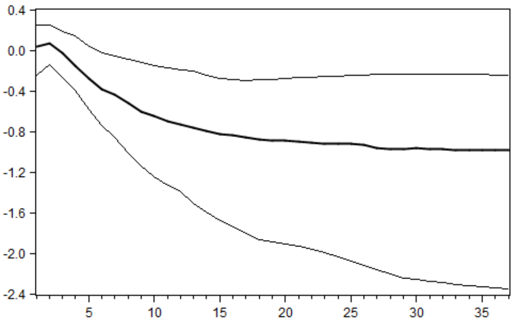

Fig. 1b

*Responses of Japan **equity index** to an uncertainty (EPU) shock in Usa (Fig. 2a) and Emu (Fig. 2b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

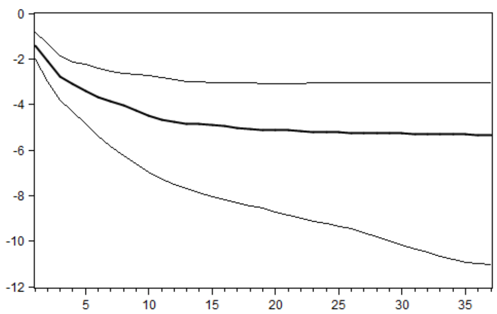

Fig. 2a

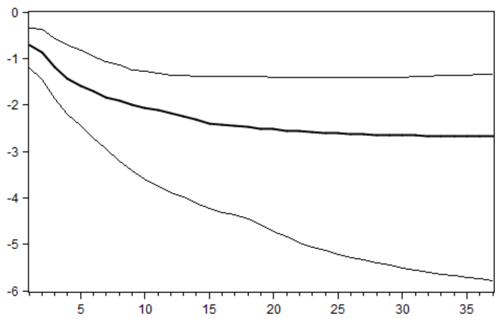

Fig. 2b

*Responses of Japan **fx rate** to an uncertainty (EPU) shock in Usa (Fig. 3a) and Emu (Fig. 3b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

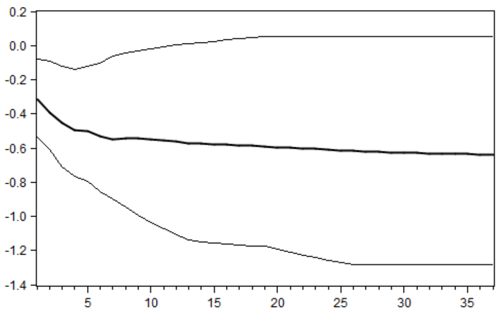

Fig. 3a

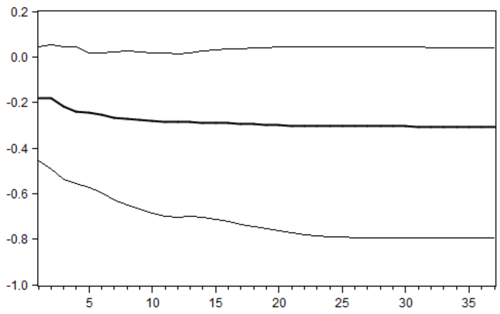

Fig. 3b

C.11 Russia model-responses

*Responses of Russia **output** to an uncertainty (EPU) shock in Usa (Fig. 1a) and Emu (Fig. 1b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

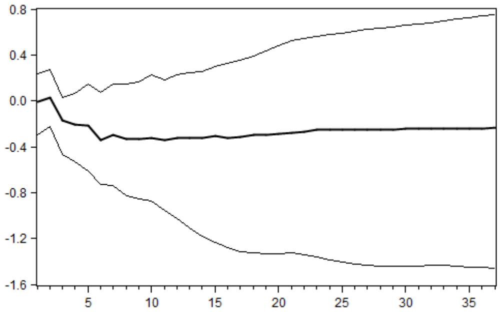

Fig. 1a

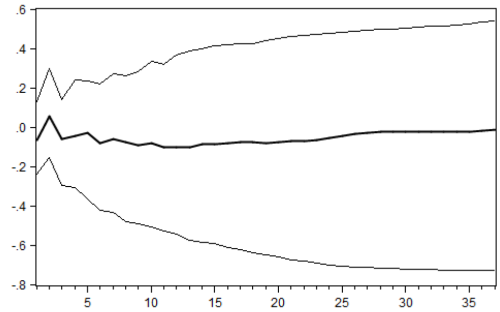

Fig. 1b

*Responses of Russia **equity index** to an uncertainty (EPU) shock in Usa (Fig. 2a) and Emu (Fig. 2b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

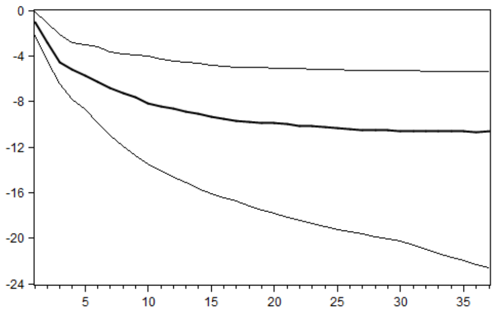

Fig. 2a

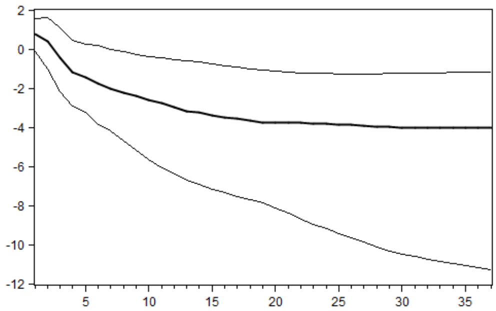

Fig. 2b

*Responses of Russia **fx rate** to an uncertainty (EPU) shock in Usa (Fig. 3a) and Emu (Fig. 3b). Bootstrap median estimate (bolded line) and 90% bootstrap error bounds.*

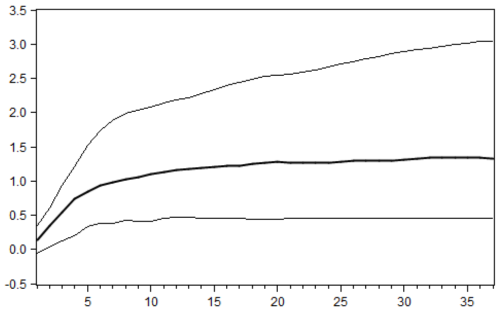

Fig. 3a

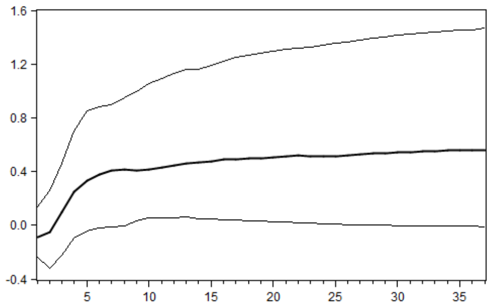

Fig. 3b

APPENDIX D: Tables

D.1 Evolution of intensity of foreign trade

Here it is shown the evolution of country-specific (pairwise) intensity of foreign trade, measured as sum of mutual imports, over the time period 1999-2013. Values in %.

	AU	BEL	FIN	FRA	GER	ITA	NET	SPA	UK	DEN	NOR	SWE	SWIS	TUR	POL	CZE	ROM	HUN	SKO	INDO	THAI	MAL	SING	HONG	PHIL	MEX	BRA	CHIL	USA	CAN	INDI	CHIN	JAP	RUS
AU	0	127	52	103	142	118	103	85	60	69	281	139	174	276	406	262	615	141	356	135	207	361	272	86	127	358	287	455	122	132	55	804	823	641
BEL	127	0	135	150	165	107	210	116	81	73	373	136	176	315	405	565	512	139	161	80	133	81	522	207	112	485	217	467	109	112	220	562	99	860
FIN	52	135	0	33	79	42	179	33	2	27	121	147	17	148	200	151	432	75	269	151	38	115	45	-34	-12	161	193	285	44	165	737	198	-19	470
FRA	103	150	33	0	98	58	108	79	25	26	54	74	76	180	313	370	443	216	162	199	113	163	196	169	72	141	174	180	32	54	437	461	44	594
GER	142	165	79	98	0	73	227	88	82	109	265	142	141	195	353	313	504	166	226	129	164	171	109	58	68	177	174	245	62	145	432	640	28	581
ITA	118	107	42	58	73	0	85	106	20	56	55	64	99	292	219	324	242	138	169	262	198	131	144	110	68	261	131	169	55	85	351	500	29	367
NET	103	210	179	108	227	85	0	152	113	103	444	102	52	174	534	1010	619	235	157	190	86	122	265	19	-24	708	390	439	105	251	599	1224	65	1437
SPA	85	116	33	79	88	106	152	0	61	124	170	44	213	410	413	458	1144	290	77	115	83	96	82	113	84	387	210	339	83	177	565	545	31	899
UK	60	81	2	25	82	20	100	43	0	97	246	84	134	237	421	378	324	204	56	47	116	36	70	-13	-57	167	173	137	23	142	186	692	-15	682
DEN	69	73	27	26	109	56	103	124	97	0	160	172	30	280	243	432	627	416	92	61	109	81	148	179	76	251	282	227	86	106	277	456	-1	337
NOR	281	373	121	54	265	55	444	170	246	160	0	164	169	468	412	211	627	203	493	268	456	264	537	46	260	233	453	315	86	150	867	702	61	350
SWE	139	136	147	74	142	64	102	44	84	172	164	0	22	110	330	337	323	264	200	511	187	94	99	20	98	91	62	114	27	105	532	309	-4	898
SWIS	174	176	17	76	141	99	52	213	134	30	169	22	0	453	197	300	542	100	145	224	980	78	203	412	76	184	272	95	189	235	972	1432	124	155
TUR	276	315	148	180	195	292	174	410	237	280	468	110	453	0	1573	1407	775	755	548	944	811	453	233	104	628	1151	953	1263	254	616	2173	2534	170	1147
POL	406	405	200	313	353	219	534	413	421	243	412	330	197	1573	0	642	1203	559	205	118	337	110	58	453	61	817	228	369	189	330	713	784	110	822
CZE	262	565	151	370	313	324	1010	458	378	432	211	337	300	1407	642	0	1210	594	1079	201	1019	279	788	998	697	1103	449	616	200	178	647	1529	224	582
ROM	615	512	432	443	504	242	619	1144	324	627	627	323	542	775	1203	1210	0	1289	296	473	314	330	433	264	163	865	429	475	226	347	1167	1803	369	540
HUN	141	139	75	216	166	138	235	290	204	416	203	264	100	755	559	594	1289	0	312	183	226	90	18	184	160	430	78	412	56	326	805	1264	38	484
SKO	356	161	269	162	226	169	157	77	56	92	493	200	145	548	205	1079	296	312	0	420	408	171	445	134	112	386	693	497	84	176	885	848	160	1070
INDO	135	80	151	199	129	262	190	115	47	61	268	511	224	944	118	201	473	183	420	0	860	845	480	162	400	386	693	133	134	207	1446	1331	255	3929
THAI	207	133	38	113	164	198	86	83	116	109	456	187	980	811	337	1019	314	226	408	860	0	401	119	210	299	752	1189	843	85	165	1057	1337	248	1306
MAL	361	81	115	163	171	131	122	96	36	81	264	94	78	453	110	279	330	90	171	845	401	0	151	174	64	359	698	98	28	78	471	1432	116	444
SING	272	522	45	196	109	144	265	82	70	148	537	99	203	233	58	788	433	18	445	480	119	151	0	217	133	169	513	41	58	112	820	593	35	2696
HONG	86	207	-34	169	58	110	19	113	-13	179	46	20	412	104	453	998	264	184	134	162	210	174	217	0	145	89	300	239	36	4	513	200	83	263
PHIL	127	112	-12	72	68	68	-24	84	-57	76	260	98	76	628	61	697	163	160	112	400	299	64	133	145	0	263	187	-10	-7	47	561	1287	44	2031
MEX	358	485	161	141	177	261	708	387	167	251	233	91	184	1151	817	1103	865	430	386	386	752	359	169	89	263	0	505	220	115	285	1833	3059	228	1834
BRA	287	217	193	174	174	131	390	210	173	282	453	62	272	953	228	449	429	78	693	693	1189	698	513	300	187	505	0	457	205	278	1468	4573	270	507
CHIL	455	467	285	180	245	169	439	339	137	227	315	114	95	1263	369	616	475	412	497	133	843	98	41	239	-10	220	457	0	352	302	2308	2550	284	773
USA	122	109	44	32	62	55	105	83	23	86	86	27	189	254	189	200	226	56	84	134	85	28	58	36	-7	115	205	352	0	64	409	441	13	438
CAN	132	112	165	54	145	85	251	177	142	106	150	105	235	616	330	178	347	326	176	207	165	78	112	4	47	285	278	302	64	0	425	778	54	499
INDI	804	220	737	437	432	351	599	565	186	277	867	532	972	2173	713	647	1167	805	885	1446	1057	471	820	513	561	1833	1468	2308	409	425	0	3348	307	510
CHIN	823	562	198	461	640	500	1224	545	692	456	702	309	1432	2534	784	1529	1803	1264	848	1331	1337	1432	593	200	1287	3059	4573	2550	441	778	3348	0	377	1770
JAP	55	99	-19	44	28	29	65	31	-15	-1	61	-4	124	170	110	224	369	38	160	255	248	116	35	83	44	228	270	284	13	54	307	377	0	763
RUS	641	860	470	594	581	367	1437	899	682	337	350	898	155	1147	822	582	540	484	1070	3929	1306	444	2696	263	2031	1834	507	773	438	499	510	1770	763	0

D.2 Determining rank orders: test results

Here down there are shown the cointegration results for Trace and Maximal Eigenvalues tests.

	Country (domestic, foreign)	USA (7,2)	EMU (7,6)	WEU (6,6)	CEU (6,6)	SEA (6,6)	CLA (6,6)	CAN (6,6)	INDI (6,6)	CHIN (6,6)	JAP (6,6)	RUS (6,6)
r=0	Maximal Eigenvalue Statistics	116,6	183,6	153,1	104,3	124,2	99,6	174,4	136,7	344,0	130,1	82,6
	Trace Statistics	288,4	430,9	376,0	240,8	315,2	244,5	321,9	302,8	620,0	303,2	244,5
	critical value at 5%	181,7	242,9	197,7	197,7	197,7	197,7	197,7	197,7	197,7	197,7	197,7
r=1	Maximal Eigenvalue Statistics	70,1	90,1	97,8	56,7	69,7	64,5	54,1	71,2	125,7	66,4	69,8
	Trace Statistics	171,8	247,3	223,0	**136,5**	**111,1**	**144,9**	**147,5**	**103,2**	276,0	173,1	161,9
	critical value at 5%	144,7	197,7	156,4	**156,4**	**156,4**	**156,4**	**156,4**	**119,0**	156,4	156,4	156,4
r=2	Maximal Eigenvalue Statistics	40,9	69,5	63,5	33,4	56,8	36,9	31,9	62,8	33,0	41,5	29,1
	Trace Statistics	**101,8**	157,2	125,2	79,8	111,4	80,4	93,3	146,2	**74,3**	**106,7**	**92,1**
	critical value at 5%	**111,7**	156,4	119,0	119,0	119,0	119,0	119,0	156,4	**85,4**	**119,0**	**119,0**
r=3	Maximal Eigenvalue Statistics	24,5	39,8	28,5	20,1	29,1	21,3	27,3	30,6	76,0	33,0	25,9
	Trace Statistics	60,8	**87,6**	**61,7**	46,4	64,6	43,4	61,4	55,5	115,0	65,2	63,0
	critical value at 5%	82,6	**119,0**	**85,4**	85,4	85,4	85,4	85,4	85,4	119,0	85,4	85,4
r=4	Maximal Eigenvalue Statistics	23,1	21,2	18,9	15,1	25,0	14,4	23,2	14,0	24,6	21,2	20,0
	Trace Statistics	36,4	47,8	33,1	26,3	35,5	22,1	34,1	24,9	41,3	32,2	37,2
	critical value at 5%	57,5	85,4	55,5	55,5	55,5	55,5	55,5	55,5	55,5	55,5	55,5
r=5	Maximal Eigenvalue Statistics	8,9	19,0	14,2	11,2	10,4	7,7	11,0	10,9	16,8	11,1	17,1
	Trace Statistics	13,3	26,6	14,2	11,2	10,4	7,7	11,0	10,9	16,8	11,1	17,1
	critical value at 5%	36,1	55,5	28,8	28,8	28,8	28,8	28,8	28,8	28,8	28,8	28,8
r=6	Maximal Eigenvalue Statistics	4,4	7,6									
	Trace Statistics	4,4	7,6									
	critical value at 5%	18,3	28,8									

D.3 Eigenvalues of GVAR(3) model

Recall the companion matrix $\boldsymbol{F}$ given in (15), here there are listed eigenvalues (in their corresponding moduli as in (17)) of the determinantal polynomial given in (16).
In particular, 48 out of 206 are equal to 1 while 130 are between 1 and 0.

1	1	0,5168778	0,209313318	0,087162832
1	1	0,5168778	0,208806142	0,049118889
1	1	0,5128787	0,208806142	0,049118889
1	1	0,5128787	0,206400662	0,039647053
1	1	0,5019839	0,368921622	0,03152801
1	1	0,5019839	0,354298153	0,03066248
1	1	0,50046	0,354298153	0,016779681
1	0,9273911	0,50046	0,349503241	1,29904591244908000E-14
1	0,8828651	0,4969601	0,349503241	1,29904591244908000E-14
1	0,8828651	0,4650949	0,345481237	1,70801495792377000E-15
1	0,7518549	0,4650949	0,345481237	6,47071417728112000E-16
1	0,7518549	0,4640222	0,340677811	5,79344960157927000E-16
1	0,7223464	0,4420782	0,340677811	5,79344960157927000E-16
1	0,7223464	0,4379853	0,330719812	4,11376645397900000E-16
1	0,6687734	0,4379853	0,330719812	3,03886385162982000E-16
1	0,6687734	0,4314516	0,325450318	1,89179018564195000E-16
1	0,6409856	0,4314516	0,325450318	6,89253497336834000E-17
1	0,6409856	0,4289357	0,31907755	0
1	0,6392195	0,4289357	0,31907755	0
1	0,6392195	0,4275765	0,318760537	0
1	0,6354979	0,4275765	0,318760537	0
1	0,6354979	0,423697	0,318056409	0
1	0,5974031	0,423697	0,312176616	0
1	0,5974031	0,4160008	0,312176616	0
1	0,5971851	0,4160008	0,279653193	0
1	0,5920653	0,4075438	0,277766769	0
1	0,5920653	0,4022532	0,256713328	0
1	0,5664671	0,4022532	0,256713328	0
1	0,5664671	0,3909208	0,253916189	0
1	0,5560954	0,3909208	0,253916189	0
1	0,5560954	0,3894366	0,176394129	0
1	0,5531113	0,3894366	0,176394129	0
1	0,5531113	0,383714	0,161151305	0
1	0,5323191	0,383714	0,141777151	0
1	0,5280926	0,3726535	0,141777151	0
1	0,5280926	0,3726535	0,129564322	0
1	0,5203793	0,3689216	0,129564322	0
1	0,5203793	0,2315201	0,122104324	0
1	0,5170214	0,2315201	0,114025016	0
1	0,5170214	0,2093133	0,100503648	0

D.4 Impact elasticity of foreign variables on domestic counterparts

Contemporaneous effects of foreign variables on domestic counterparts with corresponding standard error. Heteroskedastic-robust (e.g. White's and Newey-West's) SE are also provided.

Model	Effect on domestic:	y	p	eq	lr	sr
USA	**Coefficient**	**0,042493**				
	Standard error	0,043016				
	White's SE	0,048713				
	Newey-West's SE	0,045779				
EMU	**Coefficient**	**1,20755**	**0,413913**	**0,946076**	**-0,14953**	**0,24433**
	Standard error	0,084688	0,051361	0,046177	0,031156	0,016035
	White's SE	0,094443	0,055425	0,054787	0,10182	0,052776
	Newey-West's SE	0,110006	0,063965	0,063652	0,102017	0,052427
WEU	**Coefficient**	**0,971814**	**0,558676**	**0,807853**	**0,309877**	**1,604496**
	Standard error	0,058666	0,065673	0,022454	0,104678	0,174761
	White's SE	0,061001	0,075298	0,027999	0,38767	0,763462
	Newey-West's SE	0,05224	0,057687	0,029294	0,387734	0,782143
CEU	**Coefficient**	**0,856973**	**1,250966**	**0,98232**	**-0,12692**	**2,235335**
	Standard error	0,052984	0,228377	0,071054	0,135661	0,912307
	White's SE	0,066311	0,251362	0,077719	0,431795	2,987053
	Newey-West's SE	0,079718	0,294054	0,082638	0,428519	3,00349
SEA	**Coefficient**	**0,475365**	**0,308954**	**0,87267**	**0,804593**	**0,118734**
	Standard error	0,104811	0,08525	0,057974	0,095965	0,164668
	White's SE	0,079812	0,088726	0,061961	0,379722	0,511768
	Newey-West's SE	0,08233	0,081905	0,066559	0,381585	0,50989
CLA	**Coefficient**	**0,596703**	**0,045091**	**0,961694**	**2,807156**	**0,186582**
	Standard error	0,084967	0,069824	0,054123	0,521524	0,372488
	White's SE	0,108232	0,063239	0,058478	1,917098	1,228459
	Newey-West's SE	0,10259	0,053844	0,070768	1,912527	1,233732
CAN	**Coefficient**	**0,696022**	**0,949634**	**0,806962**	**0,831024**	**0,935643**
	Standard error	0,091799	0,06994	0,042742	0,049156	0,048826
	White's SE	0,101912	0,077136	0,047771	0,161701	0,204021
	Newey-West's SE	0,09917	0,070334	0,062284	0,161447	0,205258
INDI	**Coefficient**	**0,177502**	**-0,50412**	**0,799142**	**0,385498**	**2,32163**
	Standard error	0,075709	0,284791	0,066772	0,153197	0,206597
	White's SE	0,080535	0,263246	0,064505	0,472073	0,743047
	Newey-West's SE	0,070637	0,22486	0,069749	0,471844	0,744011
CHIN	**Coefficient**	**0,173424**	**0,359883**	**1,159142**	**0,287456**	**0,361979**
	Standard error	0,143757	0,198385	0,103165	0,100038	0,118961
	White's SE	0,117002	0,18145	0,106877	0,242446	0,279086
	Newey-West's SE	0,120853	0,200426	0,120953	0,24579	0,277493
JAP	**Coefficient**	**0,638729**	**0,301449**	**0,689522**	**0,302944**	**0,109917**
	Standard error	0,127688	0,068189	0,064125	0,04047	0,017495
	White's SE	0,125744	0,066928	0,067861	0,156077	0,050462
	Newey-West's SE	0,122366	0,052721	0,063268	0,156324	0,05064
RUS	**Coefficient**	**0,448141**	**0,179648**	**1,20149**	**-0,83716**	**0,487737**
	Standard error	0,074003	0,192232	0,140042	1,803152	0,440573
	White's SE	0,094806	0,183977	0,178358	2,713104	1,163334
	Newey-West's SE	0,101595	0,180151	0,205466	2,768274	1,173026

D.5 Detailed results of unit-roots tests

In the following tables, results of ADF and WS-DF tests are presented for both domestic and foreign variables expressed either in level or in first difference.

Variable	Statistics	Crititcal value	USA	EMU	WEU	CEU	SEA	CLA	CAN	INDI	CHIN	JAP	RUS
unc	ADF	-3,45	-3,2471	-3,31247									
	WS	-3,24	**-3,3499**	-3,32302									
Δunc	ADF	-2,89	-10,5841	-10,299									
	WS	-2,55	-10,7079	-10,356									
y	ADF	-3,45	-1,12078	-1,98451	-1,97358	-2,14011	-4,01909	-2,67693	-2,47927	1,339617	-2,05241	-2,382	-2,52015
	WS	-3,24	-1,38524	-1,73859	-2,20663	-2,11812	-2,45224	-2,71928	-2,11632	1,157755	-1,17368	-2,37436	-0,94805
Δy	ADF	-2,89	-7,68799	-8,77443	-22,505	-7,51858	-11,3106	-12,5829	-5,54017	-12,6986	-11,8738	-9,18454	-10,6509
	WS	-2,55	-7,76962	-8,27591	-22,4489	-7,59394	-11,126	-12,7297	-5,65889	-12,72	-11,8275	-9,24888	-10,4046
p	ADF	-3,45	**-9,35147**	**-7,2583**	**-7,66639**	**-4,41999**	**-7,0125**	**-6,20309**	**-10,4463**	**-9,40658**	**-8,0673**	**-8,57071**	**-7,46817**
	WS	-3,24	**-9,39887**	**-7,29456**	**-7,79843**	**-4,47459**	**-7,06747**	**-5,1192**	**-10,5782**	**-8,88005**	**-8,18849**	**-8,6546**	-0,70272
Δp	ADF	-2,89	-12,9162	-12,703	-11,7303	-10,693	-14,8278	-10,6862	-13,5021	-11,794	-11,748	-13,8956	-9,11024
	WS	-2,55	-13,0091	-12,8425	-11,8998	-10,8943	-14,6517	-10,5483	-13,6942	-11,4688	-11,9483	-13,9359	-4,33724
eq	ADF	-3,45	-1,27428	-1,81675	-1,80611	-2,0678	-2,4559	-1,44009	-2,34306	-1,54468	-1,75427	-1,80218	-2,68334
	WS	-3,24	-1,45939	-2,09185	-2,04915	-2,15278	-2,67608	-1,4102	-2,42932	-1,53804	-1,75842	-1,95984	-1,87717
Δeq	ADF	-2,89	-8,1627	-7,82088	-8,3127	-7,98598	-5,4999	-6,29213	-7,30581	-7,01894	-7,7236	-7,0396	-8,32447
	WS	-2,55	-8,19065	-7,94245	-8,39081	-7,78333	-5,10003	-5,63916	-7,42804	-7,09907	-7,76219	-7,15637	-8,34774
fx	ADF	-3,45		-2,21878	-2,39793	-1,93114	-2,80455	-2,35392	-1,71328	-2,61436	-2,10317	-1,39676	-1,72312
	WS	-3,24		-1,99569	-2,44778	-2,12185	-2,50205	-2,43593	-1,93108	-1,81639	-0,55313	-1,32474	-1,90813
Δfx	ADF	-2,89		-8,4735	-7,99936	-8,97387	-6,55316	-6,95911	-7,80315	-7,92094	-5,0432	-8,14864	-5,92095
	WS	-2,55		-8,50924	-8,11914	-8,95215	-6,704	-7,08536	-7,92174	-7,91166	-5,10508	-8,12882	-6,05474
lr	ADF	-3,45	-2,34183	-2,58923	-2,35142	-2,58059	-2,03561	-3,25481	-3,1776	-1,83948	-2,89465	-1,69948	-3,11549
	WS	-3,24	-2,53196	-2,50178	-2,18108	-2,77033	-2,16423	-1,8047	-2,46289	-0,9502	-2,97771	-1,94736	-0,41254
Δlr	ADF	-2,89	-9,51992	-9,41162	-9,49536	-9,61361	-9,79228	-9,61668	-9,68727	-9,39635	-9,32746	-9,4393	-9,52571
	WS	-2,55	-9,65128	-9,54385	-9,62691	-9,74424	-9,92157	-9,74728	-9,81733	-9,5287	-9,46037	-9,5713	-9,65702
sr	ADF	-3,45	-1,84346	-2,38009	-2,16055	-1,78163	-2,77313	-3,35679	-2,09182	-1,93153	-2,94941	-1,80246	-2,5718
	WS	-3,24	-2,12424	-2,44859	-2,22369	-1,80531	-2,0489	-2,08527	-2,342	-1,73256	-3,0915	-2,08452	-1,60001
Δsr	ADF	-2,89	-9,38802	-9,82972	-9,41737	-9,62032	-9,50205	-9,59501	-9,39359	-9,33114	-9,3334	-9,32745	-9,37378
	WS	-2,55	-9,52043	-9,95873	-9,54955	-9,7509	-9,63355	-9,72578	-9,52596	-9,46403	-9,46626	-9,46037	-9,50631
y*	ADF	-3,45	-2,47853	-2,0213	-2,04152	-2,04318	-2,22423	-2,34219	-2,51808	-2,39102	-2,71613	-2,33082	-2,01959
	WS	-3,24	-2,04778	-2,27444	-1,90581	-2,04804	-1,97804	-2,14297	-2,62231	-2,03155	-2,55104	-1,31684	-1,96734
Δy*	ADF	-2,89	-6,10296	-6,65364	-7,43224	-7,71952	-6,83501	-5,95269	-4,54016	-6,64511	-5,92283	-7,83803	-7,20585
	WS	-2,55	-6,15788	-6,74998	-7,1111	-7,51805	-6,98301	-5,91918	-4,62515	-6,49676	-5,94487	-7,89638	-7,01076
p*	ADF	-3,45	**-9,35147**	**-6,53246**	**-7,07047**	**-7,1165**	**-7,38918**	**-7,53625**	**-8,74495**	**-6,85045**	**-7,21895**	**-6,68098**	**-6,53192**
	WS	-3,24	**-9,39887**	**-6,15031**	**-7,20007**	**-6,8669**	**-7,49152**	**-7,64409**	**-8,82941**	**-6,96571**	**-7,31605**	**-6,80197**	**-6,66294**
Δp*	ADF	-2,89	-12,9162	-9,57429	-12,4802	-12,1152	-12,9585	-12,1718	-12,4071	-13,7409	-13,3676	-14,2319	-12,0946
	WS	-2,55	-13,0091	-9,20235	-12,6524	-12,1544	-13,11	-12,324	-12,5242	-13,8427	-13,4015	-14,3329	-12,2231
eq*	ADF	-3,45	-1,27428	-2,09045	-1,96787	-2,05636	-1,84757	-1,91989	-1,72233	-2,07463	-2,093	-2,10372	-1,93887
	WS	-3,24	-1,45939	-2,32061	-2,22734	-2,29124	-2,09717	-2,16613	-1,93375	-2,32007	-2,33151	-2,31806	-2,20821
Δeq*	ADF	-2,89	-8,1627	-7,76537	-7,64163	-7,66137	-7,51476	-7,60264	-7,96145	-7,53748	-7,46828	-7,44257	-7,66482
	WS	-2,55	-8,19065	-7,81724	-7,75069	-7,77297	-7,64453	-7,72533	-8,03236	-7,66056	-7,55885	-7,57271	-7,76862
fx*	ADF	-3,45	-2,28383										
	WS	-3,24	-1,9585										
Δfx*	ADF	-2,89	-7,99523										
	WS	-2,55	-7,95153										
lr*	ADF	-3,45	-2,34183	-2,81899	-2,23378	-2,78089	-2,64621	-2,32165	-2,40855	-2,46016	-2,46399	-2,5215	-2,56406
	WS	-3,24	-2,53196	-0,879	-1,8734	-0,74317	-1,77647	-2,20749	-2,54344	-1,89924	-1,39031	-1,49158	-2,74244
Δlr*	ADF	-2,89	-9,51992	-9,76093	-9,77484	-9,69305	-9,64118	-9,71519	-9,71858	-9,87821	-9,91471	-9,81843	-9,61246
	WS	-2,55	-9,65128	-9,89045	-9,90426	-9,82307	-9,77159	-9,84504	-9,84841	-10,0069	-10,0431	-9,94752	-9,74309
sr*	ADF	-3,45	-1,84346	-1,88712	-2,00499	-2,1059	-2,03965	-1,89053	-1,83204	-2,03452	-2,06316	-2,04817	-2,17034
	WS	-3,24	-2,12424	-2,14198	-2,2488	-2,02194	-2,20283	-2,144	-2,09141	-2,06089	-1,86533	-1,86988	-2,25773
Δsr*	ADF	-2,89	-9,38802	-9,831	-9,90395	-9,66811	-9,42446	-9,50061	-9,43598	-9,663	-9,66448	-9,54876	-9,82522
	WS	-2,55	-9,52043	-9,96001	-10,0324	-9,79832	-9,55658	-9,63212	-9,56801	-9,79325	-9,79472	-9,67989	-9,95427
poil	ADF	-3,45	-3,35046	-3,35046	-3,35046	-3,35046	-3,35046	-3,35046	-3,35046	-3,35046	-3,35046	-3,35046	-3,35046
poil	WS	-3,24	-3,0004	-3,0004	-3,0004	-3,0004	-3,0004	-3,0004	-3,0004	-3,0004	-3,0004	-3,0004	-3,0004
Δpoil	ADF	-2,89	-7,63686	-7,63686	-7,63686	-7,63686	-7,63686	-7,63686	-7,63686	-7,63686	-7,63686	-7,63686	-7,63686
Δpoil	WS	-2,55	-7,69119	-7,69119	-7,69119	-7,69119	-7,69119	-7,69119	-7,69119	-7,69119	-7,69119	-7,69119	-7,69119

D.6 Average pairwise cross-section correlations

Here average pairwise cross-section correlations are illustrated.at individual-variables level. $(n) \rightarrow (m)$ indicate the variation of correlation of model m with respect to model n.

Variable	Model	VAR level (1)	VAR first diff (2)	VECMX (3)	(1) → (2)	(2) → (3)
unc	USA	0,8578	0,4874	0,3744	-0,43	-0,23
	EMU	0,8771	0,5029	0,3744	-0,43	-0,26
y	USA	0,6160	0,0505	-0,0486	-0,92	-1,96
	EMU	0,6711	0,4016	-0,0915	-0,40	-1,23
	WEU	0,6355	0,3540	-0,0358	-0,44	-1,10
	CEU	0,2791	0,3967	0,0060	0,42	-0,98
	SEA	0,6411	0,2219	-0,0062	-0,65	-1,03
	CLA	0,6608	0,2766	0,0170	-0,58	-0,94
	CAN	0,6072	0,2428	0,0006	-0,60	-1,00
	INDI	0,1384	0,1425	0,0137	0,03	-0,90
	CHIN	0,5872	0,0717	-0,0658	-0,88	-1,92
	JAP	0,3668	0,2531	-0,0271	-0,31	-1,11
	RUS	0,5934	0,2549	0,0027	-0,57	-0,99
p	USA	0,2994	0,2021	0,0128	-0,33	-0,94
	EMU	0,2931	0,1575	-0,0591	-0,46	-1,38
	WEU	0,2532	0,1682	0,0012	-0,34	-0,99
	CEU	0,0998	0,0909	-0,0208	-0,09	-1,23
	SEA	0,1830	0,0787	-0,0182	-0,57	-1,23
	CLA	0,1135	0,0711	0,0589	-0,37	-0,17
	CAN	0,2499	0,1555	-0,0057	-0,38	-1,04
	INDI	0,0491	0,0038	-0,0031	-0,92	-1,82
	CHIN	0,0658	-0,0052	-0,0850	-1,08	15,28
	JAP	0,1489	0,1064	-0,0064	-0,29	-1,06
	RUS	0,1002	0,0467	0,0030	-0,53	-0,94
eq	USA	0,4819	0,7251	0,0284	0,50	-0,96
	EMU	0,5845	0,7163	-0,1308	0,23	-1,18
	WEU	0,6725	0,7399	-0,0476	0,10	-1,06
	CEU	0,6728	0,6634	-0,0177	-0,01	-1,03
	SEA	0,5189	0,6500	-0,0338	0,25	-1,05
	CLA	0,5132	0,7182	0,0311	0,40	-0,96
	CAN	0,6228	0,7062	0,0452	0,13	-0,94
	INDI	0,0534	0,6456	0,0446	11,10	-0,93
	CHIN	0,5640	0,5844	-0,1861	0,04	-1,32
	JAP	0,4512	0,6452	0,0524	0,43	-0,92
	RUS	0,4899	0,5963	-0,0178	0,22	-1,03
fx	EMU	0,8877	0,4517	0,3899	-0,49	-0,14
	WEU	0,8664	0,4746	0,3556	-0,45	-0,25
	CEU	0,9088	0,4663	0,3278	-0,49	-0,30
	SEA	0,9250	0,4269	0,2713	-0,54	-0,36
	CLA	0,8932	0,3745	0,2080	-0,58	-0,44
	CAN	0,9291	0,4281	0,2575	-0,54	-0,40
	INDI	0,9266	0,3513	0,2138	-0,62	-0,39
	CHIN	0,8739	0,1722	0,1280	-0,80	-0,26
	JAP	0,6916	0,1209	0,1945	-0,83	0,61
	RUS	0,9135	0,3626	0,2121	-0,60	-0,42

Variable	Model	AR level (	R first diff	VECMX (3)	(1) → (2)	(2) → (3)
lr	USA	0,6966	0,3858	0,1638	-0,45	-0,58
	EMU	0,6499	0,3122	0,1180	-0,52	-0,62
	WEU	0,6650	0,4093	0,0736	-0,38	-0,82
	CEU	0,6991	0,3422	0,1006	-0,51	-0,71
	SEA	0,7299	0,4562	0,0577	-0,37	-0,87
	CLA	0,6448	0,0620	-0,2459	-0,90	-4,96
	CAN	0,6585	0,3303	-0,0241	-0,50	-1,07
	INDI	0,3730	0,2788	-0,0430	-0,25	-1,15
	CHIN	0,1190	0,1625	-0,0067	0,37	-1,04
	JAP	0,5628	0,3803	0,0793	-0,32	-0,79
	RUS	0,5442	0,1426	-0,0524	-0,74	-1,37
sr	USA	0,5396	0,2791	-0,0255	-0,48	-1,09
	EMU	0,5225	0,3884	0,0760	-0,26	-0,80
	WEU	0,5502	0,4346	0,0886	-0,21	-0,80
	CEU	0,4085	0,0123	-0,1345	-0,97	-11,94
	SEA	0,5739	0,2853	-0,0314	-0,50	-1,11
	CLA	0,4855	0,1365	-0,0380	-0,72	-1,28
	CAN	0,5790	0,3739	0,1396	-0,35	-0,63
	INDI	0,3140	0,4275	0,0760	0,36	-0,82
	CHIN	-0,1887	0,1303	-0,0328	-1,69	-1,25
	JAP	0,1085	0,3639	0,1385	2,35	-0,62
	RUS	0,3377	0,0104	-0,0967	-0,97	-10,27

D.7 Structural breaks tests: test statistics and critical values

Maximal OLS CUSUM statistics (Ploberger-Kramer, 1992) – PK sup

PK sup	unc	y	p	eq	fx	lr	sr	poil	Critical value	unc	y	p	eq	fx	lr	sr	poil
USA	0,466238	1,017595	0,612674	1,170727		0,36229	0,503743	1,045745	USA	1,038836	0,984335	0,820086	1,107224		0,969438	1,043348	1,0318
EMU	0,326178	0,876605	0,452849	0,776244	0,601178	0,853676	1,053644		EMU	1,002227	0,842652	0,58192	0,962083	1,04204	0,939136	1,038784	
WEU		0,684421	0,462324	0,691842	0,899455	0,802461	0,711929		WEU		0,613205	0,690317	0,954061	1,118568	1,127763	0,716595	
CEU		0,766154	0,512123	0,808594	0,976918	0,624823	0,864064		CEU		1,108296	0,805057	1,096192	1,034399	1,036427	1,124637	
SEA		0,735084	0,401486	0,786016	0,754107	0,511437	0,708942		SEA		0,838062	0,68447	1,064677	1,015794	1,064337	1,06587	
CLA		0,632991	0,45093	1,782155	0,871711	0,790454	0,791594		CLA		1,147826	0,905379	1,08116	1,200186	1,146757	1,189971	
CAN		0,75735	0,883862	1,356926	0,938748	1,10742	0,433627		CAN		1,038799	0,696409	1,041512	1,018921	1,224479	1,164622	
INDI		1,461354	1,276283	0,779524	0,524731	1,235651	0,60436		INDI		0,97742	0,933436	1,191502	1,10843	1,079057	1,090275	
CHIN		0,439086	0,383006	0,815898	0,60925	0,554464	0,696924		CHIN		0,950402	0,754524	0,953748	0,778918	1,051185	0,937245	
JAP		0,627246	0,57829	1,206245	1,041066	1,136013	0,880565		JAP		0,746975	0,566596	1,099828	1,132108	1,185381	1,04699	
RUS		0,580856	0,448734	1,268178	1,015617	0,618926	0,605853		RUS		0,832423	0,876969	0,973489	0,972284	0,70359	0,985196	

Mean square version - PK msq

PK msq	unc	y	p	eq	fx	lr	sr	poil	Critical value	unc	y	p	eq	fx	lr	sr	poil
USA	0,048953	0,120278	0,086922	0,272798		0,030527	0,048038	0,286718	USA	0,316667	0,211964	0,152518	0,28114		0,195543	0,270414	0,2521
EMU	0,01659	0,115055	0,031305	0,129004	0,073152	0,275529	0,24985		EMU	0,221603	0,164195	0,055696	0,237085	0,266019	0,250426	0,256338	
WEU		0,063172	0,047548	0,090064	0,093159	0,259802	0,066771		WEU		0,059764	0,075045	0,244939	0,300897	0,376891	0,084707	
CEU		0,074379	0,062739	0,115455	0,212452	0,079425	0,097473		CEU		0,284811	0,119743	0,320039	0,238698	0,232002	0,316154	
SEA		0,146434	0,043355	0,168932	0,077262	0,055114	0,07691		SEA		0,131807	0,09129	0,267945	0,257837	0,290672	0,27102	
CLA		0,076127	0,027971	1,357746	0,103923	0,20097	0,23512		CLA		0,359171	0,159098	0,299159	0,353158	0,308361	0,317321	
CAN		0,065855	0,127785	0,624543	0,262566	0,311459	0,035135		CAN		0,237805	0,094047	0,275035	0,241873	0,404168	0,330778	
INDI		0,643806	0,568077	0,123871	0,068876	0,588738	0,08997		INDI		0,186617	0,218843	0,382279	0,277875	0,326716	0,295718	
CHIN		0,024768	0,025773	0,16585	0,061551	0,037712	0,108084		CHIN		0,233997	0,095655	0,225835	0,137078	0,244862	0,192035	
JAP		0,030221	0,032635	0,257813	0,215023	0,319908	0,100888		JAP		0,102442	0,04465	0,354944	0,337717	0,32427	0,256068	
RUS		0,038948	0,044013	0,531719	0,441993	0,099137	0,141418		RUS		0,161748	0,167149	0,21771	0,217328	0,092816	0,23792	

Random Walk alternative (Nyblom, 1989) - Nyblom

Nyblom	unc	y	p	eq	fx	lr	sr	poil	Critical value	unc	y	p	eq	fx	lr	sr	poil
USA	2,75459	2,093373	3,981728	2,043058		2,008868	1,770982	3,49187	USA	3,529126	3,392016	3,352271	3,583931		3,470475	3,7159	3,438276
EMU	2,190149	5,589486	3,315257	5,691525	3,730554	4,120678	5,276505		EMU	4,140072	4,150253	4,25847	4,115261	4,477248	4,227273	4,341958	
WEU		2,842277	0,902416	1,327961	3,927984	5,118367	6,097621		WEU		2,031666	2,016963	2,044659	2,193368	2,238135	1,990399	
CEU		2,916041	3,285447	3,469195	2,8912	4,277628	3,777765		CEU		3,927943	3,616052	3,57161	3,874072	3,673298	3,722533	
SEA		4,189611	2,68281	4,832237	3,607426	6,6523	4,110167		SEA		3,631822	3,56442	3,956389	3,866367	3,890754	4,070613	
CLA		1,958485	1,854376	3,748269	3,105277	4,847955	4,178453		CLA		2,754414	2,715632	2,708084	2,887774	2,800355	2,74488	
CAN		2,657755	2,394666	3,231492	3,019116	8,142065	3,202705		CAN		2,738755	2,548789	2,81983	2,841281	2,648611	2,989251	
INDI		3,359243	2,979068	3,156293	3,361585	8,737856	3,529751		INDI		3,826416	3,558556	3,799038	3,707942	3,620757	3,685458	
CHIN		6,418687	5,85069	2,765387	2,175097	3,626315	3,432666		CHIN		4,507023	4,558935	4,630891	4,4174	4,444124	4,339527	
JAP		0,485199	0,570682	1,43695	2,478063	3,494614	3,261026		JAP		1,837403	1,771927	2,087205	2,099987	2,109471	1,896029	
RUS		4,533941	4,633232	4,769016	6,117327	10,15659	6,326735		RUS		4,390105	4,66592	4,592067	4,418804	4,344264	4,565842	

Robust Nyblom

Robust Nyblom	unc	y	p	eq	fx	lr	sr	poil	Critical value	unc	y	p	eq	fx	lr	sr	poil
USA	3,331555	2,960263	3,586539	2,782673		3,985464	3,965598	3,768668	USA	3,908301	3,771492	3,749409	3,881176		3,891229	3,803709	3,895636
EMU	3,176397	6,338484	3,895081	4,63508	3,685326	3,847594	3,125406		EMU	4,73639	4,738615	4,882181	4,530457	5,026296	4,690103	4,755757	
WEU		2,510935	0,920172	1,331921	2,723081	1,696858	1,287707		WEU		2,110636	2,116888	2,250521	2,390358	2,133979	2,068857	
CEU		2,796901	3,86808	2,994644	3,190002	3,14302	2,770196		CEU		4,076858	4,122505	4,130489	4,30644	4,101713	4,181468	
SEA		4,244307	3,556415	4,082917	4,007326	3,523732	2,836344		SEA		4,246499	4,127355	4,413485	4,102994	4,323465	4,440709	
CLA		2,053944	1,945291	4,286781	2,341948	2,542101	2,246043		CLA		2,886784	2,926922	2,971077	2,949	2,997011	2,933406	
CAN		2,404707	1,960072	3,297288	2,040034	3,590002	2,473784		CAN		2,987529	2,879752	3,124411	2,951867	2,955213	3,160774	
INDI		3,803142	3,713028	3,539853	3,869098	3,620636	3,962988		INDI		4,219485	3,913866	4,212443	3,954208	4,050121	4,071984	
CHIN		4,676561	4,68206	3,714729	3,785414	4,199325	4,07892		CHIN		5,168912	5,23941	5,386061	5,305694	5,314701	5,182698	
JAP		0,679119	0,662717	1,370735	1,870914	1,485088	1,213664		JAP		1,921285	1,881089	2,204976	2,153139	2,089698	1,908407	
RUS		5,091219	5,180331	4,31355	5,060318	4,540149	5,063287		RUS		5,077167	5,487783	5,286271	5,298926	5,184553	5,40119	

Sequential Wald statistics in likelihood ratio form (Quandt, 1960) - QLR

QLR	unc	y	p	eq	fx	lr	sr	poil	Critical value	unc	y	p	eq	fx	lr	sr	poil
USA	26,99566	28,13766	56,35518	35,67811		18,6283	23,46828	41,98925	USA	38,45955	39,73015	36,4529	38,76841		38,83985	41,73789	38,79667
EMU	20,66719	59,77725	30,74914	62,84769	53,60824	134,0945	147,2253		EMU	47,61632	45,23176	45,58199	46,72617	48,84042	47,1301	49,94179	
WEU		28,11514	13,56363	13,03391	47,59633	60,17872	137,4114		WEU		22,22241	23,87065	24,0953	24,51032	26,32014	21,94247	
CEU		32,78208	45,41189	48,00585	35,25663	146,5942	174,8222		CEU		40,23425	40,37255	38,78784	43,23175	40,83319	40,38569	
SEA		63,88102	27,18578	96,52607	88,52	169,6476	106,2223		SEA		44,75854	37,94394	43,76216	43,33494	43,97526	43,45497	
CLA		27,24373	28,47445	36,8137	40,731	196,5096	110,8633		CLA		30,03737	29,55697	29,87537	32,1379	30,28768	28,24055	
CAN		40,96699	26,89663	38,18367	36,42405	187,7287	122,3267		CAN		29,32383	28,01876	30,42199	30,07152	29,23947	31,62771	
INDI		49,53659	61,97197	34,58666	34,93095	166,8667	87,50124		INDI		41,83595	39,98184	43,31217	40,12634	39,58318	39,3362	
CHIN		154,8449	91,06953	68,59847	38,80622	51,14499	43,33678		CHIN		49,36975	49,6557	52,03302	51,66979	52,2672	48,82369	
JAP		10,58162	8,681254	14,4931	38,1749	114,7327	50,41313		JAP		20,28064	22,53576	23,87741	23,65658	22,07924	21,59289	
RUS		59,96113	64,33682	84,88688	125,5367	326,5539	149,5395		RUS		48,73796	54,49328	50,05143	52,4963	48,82558	48,64447	

Robust QLR

Robust QLR	unc	y	p	eq	fx	lr	sr	poil	Critical value	unc	y	p	eq	fx	lr	sr	poil
USA	31,66127	27,94694	34,05247	24,66861		12,75326	10,09449	28,29307	USA	31,87028537	32,36511	32,62168	33,76288		33,56647	32,99857	32,62711
EMU	32,13633	48,12437	30,51121	31,0181	34,12543	12,34317	12,74377		EMU	38,34875863	38,63651	40,22685	39,02222	38,93527	38,72687	42,08381	
WEU		17,99393	12,70895	12,31112	25,22556	12,29849	11,25351		WEU		19,41176	20,27245	20,8101	21,21135	21,53448	19,65572	
CEU		23,3328	36,15283	25,57653	27,26991	11,21827	11,47867		CEU		33,69904	33,43628	35,39801	37,89341	35,20772	35,13158	
SEA		39,04709	34,77254	32,16133	36,73203	13,01107	15,0101		SEA		36,30147	35,47456	35,43781	34,98399	36,73893	37,16759	
CLA		16,76675	24,67	33,55981	21,30583	10,10724	11,29334		CLA		25,3404	25,54604	25,96712	25,92396	26,94001	25,92749	
CAN		23,70961	20,51375	26,84568	20,89871	11,59131	9,795432		CAN		26,22454	24,95044	27,72097	25,76182	27,28588	27,53936	
INDI		33,95645	33,0584	32,98063	35,09898	12,31425	10,99279		INDI		34,70965	33,06855	35,27928	34,27045	33,16138	34,99769	
CHIN		52,8966	43,52776	29,74497	36,72641	14,43734	9,74442		CHIN		42,99225	43,17461	45,48036	43,83384	43,57632	42,11052	
JAP		9,334604	7,706803	11,85863	25,24448	10,0489	6,034924		JAP		17,94469	19,4329	20,61131	20,20876	19,62254	18,57314	
RUS		33,40763	39,01791	30,68924	40,2747	58,50133	13,56944		RUS		42,72683	43,69503	43,98338	45,83702	42,70588	44,50224	

Sequential Wald statistics in mean form (Hansen, 1992) – MW

MW	unc	y	p	eq	fx	lr	sr	poil	Critical value	unc	y	p	eq	fx	lr	sr	poil
USA	19,64228	18,78495	39,15505	15,56234		14,82058	14,239	31,53865	USA	24,58843072	24,69387	24,56337	25,80266		23,99487	26,90913	25,66127
EMU	15,73592	42,83227	23,29607	38,62005	33,24639	57,54033	118,0033		EMU	32,2703782	31,30483	31,342	30,62366	33,00324	31,09185	32,9609	
WEU		21,50857	5,888301	8,017179	29,85356	39,43567	89,27039		WEU		13,91339	13,43493	14,81895	14,84833	16,5601	13,60945	
CEU		21,24286	22,08368	22,96825	21,6993	56,31781	21,90251		CEU		27,46705	24,62331	26,48182	28,47921	25,94701	26,94879	
SEA		37,15074	19,38729	39,12669	39,70151	95,71827	29,95536		SEA		27,63816	25,23306	29,39604	27,16229	28,92887	29,24912	
CLA		17,47635	17,0726	26,25208	24,88085	45,1621	27,8869		CLA		19,06838	19,68408	18,12131	20,32922	19,46142	18,56867	
CAN		21,04818	20,07598	20,69194	24,12978	80,5478	40,3288		CAN		18,68724	18,05615	20,72534	20,93604	18,93498	21,17551	
INDI		26,45544	25,6367	24,05438	25,77481	122,2741	36,86193		INDI		28,41615	27,79789	27,91585	26,2803	25,3577	27,36153	
CHIN		80,70964	59,06336	27,14518	22,9822	31,54027	27,31542		CHIN		33,02547	33,98692	35,40882	33,35675	33,96153	32,78173	
JAP		3,437905	3,795721	8,958526	23,90385	39,53574	31,89631		JAP		12,23175	12,41712	14,23479	14,90618	14,23749	13,20432	
RUS		25,66633	46,11122	33,43052	72,33657	114,6371	53,69597		RUS		33,77618	37,42924	35,74985	34,17645	32,8553	34,96953	

Robust MW

Robust MW	unc	y	p	eq	fx	lr	sr	poil	Critical value	unc	y	p	eq	fx	lr	sr	poil
USA	21,59617	21,97817	26,51161	18,32737		11,45077	9,178147	23,7147	USA	24,42890451	25,02005	24,84758	24,95402		24,56698	24,63423	24,18311
EMU	25,73786	37,28175	25,14621	24,18764	25,88581	11,65663	11,86452		EMU	29,95815353	29,90928	31,44583	30,26888	31,27819	30,35071	31,33653	
WEU		12,2547	5,142426	7,308291	17,45935	10,58744	7,362623		WEU		13,50221	13,60028	14,48083	15,17003	13,9584	13,17839	
CEU		18,27063	23,62491	20,50105	21,92128	9,288186	10,12436		CEU		25,44881	25,73344	26,4151	28,43226	26,18307	26,44151	
SEA		29,78844	26,91809	23,04261	26,57356	11,28404	13,3567		SEA		27,44464	27,50914	27,37562	26,22645	28,86679	28,19372	
CLA		13,11778	16,32997	26,27399	16,99057	7,805252	9,794434		CLA		17,99708	18,39347	18,77296	18,86666	19,36148	18,62554	
CAN		17,16496	15,37004	18,81659	15,47722	10,27562	8,109572		CAN		18,46102	18,42672	19,82821	18,63127	19,5776	20,43498	
INDI		25,60475	25,36961	26,03119	28,32408	10,69444	9,932556		INDI		26,72021	26,07197	27,56447	25,14279	25,38179	26,2715	
CHIN		35,7864	31,25466	23,11561	26,27641	12,61749	7,483817		CHIN		33,34063	33,52167	35,55229	34,60004	34,73999	33,88885	
JAP		4,77975	3,841333	8,19761	17,08932	8,084482	5,359108		JAP		11,47733	12,28192	13,99446	13,41686	12,90504	12,33869	
RUS		28,52669	32,40011	25,68965	31,9727	9,916073	12,30427		RUS		33,21222	35,63875	34,22375	34,30008	34,39895	34,83779	

Sequential Wald statistics in exponential average form (Andrews-Ploberger, 1994) – APW

APW	unc	y	p	eq	fx	lr	sr	poil	Critical value	unc	y	p	eq	fx	lr	sr	poil
USA	11,24912	11,51996	25,06616	14,02523		7,821086	8,87009	18,03208	USA	16,65556416	17,10932	15,77274	16,50095		16,47398	17,44007	16,44821
EMU	8,838131	27,91613	13,24362	28,02969	23,57616	63,2306	70,8648		EMU	20,62591562	19,79188	19,77317	20,43084	20,9454	20,57376	21,75988	
WEU		12,29299	4,254703	4,813386	20,59641	26,9847	66,05387		WEU		8,76181	8,890614	9,594916	9,597806	10,47447	8,439848	
CEU		13,97142	19,32906	19,74226	14,27529	71,04245	83,60434		CEU		17,19441	17,03516	16,56834	18,74073	17,47898	16,64412	
SEA		27,86186	11,54657	43,76888	40,16393	82,19496	50,49277		SEA		19,12069	16,20679	18,4711	18,87428	18,52702	18,38187	
CLA		11,10977	10,91533	15,64853	16,91751	94,75612	51,09715		CLA		12,4838	12,17384	11,66377	13,44575	12,48796	11,61118	
CAN		17,43051	11,91711	15,66788	15,55971	91,36552	59,02089		CAN		11,91089	10,91751	12,54799	12,40527	11,89925	13,1057	
INDI		21,27278	27,33181	14,60856	15,13882	79,58559	41,3519		INDI		17,89358	16,76655	18,89238	17,38747	16,90213	16,80932	
CHIN		72,92264	41,14968	29,81643	16,0441	22,93631	18,92821		CHIN		21,54066	21,52317	23,20881	22,90195	22,63965	21,37337	
JAP		2,524231	2,367991	5,365075	16,49926	54,86597	21,85686		JAP		7,889582	8,320966	9,170962	9,125844	8,803363	8,089541	
RUS		25,48107	27,91648	37,94368	58,26872	159,4718	70,80187		RUS		20,89741	24,47544	22,11504	22,62216	21,15428	21,34286	

Robust APW

Robust APW	unc	y	p	eq	fx	lr	sr	poil	Critical value	unc	y	p	eq	fx	lr	sr	poil
USA	13,54529	11,88372	14,61956	10,077		5,794389	4,676385	12,35587	USA	13,52574909	13,77715	13,74501	14,4762		14,23253	14,33955	13,86429
EMU	14,10425	20,99861	13,26689	13,10878	14,71209	5,870421	5,963994		EMU	16,86407555	16,43433	17,83061	16,9897	17,25363	17,0603	18,37003	
WEU		6,729135	3,753712	4,34024	10,66796	5,499901	3,924565		WEU		7,634766	8,018388	8,152529	8,723588	8,345134	7,618324	
CEU		9,757841	15,41346	10,92374	11,75488	4,836021	5,190777		CEU		14,70906	14,50743	14,93252	16,60681	15,22652	14,94867	
SEA		16,24951	15,28248	14,38847	15,47644	5,843759	6,901901		SEA		15,8701	15,57594	15,37994	14,96201	15,96612	15,87498	
CLA		7,018791	10,112	14,59996	9,16365	4,131001	4,977071		CLA		10,50355	10,62385	10,74058	10,76256	10,96855	10,59416	
CAN		9,716817	8,580136	10,76193	8,452234	5,230998	4,336307		CAN		10,77955	10,39395	11,34212	10,60667	11,35407	11,79601	
INDI		14,60573	14,02777	14,4748	15,40497	5,474496	5,053613		INDI		15,14143	14,48822	15,28181	14,49223	14,12596	14,95854	
CHIN		23,18906	19,51951	12,71537	15,97038	6,65737	3,981471		CHIN		18,74404	19,29974	20,32066	19,37182	19,52924	18,7789	
JAP		2,740707	2,255609	4,480747	10,5869	4,335552	2,709977		JAP		7,073322	7,532246	8,19544	8,088522	7,652457	7,441844	
RUS		15,24076	17,95434	13,61295	17,88319	24,75086	6,299115		RUS		18,51284	19,65028	19,55811	20,27762	19,01142	19,47249	

D.8 Descriptive statistics of VECM residuals

Here it is shown descriptive statistics of VECM residuals u_{it} given in (2) for all models.

USA	Mean	Median	Maximum	Minimum	Std. dev.
unc	1,79E-16	-0,01741	0,743353529	-0,51651575	0,16105
y	2,62E-17	0,000693	0,032696297	-0,036027202	0,006954
p	-1,3E-18	5,65E-05	0,007008539	-0,007891321	0,002287
eq	-3,5E-17	0,000192	0,074538393	-0,096256466	0,030204
lr	3,7E-19	1,2E-05	0,000457567	-0,000736443	0,000121
sr	1,03E-18	1,78E-05	0,001536882	-0,00222972	0,000319
poil	1,56E-16	0,000106	0,169954139	-0,19786524	0,066664
EMU	**Mean**	**Median**	**Maximum**	**Minimum**	**Std. dev.**
unc	-4,6E-15	0,002439	0,574153828	-0,348213194	0,12693
y	4,22E-16	-0,00052	0,036753509	-0,035838126	0,013779
p	-2,8E-17	3,96E-05	0,002285609	-0,002491499	0,00083
eq	-7E-16	0,000356	0,064820764	-0,077365502	0,020892
fx	3,55E-16	0,000477	0,025843258	-0,02402371	0,008825
lr	-3,1E-18	-1,8E-06	0,000347939	-0,00046266	7,58E-05
sr	4,75E-20	1,21E-06	0,000140984	-0,00017037	3,06E-05
WEU	**Mean**	**Median**	**Maximum**	**Minimum**	**Std. dev.**
y	3,97E-16	8,24E-05	0,06303741	-0,069145214	0,017732
p	-1,1E-17	-9,2E-05	0,004034335	-0,003219071	0,001084
eq	3,35E-17	-0,00046	0,040083418	-0,033321405	0,011668
fx	2,26E-17	-0,00092	0,058210898	-0,05264336	0,018105
lr	-7,1E-20	-1,8E-06	0,000541533	-0,000628878	8,93E-05
sr	-4,2E-18	-1,1E-05	0,00065467	-0,001019663	0,000136
CEU	**Mean**	**Median**	**Maximum**	**Minimum**	**Std. dev.**
y	1,39E-17	0,000664	0,039727259	-0,044454665	0,013583
p	-2,6E-17	-1,3E-05	0,018491203	-0,006662942	0,003099
eq	6,73E-17	-0,00222	0,10263678	-0,130197479	0,034014
fx	5,95E-17	0,000153	0,060765837	-0,054861495	0,020053
lr	-1,8E-19	7,32E-06	0,001283616	-0,002477404	0,000255
sr	-3E-19	8,5E-05	0,003552404	-0,00542472	0,0008
SEA	**Mean**	**Median**	**Maximum**	**Minimum**	**Std. dev.**
y	-7E-17	0,000613	0,048870492	-0,075234891	0,017677
p	4,74E-18	-0,00012	0,014610808	-0,00619346	0,001884
eq	-1,2E-16	-0,00074	0,157910803	-0,081907881	0,028101
fx	-1,3E-17	-0,00039	0,044090057	-0,04252435	0,011442
lr	-8,7E-20	9,3E-06	0,000509311	-0,00060548	8,56E-05
sr	5,08E-19	1,84E-05	0,001073197	-0,001384383	0,000205
CLA	**Mean**	**Median**	**Maximum**	**Minimum**	**Std. dev.**
y	1,54E-16	0,001304	0,058882955	-0,095840887	0,015018
p	3,79E-17	-2,8E-05	0,007190534	-0,003441039	0,001363
eq	-2,9E-17	-7,4E-05	0,080517292	-0,066389869	0,025662
fx	1,86E-16	-0,00128	0,082132802	-0,047201598	0,01861
lr	1,37E-19	5,63E-05	0,001689659	-0,004452451	0,000445
sr	-2,1E-18	5,88E-05	0,00202197	-0,004378478	0,000496

CAN	Mean	Median	Maximum	Minimum	Std. dev.
y	-8,5E-18	-0,00062	0,031640556	-0,02599253	0,008995
p	-1,6E-17	-2,3E-05	0,006102544	-0,00882422	0,001951
eq	-3,2E-17	-2,5E-05	0,095470409	-0,06090578	0,019478
fx	-1,5E-17	-0,00029	0,045682479	-0,05008637	0,014519
lr	-4,4E-20	3,01E-06	0,000348998	-0,00027955	5,05E-05
sr	-1E-19	2,14E-06	0,000585326	-0,00089007	0,000118
INDI	Mean	Median	Maximum	Minimum	Std. dev.
y	1,09E-17	-0,00074	0,050566044	-0,043758	0,014309
p	1,42E-17	-0,00024	0,016025317	-0,01512975	0,00483
eq	4,87E-18	0,000333	0,095658147	-0,07720353	0,03148
fx	-4,8E-18	8,44E-05	0,048250427	-0,03313962	0,013257
lr	-6,1E-20	-1,4E-05	0,000829482	-0,00088766	0,000139
sr	-1,3E-19	-3,1E-05	0,001815393	-0,00090632	0,00025
CHIN	Mean	Median	Maximum	Minimum	Std. dev.
y	-2,8E-17	0,001136	0,079400295	-0,08686215	0,021637
p	-3,5E-17	-3,4E-05	0,0079599	-0,01434949	0,002982
eq	4,23E-17	0,00174	0,164864834	-0,1196653	0,044346
fx	6,35E-18	1,01E-05	0,006405192	-0,00982456	0,002167
lr	4,08E-19	7,82E-08	0,000682895	-0,00045184	0,000102
sr	4,9E-20	-4,7E-06	0,001157112	-0,00109153	0,000149
JAP	Mean	Median	Maximum	Minimum	Std. dev.
y	-8,1E-17	0,002719	0,040937352	-0,13381951	0,022176
p	7,39E-18	-9,2E-07	0,00487279	-0,00517425	0,001606
eq	-3,2E-17	-0,00079	0,094569569	-0,11610165	0,034755
fx	1,96E-20	-0,00015	0,052826752	-0,0625035	0,021364
lr	8,64E-21	-1,9E-06	0,000322317	-0,00014232	4,4E-05
sr	-7E-20	-1,9E-06	0,000242211	-0,00015658	2,65E-05
RUS	Mean	Median	Maximum	Minimum	Std. dev.
y	-2,1E-17	-0,00036	0,109909939	-0,05350285	0,016782
p	-3,5E-18	6,88E-05	0,01028401	-0,00881643	0,002843
eq	-4,6E-17	-0,00161	0,246265759	-0,20986418	0,063399
fx	-3,3E-17	-0,00056	0,072757576	-0,05472323	0,015742
lr	-5,5E-18	0,000157	0,004834855	-0,01270779	0,00158
sr	-5,1E-20	1,04E-05	0,002461739	-0,00315255	0,000545