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Determinants, Dynamics and Implications of International Portfolio Capital Flows

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Declaration of Authorship

I, Zeyyad Mandalinci, declare that this thesis titled, 'Determinants, Dynamics and Implications of International Portfolio Capital Flows' and the work presented in it are my own. I confirm that:

- This work was done wholly while in candidature for a research degree at this University.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.

Signed: Zeyyad MANDALINCI

Date: 14 January 2014

UNIVERSITY OF WARWICK

Abstract

Faculty of Social Sciences
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Determinants, Dynamics and Implications of International Portfolio Capital Flows

by Zeyyad MANDALINCI

This thesis examines the determinants, the dynamics and the implications of international portfolio capital flows (PCF) to Emerging Markets (EM). It consists of 3 separate chapters focussing on different aspects of international PCFs.

The literature documents that international portfolio equity investment depends on factors additional to returns and variance/covariances. First chapter presents a portfolio selection problem that takes into account the presence of additional factors and can match the actual United States (US) investment data.

A recent series of IMF Staff Discussion Notes warns that capital controls may deflect PCFs across countries. The second chapter investigates whether these effects exist in a comprehensive global econometric model. Overall, results indicate that there are no significant deflection effects. Furthermore, it studies the domestic effects and the drivers of PCFs.

The third chapter analyses the time-varying global drivers of PCFs to EMs in recent decades. Moreover, it involves identifying surge and stop episodes and comparing their time-varying characteristics. Finally, it investigates the effects of the US Quantitative Easing (QE) program on PCFs to EMs in 2009 by conducting a counterfactual exercise. Results indicate that there have been changes in the importance of different factors over time and QE had a significant positive effect on PCFs during 2009.

Abbreviations

ADF	**A**ugmented **D**ickey **F**uller
AREAER	**A**nnual **R**eports on **E**xchange **A**rrangements and **E**xchange **R**estrictions
CBOE	**C**hicago **B**oard **O**ptions **E**xchange
CC	**C**apital **C**ontrol
CF	**C**apital **F**low
CI	**C**o-**I**ntegration
CPIS	**C**oordinated **P**ortfolio **I**nvestment **S**urveys
EM	**E**merging **M**arket
ESDS	**E**conomic and **S**ocial **D**ata **S**ervice
GDP	**G**ross **D**omestic **P**roduct
GFEVD	**G**eneralized **F**orecast **E**rror **V**ariance **D**ecomposition
GIRF	**G**eneralized **I**mpulse **R**esponse **F**unction
GVAR	**G**lobal **V**ector **A**utoregressive
IFC	**I**nternational **F**inance **C**orporation
IMF	**I**nternational **M**onetary **F**und
MCMC	**M**arkov **C**hain **M**onte **C**arlo
NYSE	**N**ew **Y**ork **S**tock **E**xchange
PCF	**P**ortfolio **C**apital **F**low
PCA	**P**rinciple **C**omponent **A**nalysis
PPP	**P**urchasing **P**ower **P**arity
QE	**Q**uantitative **E**asing
S&P	**S**tandard & **P**oor's
SEC	**S**ecurities and **E**xchange **C**ommission
SVAR	**S**tructural **V**ector **A**utoregressive
TIC	**T**reasury **I**nternational **C**apital System
TVP	**T**ime **V**arying **P**arameter
UK	**U**nited **K**ingdom
US	**U**nited **S**tates
USD	**U**nited **S**tates **D**ollar
VECM	**V**ector **E**rror **C**orrection **M**odel

Dedicated to my family...

Chapter 1

Introduction

With the acceleration of global financial integration of EMs, international CFs have become a key source of finance for these countries. Since EM countries are on the path of convergence to developed countries and require capital for productive investment opportunities (Lucas [1990]), CFs can be beneficial for EMs. On the other hand, CFs have played major roles during the past major crises EMs had witnessed including the East Asian and Latin American Crisis; underlining the possible dangers CFs may constitute for EMs. That makes the management of international CFs a key issue for these countries, which naturally involves understanding the nature of CFs. However, the literature documents that not all types of CFs are equal. In other words, different kinds of flows seem to have different dynamics over time. For instance, Sarno & Taylor [1999] study different category of flows and find important differences in their characteristics. Furthermore, Forbes & Warnock [2012b] document differences in the characteristics among the subcategories of PCFs; equity and debt. In the light of these considerations, the objective of this thesis is to examine the determinants, dynamics and implications of PCFs, which is one of the most volatile categories of CFs. The first chapter suggests a portfolio selection problem, through which it is possible to match the observed patterns of US foreign portfolio equity investment, unlike the classical portfolio selection theories. In the second chapter, I present a global econometric model for PCFs and document evidence on the multilateral implications of capital controls. Finally, in the last chapter, I study the time-varying drivers of PCFs and examine the role of QE in driving PCFs to EMs.

In Chapter 2, I examine the determinants of US foreign portfolio equity investment. Portfolio selection theories would suggest the importance of expected returns, variance and covariances as the primary drivers of international portfolio investment (Markowitz

[1952, 1959]). However, the literature identifies various additional factors that are important (Ahearne et al. [2004], Fernandez-Arias & Montiel [1996], Taylor & Sarno [1997]). Here, I suggest a 2-Step Portfolio Selection procedure which allows for the presence of additional factors. It reflects the trade-offs an investor faces between mean variance efficiency and exposure to various risks or portfolio characteristics. Predictions based on the mentioned 2-Step procedure are similar to the observed US foreign holdings. With a sample of 36 countries and 2 additional factors representing sovereign risk and cross listings, the correlation of predicted and actual weights exceeds 60%.

In the aftermath of the global financial crisis, EM countries faced a notable surge in PCFs. This has led many of these countries to resort to capital controls to prevent macroeconomic and/or financial stability risks accompanied with excessive inflows. However, as highlighted in a recent series of IMF Staff Discussion Notes (Ostry et al. [2012]), imposition of controls may have negative externalities on other countries by deflecting flows. The third chapter attempts to assess whether these deflection effects exist for PCFs in a comprehensive global econometric model. The proposed model covers 42 countries with almost 90% of world GDP. It also involves both stationary and non-stationary endogenous and exogenous variables. Additionally, it investigates the domestic implications and the underlying fundamentals of PCFs. Results suggest that inflow surges are followed by overheating pressures in recipient countries. Regarding the drivers, there is significant variation across countries in the importance of domestic and external factors for flows. I find that, spatial dependencies are more important for flows to countries with smaller economies. Finally, deflection effects do not exist for most EMs, but there exists some evidence for intra-regional effects in Latin America.

In the final chapter, I analyse the time-varying global drivers of PCFs to EMs in recent decades using TVP regression and TVP-SVAR models, estimated with MCMC methods. Results indicate notable time-variation in the importance of different fundamentals. Conditions in the developed-world seem to have played a major role in driving flows; however, the importance of EM specific fundamentals has increased remarkably over time. About the possible implications of future monetary policy reversals in the US, portfolio flows to EMs have been primarily driven by US short interest rates and global risk appetite following the global financial crisis. Moreover, I identify surge and stop episodes in PCFs and compare their characteristics. Results indicate heterogeneity across episodes with time-varying sensitivity of flows to different fundamentals, which suggests that the findings in the literature that pools together episodes across decades are questionable. Finally, I examine the role of QE in driving PCFs by conducting a counterfactual exercise. Results suggest that QE had contributed significantly to the surge in PCFs to EMs in 2009.

Chapter 2

The Allocation of US Foreign Portfolio Equity Investment

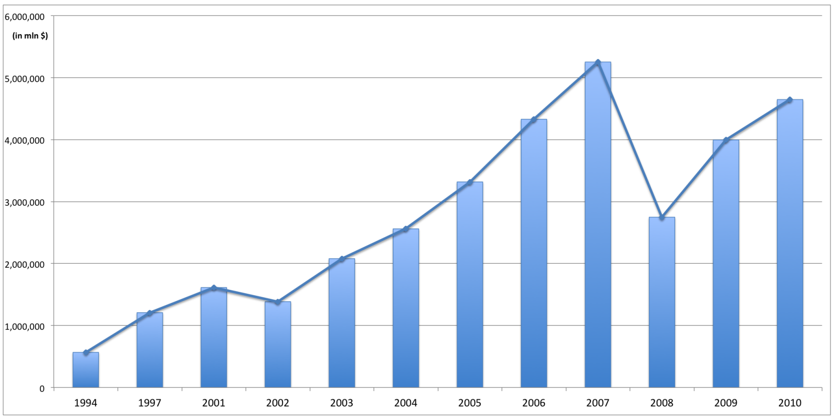
2.1 Introduction

Unlike the suggestions of the traditional portfolio selection models (Markowitz [1952, 1959]), the patterns of international foreign portfolio investment are considered and shown in the literature to be dependent on various factors other than expected returns, variance and covariances. This chapter presents a simple 2 step portfolio selection problem that incorporates both of these views and can reasonably match the observed patterns in US foreign portfolio equity investment.

Figure 2.1 depicts the evolution of total foreign equity holdings of United States starting from 1994 to 2010 according to the IMF CPIS and US TIC Data.

The international economics literature has tried to examine many aspects of capital flows. One of the most important contributions has been made by Lucas [1990], who argued that the observed investment patterns are against the argument that capital should flow towards markets where its productivity is higher. There have been many attempts to explain this finding, for instance Alfaro et al. [2008] examine the role of institutional quality on Lucas Paradox. One another interesting finding, documented by French & Poterba [1991], is that investors seem to overweight their home equity assets heavily compared to foreign assets, an inconsistent evidence with the theoretical predictions; named to be the Home Bias Puzzle. Many researchers discussed the puzzle; out of many, Portes & Rey [2005] find that information costs and transmission can shed some light on the puzzle, whereas Tesar & Werner [1994] comment that the observed

Figure 2.1: US Foreign Portfolio Equity Investment



turn-over rates which are higher for investment abroad compared to home can be taken as counter-evidence for the higher variable transaction costs in foreign markets causing the home bias. Moreover, Fidora et al. [2006] lay evidence on the role of real exchange rate volatility in explaining the puzzle.

Concerning the dynamics, Taylor & Sarno [1997], Chuhan et al. [1998], Sarno & Taylor [1999], Mody et al. [2001] have documented that equity flows are sensitive to both global and local developments and have significant temporary components. Some argue that it may be this reversibility and the past experience that causes many countries to accumulate high reserves, just to be ready when they need to take action in the face of likely sudden reversals.[1] Not only in terms of precautionary behaviour they oblige on the recipient country, but also the macroeconomic distortions they create are important issues of concern. Apart from benefits discussed, Calvo et al. [1996] comment on the possible macroeconomic distortions accompanied with international capital flows and point out that international capital flows, in fact, should be very well understood and studied by the authorities of recipient countries.

According to the mean-variance model, the risk of investment is characterized by its standard deviation and the return by its expected return. However, the literature has documented many factors that influence the investment decisions of international investors. To motivate the theoretical section, following the literature I illustrate the importance of some of these additional factors via simple correlation and cross-sectional regression analysis. Overall, risk-adjusted returns have almost no relationship with the international allocation of US portfolio equity investment. On the other hand, sovereign risk and cross listings variables are found to be significantly correlated with US investment.

[1] See Bernanke [2005].

The recent literature that identifies extreme capital movements document evidence on spatial dependencies across countries in attracting capital flows.[2] Not only the literature on extreme capital movements, but also various other papers and research reports published extensively do consider various groups of countries which are somehow spatially related, as if they altogether constitute destinations for foreign portfolio investment; see for instance, Bank for International Settlements [2009] or The Institute of International Finance [2011]. In different cases, these groups of countries are countries in the same region (e.g. Asia, Latin America) or countries in the same income group. Formally, spatial dependence in foreign portfolio investment across countries may arise for various reasons. For instance, investor perceptions for markets, which offer similar rates of returns with similar financial depth, risks and other characteristics, may cause investment patterns on these countries to be similar. Also, investment in a group of countries could be dependent on each other because the return and risk on the assets of these countries may be correlated with each other. It is well known from the literature on international linkages that countries related via trade or financial channels do feature substantial economic dependencies on each other; see, for instance, Dées et al. [2007b] or Chudik & Fratzscher [2011]. Lastly, as in the literature on international financial crises and contagion, herding, investor irrationality or other liquidity and incentive problems can as well be other reasons.[3] Given such concerns, I check for the presence of dependencies across countries in the same regions and income groups by including dummy variables in the cross-sectional regressions. However, they seem to be absent in the results obtained in here.

As a possible explanation for how international investors form their portfolios, I lay out a portfolio selection problem based on the possible trade-offs faced by an investor while choosing between optimal volatility-adjusted-returns (tangency portfolio) and portfolio exposure to various risks and/or certain characteristics of the chosen portfolio. This 2-Step Portfolio Choice Problem involves obtaining the tangency portfolio of Markowitz [1952, 1959] and modifying the implied weights with respect to the desired portfolio characteristics. Later, I compare the actual data with mean variance predictions and the predictions resulting from the 2-Step Procedure presented here. Results indicate that the investment pattern predicted by the 2-Step Procedure is able to match the observed investment pattern fairly well, with above 60% correlation across 36 countries.

The organisation of this part is as follows; Section 2.2 outlines the data used and the sources; Section 2.3 consists of the data analysis; Section 2.4 presents the theoretical illustration based on a 2-Step Portfolio Selection Problem; Section 2.5 concludes.

[2] See for instance Forbes & Warnock [2012a], Ghosh et al. [2012]

[3] See, for instance, Claessens et al. [2000]

2.2 Data

The most important dataset for the analysis presented in this chapter naturally is US foreign portfolio equity investment data which is obtained from the IMF CPIS and US TIC Cross-Border Portfolio Holdings. IMF CPIS and US TIC are the most widely used datasources in the literature as they are the most comprehensive and reliable datasources available for a large number of countries. [4] In each case, portfolio weight of a country (w) is, US holdings of respective country divided by the total US foreign holdings. In constrast to the following chapters that focus on the emerging market, here the sample countries involve developed countries as well. As the objective of this chapter is to examine US investors' allocation from a portfolio perpective, I include both developed and developing countries.

Throughout the investigation, by taking guidance from the theory and the literature, a total of 3 explanatory variables have been chosen, representing pull factors, information transmission/costs as well as financial liberalization. Namely, the variables are credit ratings (cr, sovereign risk), (risk adjusted) stock market returns (r) and cross listings (cl).

Credit ratings variable is based on the Institutional Investors semi-annual credit ratings.[5] It is based on surveys conducted on experts and economist working in the finance industry. It represents respondents' assessments of probability of default for a given country from 0 to 100 (in reverse order). The data shows significant variation across countries considered in here. For instance as of 2009, Pakistan has the highest sovereign risk with 23.4 and Switzerland has the lowest with 92.8. [6]

Stock market index/return data is from Morgan Stanley MSCI indexes.[7] Cross Listings variable is from the yearly market summary reports of US SEC[8] and Datastream. It represents the fraction of the stock market capitalization of a given country, cross-listed on NYSE, NASDAQ or AMEX. Stock market capitalization data is from World Bank and World Federation of Exchanges.[9] For the spatial dummies based on income

[4] http://www.imf.org/external/np/sta/pi/datarsl.htm,
http://www.treasury.gov/resource-center/data-chart-center/tic/Pages/fpis.aspx

[5] http://www.institutionalinvestor.com/

[6] Apart from the way the variable is used in here, a futher improvement can also be made by dividing the sample countries with respect to their credit ratings from major credit rating agencies and repeat the empirical exercises presented in the next section with subsamples. However, given that the number of countries is limited, it has not been considered here.

[7] www.msci.com

[8] http://www.sec.gov/

[9] http://www.worldbank.org/, http://www.world-exchanges.org/

groups, World Bank Income Group Classification tables are used.[10]

Some of the variables are normalized or calculated differently during the analysis, which is described and/or mentioned in each specific case.

2.3 Data Analysis

This section presents some of the features of the dataset about the relationship between US foreign portfolio investment and various fundamentals, and hence motivates the subsequent section.

Ahearne et al. [2004] and Edison & Warnock [2008] document that cross listings are relevant drivers for US investment. They argue, cross listed firms which report to US SEC provide quality and similarly documented information about the company and increase visibility of their firms by listing in US stock exchanges. So one may expect US investors to favour countries with which they are more familiar and which have in total more firms with high quality and similarly disclosed information. Also, following Ahearne et al. [2004], I include a risk adjusted return variable, which is calculated as domestic returns divided by standard deviation of returns. Final variable, credit ratings, has been found to be an important country specific factor in the literature, for instance by Taylor & Sarno [1997].

For the analysis to be presented, weights variable (w) is calculated as the ratio of US holdings of a given country's securities to total US foreign holdings, as of 2010. Risk-adjusted returns variable (r) represents the ratio of average USD monthly returns (01/1995-12/2009) on the local stock markets to the standard deviation of returns.[11] Credit Ratings variable (cr) is as of end-2009 and normalized to be between 0 and 1. Cross Listings (cl) variable is in percentage points.

Table 2.1 presents the correlation of the US foreign portfolio weights with above described fundamentals for 36 sample countries.[12] One can observe that the correlation of weights with the risk adjusted returns variable is very low and insignificant. On the other hand, US investment seems to be significantly and highly correlated with sovereign risk and cross listings.

[10] http://data.worldbank.org/about/country-classifications

[11] Given the fact that Emerging Market returns often go through waves of high and low returns in different periods, a long sample size has been chosen to calculate local returns. For instance, a shorter sample period might have biased the returns of some of the BRIC markets with rise of BRICs in 2000s.

[12] The sample of countries are chosen on the basis of data availablity.

Table 2.1: Correlations of Variables

	w	r	cr
w			
r	0.07		
cr	0.47***	0.24	
cl	0.39**	0.24	0.23

*,**,*** indicate significance at respectively 10%, 5% and 1% levels.

Sample: Argentina, Australia, Austria, Belgium, Brazil, Chile, Colombia, Czech Republic, Egypt, France Germany, Hungary, India, Indonesia, Italy, Japan, Korea, Malaysia, Mexico, Morocco, Netherlands, Norway, Pakistan, Peru, Philippines, Poland, Russia, Singapore, South Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Kingdom.

In addition to the correlation analysis, simple cross-sectional regressions have been estimated with the same variables.[13] More specifically, dependent variable has been set to US portfolio weights across different countries and the explanatory variables have been set to credit ratings and cross listings across different countries, calculated as described above. Table 2.2 summarizes the results from the regression analysis. All specifications include the weights as the dependent variable and different sets of variables plus a constant as explanatory variables. Similar to the findings from the correlation analysis, the risk adjusted returns variable is highly insignificant and cannot explain any variation in the US investment across countries. On the other hand, both credit ratings and cross listings variables seem to be significant with expected signs. In the final specification, these two variables seem to be able to explain almost a third of the cross-country variation in US foreign portfolio equity investment. Furthermore, dummies that capture dependencies among countries in the same regions and income groups have been included in the regression. However, they appear to be highly insignificant, indicating the absence of spatial dependencies. As diagnostics, pair-wise correlations presented in Table 2.1 suggest the absence of multi-collinearity among the explanatory variables. On the other hand, Jarque Bera residual normality test suggest that the residuals are not normally distributed. In fact, residuals seem to exhibit skewness and excess kurtosis, which is mainly due to the outliers observed for Japan, Switzerland and United Kingdom. Durbin-Watson statistic is not far from 2 in the final specification, suggesting the absence of residual dependence across different cross-sections.

To shed light on the above documented features of the data, next section presents a portfolio selection problem in which investors form their portfolios in the presence of other factors additional to returns, variance and covariances.

[13] Given the availability of data, panel data models can also be estimated. However, panel models may involve non-linear cross sectional dependence over time as investors may withdraw their investments from one country and invest in others in a non-linear fashion. As the purpose of this empirical exercise is to motivate the importance of additional factors, a simple cross-sectional analysis is preferred here.

Table 2.2: Cross-Sectional Regressions

	Specification			
	(1)	(2)	(3)	(4)
r	0.038			-0.05346
cr		0.00076***		0.00069***
cl			0.07393**	0.06003**
No of Obs.	36	36	36	36
R^2	0.01	0.22	0.15	0.31
Adj. R^2	-0.02	0.20	0.12	0.25
Prob(F-Stat)	0.669	0.003	0.020	0.007
Jarque-Bera (pval)	0	0	0	0
Durbin-Watson (stat)	1.56	1.66	1.58	1.70

*,**,*** indicate significance at respectively 10%, 5% and 1% levels. Dependent Variable: w.

2.4 A 2-Step Portfolio Selection Problem

The foundation of modern portfolio theory, Mean-Variance model of Markowitz [1952, 1959] allows one to calculate the portfolio weights that yield the minimum portfolio risk (volatility) for given portfolio expected returns. Among the set of possible portfolios, the set that has the minimum standard deviation for given expected returns is called the Portfolio Frontier. From the points on the portfolio frontier, depending on the risk free rate, every investor will choose the same tangency portfolio which offers, combined with a given risk free rate, highest expected return per unit of risk. Calculation of the Portfolio frontier, involves;

$$w^\star = \underset{w}{\operatorname{argmin}}\{P\}$$

$$P = \frac{1}{2}(w'Vw) + \lambda(\bar{r_p} - w'r) + \mu(1 - w'I)$$

where, $w^\star$ is the (Nx1) vector of portfolio weights on the portfolio frontier; V is the (NxN) variance covariance matrix of returns, r is the (Nx1) vector of expected returns; I is a vector of ones; $\bar{r_p}$ is a scalar.[14]

A point to note about the simple portfolio selection problem presented above could be that it does not involve taking into account possible skewness and/or co-skewness of asset returns. In fact, Harvey & Siddique [2000] show that conditional skewness can

[14] It is assumed that US investors do not hedge their foreign currency risk and have adaptive expectations. Hau & Rey [2006] discuss that only a small portion of foreign equity investment is indeed hedged. However, the authors present a theoretical model without complete hedging and show that foreign equity investment can generate movements in both foreign equity returns and the exchange rate. However, for the sake of simplicity, in here it is assumed that US investors do not take into account these channels. In fact, the theoretical model in Hau & Rey [2006] features 2 countries, whereas in reality demand from the rest of the world may result in these channels to be at least partially ineffective from the US investors' perspective ex-ante.

explain a significant portion of the cross-sectional variation in excess returns. Bekaert & Harvey [2013] argue that returns in the majority of emerging market countries involve skewness. Also, Barberis & Huang [2008] show that in a non-expected utility framework featuring cumulative prospect theory, skewness in assets can itself be priced in assets. Hence, as a venue for further research the 2-Step procedure presented in here can be augmented to incorporate the skewness in returns.

Portfolio Frontier, as outlined above, yields the optimal portfolio weights, in terms of minimum portfolio variance, for given level of expected portfolio returns. The relevant question in the topic of our interest is what if there are other imperfectly priced factors that are considered by investors while they do make investment decisions? As discussed in the literature, there seems to be many other empirically identified factors other than standard deviation and covariances. For an investor, if we assume that, apart from expected returns, variances and covariances, all assets bear identical characteristics; then we would expect the US investor to choose the tangency portfolio from the efficient frontier which offers the highest return per unit of standard deviation combined with a given risk free rate. On the other hand, one can imagine an investor facing a trade-off between mean variance efficiency (tangency portfolio), which yields highest expected return for given standard deviation, and portfolio exposure to various other factors or certain portfolio characteristics, which are either imperfectly priced or not priced at all. Following 2-Step Portfolio Choice Setting attempts to illustrate as such trade off and its implications.

The portfolio choice problem of an investor with K additional factors incorporates a trade-off between choosing tangency portfolio and portfolio exposure to K additional factors[15], which can be well characterized via following quadratic objective function to be minimized;

$$L = \left[\left(\sum_{i=1}^{N} (w_i - w_i^\star)^2 \right) + \left(\sum_{k=1}^{K} \left(\sum_{i=1}^{N} (w_i - w_i F_{ik})^2 \right) \kappa_k \right) \right] \quad s.t. \quad \sum_{i=1}^{N} w_i = 1$$

where $w_i^\star$ is the tangency portfolio weight for asset i of country i, satisfying for N total assets/countries, $\sum_{i=1}^{N} (w_i^\star) = 1$; F_{ik} is the additional factor k of country i normalized such

[15] Naturally, I assume that the factors are, at best, imperfectly priced. There may be various reasons for these factors to be imperfectly priced across different countries, including the presence of capital controls, different levels of informational frictions in different markets or market inefficiency. For instance, in the presence of capital controls, local investors may not be able to diversify sovereign risk well, which may cause the local assets to be imperfectly priced. Or, informational frictions literature argues that, prices of assets may deviate from the fundamental price of assets in the presence of informational frictions, leading to market inefficiencies, as discussed in Allen et al. [2006]. Market inefficiency may also be the result of other issues examined in the behavioral finance literature, see for instance Barberis & Thaler [2003].

that $0 \leq F_{ik} \leq 1$; κ is a weighting scalar;$(\sum\limits_{i=1}^{N}(w_i - w_i F_{ik}))$ is the portfolio exposure to factor k. Formally, the adjusted weights from the 2-Step Procedure are obtained from the constrained optimisation problem,

$$w_i^{adj} = \underset{w_i}{\operatorname{argmin}}\{L\}$$

$$L = \left[\left(\sum_{i=1}^{N}(w_i - w_i^{\star})^2\right) + \left(\sum_{k=1}^{K}\left(\sum_{i=1}^{N}(w_i - w_i F_{ik})^2\right)\kappa_k\right)\right] - \lambda\left(\sum_{i=1}^{N} w_i - 1\right)$$

One can observe that, if none of the factors of any asset is less than one, then the second term in the objective function would be equal to zero and the solution to above problem would simply yield the tangency portfolio of mean variance model.

First order conditions for the above minimization yield the following expression for each portfolio weight;

$$\begin{aligned} w_i^{adj} = &\left(\frac{w_i^{\star}}{1 + \sum\limits_{k=1}^{K}(\kappa_k - 2\kappa_k F_{ik} + \kappa_k F_i k^2)}\right) \qquad (2.1)\\ &+ \left(1 - \sum_{j=1}^{N}\left(\frac{w_j^{\star}}{1 + \sum\limits_{k=1}^{K}(\kappa_k - 2\kappa_k F_{jk} + \kappa_k F_{jk}^2)}\right)\right)\left(\frac{\left(\frac{1}{1+\sum\limits_{k=1}^{K}(\kappa_k - 2\kappa_k F_{ik} + \kappa_k F_{ik}^2)}\right)}{\sum\limits_{j=1}^{N}\left(\frac{1}{1+\sum\limits_{k=1}^{K}(\kappa_k - 2\kappa_k F_{jk} + \kappa_k F_{jk}^2)}\right)}\right) \end{aligned}$$

To simplify the expression, define:

$$\Theta_i = \left(\frac{1}{1 + \sum\limits_{k=1}^{K}(\kappa_k - 2\kappa_k F_{ik} + \kappa_k F_{ik}^2)}\right) \tag{2.2}$$

Rewriting (2.1) with (2.2) yields,

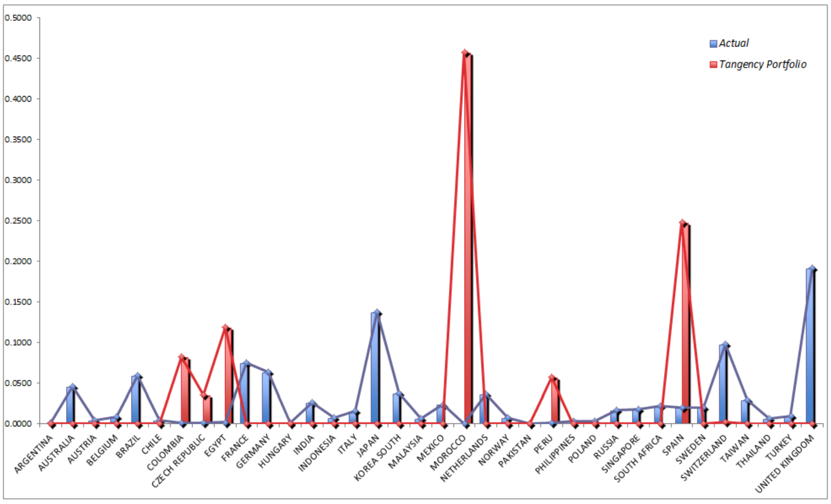
$$w_i^{adj} = (w_i^{\star}\Theta_i) + \left(1 - \sum_{j=1}^{N}(w_j^{\star}\Theta_j)\right)\left(\frac{\Theta_i}{\sum\limits_{j=1}^{N}\Theta_j}\right) \tag{2.3}$$

One may define Θ_i as the discount factor for asset i, which is a function of additional factors of country i and the weighting scalars $\{\kappa_k\}_{k=1}^{K}$.

There are several interesting conclusions that emerge from the results. The first term in (2.3) states, if, for instance, credit rating for country i is less than 1, then depending on the weighting scalar (also on the magnitude of the second term) adjusted portfolio weight will be smaller than the tangency portfolio weight.

Second term in (2.3) represents the fact that, if there are assets with sovereign risk in the portfolio (may be asset i or not), then weights of all assets will receive a positive feedback; overweighting. The magnitude of this 'positive feedback' depends on the ratio, $(\Theta_i/(\sum_{j=1}^{N}\Theta_j))$; which is larger for relatively less risky assets and smaller for relatively more risky assets. So the results show that, a trade-off between mean variance optimality and exposure to other risk factors or implied portfolio characteristics would force investors to heavily under-weight risky assets and over-weight rather safe assets. One more point to note about the results is, the magnitude of positive feedback received by each asset depends on how respective asset discount factor compares with all asset discount factors.

FIGURE 2.2: Actual vs Tangency Foreign Portfolio



The results from the 2-Step Procedure above would suggest, with additional factors, the portfolio weights are expected to be considerably different to mean-variance-weights. Figure 2.2 portrays the actual and tangency weights for 36 countries as end of 2010.[16] Countries include developed and emerging; European, Asian and Latin American Countries.[17] Note that the total US portfolio equity investment in 36 countries depicted here corresponds to more than 70% of all US foreign portfolio equity investment.[18] One can

[16] For the sources of the data used in calculations please refer to Section 2.2.

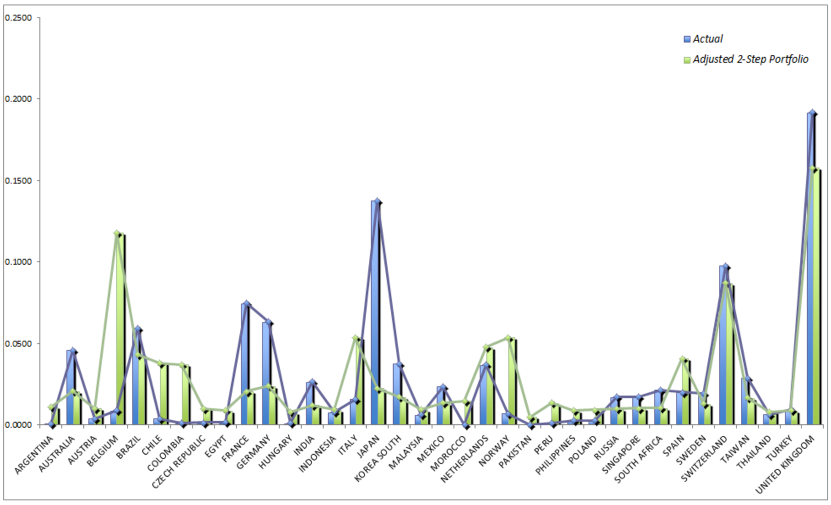
[17] Calculated with risk free rate as end-2010 T-Bill Rate, expected returns as 01/1995 - 12/2009 monthly average realized returns, variance-covariance matrix of monthly returns from 01/1995 - 12/2009.

[18] Sum of weight series is normalized to 1 for both calculation and illustration purposes.

clearly observe that, mean-variance predictions are far from reality.

Figure 2.3 depicts the actual US foreign portfolio equity investment weights and the adjusted weights resulting from the 2-Step Procedure presented above, using the credit ratings (CR) and cross listings (CL) for additional factors.[19] The parameters governing the importance of each factor (κ parameters with above notation) have been set such that the relative weights attributed to factors are as 20% mean variance optimality, 55% credit ratings, 25% cross listings.[20] In contrast to the mean variance predictions, when adjusted to incorporate sovereign risk and cross listings, with the methodology described above, results seem to fit the actual data substantially better.

Figure 2.3: Actual vs Adjusted Foreign Portfolio



One can clearly observe that the relative importance of countries with respect to each other in the predicted portfolio is notably similar to the actual data for many countries. However, for Belgium, France, Germany, Japan and Norway the actual weights are considerably different the predicted values. One may argue that these countries are all developed countries and they may share a common factor which might be imperfectly reflected by sovereign ratings or cross-listings. There are some noticeable results for UK and Switzerland. At first sight the actual weights of UK and Switzerland in US investors' portfolio seem difficult to explain, as it is the case for Brazil and Netherlands as well. On

[19]Cross Listings (CL) is ratio of the total market capitalization of stocks that are cross listed in NYSE or NASDAQ to the stock market capitalization of respective country; hence do not include OTC programmes. In every case follows, cross listings and credit ratings variables are 1 for the country with highest cross listings and credit ratings among the countries in each case and others are normalized with respect to this country.

[20]In other words κ parameters for credit ratings and cross listings factors are respectively 99 and 45. The values are chosen manually to improve the fit of the predicted weights. A more formal approach to consider as future research is to estimate these parameters to maximise the fit.

the other hand, above described methodology employed with only 2 additional factors is able to predict the actual investment patterns for these countries not perfectly, but remarkably well. In fact, the correlation between the actual and adjusted portfolio weights for 36 countries depicted in Figure 2.3 is above 60% and significant. Furthermore, even after excluding major outliers of Australia, Belgium, France, Germany, Japan, Norway, Switzerland and UK, the correlations of actual and predicted weights remain above 45% and significant.

Apart from the 2 factors considered here, there may be other factors that influence investors' decisions. For instance, it could be the intensity of capital controls (see Ahearne et al. [2004]), exchange rate regime and risk (see Fidora et al. [2006]), Monetary Policy Frameworks (see De Santis [2010]), Contagion and Spatial dependencies (see next Chapter) and global risk (see Forbes & Warnock [2012a]).

2.5 Conclusion

The main contribution of this chapter is to show that, observed foreign portfolio equity investment patterns of US investors can be well characterized with a 2-Step Portfolio Selection Problem, constructed on the basis of possible trade-off's faced by an investor who is to choose between mean-variance optimality and portfolio exposure to various different factors or changes in desired portfolio characteristics.

Findings suggest the importance of sovereign risk and cross listings in US markets in attracting US portfolio equity investment to respective countries as of 2010, which are in line with the previous findings in the literature, including Portes & Rey [2005] and Ahearne et al. [2004]. Also, there seems to be no spatial dependence among countries in the same income groups and/or in the same regions in attracting US investment.

It has been shown that the predictions of the mean variance model are inconsistent with the actual data on US foreign portfolio equity investment. On the other hand, with only 2 additional factors representing informational asymmetries and sovereign risk, the predictions of the 2-step procedure can match the actual holdings data fairly well.

As the first part of the Thesis, this chapter investigated the allocation of US international portfolio equity investment. The following chapters will focus more on the adjustment mechanism of international portfolio investment by studying the dynamics and the determinants of country specific capital flows data.

Chapter 3

Modelling Portfolio Capital Flows in a GVAR Framework: Multilateral Implications of Capital Controls

3.1 Introduction

Since the middle of 1980s, EMs have experienced a rapid increase in inward financial investment from the rest of the world. From one perspective, there are many gains from global financial integration; hence the rise in international CFs should be welcomed.[1] However, as it is mentioned in Chapter 1 the experiences of the last decades suggest, opening up domestic markets to free capital flows introduces various risks for the recipient countries. These concerns were highlighted again during and after the recent global financial crisis. Many countries faced a sudden collapse, followed by a surge in CFs. These events have brought about a renewed interest in the application of capital controls, and how to design optimal policy responses to changes in CFs.[2] A recent IMF Staff Discussion note has recognized the use of controls as appropriate under certain conditions. Ostry et al. [2012] argues that one of these conditions involves taking into account the possible externalities on other countries in the form of deflection of flows. However, empirically documenting and studying these effects are difficult. To do so, one must disentangle various domestic and international dependencies that drive flows.

[1] See Kose et al. [2009] for a discussion on the benefits of global financial integration.
[2] See Table A.11 for several key indicators of selected EMs before, during and after the crisis.

This requires a comprehensive global perspective. It is well known that omitting relevant information in empirical models can easily lead to incorrect conclusions.[3] Hence, my first objective is to construct a global econometric model that can capture these dependencies. Then, I attempt to document evidence on the deflection effects resulting from the imposition of capital controls.

As it has been depicted in the previous chapter, the patterns of international investment seem to have various drivers, both domestic and international, which makes capital flows a global phenomenon. This necessitates the use of methodologies that can account for domestic, foreign, observed/unobserved factors and spatial dependencies in both flows and their underlying fundamentals for the purpose of comprehensive modelling. The early literature on modelling PCFs focussed on the source and recipient country factors.[4] However, there may be other observed and/or unobserved factors that may result in spatial dependencies and/or contagion in PCFs to EMs. Several recent papers, including Forbes & Warnock [2012a] and Ghosh et al. [2012], document evidence of such dependencies. Apart from omitting relevant information, incorporating relevant channels of transmission of shocks across countries is crucial for understanding the international transmission of policy shocks. With these features, the advantage of my global model is its ability to model international linkages and transmission channels simultaneously in a flexible framework where all variables of all countries are potentially endogenous.[5]

A truly global model would call for the inclusion of both developed and developing countries. For that reason, I include 42 countries (25 emerging and 17 developed/other countries) in my GVAR model. However, there are technical difficulties associated with constructing such a model, since the capital flows data appears as stationary, whereas fundamentals are non-stationary. This leads me to adopt an empirical methodology by which stationary flow variables and non-stationary fundamentals are modelled in a global error-correction framework simultaneously. The ability of the model to test for and incorporate possible cointegration properties of underlying fundamentals is a valuable feature. The resulting GVAR Model has more than 200 endogenous variables and 46 cointegration relationships.

Optimal policy design against inflow surges involves disentangling the contribution of CFs in generating domestic risks and uncovering their underlying drivers. Consequently,

[3]For instance, the literature on the transmission of monetary policy has been haunted by the price puzzle for a long time. It has been argued recently that omitting relevant information from empirical models results in the puzzle. See Bernanke et al. [2005], Korobilis [2011].

[4]See for instance Calvo et al. [1993], Taylor & Sarno [1997], Edison & Warnock [2008].

[5]See Dées et al. [2007b] for a detailed discussion about the GVAR Model and alternatives.

in addition to the deflection effects, I present evidence on the domestic effects of inflow surges and the underlying drivers of PCFs via the constructed GVAR model.

Overall, even though results reveal modest evidence on the presence of intra-regional deflection effects, they seem to be absent for most country-pairs in the sample. Regarding the key drivers of PCFs, push factors, among which global risk appetite and the dynamics of stock markets in developed world stand out as major determinants of flows. The other important domestic fundamentals for capital flows are real GDP, real equity prices, real effective exchange rates and reserves to short term debt. Flows to other countries have notably high explanatory power on flows to individual countries, even after controlling for all fundamentals. Countries that are smaller in size are especially subject to spatial dependencies relative to larger countries. Furthermore, I present evidence of overheating following a surge in portfolio inflows. Typical effects of inflow surges are an increase in real GDP, asset prices and inflation, real exchange rate appreciation and a worsening of the current account; in line with expectations.

The presence of deflection effects is an important consideration for both optimal policy design from the perspective of the individual recipient countries and the efficiency of the allocation of international CFs across countries. To the degree that surges in PCFs are synchronized, the macroeconomic and financial stability risks that EMs face will be similarly synchronized. In this case, as Ostry et al. [2012] argue, the presence of deflection effects may lead to an inefficient equilibrium where countries impose controls that are too high compared to a setting without deflection effects. My results suggest that for most country pairs, such deflection effects are absent, consequently the constraint placed by Ostry et al. [2012] on the use of controls does not seem to bind.

The organization of this chapter is as follows: Section 3.2 discusses the related literature; Section 3.3 presents the theoretical model; Section 3.4 outlines the empirical methodology; Section 3.5 describes the Benchmark GVAR model; Section 3.6 presents the results from the Benchmark GVAR model; Section 3.7 applies the GVAR model to study the deflection effects resulting from capital controls; Section 3.8 concludes.

3.2 Discussion of the Related Literature

Previous work done in the literature, including Calvo et al. [1993], Mody et al. [2001], Chuhan et al. [1998] distinguishes between domestic-pull and global-push factors as the determinants of international capital flows. Improving investment conditions in emerging markets, including creditworthiness or returns, *pull* foreign investment in respective countries. Alternatively, worsening investment conditions in developed countries, including lower interest rates, *push* capital towards emerging markets.

Theoretically, with perfect capital mobility and no transaction, adjustment or information costs, one may expect the dynamics of capital flows to reflect the adjustment towards the optimal portfolio chosen by international investors. However, there is extensive evidence against investors forming their portfolios with respect to traditional portfolio choice models. One example is the home-bias puzzle (French & Poterba [1991]). Fernandez-Arias & Montiel [1996] argue that the observed flows are part of an adjustment mechanism, which ensures that the risk-adjusted project level domestic returns equal the alternative (foreign) returns. Authors argue that, in emerging markets, where creditworthiness is low, second moments (volatility and covariance of returns) may not be as important as traditional portfolio selection models emphasize. Another related strand of literature explores contagion; for instance Claessens et al. [2000]. At times, markets in different countries seem to exhibit correlations that are above the level that can be justified with real or financial linkages. Both contagion and herding can further increase the volatility and the inter-dependencies of capital flows to emerging markets.

In the light of the findings in the literature, capital flows seem to have many determinants and complex dynamics that are challenging to pinpoint and model. To do so, one must recognize the necessity of accounting for both the underlying domestic and foreign determinants, as well as other channels through which shocks may propagate. Mody et al. [2001], for that purpose, construct Vector Error Correction Models (VECMs) for emerging market countries in which the dynamics of flows are conditioned on both domestic and foreign fundamentals that are modelled in a separate Vector Autoregressive model (VAR) without any feedback from emerging market VECMs. More generally, there is a growing literature on modelling observed and unobserved international linkages globally. For instance, Dées et al. [2007b] argue for the need of a global modelling perspective to account for the rise in international interdependencies as a result of increasing real and financial linkages across countries. As a solution, they employ a Global Vector Autoregressive (GVAR) Model, in which standard VAR/VECM country models are augmented with cross sectional averages that are supposed to proxy for unobserved global factors. Then, resulting conditional models, VARX* and VECX*, are solved to yield a single Global VAR Model.

In the context of capital flows, there are many channels through which co-movements or interdependencies may result. Changes in the global push factors may result in a change in the total supply of capital to be invested in emerging markets. Apart from push factors, as in Dées et al. [2007b] or Chudik & Fratzscher [2011], the literature clearly identifies interdependencies among countries with strong financial or real linkages. Hence, developments in one country would affect the expected returns on foreign investment not only in that country, but also in other countries that have linkages with it. Assuming forward-looking rational investors, these developments need not be macro-financial, but may include other considerations that may influence future expected returns on investment, such as geo-political risks. Changes in investor sentiment, combined with herding, may result in surges or stops in capital flows to different countries simultaneously.[6] Such sudden stops and interdependencies may not necessarily result from irrational behaviour. Claessens et al. [2000] argue that transmission of shocks to capital flows, asset prices or exchange rates among recipient countries can be explained by liquidity and incentive problems faced by rational investors. Overall, these mechanisms would naturally result in spatial dependencies in foreign investment and co-movements in capital flows. In fact, recent papers in the literature suggest the presence of such dependencies across countries (see e.g. Forbes & Warnock [2012a] and Ghosh et al. [2012]). Nevertheless, given the possible presence of numerous factors that cause the observed co-movements/interdependencies among flows to different countries, it is challenging to comprehensively list all of these factors, many of which may even be unobservable. For that reason, a common drawback of any empirical investigation of capital flows may be this inability to incorporate various relevant factors.

Apart from the well-documented domestic and global factors related to the dynamics, there is a growing interest in the multilateral dimension of issues related to international capital flows. In an on-going attempt by the International Monetary Fund to establish a coherent and comprehensive framework about how to deal with inflow surges, multilateral concerns are underscored to be important considerations in choosing an appropriate policy response.[7] Following Ostry et al. [2012], one of these concerns is the possible deflection of capital flows from recipient countries that impose capital controls toward other recipient countries. In fact, Fratzscher et al. [2012a] document the presence of negative externalities resulted from the imposition of controls in Brazil recently.

[6] In this chapter, I define "surges" and "stops" as significant increases and decreases in gross capital flows, following Forbes & Warnock [2012a].

[7] See for instance Ostry et al. [2010], Ostry et al. [2011a], Ostry et al. [2012], IMF [2011b], IMF [2011c].

3.3 Theory

Fernandez-Arias & Montiel [1996] proposed an arbitrage condition, where capital flows serve as part of the adjustment mechanism for the condition to hold. The intuition is that, risk adjusted expected returns on domestic projects should equal the opportunity cost of investing in respective projects,

$$G_s(g, F) \cdot C_s(c, S_{-1} + F) = V_s(v, f, S_{-1} + F), \tag{3.1}$$

where G_s represents the expected return on asset s, which is a function of its underlying fundamentals g and the total flows going into the project F. C_s represents the creditworthiness of the country, which is a function of its fundamentals c and the total amount of liabilities $S = S_{-1} + F$. V_s represents the opportunity cost of investing in asset s, which is a function of observed global factors v, and because investors would like to diversify, total liabilities S. The f is a new term in the arbitrage equation, which represents unobserved global-push factors.

Required level of flows, F, can be solved from (3.1),

$$F = F(g, c, v, f, S_{-1}). \tag{3.2}$$

As in Mody et al. [2001], if one total differentiates (3.2) and substitutes first differences for the derivatives, one obtains

$$\begin{aligned} \Delta F &= F_1 \Delta g + F_2 \Delta c + F_3 \Delta v + F_4 \Delta f + F_5 \Delta S_{-1} \\ F &= F_1 \Delta g + F_2 \Delta c + F_3 \Delta v + F_4 \Delta f + \phi F_{-1}, \end{aligned} \tag{3.3}$$

where $\phi = (1 + F_5)$. Notice that in (3.3), $\phi \in (0, 1)$ if $-1 < F_5 < 0$.

Alternatively, one may consider the cumulated flows over the period through which adjustment takes place from the old steady state toward the new steady-state[8]. These cumulative flows are given by;

$$F^* = F_1^m \Delta g + F_2^m \Delta c + F_3^m \Delta v + F_4^m \Delta f, \tag{3.4}$$

[8] A Steady-State refers to a state in which (3.1) holds without any adjustment for some non-unique combination $(g^{ss}, c^{ss}, v^{ss}, f^{ss}, S_{-1}^{ss})$ and hence in which $F = 0$.

where F_i^m is the multiplier of the changes in associated fundamental i on the cumulative flows, F^*, over the period of adjustment. Namely,

$$F_i^m \cong \frac{1}{1-\phi} \cdot F_i.$$

Equation (3.4) states that the observed flows are functions of changes in underlying fundamentals; pull factors, observed and unobserved push factors.

3.4 Empirical Methodology

There are several methodological concerns. Theoretical predictions of Section 3.3 imply that the levels of flows are related to the first differences in underlying fundamentals. Furthermore, unit root tests indicate that flows data are stationary, while most of the fundamentals are non-stationary. Hence, the model must be able to incorporate both stationary and non-stationary endogenous variables, in line with the theoretical implications.

Another concern is how to account for the unobserved global factors. Following Dées et al. [2007b], cross-sectional averages of domestic variables can be used as proxies for common unobservable factors. The authors' proof of this statement is related to the common correlated effects (CCE) estimator of Pesaran [2006] proposed for panel data models with cross-sectional dependence.

The last major issue to consider is the estimation of country models. Since most of the fundamentals are non-stationary and are likely co-integrated, one has to model co-integration between fundamentals together with stationary flows in an error correction framework.

These concerns lead me to present the empirical methodology in 3 subsections. In the first subsection, I present the system of equations for model variables and the method of accounting for unobserved factors (f). In the second subsection, I discuss the estimation strategy. Finally, the third subsection illustrates how the country-specific models are combined to solve for the Global VAR.

3.4.1 VARX* Model

In order to capture the dynamic interaction of capital flows (F) and their underlying domestic (X), global observed (d) and unobserved (f) fundamentals, similar to Mody et al. [2001] for country i one may consider the following system of equations in which the dynamics of capital flows are specified with respect to the theoretical implications presented in Section 3.3.

$$\begin{aligned} F_{it} &= \delta_{0iF} + \delta_{1iF}t + \sum_{l=1}^{p} \Gamma_{ilFF} F_{it-l} + \sum_{l=1}^{p-1} \Gamma_{ilFX} \Delta X_{it-l} \\ &\quad + \sum_{l=0}^{q-1} \Gamma_{ilFd} \Delta d_{t-l} + \sum_{l=0}^{q-1} \Gamma_{ilFf} \Delta f_{t-l} + \varepsilon_{iFt} \end{aligned} \tag{3.5}$$

$$\begin{aligned} X_{it} &= \delta_{0iX} + \delta_{1iX}t + \sum_{l=1}^{p} \Gamma_{ilXF} F_{it-l} + \sum_{l=1}^{p} \Gamma_{ilXX} X_{it-l} \\ &\quad + \sum_{l=0}^{q} \Gamma_{ilXd} d_{t-l} + \sum_{l=0}^{q} \Gamma_{ilXf} f_{t-l} + \varepsilon_{iXt} \end{aligned} \tag{3.6}$$

Rewriting (3.5),

$$\begin{aligned} F_{it} &= \delta_{0iF} + \delta_{1iF}t + \sum_{l=1}^{p} \Gamma_{ilFF} F_{it-l} + \sum_{l=1}^{p} \Gamma^{*}_{ilFX} X_{it-l} \\ &\quad + \sum_{l=0}^{q} \Gamma^{*}_{ilFd} d_{t-l} + \sum_{l=0}^{q} \Gamma^{*}_{ilFf} f_{t-l} + \varepsilon_{iFt}, \end{aligned} \tag{3.7}$$

where, $\Gamma^{*}_{i1FX} = \Gamma_{i1FX}$, $\Gamma^{*}_{ipFX} = -\Gamma_{i(p-1)FX}$, $\Gamma^{*}_{ijFX} = \Gamma_{ijFX} - \Gamma_{i(j-1)FX}$ with $j \in \{2, 3, ...(p-1)\}$ and for $\alpha \in \{d, f\}$, $\Gamma^{*}_{i0F\alpha} = \Gamma_{i0F\alpha}$, $\Gamma^{*}_{ipF\alpha} = -\Gamma_{i(p-1)F\alpha}$, $\Gamma^{*}_{ijF\alpha} = \Gamma_{ijF\alpha} - \Gamma_{i(j-1)F\alpha}$ with $j \in \{1, 2, ...(q-1)\}$.

Combining (3.6) and (3.7), one obtains a VARX* Model with both I(0) and I(1) endogenous as well as I(1) exogenous variables,

$$y_{it} = \delta_{0i} + \delta_{1i}t + \sum_{l=1}^{p} \Gamma_{ily} y_{it-l} + \sum_{l=0}^{q} \Gamma_{il\gamma} \gamma_{t-l} + \varepsilon_{it}, \tag{3.8}$$

where $y_{it} = (F'_{it}, X'_{it})'$, $\gamma_t = (d'_t, f'_t)'$, $\varepsilon_{it} = (\varepsilon'_{Fit}, \varepsilon'_{Xit})'$, $\delta_{0i} = (\delta_{0Fi}, \delta'_{0Xi})'$, $\delta_{1i} = (\delta_{1Fi}, \delta'_{1Xi})$, $\Gamma_{ily} = (\Gamma_{ilFF}, \Gamma^{*}_{ilFX}; \Gamma_{ilXF}, \Gamma_{ilXX})$ and $\Gamma_{il\gamma} = (\Gamma^{*}_{ilFd}, \Gamma^{*}_{ilFf}; \Gamma_{ilXd}, \Gamma_{ilXf})$.

Following Dées et al. [2007b], one can account for unobserved global-push factors, f, by including cross-sectional averages of the domestic variables in the estimation equations. Substituting the cross sectional averages of flows and fundamentals ($F^\star$, $X^\star$) for f_t in

(3.8) yields the final country-specific models. Rewrite (3.5) and (3.6) as,

$$\begin{aligned} F_{it} &= \delta_{0iF} + \delta_{1iF}t + \sum_{l=1}^{p} \Gamma_{ilFF} F_{it-l} + \sum_{l=1}^{p-1} \Gamma_{ilFX} \Delta X_{it-l} + \sum_{l=0}^{q-1} \Gamma_{ilFd} \Delta d_{t-l} \\ &\quad + \sum_{l=0}^{q} \Gamma_{ilFF^\star} F^\star_{it-l} + \sum_{l=0}^{q-1} \Gamma_{ilFX^\star} \Delta X^\star_{it-l} + \varepsilon_{iFt}, \end{aligned} \tag{3.9}$$

$$\begin{aligned} X_{it} &= \delta_{0iX} + \delta_{1iX}t + \sum_{l=1}^{p} \Gamma_{ilXF} F_{it-l} + \sum_{l=1}^{p} \Gamma_{ilXX} X_{it-l} + \sum_{l=0}^{q} \Gamma_{ilXd} d_{t-l} \\ &\quad + \sum_{l=0}^{q} \Gamma_{ilXF^\star} F^\star_{it-l} + \sum_{l=0}^{q} \Gamma_{ilXX^\star} X^\star_{it-l} + \varepsilon_{iXt}. \end{aligned} \tag{3.10}$$

Rewriting (3.9) similarly to (3.7) yields,

$$\begin{aligned} F_{it} &= \delta_{0iF} + \delta_{1iF}t + \sum_{l=1}^{p} \Gamma_{ilFF} F_{it-l} + \sum_{l=1}^{p} \Gamma^*_{ilFX} X_{it-l} + \sum_{l=0}^{q} \Gamma^*_{ilFd} d_{t-l} \\ &\quad + \sum_{l=0}^{q} \Gamma_{ilFF^\star} F^\star_{it-l} + \sum_{l=0}^{q} \Gamma^*_{ilFX^\star} X^\star_{it-l} + \varepsilon_{iFt}, \end{aligned} \tag{3.11}$$

where, $\Gamma^*_{i1FX} = \Gamma_{i1FX}$, $\Gamma^*_{ipFX} = -\Gamma_{i(p-1)FX}$, $\Gamma^*_{ijFX} = \Gamma_{ijFX} - \Gamma_{i(j-1)FX}$ with $j \in \{2, 3, ...(p-1)\}$ and for $\alpha \in \{d, X^\star\}$, $\Gamma^*_{i0F\alpha} = \Gamma_{i0F\alpha}$, $\Gamma^*_{ipF\alpha} = -\Gamma_{i(p-1)F\alpha}$, $\Gamma^*_{ijF\alpha} = \Gamma_{ijF\alpha} - \Gamma_{i(j-1)F\alpha}$ with $j \in \{1, 2, ...(q-1)\}$.

Combining (3.11) and (3.10) yields the final country-specific models,

$$y_{it} = \delta_{0i} + \delta_{1i}t + \sum_{l=1}^{p} \Gamma_{ily} y_{it-l} + \sum_{l=0}^{q} \Gamma_{ily^\star} y^\star_{it-l} + \sum_{l=0}^{q} \Gamma_{ild} d_{t-l} + \varepsilon_{it}, \tag{3.12}$$

where $y_{it} = (F'_{it}, X'_{it})'$, $y^\star_{it} = (F'^\star_{it}, X'^\star_{it})'$, $\varepsilon_{it} = (\varepsilon'_{Fit}, \varepsilon'_{Xit})'$, $\delta_{0i} = (\delta_{0Fi}, \delta'_{0Xi})'$, $\delta_{1i} = (\delta_{1Fi}, \delta'_{1Xi})$, $\Gamma_{ily} = (\Gamma_{ilFF}, \Gamma^*_{ilFX}; \Gamma_{ilXF}, \Gamma_{ilXX})$, $\Gamma_{ily^\star} = (\Gamma_{ilFF^\star}, \Gamma^*_{ilFX^\star}; \Gamma_{ilXF^\star}, \Gamma_{ilXX^\star})$ and $\Gamma_{ild} = (\Gamma^*_{ilFd}; \Gamma_{ilXd})$.

3.4.2 Estimation of Country-Specific Models

Given that the underlying fundamentals of flows are non-stationary, one has to consider possible long-run (cointegration) relationships between domestic and foreign I(1) variables. The majority of the VAR/VECM applications in the existing literature involve variables integrated of the same order. Some early studies (see Pagan & Pesaran [2008] for a discussion) involving stationary and non-stationary variables employ VAR models in first-differenced I(1) variables together with a priori known/specified long term relationships (error-correction terms). In fact, Pagan & Pesaran [2008] show that such VAR models can be reparameterized back into a corresponding VECM form. However, this approach requires the knowledge of the cointegration (CI) rank and relationships ex-ante. A method for testing the existence of CI in the presence of I(0) and I(1) variables is to employ the Bounds Testing approach of Pesaran et al. [2001]. But, it is only applicable in the possible presence of a single CI relationship.

One approach that can accommodate multiple CI relationships together with I(0) endogenous variables is to specify a VAR model in levels of I(0) and I(1) variables and re-parameterize it (with both I(0) and I(1) variables equations) into a VECM form in a standard way, see for instance Dungey & Vehbi [2011]. In this case, one has to create pseudo error correction terms for stationary variables. However, either the cointegration rank has to be known a priori, or has to be determined. In the absence of I(0) exogenous variables, Johansen [1995] and Hjalmarsson & Österholm [2010] argue that the result of the standard Johansen [1988, 1991, 1992, 1995] CI tests would yield the true CI rank plus the number of stationary variables in the system. However in the presence of I(0) exogenous variables, standard tests are not applicable as discussed by Rahbek & Mosconi [1999], who argue that in this case one can include cumulated I(0) exogenous variables as I(1) exogenous variables in the system to test for CI using the testing procedure in Pesaran et al. [2000]. As it is depicted in the previous section, the country models to be estimated here involve both endogenous and exogenous I(0) variables. So, in this chapter the cointegration rank and the long-run relationships are obtained together from a model on I(1) endogenous variables conditioned on I(1) exogenous, I(0) endogenous and exogenous variables. Hence, as an alternative procedure, the modelling strategy in here does not require the re-parameterization of I(0) variables equations and creation of restricted pseudo CI vectors. Furthermore, an advantage of this procedure is the ability to directly test for the absence of cointegration relationships between I(1) endogenous variables and cumulated I(0) endogenous variables along with other conditioning variables, following the procedure in Rahbek & Mosconi [1999].[9]

[9]The possibility of the presence of cumulated I(0) endogenous variables in the CI vectors can be an important consideration. For instance in here, since cumulated flow variables partially (without valuation effects) represent a category of total external liabilities, some of the domestic I(1) variables could be related in the long-run to the cumulated flow variables.

Equation (3.10) can be rewritten in error correction form with $p = q = 2$ as,

$$\begin{aligned} \Delta X_{it} &= \delta_{0iX} + \Pi(\xi_{it-1}) + \Phi_{i0X^{\star}}\Delta X^{\star}_{it} + \Phi_{i1z}\Delta z_{it-1} + \sum_{l=1}^{2}\Gamma_{ilXF}F_{it-l} \\ &\quad + \sum_{l=0}^{1}\Phi_{ild}\Delta d_{t-l} + \sum_{l=0}^{2}\Gamma_{ilXF^{\star}}F^{\star}_{it-l} + \varepsilon_{iXt}, \end{aligned} \tag{3.13}$$

where $z_{it} = (X'_{it}, X'^{\star}_{it})'$, $\xi_{it-1} = (z'_{it-1}, d'_{t-1})'$. One can observe from (3.13) that, equation (3.10) has been reparameterized such that stationary endogenous and exogenous variables do not enter into the cointegration relationships.

Consistent with (3.9), by adopting the weak exogeneity assumption of F_{it} with respect to the cointegrating vectors, cointegration rank and error correction terms can be obtained from a conditional model on foreign, global as well as F_{it} variables. Namely from,

$$\begin{aligned} \Delta X_{it} &= \dot{\delta}_{0iX} + \alpha_i\beta'_i(\xi_{it-1} - \mu_i(t-1)) + \dot{\Phi}_{i0X^{\star}}\Delta X^{\star}_{it} + \dot{\Phi}_{i1z}\Delta z_{it-1} \\ &\quad + \sum_{l=0}^{2}\dot{\Gamma}_{ilXF}F_{it-l} + \sum_{l=0}^{1}\dot{\Phi}_{ild}\Delta d_{t-l} + \sum_{l=0}^{2}\dot{\Gamma}_{ilXF^{\star}}F^{\star}_{it-l} + u_{iXt}, \end{aligned} \tag{3.14}$$

where Ω is the variance-covariance matrix of residuals $(\varepsilon'_{iFt}, \varepsilon'_{iXt})'$, $\dot{\delta}_{0iX} = \delta_{0iX} - \Omega_{XF}\Omega^{-1}_{FF}\delta_{0iF}$, $\alpha_i\beta'_i = \Pi$, $\dot{\Phi}_{i0X^{\star}} = \Phi_{i0X^{\star}} - \Omega_{XF}\Omega^{-1}_{FF}\Gamma_{i0FX^{\star}}$, $\dot{\Phi}_{i1z} = \Phi_{i1z} - \Omega_{XF}\Omega^{-1}_{FF}(\Gamma_{i1FX}, \Gamma_{i1FX^{\star}})$, $\dot{\Gamma}_{i0XF} = -\Omega_{XF}\Omega^{-1}_{FF}$, $\dot{\Phi}_{i0d} = \Phi_{i0d} - \Omega_{XF}\Omega^{-1}_{FF}\Gamma_{i0Fd}$, $\dot{\Phi}_{i1d} = \Phi_{i1d} - \Omega_{XF}\Omega^{-1}_{FF}\Gamma_{i1Fd}$, $\dot{\Gamma}_{ilXj} = \Gamma_{ilXj} - \Omega_{XF}\Omega^{-1}_{FF}\ \Gamma_{ilFj}$ for $l \in \{1,2\}$, $j \in \{F, F^{\star}\}$, $u_{iXt} = \varepsilon_{iXt} - \Omega_{XF}\Omega^{-1}_{FF}\varepsilon_{iFt}$, $\beta'_i(\xi_{it} - \mu_i t) = (\beta'_{iX}X_{it} + \beta'_{iX^{\star}}X^{\star}_{it} + \beta_{id}d_t - (\beta_i\mu_i)t)$.

However, as discussed in Rahbek & Mosconi [1999] and Pesaran et al. [2000], inclusion of $I(0)$ weakly exogenous variables as in (3.14) causes the limiting distributions of the (log) likelihood ratio tests for cointegration rank to be dependent on nuisance parameters. In order to overcome this problem, we follow the suggestions of Rahbek & Mosconi [1999] and include cumulated $I(0)$ variables as $I(1)$ weakly exogenous variables and test for cointegration; in which case, specification in (3.14) is all the same except the presence of cumulated variables in the cointegrating vectors.

Once the cointegration rank has been determined from the augmented model and the β_i has been obtained from (3.14), other short-run parameters can be estimated by applying Seemingly Unrelated Regressions (SUR) estimation to the system of equations given by (3.9) and (3.13).

3.4.3 Solving the Global VAR Model

Once the estimation of country specific models are completed, error-correction models can be re-parametrized back into VARX* representation. Then, GVAR model can be obtained simultaneously, following Smith & Galesi [2011]. Consider the following VARX*(2,2) specification as in (3.12),

$$\begin{aligned} y_{it} &= \delta_{0i} + \delta_{1i}t + \Gamma_{i1y}y_{it-1} + \Gamma_{i2y}y_{it-2} + \Gamma_{i0y^\star}y^\star_{it} + \Gamma_{i1y^\star}y^\star_{it-1} \\ &\quad + \Gamma_{i2y^\star}y^\star_{it-2} + \Gamma_{i0d}d_t + \Gamma_{i1d}d_{t-1} + \Gamma_{i2d}d_{t-2} + \varepsilon_{it}. \end{aligned} \tag{3.15}$$

Rewriting (3.15),

$$A_{i0}\kappa_{it} = \delta_{0i} + \delta_{1i}t + A_{i1}\kappa_{it-1} + A_{i2}\kappa_{it-2} + \varepsilon_{it}, \tag{3.16}$$

where $\kappa_{it} = (y'_{it}, y'^\star_{it}, d'_t)'$, $A_{i0} = (I_{k_i}, -\Gamma_{i0y^\star}, -\Gamma_{i0d})$, $A_{i1} = (\Gamma_{i1y}, \Gamma_{i1y^\star}, \Gamma_{i1d})$, $A_{i2} = (\Gamma_{i2y}, \Gamma_{i2y^\star}, \Gamma_{i2d})$.

In order to construct the GVAR Model, the next step is to introduce the link matrices, W_i's. As an example, for simplicity, assume 1 developed country ($i = 1$) and 3 developing countries ($i = 2, 3, 4$), with 2 fundamentals for each country to be included and 1 global variable. Notice that any global variable, which enters emerging market country-specific models as a weakly exogenous variable, should be endogenous in one developed country model.

Define $y_{1t} = (d'_t, x'_{1,1t}, x'_{2,1t})'$, $y^\star_{1t} = (x'^\star_{1,1t}, x'^\star_{2,1t})' = (\sum\limits_{j=1}^{3} w_{1j}x'_{1,jt}, \sum\limits_{j=1}^{3} w_{1j}x'_{2,jt})'$ and $y_{it} = (F'_{it}, x'_{1,it}, x'_{2,it})'$, $y^\star_{it} = (F'^\star_{it}, x'^\star_{1,it}, x'^\star_{2,it})' = (\sum\limits_{j=1}^{3} w_{ij}F'_{jt}, \sum\limits_{j=1}^{3} w_{ij}x'_{1,jt}, \sum\limits_{j=1}^{3} w_{ij}x'_{2,jt})'$ for $i \in \{2, 3, 4\}$ $y_t = (y'_{1t}, y'_{2t}, y'_{3t}, y'_{4t})'$. The link matrices, W_i, in our example, have the dimension of (5×12) for $i = 1$ and (7×12) for $i \in \{2, 3, 4\}$. For instance, W_1 and W_2 reads as,

$$\mathbf{W}_1 = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & w_{12} & 0 & 0 & w_{13} & 0 & 0 & w_{14} & 0 \\ 0 & 0 & 0 & 0 & 0 & w_{12} & 0 & 0 & w_{13} & 0 & 0 & w_{14} \end{pmatrix}$$

$$
\mathbf{W}_2 = \begin{pmatrix}
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & w_{23} & 0 & 0 & w_{24} & 0 & 0 \\
0 & w_{21} & 0 & 0 & 0 & 0 & 0 & w_{23} & 0 & 0 & w_{24} & 0 \\
0 & 0 & w_{21} & 0 & 0 & 0 & 0 & 0 & w_{23} & 0 & 0 & w_{24} \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}.
$$

Using the link matrices, it is possible to express country-specific variables κ_{it} as,

$$\kappa_{it} = W_i y_t. \tag{3.17}$$

Using (3.17) in (3.16), for $i \in \{1, 2, \cdots, N\}$,

$$A_{i0} W_i y_t = \delta_{0i} + \delta_{1i} t + A_{i1} W_i y_{t-1} + A_{i2} W_i y_{t-2} + \varepsilon_{it}. \tag{3.18}$$

Stacking all country-specific models given by (3.18) one obtains,

$$G_0 y_t = \delta_0 + \delta_1 t + G_1 y_{t-1} + G_2 y_{t-2} + \varepsilon_t, \tag{3.19}$$

where $G_0 = (A_{10}W_1; A_{20}W_2; \cdots ; A_{N0}W_N)$, $G_1 = (A_{11}W_1; A_{21}W_2; \cdots ;\ A_{N1}W_N)$ and $G_2 = (A_{12}W_1; A_{22}W_2; \cdots ; A_{N2}W_N)$. Final step to get the Global VAR representation is to multiply both sides of equation (3.19) by G_0^{-1},

$$y_t = a_0 + a_1 t + B_1 y_{t-1} + B_2 y_{t-2} + \upsilon_t, \tag{3.20}$$

where $a_0 = G_0^{-1}\delta_0$, $a_1 = G_0^{-1}\delta_1$,$B_1 = G_0^{-1}G_1$, $B_2 = G_0^{-1}G_2$ and $\upsilon_t = G_0^{-1}\varepsilon_t$.

3.5 Benchmark GVAR Model

3.5.1 Data Construction and Variables

The empirical methodology described above has been implemented for 42 countries with quarterly data from Q3-1987 to Q4-2010.[10] 25 out of 42 are emerging market countries; namely, Argentina, Brazil, China, Chile, Colombia, Egypt, Hong Kong, Hungary, India,

[10]Matlab codes provided by Smith & Galesi [2011] have been modified by the author to carry out the estimation.

Indonesia, Korea, Lebanon, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, Romania, South Africa, Singapore, Taiwan, Thailand and Turkey. Other 17 developed/other countries include, Australia, Austria, Canada, Finland, France, Germany, Italy, Japan, Netherlands, Norway, New Zealand, Saudi Arabia, Spain, Sweden, Switzerland, United Kingdom and United States. The choice of sample period, countries and variables have been made by taking into account the data availability and to obtain an econometric model that can comprehensively represent the global economy.

Fundamentals chosen for modelling portfolio equity (EF) and debt (DF) flows are real GDP (Y), real equity prices (SM), inflation ($Dcpi$), short interest rates (SR), sovereign credit ratings (CR), real effective exchange rate ($REER$), current account (CA), reserves to short term debt (RSD) and VIX Index (VIX). Variables are calculated as:

$$
\begin{aligned}
EF_{it} &= geif_{it}/ngdp_{it} & SR_{it} &= 0.25 \times ln(1 + r_{it}/100) \\
DF_{it} &= gdif_{it}/ngdp_{it} & Dcpi_{it} &= ln(cpi_{it}) - ln(cpi_{it-1}) \\
Y_{it} &= ln(ngdp_{it}/cpi_{it}) & SM_{it} &= ln(1 + nsm_{it}/cpi_{it}) \\
CA_{it} &= ca_{it}/ngdp_{it} & REER_{it} &= ln(reer_{it}) \\
CR_{it} &= ln(cr_{it}) & VIX_t &= vxo_t \\
RSD_{it} &= res_{it}/std_{it} & &
\end{aligned}
$$

where $ngdp_{it}$ is nominal gross domestic product, r_{it} is short term interest rates, cpi_{it} is consumer price index, ca_{it} is current account balance in US Dollars, nsm_{it} is nominal equity prices, cr_{it} is credit ratings, $reer_{it}$ is real effective exchange rate, res_{it} is central bank reserves in US Dollars, std_{it} is short term external debt of country i and vxo_t is CBOE S&P 100 Volatility Index at time t. $geif_{it}$ and $gdif_{it}$ are *gross* portfolio inflows, defined as the non-residents' net purchases of domestic assets, equity and debt respectively.[11]

In the light of the literature, country-specific variables are chosen both on the basis of their importance for flows and to construct a comprehensive global model that allows for rich dynamics between flows and/or their underlying fundamentals. Following Kaminsky et al. [2005], capital flows are found to be pro-cyclical and related to the business cycle. As an indicator of the business cycle and overall economic activity, real GDP has been included. For real GDP, Ghosh et al. [2012] argue that higher growth may increase both financing requirements and possible return on foreign investment in the respective country. real equity prices is related to the developments and returns in the local market

[11]The reason behind using gross rather than net flows comes from the findings of Forbes & Warnock [2012a]. The authors show that the dynamics of non-resident investment in domestic market are significantly different than the resident investment in foreign markets.

which may be relevant for flows, as Bohn & Tesar [1996] document evidence for return chasing behaviour of foreign investors. Inflation is another important macroeconomic indicator, as it may erode the real value of returns on unhedged investment. Interest rates is a proxy for domestic returns. As in Taylor & Sarno [1997] and Mody et al. [2001] credit ratings has been included as an indicator of creditworthiness. Calvo et al. [1993] and Ghosh et al. [2012] document that real effective exchange rate is closely related to flows. Current account represents external financing needs. As documented by IMF [2000], reserves to debt is a good indicator of both occurrence and severity of crises across countries. Finally, VIX has been included as an indicator for global risk appetite, since it has been depicted to be an important driver of capital flows as in Forbes & Warnock [2012a], Ghosh et al. [2012].

To construct some of the variables in the dataset, four different interpolation methods have been used. For instance, in the absence of quarterly data for flows, yearly data have been interpolated using the methodology of Chow & Lin [1971]; in which US TIC System data on US portfolio capital flows has been used as a high frequency related indicator to obtain high frequency flows data. Other methods employed include the procedure described in Dées et al. [2007b], Boot et al. [1967] and 1D Interpolation.[12] Detailed sources of variables in the dataset, as well as a more comprehensive description for the usage of interpolation procedures can be found in the Appendix.[13]

With the objective of obtaining the most accurate high frequency interpolated series of the true variables, I have assessed the outcomes of different interpolation procedures. The accuracy of the interpolated series can examined for some of the interpolated variables as the high frequency versions of the variables exist for a subset of the sample period considered here. For example, quarterly real GDP series for Brazil is not available for the period of 1987-1995, but it is available for the rest of the sample period. Hence, different interpolation procedures can be used to interpolate not only the missing observations, but also the rest of the sample period. Then, one can assess the accuracy of different interpolation procedures by comparing the interpolated series and the actual series. In case of real GDP of Brazil, this would involve comparing the interpolated and actual series for the period of 1995-2010. Furthermore, another exercise has been performed to assess whether the high frequency related indicator used in the procedure of Chow & Lin [1971] is indeed useful. Firstly, a random white noise series has been

[12] Matlab library on temporal disaggregation and interpolation provided by Quilis [2009] has been used for Chow & Lin [1971] and Boot et al. [1967]. 1D interpolations are carried out using built-in Matlab codes. Interpolation procedure described by Dées et al. [2007b] has been coded in Matlab by the author.

[13] Note that the data quality may be an issue to consider, given the presence of many different data sources used. As a further robustness check to be considered in future research, countries with less reliable datasoures can be dropped to assess whether the data quality issues drive the results.

created by drawing from a normal distribution with zero mean and unit variance. Then, the white noise series have been used as a high frequency indicator to perform the interpolation with Chow & Lin [1971] procedure. If the candidate related variable is truely a good indicator for the interpolated variable, then the interpolated series obtained with the candidate indicator should be more accurate than the one obtained with a white noise series.

Formally, to assess the accuracy of different interpolation procedures as described above, Root Mean Square Error (RMSE) of different interpolation methods have been compared, if the actual high frequency data is available. Additionally, correlations of interpolated series with the actual data are examined, again if it is available. The correlations are also useful to assess whether different procedures yield substantially different series that may possibly affect the results obtained from the model.

[Table A.1 in here]

Table A.1 reports the RMSE and correlations for interpolated real GDP and portfolio capital flows series of countries for which actual high frequency data exists for a subset of the sample period. First rows of each table reports the RMSE of Chow & Lin [1971] with industrial production as the related indicator. The second rows depict the RMSE of Chow & Lin [1971] with white noise as the related indicator. The third and fourth rows report the RMSE of Dées et al. [2007b] and Boot et al. [1967] procedures. Finally, the last four rows in each table reports the correlation of actual high frequency data with series interpolated with different procedures. Note that the correlations reported for real GDP are obtained for the growth rates of the respective series.

One can observe that in most cases the correlations reported for different procedures are not substantially different than each other. However, the correlations of Chow & Lin [1971] procedure with industrial production are higher for the majority of countries in the case of real GDP. For portfolio capital flows, none of the Chow & Lin [1971] and Boot et al. [1967] procedures seem to dominate the other. Also, comparing for both real GDP and portfolio capital flows, Chow & Lin [1971] with actual indicator series seem to dominate the one with white noise series. This result suggests that industrial production and US flows data are both relevant indicators for the respective interpolated series. Comparing the RMSE results, Chow & Lin [1971] procedure seem to be most accurate procedure with the smallest statistics for most of the countries' real GDP. Examining the reported RMSE statistics for capital flows, Chow & Lin [1971] and citebfl seem to yield similar results. Overall, one can conclude that the Chow & Lin [1971] procedure with the proposed indicators performs well.

Construction of country specific foreign-star variables, involves choosing appropriate weight matrices to obtain weighted cross-sectional averages. Following the literature, all foreign-star variables, except flows, are constructed using trade data from IMF Direction of Trade Statistics, IMF [2012], obtained from ESDS. Total volume of trade (average of Exports-plus-Imports during 1998-2001) is taken as a measure of interconnectedness between countries.

Even though trade weights are appropriate for other foreign-star variables, they may not clearly be the most appropriate choice as weights for the construction of foreign flow variables. A more appropriate alternative to consider is financial weights, which can be constructed from IMF Portfolio Investment Surveys. On the other hand, it is unclear whether strong financial linkages is the single most important factor behind investors choosing to invest in different countries in similar patterns over time. In fact, Forbes & Warnock [2012a] show that both trade, financial and regional linkages are relevant for extreme capital movements to different countries. Given the complexity of the underlying dynamics, a data driven approach for choosing appropriate weights for flows could be favoured; for instance, PCA. However, with PCA one has to decide from which component the weights should be extracted from. In the presence of the above mentioned complications, a more general data-driven approach has been employed here by using pair-wise correlations among flows to different countries. Namely, weights between countries have been set equal to the pair-wise correlation coefficients of flows to respective countries. Later, weights are normalized such that the total weights sum up to one for each country.

Depending on the data availability, a typical emerging market country model includes as domestic fundamentals $Y_{it}, SR_{it}, Dcpi_{it}, Reer_{it}, SM_{it}, CR_{it}, CA_{it}$, RSD_{it}, as foreign-star variables $Y^\star_{it}, SR^\star_{it}, Dcpi^\star_{it}, SM^\star_{it}, CR^\star_{it}, CA^\star_{it}, RSD^\star_{it}$ and as global variables VIX_t. For portfolio equity and debt flows, different GVAR Models have been constructed, with the same specification. Hence, together with above mentioned fundamentals, conditional country models in $GVAR-EF$ and $GVAR-DF$ models respectively include EF_{it} and DF_{it} as domestic, $EF^\star_{it}$ and $DF^\star_{it}$ as foreign-star variables. Furthermore, considering the centre of attention for the analysis is on the emerging markets, other country variables are aggregated using GDP-PPP (averages of 2006-2008) weights and a single model (named Developed Countries (DC)[14]) is estimated with the aggregated variables, as it is similarly done for the Euro-zone in Dées et al. [2007b]. In DC model, considering the weak-exogeneity assumption, only $Y^\star_{it}$ has been included as a foreign variable. Specifications of country-specific models are presented in Table A.2.

[14] Saudi Arabia has also been included in the model for Developed Countries.

[Table A.2 in here]

3.5.2 Model Specification

Results obtained from the ADF Test of Dickey & Fuller [1979] and Weighted-Symmetric ADF (WS-ADF) Test of Park & Fuller [1995], indicate that the flow variables are stationary, whereas most of the fundamentals are non-stationary. Therefore, flow variables (both domestic and foreign-star) are assumed to be I(0) whereas the fundamentals I(1).

[Table A.3 in here]

A point to note here is that inflation, credit ratings and interest rates variables have been treated as I(1) although economically they are not. On the other hand, these variables are very persistent and near I(1). In different GVAR applications in the literature, they are treated as I(1), see for instance Dées et al. [2007b], Dées et al. [2007a]. Unlike the aforementioned papers, the GVAR model presented in this chapter can formally account for the presence of I(0) variables. However, estimating the GVAR model with variables that behave as if I(1) may easily result in the estimated GVAR model that is unstable. It is for that reason, I have followed the existing literature and treated these variables as I(1).

Considering the limited sample size, lag orders for the domestic and foreign variables are set to (2,1).[15] In addition, dummy variables are included in the country models by examining the outliers in the residuals.[16] Apart from residual normality, given that emerging market countries have been subject to various reforms as well as periods of relative instability during the sample period, the dummies can capture some of the structural breaks in the model variables. In fact, some of the GVAR applications in the literature use dummy variables to account for possible structural breaks, see for instance Greenwood-Nimmo et al. [2012].[17]

Table A.4 summarize the results of the trace test for cointegration rank in the presence of I(1) weakly exogenous variables following Pesaran et al. [2000] and Johansen [1988, 1991,

[15] Notice that (2,1) are the minimum lags that can be chosen to be able to implement the model outlined in Section 3.4.

[16] Minimum of 0 and maximum of 7 dummies are included in different country models.

[17] A more formal approach than the one considered here could be to formally test for break dates and include relevant dummy variables. Alternatively, one can set the estimation window by considering the breaks and/or estimate GVAR with rolling windows, as discussed in Pesaran & Timmermann [2007] and Pesaran et al. [2009]. However given the number of parameters to be estimated and the limited sample size, I have chosen to estimate the model with full sample and use dummies to circumvent the possible issue of structural breaks.

1992, 1995], respectively for models with equity flows and debt flows. Results in the first column are from a VECX* model with only nonstationary endogenous and exogenous variables where EF/DF and $EF^{\star}/DF^{\star}$ variables omitted; results in the columns with the "2" superscript are from a model with cumulated EF/DF as endogenous and cumulated $EF^{\star}/DF^{\star}$ as weakly exogenous variables and the results in the columns with the "3" superscript are from the main model of interest, in which $I(1)$ endogenous variables are conditioned on the cumulated EF/DF, $EF^{\star}/DF^{\star}$ and other $I(1)$ foreign variables. Final choice of cointegration rank has been done by taking into account the stability of the resulting GVAR models and the persistence profiles of the resulting cointegrating relationships, which are presented in the last column.

[Table A.4 in here]

3.5.3 Bootstrap Procedure

Methodology described in Smith & Galesi [2011], Dées et al. [2007a] and references therein has been employed to bootstrap the Global VAR models and hence to obtain the empirical distribution of test statistics, impulse responses and forecast error decompositions. However, a modification has been made to the procedure in order to account for the presence of dummy variables. Following Smith & Galesi [2011], Dées et al. [2007a] and references therein, the modified methodology can be described as below.

The type of the bootstrap procedure employed in here is the sieve bootstrap. Dées et al. [2007a] argue that this procedure is widely used for time-series models, as investigated by Kreiss [1992], Bickel & Bühlmann [1999] and Bühlmann [1997]. The procedure assumes that the true unknown data generating process is infinite order autoregressive and the finite order model is an approximation. Hence, via the approximating model, sieve bootstrap methods can be used to obtain the empirical distributions of test statistics, impulse responses and forecast error decompositions.

First step is to obtain the orthogonalized GVAR residuals, u_t, by pre-multiplying υ_t in (3.20) by P which results from the Cholesky Decomposition of the variance-covariance matrix of residuals as $\Sigma_\upsilon = PP'$.[18] Then, for each bootstrap replication, new GVAR residuals, $\hat{\upsilon}_t$ are obtained using re-sampled orthogonalized residuals. Finally, bootstrap

[18]Note that, as discussed in Smith & Galesi [2011], when the number of endogenous variables are larger than the sample size, Σ may not necessarily be positive definite, as it is the case observed in here. So, following Smith & Galesi [2011], Dées et al. [2010] and references therein, a shrinkage estimator for the residual variance-covariance matrix has been employed, with a shrinkage parameter of 0.95.

sample for model variables are obtained from,

$$\hat{y}_t = a_0 + a_1 t + F_1 \hat{y}_{t-1} + F_2 \hat{y}_{t-2} + F_2 D_c d + \hat{\upsilon}_t, \tag{3.21}$$

where, D_c is the stacked coefficient matrix for all dummy variables of the GVAR Models. Naturally, elements of the D_c matrix which corresponds to the dummy variables of other country models are zero. Likewise, d is the stacked dummy data matrix for all dummy variables.

With each bootstrap sample, the model is re-estimated. If the resulting model is stable, the results are stored. Otherwise, another bootstrap replication is carried out. Finally, bootstrap distributions of LR tests, Impulse responses, Forecast Error Variance Decompositions and Persistence Profiles are obtained from stored results.

3.5.4 Absence of Cumulated $I(0)$ Variables in CI Vectors

The absence of cumulated stationary variables in the CI vectors are tested using an LR test. In 11 out of 25 cases for equity flows models and in 12 out of 25 cases for debt flows models, test statistics exceed the 1% critical value given by χ^2 distribution with respective degrees of freedom. However, considering the limited sample size, it may not be reasonable to compare the test statistics with asymptotic critical values. For this reason, bootstrap distributions for the LR test statistics have been obtained by applying bootstrap procedures to the calculated GVAR models. The results indicate that in 23 out of 25 cases in equity flows model and 21 out of 25 cases in debt flows model the assumption for the absence of cumulated $I(0)$ variables in the CI vectors are validated by the data at 5% significance level; 24 and 23 cases out of 25 at 1% level respectively.

[Table A.5 in here]

3.5.5 Weak Exogeneity

The assumption of weak exogeneity has been tested similar to Dées et al. [2007b], by taking guidance from Johansen [1992] and Harbo et al. [1998]. With the assumption of weak exogeneity of I(1) exogenous, cumulated I(0) endogenous and exogenous variables with respect to the cointegration vectors, the error correction terms (EC) should appear as jointly insignificant in the auxiliary equations presented below and estimated for the aforementioned variables. Defining R_i as the number of cointegration relationships, $\bar{X}_{it}$ as the vector of I(1) domestic variables, $X^{\star}_{it}$ as the vector of I(1) foreign-star variables, d_t

as the vector of global variables and C_X_{it} as the vector of cumulated I(0) endogenous and exogenous variables and $\hat{X}_{it} = (X'^{\star}_{it}, d'_t, C\_X'_{it})'$, for each country i one has to test for joint insignificance of ECs in each equation of the system,

$$\Delta\hat{X}_{it} = \delta_{0i\hat{X}} + \sum_{r=1}^{R_i} \alpha_{ir} EC_{ir,t-1} + \sum_{l=1}^{q_i} \delta_{li\hat{X}} \Delta\hat{X}_{it-l} + \sum_{l=1}^{p_i} \delta_{li\bar{X}} \Delta\bar{X}_{it-l} + \epsilon_{i\hat{X}t}.$$

[Table A.6 in here]

The results from the F-tests that are conducted for testing the joint null hypothesis of all R_i α^j_{ir} coefficients being equal to zero in equation j for variable j and country i, indicate that in almost all cases, weak exogeneity assumption seems not to be violated in the GVAR models.

3.5.6 Pair-Wise Cross-Section Correlations

As an indication of whether the cross-sectional averages and global variables are in fact able to capture the co-movements or spatial dependencies among the country-specific domestic variables, Table A.7 present the average pair-wise cross-section correlation of major country variables and model residuals similar to Dées et al. [2007b]. It can be observed that, both for flows and fundamentals, model residuals depict significantly lower cross-section correlations than the variables. For equity flows, average cross-section correlations present in the variables are markedly reduced close to zero in residuals, from around 20% in several countries including Brazil, India, Thailand, Turkey. Among other variables, notable cases are real equity prices and credit ratings. For many countries both variables, in first differences, demonstrate above 30% average correlations, whereas the residuals have correlations of approximately 0%.

[Table A.7 in here]

3.5.7 Contemporaneous Impact Coefficients

Assuming that there are positive inter-dependencies among emerging market countries in attracting portfolio investment, the contemporaneous impact of foreign flow star variables on domestic flow variables should be positive even after controlling for other factors. Table A.8 present the contemporaneous impact coefficients of foreign-star variables on several major domestic variables as in Dées et al. [2007b]. It can be observed that all flow-star variables have the expected sign and the majority of them are significant. Apart from flows, most of real GDP coefficients have the expected sign even though not all are significant. As expected from the findings in pair-wise correlations, almost all of the real equity prices and credit ratings coefficients have the correct sign and appear as significant.

[Table A.8 in here]

3.5.8 Persistence Profiles

From Lee & Pesaran [1993] and Pesaran & Shin [1996], Persistence Profiles (PPs) illustrate the evolution of the cointegration relationships over time following a shock to all variables in the given model. Following the authors and Smith & Galesi [2011], expressions for the PPs can be derived formally from the moving average representation of (3.20),

$$y_t = \upsilon_t + A_1\upsilon_{t-1} + A_2\upsilon_{t-2} + A_3\upsilon_{t-3} + ...,$$

where $A_i = 0$ for $i < 0$, $A_0 = I_k$, $A_i = \sum_{j=1}^{2} F_j A_{i-j}$ for $i = 1, 2, 3, ...$ with k being equal to the number of endogenous variables in GVAR Model. Noting that the cointegration relationships can be written as $\beta_i'\kappa_{it} = \beta_i' W_i y_t$, PP of cointegration relationship r of country i, n periods after the shock, can be expressed as,

$$PP(\beta_{ir}'\kappa_{it}; \upsilon_t, n) = \frac{\beta_{ir}' W_i A_n \Sigma_\upsilon A_n' W_i' \beta_{ir}}{\beta_{ir}' W_i A_0 \Sigma_\upsilon A_0' W_i' \beta_{ir}},$$

where Σ_υ is the variance-covariance matrix of the GVAR residuals. However, above expression should be modified to accommodate the presence of stationary variables, which can be done by re-defining the cointegrating vectors for the calculation of PPs. Consider the example given in Section 3.4, $y_{it} = (F_{it}', x_{1,it}', x_{2,it}')'$ $y_{it}^\star = (F_{it}'^\star, x_{1,it}'^\star, x_{2,it}'^\star)'$ and $\kappa_{it} = (y_{it}', y_{it}'^\star, d_t')'$. In this case, cointegration relationships between $x_{\cdot,it}, x_{\cdot,it}^\star, d_t$ variables can be expressed by re-defining the cointegrating vectors as, $\beta_{ir}' = (0, \beta_{ir}^{x_1}, \beta_{ir}^{x_2}, 0, \beta_{ir}^{x_1^\star}, \beta_{ir}^{x_2^\star}, \beta_{ir}^{d})$.

PPs provide a useful basis for model selection in GVAR modelling. By definition, if all of the specified cointegration relationships of the model exist, any shock should not result in uncorrected or persistent deviations from cointegration relationships.

[Figures A.1, A.2 in here]

Figures A.1-A.2 depict the resulting PPs of the cointegration relations of the GVAR-*EF* Model, together with their bootstrap median estimates. The model is clearly stable since the effect of a system-wide shock on the cointegration relationships are corrected for after a few years.

3.6 Benchmark Model Results

In the presence of the policy challenges EMs have been facing in the aftermath of the global financial crisis, IMF attempted to come up with a comprehensive policy framework in designing optimal policy response to surges, as it was mentioned previously. Ostry et al. [2010, 2011b] argue that optimal policy design depends, along with other considerations, on the characteristics of the surge episode and on the macroeconomic and/or financial stability concerns flows constitute. So, in effect, the optimal policy design involves quantifying the contribution of CFs in creating these risks. However, disentangling these effects and the underlying drivers can be a challenging task considering the difficulty in modelling various relevant transmission channels and dependencies that matter for CFs. It is for that reason; this section firstly attempts to lay evidence on the domestic consequences of surges in PCFs using the presented benchmark GVAR model.

Apart from the role of PCFs in generating macroeconomic or financial stability concerns, Ostry et al. [2010, 2011b] argue that the optimal policy design also depends on the characteristics of the observed flows. For instance, if the observed flows are considered to be excessive and lead to macroeconomic concerns (e.g.: an overvalued exchange rate), policy makers may consider controls that directly target the level of flows.[19] The authors argue that controls can be justified for macroeconomic reasons only if the surge in flows is temporary. Furthermore, they argue that the controls are not costless, as they may bring about distortionary costs and have other multilateral implications. Hence the optimal policy design involves studying and determining the underlying drivers and the persistence of flows. If the policy makers believe that the observed surge depends on cyclical global factors that are believed to be reversed in the near term, the argument for controls may be stronger than a case in which flows are mostly driven by domestic conditions that are believed to be more persistent. Given these considerations, this section studies the relative importance of various domestic and global fundamentals for PCFs as an attempt to shed light on the nature of PCFs. Furthermore, to document the relative reversible nature of equity vs debt flows, a global risk aversion shock is simulated for both types of flows.

Apart from the domestic effects and the underlying drivers of portfolio capital flows, the empirical model constructed in this chapter can also be used to shed light on the long run economic relationships in emerging markets. In fact, in a similar GVAR setting Dées et al. [2007a] assess the presence of long run relationships predicted by the theory

[19] Authors argue that controls should be the last option to consider once all other options are exhausted and implemented by taking into account multilateral considerations.

for some of the major developed countries. Hence, the following subsection will present evidence on these relationships for emerging market countries.

3.6.1 Long Run Economic Relationships in Emerging Markets

In the previous section 3.5, cointegration ranks of individual countries have been assessed and determined. Even though the main objectives of this chapter are to study the short run dynamics of portfolio capital flows, the constructed econometric model is well-suited to test for some of the major theoretically predicted long-term relationships for the emerging market countries, like it has been done for the developed countries by Dées et al. [2007a].

With the set of variables included in the GVAR model and following Dées et al. [2007a] and references therein, three long-run economically predicted relationships are tested. Namely, Fisher Relationship[20], Purchasing Power Parity (PPP) condition[21] and Uncovered Interest Rate Parity (UIP) condition[22] as illustrated below respectively.

$$
\begin{aligned}
SR_{it} - Dcpi_{it} &= c_{i1t} + \epsilon_{i1t} \sim I(0) && (3.22) \\
REER_{it} &= NEER_{it} - p_{it} + p^{\star}_{it} \\
&= \sum_{j=0}^{N} w_{ij}(ner_{it} - ner_{jt}) - p_{it} + p^{\star}_{it} \\
&= c_{i2t} + \epsilon_{i2t} \sim I(0) && (3.23) \\
SR_{it} - SR^{\star}_{it} &= c_{i3t} + \epsilon_{i3t} \sim I(0) && (3.24)
\end{aligned}
$$

where $NEER$ is the nominal effective exchange rate, p and $p^{\star}$ are the domestic and foreign price levels, ner is nominal exchange rate.

Equation 3.21, Fisher Relationship, tells that nominal interest rate minus inflation must be stationary, assuming that the real interest rate is stationary. Equation 3.22 tells that PPP holds if real effective exchange rate is stationary for a given country. Finally, Equation 3.23 describes the UIP condition, which states that the difference between domestic and foreign interest rates should be stationary, assuming that the expected change in the bilateral exchange rates is stationary.

[20] See Fisher, I. [1930] for more details.
[21] See Cassel [1918] and Sarno & Taylor [2002] for more details.
[22] See McCallum [1994] for more details.

Similar to the practice of Dées et al. [2007a], ten major emerging market countries are selected on the basis of economic size and global integration to test for the theoretical relationships described above. Technically, given the cointegration ranks determined in the previous section, restrictions are imposed on the cointegrating vectors of selected country-specific models. If the cointegration rank is smaller than the total number of possible relationships, which is three, stability of the GVAR model, persistence profiles and the resulting likelihood statistics are examined to select the combination from the three sets of theoretical restrictions, similar to Dées et al. [2007a].

[Table A.9 in here]

Table A.9 presents the theoretical restrictions that result in a stable GVAR, convergent persistence profiles and highest likelihood for selected emerging market countries.[23] Also, the last two columns present the Likelihood ratio test statistics (LR) with degrees of freedom and bootstrap 99% critical values (CVs) associated with the overidentifying restrictions on the cointegrating vectors. One can see that in majority of the countries considered, overidentifying restrictions are rejected, as the LR statistics are greater than the critical values reported. Examining the theoretical restrictions, in 3 out of 4 cases that the restrictions cannot be rejected, there is support for the Fisher relationship. Also, In 8 out of 10 total countries considered, Fisher relationship seems to result in a stable model with the highest likelihood. Also, in Indonesia and Thailand, results seem to support the UIP condition. On the other hand, there is little support for the PPP condition in the emerging markets. Out of 4 countries that the restrictions cannot be rejected, only in Indonesia PPP seems to hold.

Overall, one can conclude that only in few emerging market countries results indicate that Fisher relation, PPP and UIP holds. Among the theoretical relationships examined, Fisher relation is the one that seems to be the most relevant for emerging market countries, followed by the UIP condition. In contrast, Dées et al. [2007a] find more favourable evidence for the UIP condition than the Fisher relation for developed countries. But, similar to fthe indings of Dées et al. [2007a] for developed countries, there is little evidence for the PPP condition for emerging markets.

3.6.2 Generalized Impulse Response Functions

In order to examine the effects of portfolio capital flows on fundamentals, Generalized Impulse Response Functions (GIRFs) have been calculated, as introduced by Koop et al.

[23] Note that the results are obtained with the GVAR-EF Model.

[1996] and Pesaran & Shin [1998]. Dées et al. [2007b] argue, an important advantage of the GIRFs, especially in relatively large models, is that there is no need to define a specific ordering for the countries and variables, which is required to calculate the Orthogonalized Impulse Responses of Sims [1980]. Instead, GIRFs make use of the existing correlation structure in the residuals to calculate the contemporaneous impact of shocks across variables.

Following Koop et al. [1996], Pesaran & Shin [1998], Garratt et al. [2006], Dées et al. [2007b] and Smith & Galesi [2011], GIRFs[24] have been calculated in order to document the effects of a *global* one standard error positive shock to equity flows and debt flows of EMs. A *global* shock hits the same domestic variable of all country models with a magnitude depending on each country' s GDP-PPP weight. The shock can be considered as a sudden surge in gross portfolio capital flows to emerging market countries in the sample.

Surges in capital flows are considered and found to be associated with an increase in inflation, asset prices and aggregate demand, exchange rate appreciation and a deteriorating current account in the literature; see for instance World Bank [1997], Ostry et al. [2010], Ostry et al. [2011b], Cardarelli et al. [2010]. In fact, World Bank [1997] suggests aforementioned observations as possible symptoms of overheating, which may result from rapid capital inflows. Cardarelli et al. [2010] analyse 109 historical episodes of large inflows and find similar impact on domestic fundamentals across 52 countries.

Figures A.3-A.8 summarize the contemporaneous, 1 Quarter and 4 Quarters GIRFs of real GDP, real equity prices, real effective exchange rate, inflation , current account following a global positive shock to equity flows and debt flows of EMs for sample countries. Figures A.9-A.12 present the detailed time paths of the GIRFs for 8 countries in the sample for the same shock.

[Figures A.3-A.8 in here]

Starting with the global equity flows shock, The contemporaneous impact on real GDP and real equity prices seems to be positive for all countries. In case of real equity prices, the responses are either significant or close to being significant for most countries. In 1 and 4 quarters after the shock, the impact on the respective variables seems to persist. Interestingly, even though the contemporaneous impact on real GDP is insignificant for several countries, over time the effect become significant and positive. Regarding

[24]Bootstrap means together with their simulated 5 - 95 bootstrap intervals.

real equity prices, for several countries including Argentina, Chile, Korea, Taiwan and Turkey, the initial notable impact become insignificant 1Q and 4Q after the shock. The responses of other variables are less clear-cut compared to real GDP and real equity prices. The contemporaneous impact on *Reer* and inflation is positive in all cases where the response is significant, consistent with expectations. 1Q and 4Q after the shock, the initial insignificant response of real effective exchange rate becomes significant and positive for some countries, including Brazil, Colombia and Indonesia; whereas for Turkey and Morocco the effect becomes significant and negative. inflation response for several countries also become significant and positive in several quarters after the shock, including Colombia, Egypt and Korea. Lastly, current account responds insignificantly for most countries contemporaneously, but in the 4th quarter one can observe that the impact is negative in all countries where the response is either significant or close to being significant.

Regarding the debt flows shock, initial response of real GDP and real equity prices are both positive in most cases. However, the impact on real equity prices seems to be less strong compared to the case of equity flows and becomes insignificant in following periods. Initial *Reer* response is either significant and positive or insignificant. For most countries with an initial significant response, the impact seems to persist in the following periods. Initial insignificant response of inflation becomes significant and positive for several countries in 1Q and 4Q, including Egypt, Pakistan, Philippines and Turkey. In case of current account, similar to the results of the equity flows shock, the response seems to be negative in most countries where the response is significant.

[Figures A.9-A.12 in here]

Figures A.9-A.12 present the time paths of the above examined variables' responses to given capital flows shocks. In line with the previous discussions, for many countries in the figures, the impact of both shocks on real GDP and real equity prices is positive and significant; even though for some the significant initial impact becomes insignificant later or insignificant initial impact becomes significant after several quarters. Interestingly, for Brazil, notable exchange rate appreciation after few quarters following the shocks seems to cause both inflation to go down (in equity flows case) and current account to deteriorate which is intuitive considering import prices and competitiveness channels. Also, the same mechanism, at least partially, seems to be reflected in the responses of the respective variables of other countries, including Colombia, India and Mexico. Regarding the current account, the impact of the shocks is particularly strong in cases of Argentina (in equity flows case), Brazil and Turkey (in debt flows case).

Overall, results are in line with the prior expectations of overheating for many countries. Following inflow surges, there is evidence of temporary increase in GDP growth, moderating after 3-4 quarters for most countries. However, the changes in the asset prices and inflation seems to be more persistent. real equity prices seems to react positively in many countries and the response is stronger after equity flows shocks. In line with the observations in Calvo et al. [1993], significant real effective exchange rate responses appear as positive. Cardarelli et al. [2010] argue that the periods of large capital inflows are associated with increases in real GDP, real effective exchange rate and deterioration in current account, which is consistent with the evidence in here. The observed link between the dynamics and responses of current account, exchange rates and inflation for some countries highlights the increased overall volatility following inflow surges.

A point to note about the results obtained here is, there may also be possible non-linearities in the impulse response functions. In other words, a positive capital inflows shock may not have symmetric effects on model variables compared to a negative capital inflows shock. Recent literature on extreme capital flow episodes suggest that there exist differences in the nature of extreme capital inflow vs outflows episodes, see for instance Forbes & Warnock [2012a]. Furthermore, if policymakers deal with inflow and outflow episodes with different policies, this may result in asymmetric impulse responses. This asymmetry can certainly be a further issue to research.

3.6.3 Structural US Risk Aversion Shock

As described in Dées et al. [2007b] and Smith & Galesi [2011], structural identification of VIX shocks (as a risk aversion shock) has been carried out using a specific ordering of the variables in DC model by taking guidance from Sims [1980]. Notice that, this procedure involves identifying the shocks in DC model only, so the impact of structural shocks on EM models is derived from the Generalized Impulse Responses as described earlier. The ordering of the DC model variables has been set to SR, VIX, SM, $Dcpi$, $Reer$, Y for identification purposes.

[Figures A.13, A.14 in here]

The findings in the existing literature identify global risk aversion as a key determinant for capital inflows to emerging countries, including Ghosh et al. [2012], Forbes & Warnock [2012a]. Figure A.13 presents the 4 quarter cumulated impact of a one standard deviation positive structural VIX shock on portfolio debt flows to sample EM countries. In all 18 cases, the bootstrap-median response is negative and in almost all countries either the contemporaneous or one-quarter-ahead impact is significant, reflecting the importance of VIX, and hence risk aversion of foreign investors, as a major determinant of portfolio debt flows to emerging market countries. Approximately 1 standard deviation increase in the index is associated with, approximately, 0.7%-of-GDP fall in portfolio debt flows to Brazil, 0.8% for Indonesia, 1.1% for Turkey, 1.8% for South Africa, 2.2% for Hungary in 4 quarters following the shock.

Results obtained from the GVAR-EF model, presented in Figure A.14, suggest that the impact of the same shock is weaker on equity flows compared to debt flows. Even though the cumulated 4 quarter impact is negative for most of the countries, the impact appears to be not significant for many countries. This evidence seems to be in line with the findings of Forbes & Warnock [2012b], who examine surges by differentiating between equity-vs-debt dominated episodes. The authors find that debt related surges are strongly linked to risk appetite, but equity related surges are significantly less dependent on risk measures. Nevertheless, together with results from GFEVDs below, it is possible to conclude that even though it is less important compared to debt flows case, VIX is a relevant driver of equity flows.

In a related infinite-dimensional VAR application[25], based on a GVAR framework, Chudik & Fratzscher [2012] examine the transmission of 2007-08 and 2010-11 crises to the financial markets across the globe. The authors examine the effects of liquidity and risk shocks on several financial variables and capital inflows during 2005-2011. Even though their model is not specified with the particular aim of modelling capital flows and their underlying fundamentals[26], the results they obtain for risk shocks can be compared to the results in here. Chudik & Fratzscher [2012] document the evidence of strong outflows following a risk shock for both type of flows, which is broadly in line with the findings here.[27]

3.6.4 Generalized Forecast Error Variance Decompositions

Generalized Forecast Error Variance Decompositions (GFEVDs), developed by Koop et al. [1996], Pesaran & Shin [1998] serve as a useful method of finding out the amount of variability in a variable that can be attributed to itself or other model variables. Similar to GIRFs described earlier, the main advantage of this procedure is that there

[25] Introduced by Chudik & Pesaran [2011, 2013].

[26] For instance, the authors do not include any real variables which may be fundamentally important for flows and ignore possible cointegration relationships. Furthermore, for flows, they employ a measure that captures only a fraction of actual flows.

[27] The authors, however, present results with 25% - 75% bootstrap bands, which are less informative regarding the significance of responses compared to 5% - 95% bands presented here.

is no need to specify a certain ordering for the variables or countries in the model. On the other hand, given the presence of correlations across model residuals, GFEVDs do not necessarily sum up to one.

Following the above mentioned authors, Dées et al. [2007a] and Smith & Galesi [2011], Figures A.15-A.19 summarize the results from the GFEVDs for equity flows and debt flows. Precisely, Figures A.15-A.16 present the *normalized* (to sum up to one) contributions of different fundamentals, *averaged* across countries. Contributions of domestic and DC model variables are presented separately for each variable. Figures A.17-A.18 document the heterogeneity across countries regarding the importance of different fundamentals, which is not possible to see from the average contributions diagrams. Specifically, each bar that corresponds to a variable and a rank (eg: 1st or 2nd) represents the total number of times the variable is in the given order in the overall ranking of all (domestic or foreign) variables in terms of their normalized contributions across all sample countries. Finally, Figure A.19 presents the normalized percentage contributions of domestic, foreign flows and DC model variables in explaining PCFs.

[Figures A.15-A.19 in here]

Starting with equity flows, average normalized contributions in Figure A.15 depict that the developments in the local stock markets play an important role in driving flows among other domestic fundamentals. Other important domestic variables are credit ratings, real effective exchange rate and inflation. Examining Figure A.17, one can see that in only a few countries real equity prices stands as the most important domestic fundamental. For a considerable numbers of countries credit ratings, real effective exchange rate and inflation ranks as other top ranking variables in terms of their importance. The results presented imply that there is notable degree of heterogeneity across countries about the importance of different fundamentals for equity flows. One interesting observation is that real GDP seems not to be a major domestic driver of flows contemporaneously, but it is important in 4Q contributions. Also, reserves to debt appears to be the top domestic driver of flows for 6 countries in 4Q. Regarding the DC model variables, in the order of importance, real equity prices, VIX and real GDP are the most important DC fundamentals for equity flows.

Figure A.16 and A.18 indicate that there are differences in the importance of underlying fundamentals between equity flows and debt flows. Contemporaneously, real equity prices appears to be the least important fundamental for debt flows, whereas real effective exchange rate, inflation, reserves to debt and real GDP appear as important domestic fundamentals. Among DC variables, the relative ranking of real equity prices, VIX and real GDP in their importance for debt flows is the same as for equity flows. However, the contribution of real equity prices and real GDP seems to be less for debt flows compared to equity flows, whereas the importance of VIX for debt flows is notably more than it is for equity flows. This finding is in line with the findings in the previous subsection and with the general perception about the portfolio debt flows being more risky and reversible than portfolio equity flows. In 4Q, interest rates and reserves to debt gain further importance as domestic variables. Examining Figure A.18, the heterogeneity across countries about the relative importance of different fundamentals seems also to be present for debt flows, as it is observed for equity flows. However, the degree of heterogeneity is considerably more for the importance of pull factors compared to that of push factors.

From GIRFs, VIX emerges as an important determinant for portfolio capital flows, which is in line with the results in this subsection. Unlike the findings of Chudik & Fratzscher (2012, p. 45-46), on average VIX seems to contribute more towards the variability of debt flows than to equity flows in terms of its normalized contribution. Also, VIX seems to be more important than any single domestic fundamental for both type of flows and horizons.

In relation to the long-debated issue of the relative importance of pull and push factors, it turns out to be the case that the latter dominates the former as Figure A.19 depicts. On average, DC variables seem to have contributed towards the variability in PCFs by more than the domestic factors for both types of flows and in both quarters. Partial importance of domestic factors, excluding flows' own innovations from domestic contributions, seems to increase in the longer horizon of 4Q , even though they are still outweighed by the DC factors.

Concerning $EF^\star$ and $DF^\star$, which directly proxy for possible inter-linkages of flows across countries, results suggest that $EF^\star$ and $DF^\star$ variables contributes to the variability of their domestic counterparts by more than the domestic fundamentals and almost as much as DC variables on average across countries. Besides the average contributions, there are notable differences across the sample countries in the importance of these factors. Furthermore, there seems to an interesting pattern in terms of the relative importance of $EF^\star$ and $DF^\star$ with respect to DC-push factors. Flows to countries that are smaller in terms of GDP seem to depend more on flows to other countries, especially for equity flows. The correlations of economic size with $EF^\star(DF^\star)$ contributions in 0 and 4 quarters are respectively -21% (-01%) and -27% (-05%).[28] Furthermore, the correlation

[28]GDP-PPP (averages of 2006-2008) values have been used for this exercise.

between the economic size of the country and the ratio of normalized contributions of $EF^{\star}(DF^{\star})$ to DC-push factors are -41% (-14%) and -49% (-21%) in 0 and 4 quarters respectively. Hence, the findings imply that PCFs to countries that are smaller in economic size are more subject to spatial dependencies and/or contagion.

In a related GVAR application to net foreign asset positions (NFA) of 3 Latin American countries, Boschi [2007] finds that domestic factors play a greater role for NFA than the external factors, which seems not to be the case for PCFs as the evidence here implies. However, the apparent heterogeneity about the relative importance of variables is also present for the relative importance of domestic and foreign factors, even across types of flows. For instance, the country in which the average forecast errors of equity flows can be explained most by the DC factors is South Korea by approximately 27% in 0Q and 20% in 4Q, whereas the country with least equity flows dependence on push factors is Morocco by 3% in 0Q and 5% in 4Q. Similar heterogeneity of pull-vs-push factors across countries also exists for debt flows; with maximum push-factors contribution of 23% in 0Q and 21% in 4Q for South Africa; minimum of 2% in 0Q and 4% in 4Q for Colombia.

Compared to the existing literature, there are several points to be highlighted. First, the evidence from Ghosh et al. [2012] suggest that foreign interest rates are important drivers of flows, whereas the results from the GFEVDs suggest that foreign interest rates are not one of the key drivers of flows. This particular finding is in line with Forbes & Warnock [2012a], as the authors find that foreign interest rates are not related to capital inflows surges/stops. On the other hand, Forbes & Warnock [2012a] find that global growth is a key factor for surges and stops, which is consistent with the evidence obtained in here. Regarding the domestic fundamentals, Ghosh et al. [2012] suggests the importance of real effective exchange rate and real GDP whereas Forbes & Warnock [2012a] depict some evidence for the role of Y. Although their findings are broadly consistent with the results obtained in this chapter, as discussed above, there is notable degree of heterogeneity across countries for the importance of different fundamentals. Another interesting result is the relative importance of real GDP for debt flows compared to equity flows (especially in 0Q), which similarly appears among the findings of Forbes & Warnock [2012b] as the authors depict that growth shocks are much more important for debt flows related surges than equity flows related.

3.6.5 Robustness Checks

This subsection presents the robustness checks conducted to find out whether the results of the benchmark model are robust with respect to model specification. More specifically, results from two alternative model specifications are presented. First one involves a GVAR model with different number of co-integration relationships between model variables, named rGVAR. In this specification, every model involves one less cointegration relationship compared to the benchmark. The other involves a smaller model without credit ratings and reserves to debt, named sGVAR.

[Table A.10 in here]

Table A.10 depicts the robustness checks performed with alternative model specifications for EM-equity and debt shocks. Specifically, it reports 4Q-ahead cross-sectional correlations of the GIRFs obtained from alternative specifications with the benchmark GIRFs across given variables. In both rGVAR and sGVAR model, the GIRFs obtained with alternative specifications are very similar to the Benchmark case. It is possible to see that for most variables the correlations with the benchmark case is above 85%. For some variables the correlations fall, but the reason for that is single outliers observed in the results for that particular variable and specification.

[Table A.11 in here]

Table A.11 presents the cross-sectional correlations of 4Q cumulated SGIRFs, calculated for a risk aversion shock across alternative model specifications with the benchmark case. The results are clearly robust with respect to the model specification and the correlations are above 95% in all cases.

[Table A.12 in here]

Finally, Table A.12 presents the cross-sectional correlations of the average contributions of different set of variables, obtained from the GFEVDs across alternative model specifications, with the benchmark average contributions. It can be observed that the results are robust with respect to the changes in the cointegration specification of the model since the correlations for rGVAR are mostly above 90%. In case of the smaller model, correlations go down slightly, especially for domestic contributions. However, the reason for that is quite intuitive. Given the results presented in the GFEVDs section for the importance of reserves to debt and credit ratings, omitting these variables causes the overall contribution of the domestic variables to go down in each country, to the degree that these variables matter for the given country. Together with the heterogeneity across countries in the importance of these variables, it is natural to observe a slight decline in the correlations.

Overall, the findings from the robustness checks imply that the results presented in this section are robust with respect to model specification.

3.7 Multilateral Implications of Capital Controls

Capital account liberalizations and the accompanied capital inflows are considered to be beneficial for EMs since they lower the cost of borrowing, bring about required finance for investment, deepen financial markets and promote the development of regulatory frameworks.[29] However, faced with inflows that are in a speculative and volatile form, policy makers in the developing world resort to various kinds of measures[30] in order to reduce macroeconomic and financial stability risks flows constitute. One of the most controversial of these measures is capital controls. As mentioned earlier, Ostry et al. [2012] warns against the possible deflection effects that may results from imposition of controls across countries. Given these considerations and the strength of the GVAR model presented here in addressing issues related to international dependencies, this section attempts to present evidence on the presence of such effects. Subsection 3.7.1 describes the modifications to the benchmark specification and the capital control measure employed; subsection 3.7.2 discusses various robustness checks performed and finally subsection 3.7.3 presents the results.

3.7.1 The Model and the Data

The benchmark GVAR model presented in the previous section has been modified in several ways. First modification has been to change the sample period to make it consistent with the shorter sample period available for the capital controls measure employed. Namely, modified sample period covers the period of 1990Q3-2008Q3.

The specifications of country models are almost identical to the benchmark model. The only difference is in the case of Peru, where domestic inflation and interest rates are excluded since their inclusion results in a highly non-stable GVAR model.[31]

A common difficulty in studying the effects of capital controls is about how to measure capital controls. As described in Kose et al. [2009], the past literature has used various different measures of capital controls, which are classified in two categories, de jure and de facto measures. Following Kose et al. [2009], de jure measures are mostly constructed using the IMF AREAER. As the authors argue, however, these measures do not necessarily reflect actual capital account openness and how well the controls are enforced. They rather argue in favour of de facto measures, which should better reflect the actual

[29]See Kose et al. [2009] for a detailed discussion of financial integration.

[30]For instance monetary, fiscal, micro or macro prudential measures.

[31]The reason for that is certainly the fact that inflation has jumped up tremendously just in the beginning of the sample period.

financial openness/segregation of a country. The authors later employ a quantity based measure from Lane & Milesi-Ferretti [2006]. In this chapter, another de facto measure has been employed, from Edison & Warnock [2003]. But, as a robustness check, the de jure measure constructed by Chinn & Ito [2008], based on the IMF AREAER, have also been used.

The choice of Edison & Warnock [2003] measure, in particular, has been done with several considerations. The first one relates to the above discussed arguments of Kose et al. [2009]. In the context of the GVAR model here, it is a key issue to employ measures that are comparable in every aspect across countries. As discussed, de jure measures, which do not reflect how well the controls are administered, may suffer from severe biases across countries. In other words, even though the controls measure indicates that two countries have similar degree of capital account openness, one may be able to better enforce these measures compared to others. Then naturally, it is not possible to obtain meaningful results from the GVAR model since the capital control variables included in the model for different countries do not really incorporate same degree of correct information. Another consideration is certainly the need for a relatively high frequency measure. The popular (de facto) Lane & Milesi-Ferretti [2006, 2007] measure, which considers the sum of gross inflows and outflows as a percentage of GDP as a measure of openness, is available in yearly frequency and would possibly incorporate considerable noise at a high frequency. With these considerations, Edison & Warnock [2003] measure has been employed which is available in high frequency for many countries and for a large part of the overall sample period. The major shortcoming of the Edison & Warnock [2008] is the fact that it only captures the direct investment restrictions imposed on the stock market. Hence, it does not capture other types of controls, including taxes or controls imposed on other securities or derivatives. It is for that reason, robustness checks have been conducted with Chinn & Ito [2008] measure.

Edison & Warnock [2003] measure is calculated using the S&P IFCG and IFCI indices. Since the IFCI index consists of stocks that are the investable part of the stocks in the IFCG index, the ratio of the market capitalization of these indices naturally yields a measure of equity market openness and hence a measure of capital controls for a given country. Formally, the measure for country i at time t is given by,

$$FOR_{i,t} = 1 - \frac{MC_{i,t}^{IFCI}}{MC_{i,t}^{IFCG}}$$

where FOR indicates the intensity of controls and MC indicates the market capitalization of all stocks for a given index. So, if the stock market of a country is completely segmented, then the measure is equal to 1, and if the market is completely open to foreign investment, then the ratio is equal to 0. Edison & Warnock [2003] suggests that the above described measure can be improved by smoothing it to correct for asymmetric price fluctuations in two indices. In other word, ranom and independent price movements in IFCI and IFCG indices may result in the market capitalizations to change, hence the measure to change without any actual change in the intensity of controls. The smoothed measure is given by,

$$FOR_{i,t} = 1 - \frac{(MC_{i,t}^{IFCI}/P_{i,t}^{IFCI})}{(MC_{i,t}^{IFCG}/P_{i,t}^{IFCG})}$$

where P indicates the price series for a given index. In fact, the smoothed measure is the version used in this chapter. As an evidence of the accuracy of their measure, Edison & Warnock [2003] analyse the relationship of their measure with other widely used measures in the literature and find that their measure is related and comparable to other measures.

Edison & Warnock [2003] capital controls data is available from the authors, however their sample ends in 2006. So, in order to extend the sample size as much as possible, the measure has been reconstructed for all countries under consideration, using the data obtained from Datastream. Corrections to certain periods in the data have been done following the ones that are originally carried out by Edison & Warnock [2003]. The extended dataset runs from 1990Q3-2008Q3 and includes 12 countries: Argentina, Brazil, Chile, Egypt, India, Indonesia, Korea, Mexico, Philippines, Taiwan, Thailand and Turkey. Figure A.20 plots the average controls measure for 12 countries in the sample. One can see that the measure captures the increasing trend of globalization observed for emerging market countries during the period considered here.

[Figure A.20 in here]

In construction of the foreign-star variables, same methods described in the benchmark model for constructing the weights have been used for the variables from the benchmark case. For capital controls variables, a different method has been used. Given the attention on the deflection effects, the weights should reflect the relative importance of foreign countries in attracting foreign capital. So, foreign weights are constructed as $AF_i/\sum_j AF_j$, where AF_x represents average inflows to country x during the sample period.

With the above described specifications, GVAR models have been estimated for equity flows and debt flows models separately. Both models have been found to be stable.

3.7.2 Robustness Checks

In order to check for the robustness of the results with respect to the capital controls measure employed, Chinn & Ito [2008] capital account openness measure has been also used. However, since the data provided by the authors is yearly, interpolation procedures have been implemented to get quarterly version of the controls data. Also, to check for robustness with respect to the interpolation technique, 2 different interpolation procedures have been employed, Boot et al. [1967] and Chow & Lin [1971] procedures. In the latter case, quarterly Edison & Warnock [2003] measure have been used as an indicator variable to obtain the high frequency Chinn & Ito [2008] measure. Furthermore, to check whether the results are robust with respect to changes in the model specification, two additional models are estimated as it has been done in the previous section, rGVAR and sGVAR. Finally, robustness checks involving structural identification have been performed. Namely, triangular identification scheme of Sims [1980] and sign identification methodology described in Rubio-Ramirez et al. [2010] and Blake & Mumtaz [2012] have been used to identify structural capital controls shocks. Also, for both cases the robustness of results with respect to the assumption about the structure of the off-diagonal elements of the variance-covariance matrix of residuals have been checked. In other words, results are calculated by assuming both a variance-covariance matrix that is block diagonal (no contemporaneous correlation of shocks across countries) and the standard residual variance-covariance matrix.

In the triangular identification scheme, 2 different orderings for model variables are considered. In the first one, controls are allowed to respond contemporaneously to inflow shocks and in the other they do not respond to inflow and other structural shocks contemporaneously. Specific ordering of the variables, respectively for the two cases are, $SR - SM - Dcpi - Reer - CA - RSD - CR - Y - F - CC$ and $CC - SR - SM - Dcpi - Reer - CA - RSD - CR - Y - F$. The reason for examining these two cases is to check the robustness of the results with respect to the ordering of variables, as it has been similarly done by Edwards [1998] and Cardoso & Goldfajn [1998].

[Table A.18 in here]

Sign identification procedure involves imposing constraints on the signs of the impulse responses of model variables to the structural shocks. As discussed in Fry & Pagan [2011], in order to distinguish between the structural shocks, one has to impose adequate restrictions. For that reason, the GVAR model has been estimated with smaller number of domestic variables for EMs. Specifically, current account , credit ratings and reserves to debt variables have been excluded from the benchmark specifications. Then, by taking guidance from the existing literature, sign restrictions have been imposed to identify structural supply, demand, monetary policy, inflow and capital control shocks. The signs for the supply, demand and monetary policy shocks have been obtained from Rafiq & Mallick [2008], Peersman & Straub [2009] and Cassola & Morana [2004]. Following Cardarelli et al. [2010], capital inflow surges have been associated with overheating pressures, hence the inflows shock has been informally assumed to generate as such effects on domestic variables contemporaneously. Finally, controls shock is assumed to be effective in lowering the volume of inflows and resulting in a fall in real equity prices following Henry [2000]. Table A.18 summarizes the signs imposed on the contemporaneous responses of model variables to the structural shocks.

The methodology for the sign restrictions starts with taking the cholesky decomposition of sample variance-covariance matrix of country model residuals, $\Sigma_{it} = P'_{it}P_{it}$. The objective is to recover the contemporaneous impact matrix A_{it} in $A_{it}\eta_{it} = \epsilon_{it}$, where η_{it} represents the structural shocks assumed to be uncorrelated with each other with unit variances. The identification problem is certainly evident given that any matrix B with the property of $BB' = I$ can be used to express, $A_{it}A'_{it} = \Sigma_{it} = P'_{it}P_{it} = P'_{it}BB'P_{it}$. Hence, both $A_{it} = P'_{it}$ and $A_{it} = P'_{it}B$ are valid candidates. Sign identification procedure described in Rubio-Ramirez et al. [2010] and Blake & Mumtaz [2012] involves generating a random K matrix, then decomposing it using QR decomposition as $K = \bar{B}R$ with $\bar{B}\bar{B}' = I$ and finally substituting $\bar{B}$ to obtain $\bar{A}_{it} = P'_{it}\bar{B}$. If $\bar{A}_{it}$ satisfies the sign restrictions it is kept, otherwise the same procedure is applied with a new random K matrix until all sign restrictions are satisfied. Once the structural shocks are recovered for all country models, the GVAR model has been transformed following the procedure in Dées et al. [2007b].

3.7.3 Results

Tables A.14 and A.15 summarize the results from the GIRFs for country-specific positive capital controls shocks in a matrix form. For most country pairs (shock-response), equity and debt flows responses have been found to be insignificant. So, Table A.14-A.15 reports only the countries with significant responses. Furthermore, the entries in blue indicate that a given entry is robust with respect to model specification. Results suggest that only in Chile capital controls seem to be effective in changing the level of equity flows, since the contemporaneous response is negative and significant. Examining 1Q ahead responses, equity flows to Taiwan becomes strongly negative and significant, however, equity flows to Turkey become positive and significant. Overall, one can conclude that there exists weak evidence on the effectiveness of controls in changing the level of equity flows among the sample of countries; since only 3 out of 11 countries respond significantly, and among these 2 respond negatively as expected, which is consistent with the literature.[32] One has to note that, since the tightening controls imply an increase in foreign ownership restrictions, one might argue that equity flows may instantly decrease. However, mostly the new restrictions do not force old investors to liquidate their positions instantly.

[Table A.14 in here]

To the degree that equity market restrictions are introduced as part of a broader capital controls package, capital control variable captures overall tightening of controls. In fact, as mentioned earlier, Edison & Warnock [2003] find out that their measure is highly correlated with general measures of capital account openness. Moreover, even if the restriction is only in the equity market, investors' may form expectations of tougher restrictions in the given country overall.[33] Hence, Table A.15 presents the (significant) GIRFs for the debt flows responses, following a tightening of capital controls in each of the 11 countries. The only significant domestic responses are for Brazil in 0Q, Taiwan and Turkey in 1Q. Also, in Chile the 0Q response appears as close to being significant. The signs of the responses are respectively negative, negative, positive and positive. Overall, one may argue that the domestic effect of capital controls on debt flows is weak and its sign is ambiguous. The results obtained here are broadly consistent with Binici et al. [2010], who look for evidence of both the effectiveness of controls in changing the level of equity and debt inflows using panel data techniques. They conclude that controls have no significant effects on both type of flows across countries. However, one has to note that the pooled panel models may ignore the apparent heterogeneity across countries in terms of the relevant dynamics, as well as other spatial dependencies. As it has been shown here, in most cases the effects are insignificant; however for some countries there are some supportive evidence for the effectiveness of controls.

[Table A.15 in here]

Turning to the multilateral implications of controls through PCFs, Table A.14 indicates that the only significant positive deflection effects through equity flows in 0Q are for, Brazilian capital controls on Colombia; Mexican capital controls on Chile and Peru; Taiwanese capital controls on Argentina. Among the 1Q equity flows responses, the only significant responses are Argentinian capital controls on Korea (+); Brazilian capital controls on Argentina (+); Korean capital controls on South Africa (-); Taiwanese capital controls on Argentina (+), Colombia (+), Hungary (-), South Africa (-) and Thailand

[32] See Ostry et al. [2011a] for a discussion and an overview of findings in the literature.
[33] See Fratzscher et al. [2012a] for a discussion of the signalling channel.

(-). However, most of these significant responses are not robust with respect to model specification, as they become insignificant in rGVAR and/or sGVAR models.

Regarding the contemporaneous deflection effects through debt flows, Table A.15 indicates that the only significant responses are, for Brazilian capital controls on Indonesia (-) and Peru (+); Indonesian capital controls on Chile (-) and South Africa (+); Korean capital controls on Turkey (+); Mexican capital controls on Romania (+). Regarding the 1Q ahead GIRFs, the significant responses are, Korean capital controls on Peru (+) and Philippines (+); Filipino capital controls on Egypt (+). However, more than half of these responses seem not to be robust with respect to model specification.

As a further robustness check, Table A.16 presents the results from the GIRFs, using the Chinn & Ito [2008] measure, interpolated with Chow & Lin [1971] procedure. Entries in blue indicate the robustness of results with respect to the interpolation procedure. Comparing the results from Tables A.14-A.15 with Table A.16, it is possible to say that most of the significant responses reported in the tables are not robust with respect to either the model specification or the capital controls measure employed or both. However, for some country pairs the results seem to be robust across a majority of the alternative specifications and mostly have the expected signs. These country pairs are highlighted with a grey background. Moreover, examining these country pairs, there seems to be several interesting findings. Firstly, the domestic response to Brazilian and Chilean controls appear as significant, robust to model specification and almost in all cases have the expected sign. This suggests that Brazilian and Chilean controls are effective in altering the level of inflows. About the deflection effects, Brazilian controls seems to result in positive deflection effects to Colombia, since the response is significantly positive and robust across majority of the model specifications and controls measures employed. Also, Mexican controls seem to cause positive deflection effects on Chile and Peru, with mostly significant and robust responses across specifications. Given that these countries are in the same region, results seem to suggest intra-regional deflection affects in Latin America.

[Tables A.16, A.17 in here]

Table A.17 presents the results from the robustness checks involving the triangular identification procedure. Entries in blue represent robustness of the given result across the alternative specifications.[34] One can observe that the results obtained for the domestic and international effects of the Brazilian controls seem to be robust across the models estimated with triangular identification procedures. Furthermore, the table indicates

[34]Different orderings and the structure of the variance-covariance matrix.

that the countries towards which Brazilian controls result in deflection effects are also in the same region with the expected positive signs, Argentina and Peru. However, the deflection effect on Peru is not robust with respect to alternative specifications with triangular identification. Same is true for deflection effects from Mexico on Chile and Peru. Finally, the results from the GVAR model with sign restrictions indicate that there exists no deflection effects among any country pairs considered here.[35] So the results obtained with the previous specifications seem to disappear in the final robustness check involving the sign restrictions.

Overall results constitute weak evidence for the deflection effects. Among the majority of countries in the sample there appears to be no significant deflection effects. However, the signs of the responses among the country pairs with mostly robust and significant results appear to be consistent with the prior expectations. As mentioned earlier, Fratzscher et al. [2012a] analyse the effects of Brazilian controls on portfolio investment in Brazil and associated externalities for foreign investment in other countries. They find that the controls are effective in changing the level of portfolio investment in Brazil, and there are deflection effects on other countries. The evidence obtained here seems to be broadly consistent with their observation. In the benchmark and the majority of other alternative specifications, Brazilian controls seems to reduce debt flows to Brazil and cause deflection effects on other countries. One another interesting observation is that the country pairs with mostly significant and robust deflection effects locate in the same region and the responses are all positive. This is in line with the finding of Ghosh et al. [2012] who detect substitution effects within countries in the same regions. On the other hand, evidence from this chapter indicate that the findings of Fratzscher et al. [2012a] about Brazilian deflection effects seems not to be present for most of the other EM countries.

3.8 Conclusion

Following on from the analysis of Chapter 2, Chapter 3 examined the adjustment of international portfolio equity and debt investment to emerging markets. It contributes to the literature on international capital flows in various ways. Firstly, it suggests a GVAR model for modelling portfolio capital flows which incorporates stationary flow variables and non-stationary cointegrating fundamentals. Apart from the methodology, it presents evidence on both the existence of deflection effects resulting from imposition

[35] The results for the sign restrictions are not presented here to conserve space.

of capital controls and other widely debated aspects of capital flows that are relevant for optimal policy design using the model and the dataset constructed.

Through GIRFs, I determine the effects of inflow surges on domestic fundamentals. Results constitute evidence for overheating associated with capital inflow surges for many countries, demonstrating the ability of PCFs in generating macroeconomic risks. Typical effects involve increase in real equity prices, real GDP, inflation, real exchange rate appreciation and deterioration of the current account, broadly in line with Cardarelli et al. [2010]. Furthermore, by identifying structural risk aversion shocks (via VIX Index), I study the effects of an increase in risk aversion of foreign investors on portfolio capital flows. For most sample countries, the impact is significantly negative and varies across countries up to 2.2%-of-GDP fall in portfolio debt flows in 4 quarters following a one standard deviation shock. On the other hand, the impact seems to be rather muted for equity flows, which is consistent with the findings of Forbes & Warnock [2012b] about the insignificance of global risk for surge/stop episodes associated with portfolio equity flows.

GFEVDs for PCFs suggest, there exists a notable degree of heterogeneity across countries with respect to the relative importance of different fundamentals, especially for domestic variables. Global risk appetite, growth and the dynamics in the stock markets of the developed world seem to play key roles in driving flows to EMs. In fact, each of these factors' contributions heavily outweighs any domestic fundamental on average across countries. Regarding the relative importance of pull-vs-push factors, for both equity flows and debt flows, push factors seem to dominate the role of pull factors on average across countries.

Results indicate notable dependencies across PCFs to different EMs, which is in line with the recent findings in the literature, including Ghosh et al. [2012] and Forbes & Warnock [2012a]. On the other hand, from the analysis conducted here it is not possible to tell the source of this dependency or the direction of causality, which may be fundamentally important for optimal policy design both from country-specific and multilateral perspectives. However, there seems to be an interesting pattern concerning the relative importance of the spatial dependencies of flows. Flows to countries with smaller economic size are more subject to these dependencies compared to the bigger ones.

Spatial dependence is an important issue in panel data applications. Evidence from this chapter suggests that, following Pesaran [2006], previous panel data applications in the literature conducted on capital flows have possibly been subject to the problem of Cross-Sectional Dependence.

Regarding the ability of capital controls in altering the level of flows and creating deflection effects on other countries, there is no strong evidence on the effectiveness of controls in both limiting the level and causing deflection effects on flows to other countries. However, among many country-pairs investigated for deflection effects, the mostly robust and significant responses seem to be positive. Evidence presented in Fratzscher et al. [2012a] for the presence of deflection effects following Brazilian controls, seems to be present in the results obtained in here; however the same effects are not present for most of the other EMs. Moreover, examining the mostly robust and significant deflection effects, there seems to be a geographical pattern. More precisely, there seems to be intra-regional substitution effects for flows in Latin America.

Overall, findings in this chapter have important implications for policymakers across the EMs. PCFs seem to have played important roles in generating domestic risks in sample countries. Findings for the underlying drivers of PCFs reinforce the arguments of Ostry et al. [2010, 2011b] regarding the optimal policy design: it needs to take into account individual country circumstances. Flows to different countries seem to have different drivers, especially domestically. Also, flows to countries that are smaller in economic size are more subject to spatial dependencies and contagion. Finally, the constraint involving the deflection effects placed on the imposition of controls by Ostry et al. [2012], seems not to bind for the majority of countries. However, for the countries that it seems to bind, results indicate intra-regional deflection of flows.

In the next Chapter, this thesis takes a different empirical approach and focusses more specifically on the global drivers of capital flows. Furthermore, it investigates the implications of the Quantitative Easing Program implemented in the United States for international capital flows.

Chapter 4

Time-Varying Global Drivers of Portfolio Capital Flows and the Role of Quantitative Easing

4.1 Introduction

As it has been discussed in previous chapters, capital flows bring about not only many benefits and but also various dangers for EMs. The recent growing literature involving identifying capital flow episodes and their drivers is an obvious result of such concerns.[1] However, a common perspective in the empirical literature is the assumption of time-invariance of the sensitivity of capital flows with respect to the changes in underlying fundamentals. Clearly, in the presence of time-variation in the importance of underlying fundamentals, findings in the literature become questionable. It is for that reason; the first contribution of this chapter is to assess the time-varying importance of global factors for international PCFs in the last decades. Similar to the recent literature, the chapter attempts to identify episodes in PCFs and to look for heterogeneity in the characteristics of these episodes in terms of their time-varying drivers. Finally, given the recent debate on the role of QE in driving the recent surge in flows to emerging markets, I perform a counterfactual exercise to assess whether the same level of increase would be present without the QE in 2009.

Time variation in the global drivers in capital flows can be present because of various reasons. One of those reasons may be related to the composition of foreign investors investing in emerging markets and the change in their investment strategies. IMF [2011a]

[1] For instance, Forbes & Warnock [2012a] and Ghosh et al. [2012].

discuss the recent trends in asset allocation and composition of long term investors and document notable changes in both. With respect to investor behaviour, authors detect significant changes, especially during the recent crisis. In a recent related paper, Lo Duca [2012] present four reasons behind the possible time-variation in sensitivities. Author's first argument is based on the work of Mody & Taylor [2013]. Mody & Taylor [2013] model capital flows from a supply and demand perspective in which there may exist disequilibrium due to informational asymmetries. The observed flows are determined by either the supply or demand for capital, whichever is less than the other. Since the demand and supply are assumed to depend on different underlying fundamentals, depending on whether the supply or demand is larger, actual flows may depend on different fundamentals over time. Second argument is about the heterogeneity of foreign investors, which is in line with the findings of IMF [2011a]. Since investors make their investment decisions with respect to different criteria, observed flows may depend on different fundamentals over time with different active investors. Third, author argue that in turmoil times, investors with certain constraints may be pressurized to sell some of their assets in order to meet these constraints. Hence, the dynamics of certain benchmark assets may have amplified effects on observed flows. Last argument is about the change in the information set used by investors with different weights on different factors over time. In addition to Lo Duca [2012]' s four arguments, another important reason behind the time-variation could be financial liberalization of emerging markets over time. Bekaert et al. [2002] document structural break points in portfolio equity flows and observe that they coincide with equity market liberalizations. Also, Contessi et al. [2012] show some evidence for shifts in both the correlation of disaggregated capital flows with macroeconomic indicators and their second moments over time.

The time-variation in the drivers of capital flows may also be due to market inefficiencies. In fact, Grossman & Stiglitz [1980] argue that with costly information acquisition, the prices of assets in markets may not reflect completely all available information. Furthermore, Allen et al. [2006] argue that with both private and public information, prices of assets may still deviate significantly from their fundamental value. Given that emerging markets are considered to be subject to notable informational frictions, they may also be subject to market inefficiencies, which implies that noise traders can cause significant deviations in prices and hence returns. If different noise traders' actions are related to different random indicators, the prices and returns can then be correlated to different factors at different degrees over time. Finally, given that the literature, including Bohn & Tesar [1996], finds evidence for return chasing for international investors, these random fluctuations in asset prices may result in international capital flows to depend on different factors over time through noise traders. [2]

The presence of time-variation in the drivers of capital flows has important implications for examining various issues surrounding capital flows. For instance, many debate the role of the QE programme implemented in the United States (US) in driving flows to EMs during and after the recent global financial crisis and the possible implications of the termination of the program. In the existing literature time-varying parameter models have been employed to determine the effects of QE on several key macroeconomic variables.[3] Here, I perform a similar exercise to assess the role of QE in driving the observed surge in PCFs to EMs in 2009.

Previous chapter employed a GVAR model that can capture the common variation in capital flows to different countries via cross-sectional averages of country-specific domestic variables. In contrast, this chapter takes a different approach by implementing TVP models involving MCMC techniques in order to document the time-variation in the global drivers of PCFs. To abstract from country-specific factors, I extract common variations in PCFs to various EMs using PCA and include in a TVP-Regression as dependent variable with various widely debated global fundamentals. In order to carry out the counterfactual analysis, I take into account the dependencies between some of the fundamentals via a TVP-SVAR. The literature has used TVP-SVARs and TVP-FAVARs (Factor Augmented VARs) extensively to document dynamic and time-varying relationships of interest over time, with particular applications on monetary policy.[4]

Overall, results indicate notable degree of time-variation in the global drivers of PCFs. Widely debated variables like US interest rates and activity seem to have played major roles in driving flows to EMs. An interesting finding is, the impact of EM-specific fundamentals seems to be rather muted during early 90s, but it has a remarkably growing importance for flows in subsequent periods. This result possibly explains the early findings in literature, which emphasize the role of low interest rates and growth in developed countries to be the major drivers of flows in the beginning of 1990s. Using the methodology of Forbes & Warnock [2012a], I have identified a total of 5 surge and stop episodes and compare their time-varying drivers. The episodes seem to be notably heterogeneous in terms of their drivers. Lastly, results of the counterfactual exercise for QE indicate that the surge in flows during 2009 would not have happened in the absence of the QE program.

[2] Note that, even without informational frictions limits to arbitrage may cause market inefficiencies, see Barberis & Thaler [2003].

[3] See for instance Kapetanios et al. [2012] and Baumeister & Benati [2013].

[4] See for instance Primiceri [2005], Korobilis [2011], Korobilis & Gilmartin [2011], Nakajima [2011], Baumeister et al. [2010] and Mumtaz et al. [2011].

The chapter is organized as follows; Section 4.2 depicts the empirical models and the estimation, Section 4.3 discusses the dataset, Section 4.4 presents the results and finally Section 4.5 concludes.

4.2 Methodology

Following the literature, capital flows are assumed to consist of two components, one is a time-varying function of observed push factors and the other is a function of country-specific factors. Hence, by assuming that there is a common component of flows to different countries, it is possible to extract this factor from the data and investigate its time-varying relationship with the well-documented global (push) factors in the literature. This is achieved by treating the extracted factor as the dependent variable in a TVP-Regression model with various global fundamentals as explanatory variables. Main global (push) factors for portfolio flows (pcf) are chosen as US output gap (y), US short interest rates (r), US long term bond spread over the short rate (byr) and VIX index (vix). Since these variables are considered to be major global drivers of capital flows, with the results obtained here it is possible to make comparisons with the previous findings in an historical basis. Baseline global factors are augmented with an emerging market specific variable sm, which captures the common improvement or deterioration of emerging market fundamentals via emerging market stock market indices, similar to Lo Duca [2012].

In order to conduct the counterfactual exercise involving the US QE Program, one has to account for the dynamic relationship between US variables included in the TVP-Regression Model. Hence, the counterfactual time paths of US variables are obtained together from a TVP-VAR model, by taking guidance from Kapetanios et al. [2012], Baumeister & Benati [2013] on QE counterfactuals.

An alternative to estimating two separate models for portfolio capital flows and the US could have been to estimate a single TVP-VAR model with both flows and other US variables. However, given the complexity of the estimation procedure, it is important to keep the models as parsimonious as possible to avoid over-parameterization, as discussed in Koop & Korobilis [2010]. Since there is no strong prior regarding how and why the global component of portfolio capital flows to emerging markets would influence US domestic variables, it may be better to estimate a separate and more simple model for the US variables. Also, since portfolio capital flows are financial variables that are expected to adjust quickly, additional lagged explanatory variables may simply over-parameterize the model for flows.

Below subsections 4.2.1 and 4.2.2 involve, respectively, the description and the estimation of the TVP-Regression and TVP-VAR models involved in the chapter.

4.2.1 Models

4.2.1.1 TVP-Regression Model for PCFs

Observed flows to country i at time t, F_{it}, can be decomposed into two components, global (push) $Y_{it} : (1 \times T)$ and country-specific (pull) X_{it} factors.

$$F_{it} = \Lambda_i^Y Y_t + \Lambda_i^X X_{it}$$

Individual country-specific component X_{it} is assumed to have a representation as,

$$X_{it} = \Gamma_{it} e_{it}$$

where $e_{it} \sim N(0, \sigma^2_{e_i})$ is assumed to be uncorrelated with Y_t.

In line with the theoretical representation described, below factor model for PCFs is specified.

$$F_{it} = \Lambda_i^Y Y_t + u_{it}$$

where $u_{it} = \Lambda_i^X \Gamma_{it} e_{it} \quad \forall i = 1, 2, 3, ..., N$.

The common factor, Y_t, is assumed to depend on various global fundamentals $\bar{Z}_{t-1}$ via following TVP-Regression Model,

$$Y_t = \beta_{Y,t} \bar{Z}_{t-1} + (e^{\sigma^2_{\varepsilon,t}/2}) \varepsilon_{Y,t}$$

where $\bar{Z}_t = [\hat{Z}_t'; \bar{X}_t']'$, $\varepsilon_{Y,t} \sim N(0,1)$[5] and $e_{\phi,t} \sim N(0,\theta_\phi)$ $\forall \phi = \beta_Y, \sigma_\varepsilon$ in equations,

$$\begin{aligned} \beta_{Y,t} &= \beta_{Y,t-1} + e_{\beta_Y,t} \\ \sigma^2_{\varepsilon,t} &= \sigma^2_{\varepsilon,t-1} + e_{\sigma_\varepsilon,t} \end{aligned}$$

$\bar{X}_t$ represents a common component across country-specific factors that is independent of global-push factors. It may represent improved governance, policy and financial liberalization trends observed in the last decades across emerging markets.

4.2.1.2 TVP-VAR Model for the United States

As described previously, a subset of global variables in the TVP-Regression Model may depend on each other. So, in order to conduct the counterfactual analysis, one has to account for the dependencies among output gap, short interest rates, spread and *vix*. Moreover, in order to incorporate some of the key macroeconomic relationships in the model, an inflation variable is added, p. Below is the description of the TVP-VAR model estimated for the given variables.

Assume that $Z_t : (m \times T)$ includes m variables that is a subset of M variables, $\hat{Z}_t$: $(M \times T)$ that depend on each other. Z_t is assumed to follow,

$$A_t Z_t = \Pi_{t1} Z_{t-1} + \Pi_{t2} Z_{t-2} + ... + \Pi_{tp} Z_{t-p} + \Sigma_t \varepsilon_t \tag{4.1}$$

where $\varepsilon_t \sim N(0, I_{\mathbf{m}})$ and $\Omega_t = A_t^{-1} \Sigma_t \Sigma_t' A_t'^{-1}$.

$$A_t = \begin{bmatrix} 1 & 0 & . & 0 & 0 \\ a_{21,t} & 1 & . & 0 & 0 \\ . & . & . & . & . \\ a_{(k-1)1,t} & a_{(k-1)2,t} & . & 1 & 0 \\ a_{k1,t} & a_{k2,t} & . & a_{k(k-1),t} & 1 \end{bmatrix}$$

[5] Note that $\sigma^2_{\varepsilon,t}$ is the log-variance of the residual of Y_t. The reason for dividing $\sigma^2_{\varepsilon,t}$ by 2 in this representation is because the estimation procedure of Kim et al. [1998] involves taking the square and then the log of the residuals, hence 2 cancells out for simplicity.

$$\Sigma_t = \begin{bmatrix} e^{h_{1,t}/2} & 0 & . & 0 & 0 \\ 0 & e^{h_{2,t}/2} & . & 0 & 0 \\ . & . & . & . & . \\ 0 & 0 & . & e^{h_{(k-1),t}/2} & 0 \\ 0 & 0 & . & 0 & e^{h_{k,t}/2} \end{bmatrix}$$

Equation (4.1) can be rewritten as,

$$Z_t = \beta_{t1} Z_{t-1} + \beta_{t2} Z_{t-2} + ... + \beta_{tp} Z_{t-p} + A_t^{-1} \Sigma_t \varepsilon_t$$

where $\beta_{tj} = A_t^{-1} \Pi_{tj} \quad \forall j = 1, 2, 3, ..., p.$

The parameters of the model are assumed to follow the processes below.

$$\begin{aligned} \beta_{j,t} &= \beta_{j,t-1} + e_{\beta,t} \\ a_{lk,t} &= a_{lk,t-1} + e_{a,t} \\ h_{l,t} &= h_{l,t-1} + e_{h,t} \end{aligned}$$

$e_{\phi,t} \sim N(0, \Theta_\phi), \quad \forall j = 1, 2, 3, ..., p, \quad \forall l, k = 1, 2, 3, ..., m, \quad \forall \phi = \beta, a, h.$

4.2.2 Estimation

First step of the estimation procedure is to extract the common factor Y_t from the flow data, which is carried out with PCA. Even though the PCA analysis is simple to conduct, an alternative way could be to use a single step estimation procedure in which factors are treated as unobserved and estimated together with other parameters in the TVP-Regression model, as similarly discussed by Korobilis [2011]. Korobilis [2011] consider this alternative one-step estimation strategy for a TVP Factor Augmented VAR Model. The author argues that, since the TVP model already involves a complicated MCMC procedure, he prefers to use PCA as the first step of the two-step estimation strategy following Stock & Watson [2005]. Furthermore, Bai [2003] study the estimation of large time and cross section dimension factor models by PCA. The author concludes that estimators of the PCA is super-consistent and PCA can successfully be applied to obtain the factors.

Estimations of both the TVP-Regression and the TVP-VAR models have been done using similar approaches. The posterior distributions of the parameters of interest have been obtained using MCMC simulation methods, Gibbs Sampling, following the estimation strategy laid out in Primiceri [2005] and Korobilis [2011].[6] In both models, the distributions of the parameters of interest are conditional on the values of other parameters in the model. Hence, Gibbs Sampling algorithm involves generating random draws from the conditional posterior distributions of respective parameters and iterating forward. After a given number of burn-in iterations of the procedure, random draws are assumed to be independent of the initial conditions and belong to the true posterior distributions of the parameters.

Estimation, for both models, can be described in below stages.

- Priors and Initial Conditions:

For both TVP-Regression Model and TVP-SVAR Model, prior mean and variances have been set to uninformative values given the small sample size. The parameters reflect several considerations. Firstly, both TVP-Regression and the TVP-VAR Model involve stationary variables. Hence the prior means of the coefficient of interests are set to less than 1, as discussed by Blake & Mumtaz [2012]. In particular, following Koop & Korobilis [2010], to avoid any possible over-parameterizations and hence to do shrinkage, prior means of the coefficients are set to 0 in both models. However, given the relatively short sample size and the uninformativeness of the priors, it is not a sensible choice to impose tight priors via small variances. For that reason, the prior variances have been set to relatively large values. Apart from the uninformative priors, another option is to obtain the priors using a training sample, as in Primiceri [2005]. However, data availability for portfolio capital flows and VIX Index makes it impossible set a training sample with adequate observations.

For the distributions of the variance-covariances of errors (θ_ϕ in $e_{\phi,t} \sim N(0, \theta_\phi)$ $\forall \phi = \beta_Y, \sigma_\varepsilon, \beta, a, h$), commonly used class of priors have been assumed; Inverse Gamma and Inverse Wishart for TVP-Regression and TVP-VAR Models. Namely,

TVP-Regression Model TVP-VAR Model

[6] Matlab codes provided by Koop & Korobilis [2010] (for Primiceri [2005]) and Blake & Mumtaz [2012] are modified by the author to carry out the estimation.

$$
\begin{aligned}
\beta_{Y,0} &\sim N(0, 10I_{\mathbf{m}}) \\
\sigma^2_{\varepsilon,0} &\sim N(-1.5, 0.02) \\
\theta^{-1}_{\beta_Y,0} &\sim G((0.01)^2 \cdot \\
&\quad (1+M)10I_{\mathbf{m}}), 1+M) \\
\theta^{-1}_{\sigma_\varepsilon,0} &\sim G((0.01)^2 10I_{\mathbf{m}}), 2) \\
e^{\sigma^2_{\varepsilon,0}/2} &= 0.01 \\
\theta^{-1}_{\sigma_\varepsilon,0} &= 0.0001 \\
\theta^{-1}_{\beta_Y,0} &= 0.0001I_{\mathbf{m}}
\end{aligned}
$$

$$
\begin{aligned}
\beta_0 &\sim N(0, 4I_{\mathbf{K}}) \\
A_0 &\sim N(0, I_{dim(A_0)}) \\
h_{l,0} &\sim N(1, 4) \\
\theta^{-1}_{\beta,0} &\sim W((0.01)^2(1+K)I_{\mathbf{K}}, 1+K) \\
\theta^{-1}_{A,0} &\sim W((0.01)^2(1+dim(\theta^{-1}_{A,0})) \cdot \\
&\quad I_{dim(A_0)}, 1+\theta^{-1}_{A,0}) \\
\theta^{-1}_{\Sigma,0} &\sim W((0.01)^2(1+m)I_{\mathbf{K}}, 1+m) \\
\Omega_0 &= 0.01I_{\mathbf{m}} \\
\theta_{h,0} &= 0.0001I_{\mathbf{m}} \\
\theta_{\beta,0} &= 0.0001I_{\mathbf{K}} \\
\theta_{A,0} &= 0.0001I_{(\mathbf{m(m-1)/2})}
\end{aligned}
$$

where $K = p \cdot m$.

- Sampling

Once the priors and the initial conditions have been set, MCMC algorithm involves sampling a draw from $p(\beta_T|Z_T, \Omega_T, \theta_\beta)$ using the state-space methods of Carter & Kohn [1994] as described in Koop & Korobilis [2010] and employed in Primiceri [2005].[7] Next, θ_β is obtained from its updated conditional distribution $p(\theta_\beta|Z_T, \beta_T, \Omega_T)$. Similarly, $At, \theta_A, \Sigma_T, \Theta_\Sigma$ are drawn in the given order as in Primiceri [2005] via Carter & Kohn [1994] and Kim et al. [1998].

4.2.3 Identification

The counterfactual analysis to be presented in this chapter involves conditional forecasting some of the TVP-SVAR model variables. The conditional forecasts have been obtained using the procedure outlined in Blake & Mumtaz [2012], which is based on Waggoner & Zha [1999] and Doan et al. [1983]. The methodology requires the identification of Monetary Policy and Spread shocks. The identification of the aforementioned shocks have been achieved by taking guidance from Kapetanios et al. [2012], Baumeister & Benati [2013] and Gambacorta et al. [2012]. The monetary policy shock is assumed to increase short interest rates and decrease worsen the output gap, decrease inflation

[7]Note that stationarity is imposed by inspecting the resulting eigenvalues of the model with the sampled $\{\beta_i\}_{i=1}^{i=T}$. If the model is not stationary in one or more time period(s), another $\{\beta_i\}_{i=1}^{i=T}$ is sampled. However, in order to prevent the MCMC algorithm to get stuck, after 100 tries, the first set of $\{\beta_i\}_{i=1}^{i=T}$ that yields a model that is non-stationary in less than 6 periods is kept.

and long interest rates contemporaneously. The spread shock, which is used as a proxy the Quantitative Easing Program, is assumed to increase long interest rates and the vix index, worsen the output gap, decrease the inflation and have no effect on short interest rates contemporaneously. Notice that the two shocks are identified as they have effects on some of the variables with different signs. Technically, shocks are identified using both sign and zero restrictions. Table 4.1 below summarizes the restrictions.

TABLE 4.1: Identification: Sign and Zero Restrictions

	Response				
Shock	p	y	r	byr	vix
Monetary Policy	$<$	$<$	$>$	$<$	?
Spread	$<$	$<$	0	$>$	$>$

The procedure described in Rubio-Ramirez et al. [2010], Blake & Mumtaz [2012] and employed in Baumeister & Benati [2013] is implemented to impose above depicted restrictions. First step is to decompose the reduced form variance-covariance matrix Ω_t using cholesky decomposition as $\Omega_t = \Phi_t \Phi_t'$. Next, a random matrix A from $N(0,1)$ distribution is drawn and QR decomposition is applied to get the orthonormal Q matrix. Since $\Phi_t \Phi_t' = \Phi_t Q Q' \Phi_t'$, any Q that satisfies above restrictions can be considered as a candidate. Next, $\bar{\Phi}_t = \Phi_t Q$ is calculated. Before checking for sign restrictions, the zero restriction is imposed using a rotation matrix R.[8]

$$\mathbf{R} = \begin{pmatrix} \begin{matrix} cos(\lambda) & -sin(\lambda) \\ sin(\lambda) & cos(\lambda) \end{matrix} & 0 \\ 0 & I_4 \end{pmatrix}$$

where $RR = I$, $\lambda = tan^{-1}(\bar{\Phi}_{12,t}/\bar{\Phi}_{11,t})$. Rotated contemporaneous impact matrix, $\tilde{\Phi}_t = \bar{\Phi}_t R$, satisfies the zero restriction by definition. Finally, if it satisfies the sign restrictions, it is kept, otherwise a new A matrix is drawn and the procedure is repeated until all restrictions are satisfied.

[8] The variables are re-ordered before rotation, so that y, r locate in 1st and 2nd orders respectively.

4.2.4 Counterfactual Anaylsis

The methodology to obtain the counterfactual forecasts of US variables has been specified by taking guidance from Kapetanios et al. [2012] and Baumeister & Benati [2013]. Major assumptions made for the counterfactual analysis relates to the policy variable and its counterfactual time path. Similar to the mentioned papers, policy variable for QE has been taken as long term US government bond spread minus short rate (byr). US QE program is assumed to lower the spread by 60 basis points (bps) during 2009 as in Baumeister & Benati [2013], who use the estimates of Gagnon et al. [2011].

As in Kapetanios et al. [2012], 2 different scenarios (conditional forecasts) are considered and compared: With-QE and Without-QE. In the former case, forecast of inflation, output gap and the VIX index has been obtained using the estimated parameters of the TVP-SVAR at 2008Q4, conditional on the actual realizations of short interest rates and the spread during 2009. The latter scenario without QE involves the same conditional forecast, but with spread being 60 bps higher than its actual realization during 2009. Comparing the conditional forecasts under 2 scenarios, the relative impact of QE is determined.

Once the conditional forecasts of US variables are obtained with and without QE, a similar counterfactual analysis is conducted with the TVP-Regression model for PCFs. Specifically, With-QE conditional forecast is carried out based on the estimates of 2008Q4 and conditional on the actual realizations of 2009 explanatory variables. Without-QE counterfactual is carried out in a similar way, but conditional on the counterfactual paths of US variables that are calculated by subtracting/adding the difference between the 2 conditional forecasts obtained from the TVP-VAR models from/to the actual realizations of US explanatory variables. Moreover, in both models the forecasts are conducted in each Gibbs iteration. The median values for forecasts are taken from TVP-SVAR model and used in TVP-Regression Model conditional forecasts. In both scenarios, given that the US variables enter the TVP-Regression model with a lag, conditional forecasts of portfolio flows are obtained for 2009Q2-2010Q1.

4.3 Dataset

Empirical Methodology described in the previous section has been implemented for the period of 1987Q4 - 2013Q1. In contrast to Lo Duca [2012], this chapter employs quarterly data. One reason for doing so is to extend the period under investigation, as there is no

Table 4.2: List of Countries included in the TVP-Regression Model

pcf			*sm*	
Argentina	Indonesia	South Africa	Argentina	Pakistan
Brazil	Mexico	Taiwan	Brazil	South Africa
Chile	Pakistan	Thailand	Chile	Taiwan
Colombia	Peru	Turkey	Colombia	Thailand
Indonesia	Poland		Egypt	Turkey
Mexico	Romania		Hungary	

available dataset going back until 80s for daily portfolio capital flows. Another reason is, to conduct the counterfactual analysis; one has to account for the dependencies among the explanatory variables. It may not be possible to easily detect these dependencies using daily data, for instance the effect of a monetary policy shock on the output gap. In particular some of the key macroeconomic variables are not even available in monthly frequency. Also, some of the variables may depend on expectations, like inflation. On the other hand, given the persistence of these series, the effect of shocks on expectations, and through expectations the variables may take time to propagate, which may make quarterly data more appropriate.

The choice of the sample period is in line with the objectives of this chapter, which include documenting any possible time-variation in the drivers of PCFs during the widely debated recent decades and assessing whether widely-accepted findings in the literature are robust with respect to time. So, the baseline variables are chosen by taking guidance from the literature as US output gap (y), US short interest rates (r), US long term bond spread (byr) and VIX index (vix). Additionally, one may argue that the co-movement of flows extracted via PCA may incorporate not only the global push factors Y_t, but also part of the pull factors that may be common across different countries, if there exists any. So, another fundamental has been included to account for the common improvement or deterioration of emerging market fundamentals, sm. In order to prevent possible endogeneity with portfolio flows, one quarter lagged version of explanatory variables are included in the TVP-Regression.

Explanatory variables in the TVP-Regression model are obtained as follows. US output gap is constructed by applying the HP filter, discussed in Hodrick & Prescott [1997], to the logarithm of the quarterly US real GDP series obtained from Federal Reserve Bank of St. Louis (St. Louis Fed) Database.[9] US short interest rates is the effective

[9]I have preferred the HP filter because of its simplicity in implementation. But, there are other alternative ways to calculate the output gap. Billmeier [2004] discusses some of the alternative methods, including other statistical filters like Corbae & Ouliaris [2002] or theory based methods like Blanchard & Quah [1990]. The author conclude that none of the alternative measures seem to dominate the others across several European Countries.

Table 4.3: Testing for the Number of Factors

IC1	IC2	IC3	PC1	PC2	PC3	BIC3	AIC3
1	0	1	8	6	8	8	1

federal funds rate, byr is the spread between 10-Year treasury constant maturity rate and US short interest rate series obtained from St. Louis Fed. vix is VXO Chicago Board Options Exchange S&P 100 volatility index obtained from Datastream. Finally, sm is calculated by taking the first principle component of local stock market returns in countries listed in Table 4.2 and orthogonalizing with respect to all other explanatory variables and US stock market returns. Data sources for individual stock market data are given in the Appendix.

There are some differences in the explanatory variables used in this chapter compared to the ones used in Chapter 3. First of all, as this chapter focusses on the global drivers of portfolio capital flows, I have mainly excluded country-specific variables in the analysis. Also, TVP models have many parameters to estimate; hence a more parsimonious model is preferred. Regarding the global drivers, bond spread is used mainly as a proxy for the Quantitative Easing Program in the US. Another difference is for the US output gap variable. In chapter 3, one consideration in the specification of the GVAR model was to construct a comprehensive global econometric model. Hence, as the real GDP variable includes both the cyclical and the trend part of economic activity, it is favoured. On the other hand, the cyclical part of US economic activity is considered to be a major driver of portfolio capital flows.[10] For that reason, US output gap variable is used in the marginal model for portfolio capital flows.

In the TVP-SVAR Model, in addition to output gap, short interest rates, spread and vix, as a measure of inflation, implicit price deflator series p obtained from St. Louis Fed is used. Purpose for the inclusion of inflation is to construct a small representative model for the US economy.

Dependent variable in the TVP-Regression model, pcf, represents the first principle component extracted from the portfolio flows (equity+debt) data to 16 emerging market countries listed in Table 4.2. The sample countries are chosen on the basis of data availability in the sample period considered, for both portfolio equity and debt flows. Findings in Chapter 3 suggest that there is heterogeneity in the importance of pull vs push factors for portfolio capital flows. This may indicate that the first principle component of flows to different countries may account different proportion of the variation of flows to different countries. Apart from the heterogeneity, one may wonder whether

[10] See for instance Edison & Warnock [2008].

Table 4.4: Factor Loadings and Variation Explained for Sample Countries

	Arg	Bra	Chil	Col	Egy	Hun	Indo	Mex
F. Loading	0.48	0.84	0.73	0.56	1.01	1.22	1.04	1.21
R Square	4%	13%	9%	6%	19%	27%	20%	27%

	Pak	Per	Pol	Rom	Saf	Taiw	Thai	Tur
F. Loading	0.95	1.21	1.25	0.81	0.93	1.16	1.54	0.18
R Square	16%	26%	28%	12%	16%	24%	43%	1%

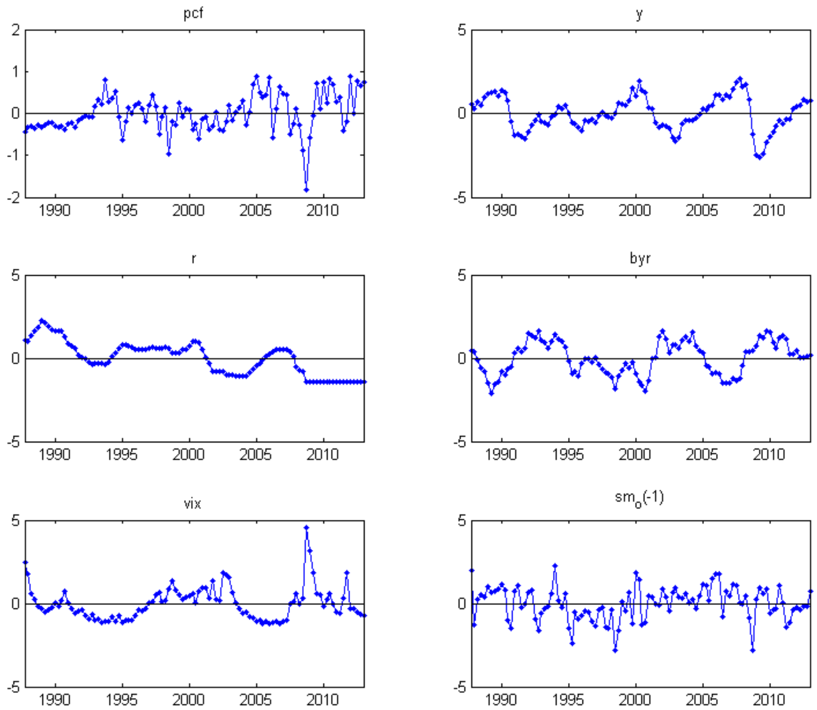
the first principle component is adequate in explaining the common variation in flows to different countries. In order to verify, various testing criteria proposed and described in Bai & Ng [2002] are calculated and used.[11] Table 4.3 presents the suggested number of principle components by Bai & Ng [2002] testing criterias.[12] One can observe that AIC3 and the majority of IC criterias suggest that a single factor is adequate. On the other hand BIC 3 and the majority PC factors seem to suggest the maximum number of factors, 8. To examine the accuracy of their suggested test criterias, Bai & Ng [2002] conduct simulation exercises with different number of cross sections and time periods. Interestingly their baseline simulations results with 20 cross-sections and 100 time observartions (closest to the case in here) indicate that IC criterias give the most precise predictions of true number of factors.[13] Hence, I conclude that the first principle component is adequate in explaining the common variation in flows to different countries.

To check whether the heterogeneity in the drivers of flows across countries observed in the results in Chapter 3, Table 4.4 presents the factor loadings and R Square statistics for flows to different countries. One can observe that the factors loadings and R Square statistics vary greatly across different countries, supporting the results obtained in Chapter 3.

Country level flow series have been normalized by nominal GDP (NGDP) and represent *gross flows*. The source of the NGDP and flow data is the dataset described in Appendix A, in which various interpolation procedures have been implemented on data from various sources in order to obtain some of the missing quarterly flow and NGDP series. Also, the dataset has been updated until 2013Q1. List of countries included in the models are given in Table 4.2.

[11]The tests are conducted using the Matlab codes provided by Hurlin [29 January 2013].
[12]Maximum number of principle components has been set to 8 as in Bai & Ng [2002].
[13]Refering to the results presented in Tables 1-3 in Bai & Ng [2002].

FIGURE 4.1: *pcf* and Variables



4.4 Results

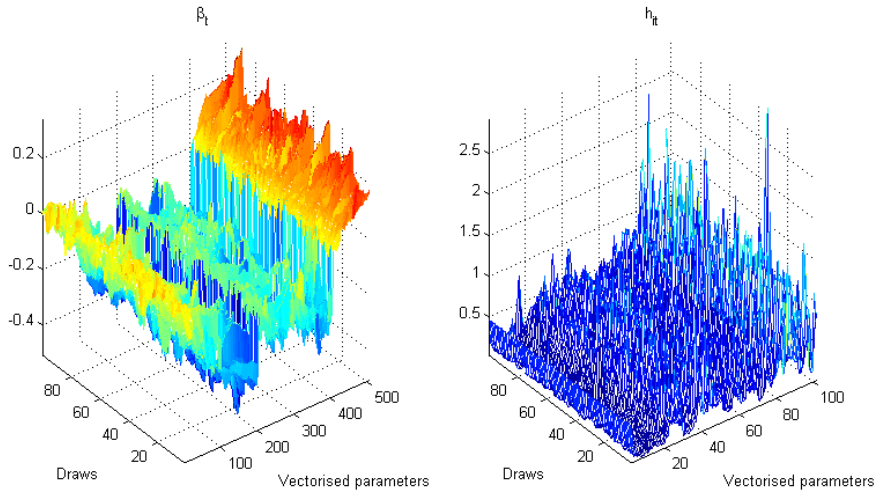
4.4.1 Time-Varying Drivers of PCFs

Before proceeding to the estimation results, Figure 4.1 presents the data for the extracted factor from portfolio flows and the fundamentals.[14] Considering portfolio flows, it is possible to observe that there seem to be several episodes with differing characteristics for flows, but the general trend seems to be upward sloping in the last decades. Overall, the dynamics of portfolio flows over time seem to be consistent with prior expectations regarding its behaviour during different episodes, which indicates that PCA is successful in extracting the co-movement in the flow series. Another observation is that the dates of regional and global turmoil during the sample period corresponds to periods of sudden drops in capital flows, underscoring the reversible nature of portfolio capital as a source of finance for emerging markets.

Results to be presented below for the TVP-Regression model have been obtained with 10.000 gibbs iterations, 7000 as burn-in and 3000 as retained draws.

[14]Note that the variables are standardized before estimation.

FIGURE 4.2: MCMC Convergence - Recursive Means of Estimated Parameters



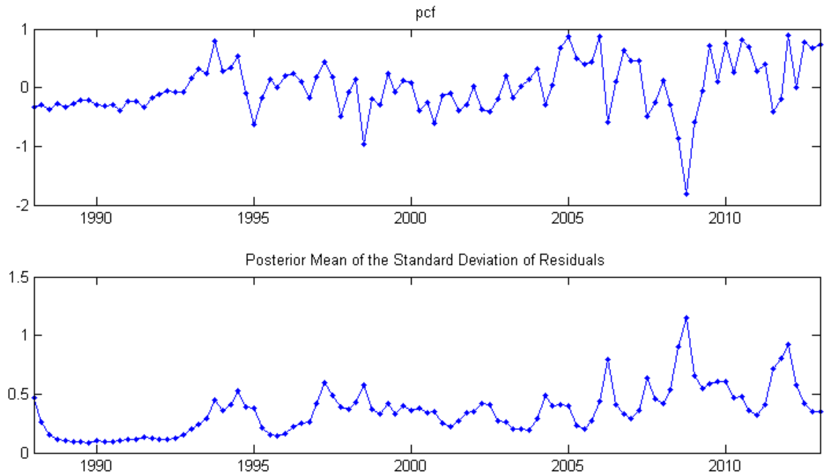
In order to check for the convergence of the MCMC procedure, recursive means are calculated from the retained draws parameters of interest. As discussed in Blake & Mumtaz [2012], if convergence has been achieved, the recursive means should display random fluctuations around steady values without any shifts. Figure 4.2 plots the recursive means of the vectorised parameters from the TVP-Regression model. Graph on the left involves estimated vectorized coefficients and the other involves residual standard deviation for each time period. It can be observed that the means display no shifts or trends, they fluctuate randomly around steady values, hence indicate convergence.

Figure 4.3 presents portfolio flows together with the calculated standard deviations (std dev) of the model residuals from the TVP-Regression Model. Results clearly indicate the presence of stochastic volatility. During the turmoil times, std dev of model residuals peak notably. In fact it seems to peak during mid-90s Mexican, end-90s East Asian and 2007-09 global financial crisis periods.

Figure 4.4 presents the time-varying coefficients of global factors on PCFs.[15] Starting with the sign of the coefficients, prior expectations are negative for the coefficients of output gap, interest rates and the spread. Following the literature including Calvo et al. [1993], Chuhan et al. [1998] and Edison & Warnock [2008], the intuition is low growth and interest rates in developed world cause investors to look for higher returns in emerging markets and hence rise in capital flows. Naturally the impact of *vix*, which is assumed to proxy risk aversion, should also be negative for flows. Turning to *sm*,

[15] Dashed lines represent 90th and 10th intervals for the parameters estimated.

FIGURE 4.3: Standard Deviation of TVP-Regression Model Residuals



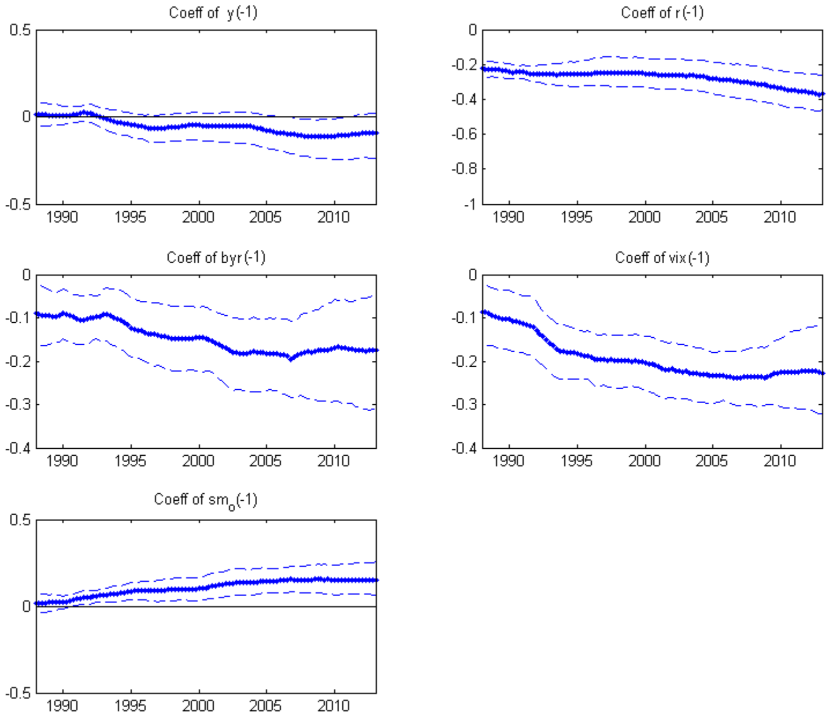
improvements in emerging market fundamentals should attract (pull) more capital, so the prior expectation is positive for the respective coefficients.

Starting with the US variables, the impacts of these well-documented global factors seem to be mostly in line with prior expectations regarding their signs. However, the magnitudes of the coefficients are different across both variables, and interestingly over time. The coefficients of output gap, interest rates and spread variables seem to exhibit notable time variation and the signs seems to be negative in most periods as expected. During the end of 80s and the beginning of 90s, output gap seems to have had a muted impact on portfolio flows, but it became strictly negative during the recent global financial crisis. In contrast to output gap, interest rates seems to have been the most important fundamental in driving flows to EMs during the late 80s and beginning of 90s. During and after the recent financial crisis, US short interest rate seems to have gained notable importance. Results suggest that the role of short interest rates in driving flows towards EMs have reached to the levels not seen before for decades in the aftermath of the recent global financial crisis.

Regarding the impact of vix, as a proxy for risk aversion, its impact seems to be strongly negative and exhibit notable time-variation. The coefficient seems to become significantly more important during the recent global financial crises. It peaks in importance during 2009. Not only during the financial crisis, but also during the period of 2003-2007, its impact has been gaining significant importance with the relative tranquillity in global financial markets and historically low levels of vix apparent in Figure 4.1.

The coefficient of sm, which proxy for common improvements and deteriorations in EM fundamentals indicate the importance of the common pull factors for PCFs. Moreover,

FIGURE 4.4: TVP-Regression Model - Coefficients of Fundamentals

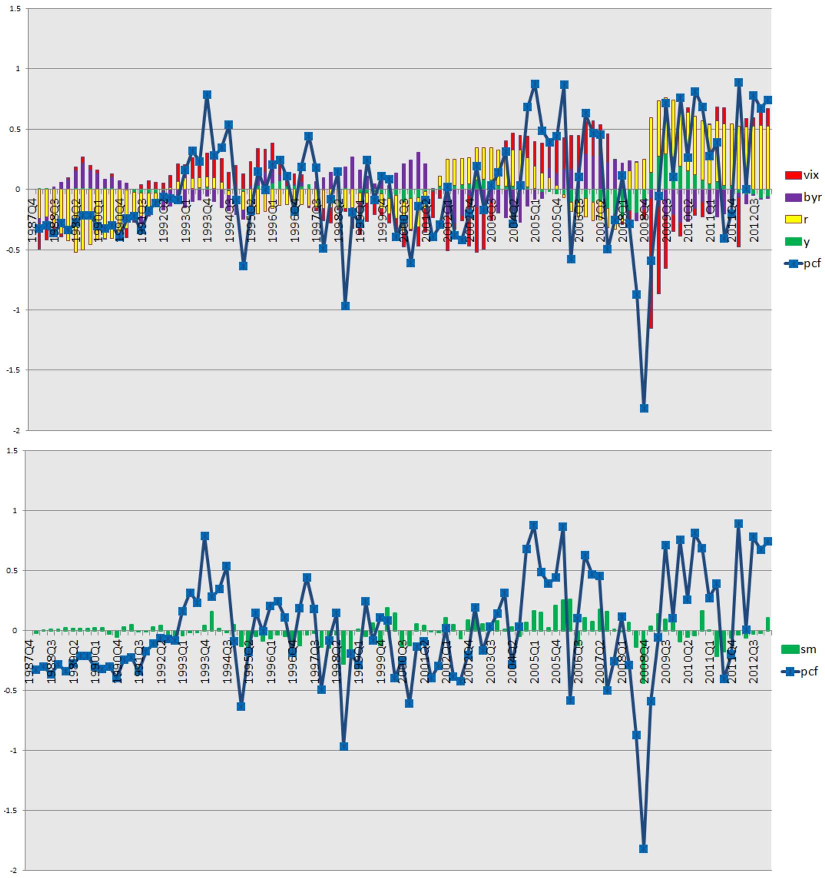


Upper and lower bounds represents 16-84 quantiles.

there exists notable time-variation in the coefficient and the variation seems to tell a clear story regarding the dependency of flows to EM fundamentals. As mentioned above, early studies in the literature point toward the global factors as the major drivers of capital flows during late 80s and early 90s. Considering the findings discussed for other fundamentals and inspecting the coefficients of *sm*, aforementioned early findings seems to be in line with the results obtained here. During the end-80s towards the mid-90s, the impact of *sm* seems to be notably muted. However, its importance has been rising during beginning-90s to the 95 Mexican crises. Likewise, Especially during the period of beginning-2000s to the global financial crisis, in which EMs displayed notable growth with the rise of BRICs, flows seem to have become ever-increasingly dependent on *sm* and stay the same through 2007-09 until 2013Q1.

Overall, from the coefficients of the TVP-Regression model one can conclude that the US factors seem to have been important drivers of flows in the sample period with notable time-variation in their importance. Although their importance have been muted in the end-80s and beginning-90s, EM specific fundamentals seem to have gained remarkable importance in driving PCFs to emerging markets with a clear upward trend during the last decades.

FIGURE 4.5: Contributions of Fundamentals



Although the estimated coefficients of the model are informative about which variables' dynamics are particularly important for portfolio flows, it is not possible to tell which variables in reality contributed the most towards driving flows. For that purpose, variable specific historical contributions have been calculated using the estimates of the coefficients and the dataset by multiplying the coefficient of a given variable with the variable in each period. Figure 4.5 displays the historical contributions resulting from the calculations. Top figure depicts the contributions of US variables and the bottom one depicts the contribution of *sm*.

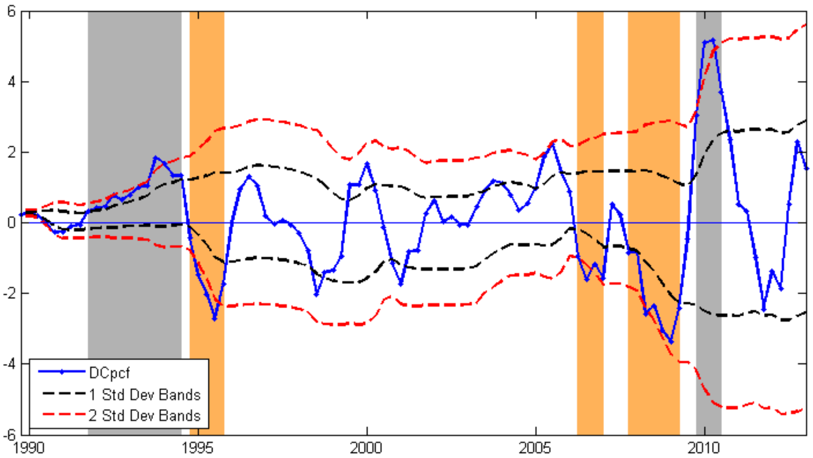
As it has been discussed above, even though *sm* seems to have gained remarkable importance during the last decades, its actual contribution seems to have been much lower than some of the US variables. Top graph in Figure 4.5 indicate that, on a historical basis, US short interest rates and *vix* seem to have been the most important drivers of portfolio flows. Only in two periods output gap had noticeable contribution towards observed portfolio flows, before and during the global financial crisis.

Regarding the recent financial crisis and its aftermath, contributions graphs indicate that mainly short interest rates and *vix* have been driving flows towards EMs during the last decades. At the peak of the recent crisis, increased uncertainty and risk aversion, represented by *vix* seems to have led to a sudden stop in portfolio flows to EMs. However, in subsequent periods, the fall in growth and historically low interest rates in US seem to have resulted in a notable rise in portfolio flows, together with the relative calmness of the markets which has been possibly associated with various policy actions across the developed world including Quantitative Easing.

Considering the latest widely debated issue regarding US monetary policy, the termination of the QE program in US later accompanied by raising US interest rates may have serious implications in the markets and economies across the globe via a slowdown in capital flows to EMs. Within the context of this chapter, whether this is true or not mainly depends on two things: The sensitivity of flows to US variables (mainly interest rates), and the role of QE in driving flows to EMs. The second point will be analysed in more detail in subsequent sections, but with the analysis depicted up until here it is possible to say several things about the former. Looking at the coefficients and the contributions graphs, in the last quarter considered here (2013Q1), portfolio flows have been mostly driven by US short interest rates and the VIX index. The pick-up in US short interest rates will certainly depend on whether the downside risks to the US economy get smaller and growth starts to pick up with lower unemployment. So, some argue that this back-to-normality will be good for the markets in and capital flows to EMs, which is validated by the coefficients and contributions of *vix*. However, US short interest rates seems to be the main driver of flows as of 2013Q1. So, results indicate that the overall effect on portfolio flows will ultimately depend on which one will be stronger between the two and effects of the termination of the QE program.

In order to check for robustness, additional variables are introduced to the TVP-Regression Model presented above. First, a time varying constant is introduced. In general across the sample period, the signs and the magnitudes of the coefficients in the alternative specification are very similar to the benchmark specification, but there are slight changes in the time paths of coefficients. As another alternative model, a time varying constant and a lagged portfolio flows term is introduced to the original specification. Again, the overall signs and magnitudes of the coefficients seem to be robust with some differences in the time paths. Figures B.1-B.2 depict the contributions of variables in alternative specifications. The graphs indicate that the relative importance and contributions of variables over time seem to be similar across specifications.

Figure 4.6: Episodes



Grey and Orange shaded periods represent surge and stop episodes respectively.

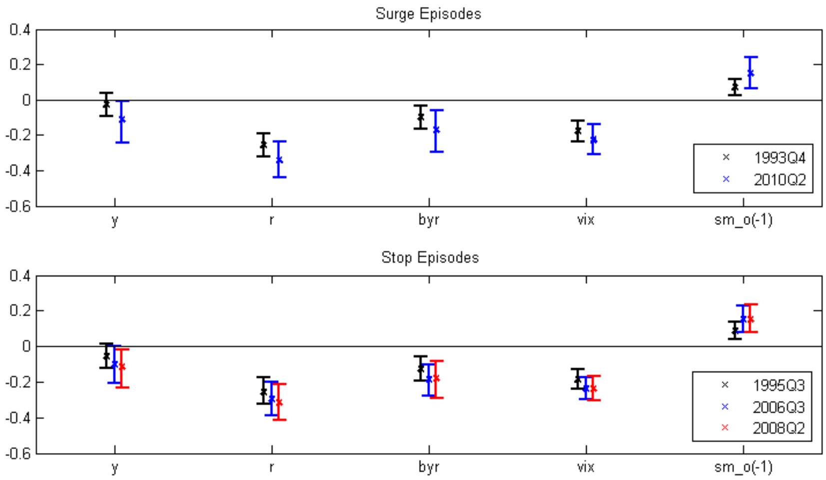
4.4.2 Time-Varying Drivers and Episodes of PCFs

Following on the work of Forbes & Warnock [2012a], the recent literature on capital flows focusses on identifying various episodes in flows as *surges, stops, flight and retrenchment*.[16] Following the identification, they are pooled together to study various aspects of these episodes, including their underlying drivers. However, as discussed in the introduction, if there exists time-variation in the importance of the underlying drivers, inference based on these pooled episodes may not be accurate. Previous subsection clearly identifies time-variation in the role of different factors. The objective of this subsection is to identify the episodes in portfolio flows and illustrate the differences in the underlying fundamentals as a critique to the common practice in the literature.

Since flows considered in this chapter are *gross*, we identify surge and stop episodes, defined as sudden increases and decreases in gross inflows. We follow the procedure employed by Forbes & Warnock [2012a] to identify the episodes in portfolio flows. It involves calculating 4 quarter cumulated flows, rolling means and rolling standard deviation of cumulated flows. A period is considered to be a surge (stop) episode if it satisfies two conditions. A surge (stop) period starts with the first period cumulated flows minus the cumulated flows four periods ago exceeds (falls below) one std dev band and ends when it falls below. Also in the given period, cumulated flows minus the cumulated flows four periods ago needs to exceed (fall below) two times the rolling std dev band in at least one time observation. Specifically,

[16] See for instance Ghosh et al. [2012]

FIGURE 4.7: Time-Varying Coefficients in Identified Episodes



Upper and lower bounds represents 16-84 quantiles.

$$
\begin{aligned}
Cpcf_t &= \sum_{i=t-3}^{t} pcf_{t-i} & \Delta Cpcf_t &= Cpcf_t - Cpcf_{t-4} \\
Rm_t &= mean(\{Cpcf_i\}_{t-19}^{t}) & Rstdd_t &= stdd(\{Cpcf_i\}_{t-19}^{t})
\end{aligned}
$$

where $Cpcf_t$ is the cumulated flows and $\Delta Cpcf_t$ is the four period change in $Cpcf_t$. A surge (stop) episode starts when $\Delta Cpcf_t$ exceeds (falls below) $Rstdd_t$, reaches $2{\cdot}Rstdd_t$ at some point and ends when it falls below $Rstdd_t$.

Figure 4.6 illustrates the procedure. Total of 5 episodes have been identified, among which 2 are surge episodes and 3 are stop episodes. The methodology seems to perform well in determining periods with extreme capital movements. The first episode corresponds to the period in which capital flows to EMs have accelerated during early 90s, second one corresponds to the stop episode of Mexican crisis, the thirds and the fourth corresponds to pre-crisis and crisis times of 2007-2009, and finally the last episode is a surge episode corresponding to the aftermath of the global financial crisis and the implementation of QE in the US.

In order to assess whether there exists differences in the characteristics of each episode over time, Figure 4.7 plots the coefficients of underlying fundamentals in surge and stop episodes, from the results obtained in the previous subsection. It can be observed that there exist notable differences in the characteristics of different episodes over time.

There are time-variations in the coefficients of all variables. For instance, the sensitivity of flows to *vix* has increased markedly over the sample period, which is reflected in the differences between episodes of 90s and late 2000s. As it was discussed in the previous subsection *sm*, which represents common improvements and deteriorations in EM specific fundamentals, seems to have gained greater importance for flows in the last decades. Hence the findings in the literature, which does not take into account this time-variation by pooling episodes of different decades, may not be accurate. Given the fact that portfolio flows variable used here represents the common component of flows to individual countries, studies in the literature pooling episodes from many countries would certainly be subject to the time-variation issue presented above.

4.4.3 The US Quantitative Easing and Surges in PCFs

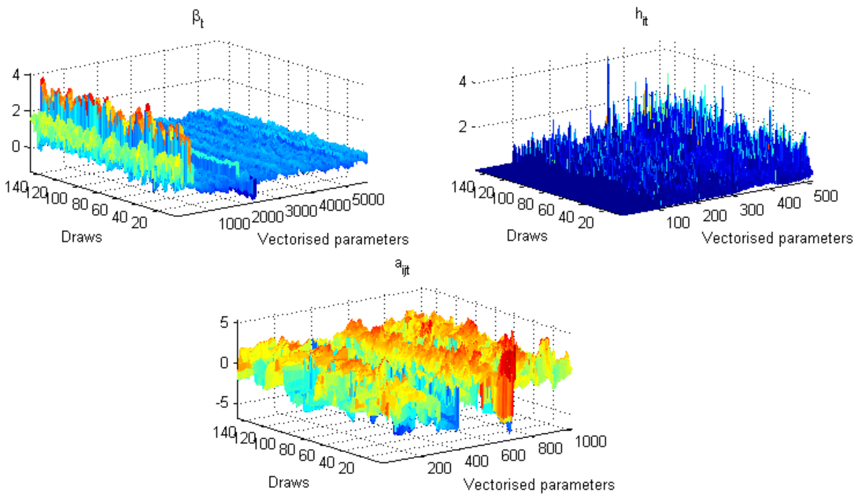
In this section a counterfactual exercise is carried out to answer below question.

-If the US FED would not have implemented the QE program in 2009, would there still be a surge in PCFs to EMs in 2009?

The question of interest carries great importance considering both the policy challenges EMs faced in the aftermath of the financial crisis and the uncertainty brought about with the possible end to the US QE program in the end-2013 or 2014. As it has been depicted in previous subsections, PCFs to EMs have accelerated significantly in the aftermath of the global financial crisis. Furthermore, many countries had signs of overheating with exchange rate appreciation, high credit and gdp growth, increased inflation and asset prices. Cardarelli et al. [2010] associate these observations with surges in PCFs. Some countries attempted to prevent exchange rate appreciation and possibly other associated effects that create macroeconomic and financial stability risks by imposing capital controls or macro-prudential measures.[17] Surprisingly, the IMF recognized capital controls to be legitimate tools under certain circumstances. In the meanwhile, US QE program became notably controversial in the EMs for its role in driving capital flows to respective countries and hence generating aforementioned risks. In a recent IMF staff discussion note, Ostry et al. [2012] warns against the multilateral implications of policies in source countries in generating various risks for recipient countries. Below quotes involve some of these issues.

[17]See Ostry et al. [2011a] for a discussion of macroeconomic and financial stability risks associated with capital flows.

FIGURE 4.8: MCMC Convergence - Recursive Means of Estimated Parameters



"Some rebalancing of macro policies in advanced economies could reduce negative externalities for emerging markets affected by unconventional monetary policies. These spillovers often complicate economic policy management in our countries and confront us with difficult tradeoffs."

Mantega (20 April 2008), IMF IMFC, Mantega [20 April 2008]

"Turkey's central bank is considering cutting interest rates in an attempt to stem excessive capital inflows, even though its economy will be one of the world's fastest-growing this year."

Financial Times (13 December 2010), Financial Times [13 December 2010]

"For the eighth time in 10 months, Peru's central bank has raised deposit requirements on dollar-denominated accounts to stem the flow of hot money..."

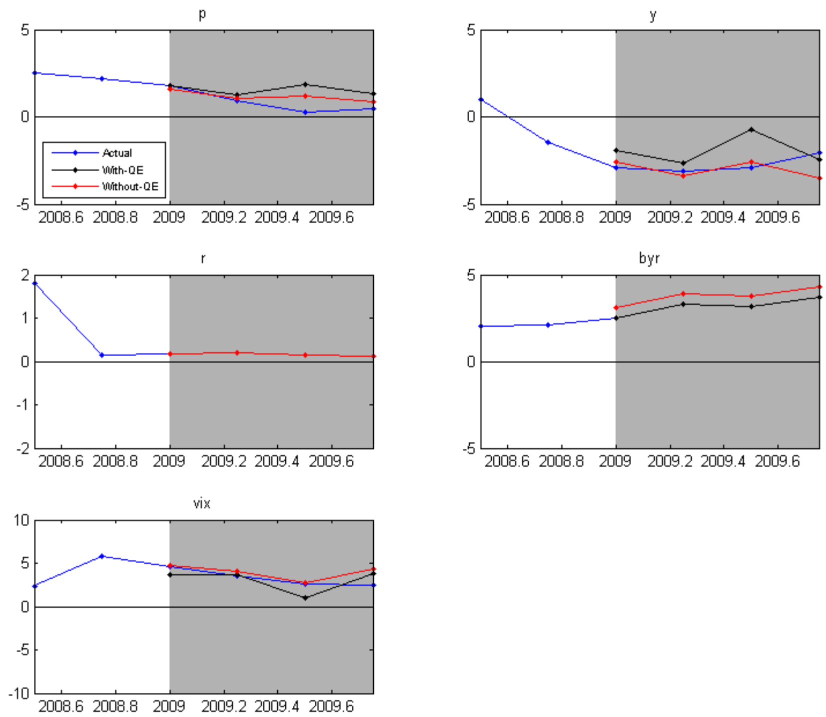
Financial Times (27 March 2013), Financial Times [27 March 2013]

"...though they [capital controls] may be in an individual country's interest, they could be multilaterally destructive..."

Ostry (7 September 2012), iMFdirect, Ostry [7 September 2012]

In the light of the considerations discussed above a counterfactual exercise is carried out using the methodologies described in previous sections. Lag length has been set to 2 in

FIGURE 4.9: Actual and Counterfactual Paths of US Variables



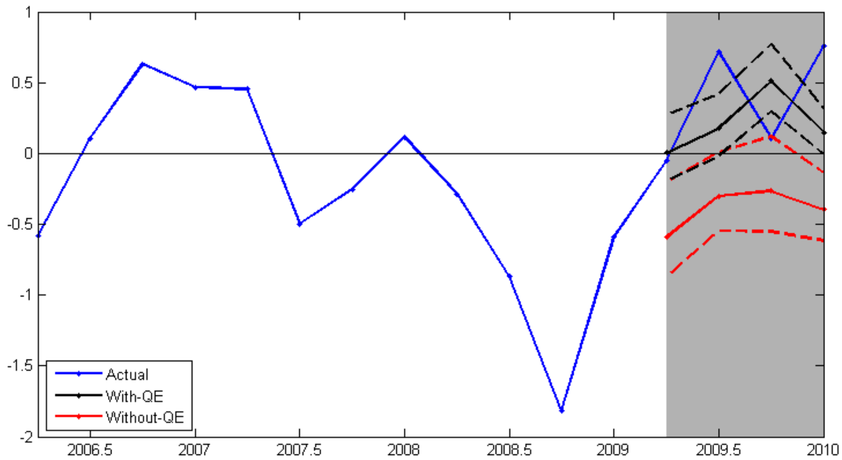
the model. First, in order to assess whether the convergence has been achieved in the TVP-SVAR model for US, Figure 4.8 depicts the rolling recursive means obtained from 10000 gibbs iterations with 7000 as burn-in. It can be seen from the first plot that the lagged coefficients of the model seem to fluctuate around a steady mean show no trends. Even though there seems to be some deviations around steady means for volatility and contemporaneous coefficients, there exist no trends or shifts in respective means.

As discussed in more detail in the methodology section, under the assumption that the QE lowered the spread by 60bps during 2009, two conditional forecasts are obtained, With-QE and Without-QE conditional on the actual realizations of the spread and short interest rates.[18] Figure 4.9 depicts the actual realizations of US variables included in the TVP-SVAR model, together with their With-QE and Without-QE counterfactual paths.

Inspecting the With-QE counterfactual, one can observe that the model predicts a sharper recovery than happened in reality during 2009. However, looking at the output

[18]In Particular, forecasts are conditioned on short interest rates in order to account for the Zero Lower Bound.

FIGURE 4.10: Actual and Counterfactual Paths of *pcf*



Upper and lower bounds represents 16-84 quantiles.

gap graph, the model seems to predict the trough point of the business cycle, and hence where the recovery begins accurately - in 2009Q2-Q3. Also, the model predicts the actual realizations of inflation one and two quarters ahead remarkable well. However, since it forecasts a sharper recovery in 2009Q3, it seems to predict a higher inflation than it had happened in reality in respective periods. Turning to *vix*, similar to the actual realizations, the model predicts a gradual fall in the index. But with a baseline forecast of a smaller output gap, *vix* forecast seems to have become more optimistic.

Comparing the counterfactual paths of model variables under the two scenarios, the impact of QE can be determined. Looking at the results for inflation and output gap, US economy would have faced a deflation in 2009Q3 and a larger than realized output gap through 2009. Also, *vix* would have stayed at levels close to its actual realization at the peak of the crisis during 2009. Overall results are broadly in line with the findings in the literature, which predicts that the QE has been effective in preventing deflation, sharper fall in output and higher uncertainty and risk-aversion in the markets.[19]

In order to obtain the counterfactual path of US variables under the Without-QE scenario for the TVP-Regression Model, the differences between With-QE and Without-QE forecasts from the TVP-SVAR model have been calculated for the US variables and then subtracted from their actual realizations. With-QE scenario in TVP-Regression Model involves the actual realizations of the US variables. With the results obtained in the

[19]See, for instance, Baumeister & Benati [2013] and Gambacorta et al. [2012].

TVP-SVAR model and under the given assumptions, Figure 4.10 plots the actual realization of portfolio flows, together with its conditional forecast under With-QE and Without-QE scenarios.

An important point to note about the results is that the time-variation in the sensitivity of flows did not strongly affected flows during 2009. One can verify this by comparing the counterfactual With-QE scenario that uses 2008Q4 coefficients and the fitted values from the model. The two series are very similar to each other. This finding is in contrast to the findings in Lo Duca [2012], which document important time-variation in the role of fundamentals in driving flows during and after the crisis.

Turning to the main question posed in the beginning of this section, Figure 4.10 provides a clear answer. In contrast to the findings of Fratzscher et al. [2012b], QE seems to have had an important role in driving the observed level of portfolio flows towards EMs in 2009. Comparing the two conditional forecasts, one can observe that Without-QE forecast significantly falls below the levels predicted by With-QE scenario and observed in reality. Even though there seems to be a recovery in the periods following the peak of the crisis, this recovery in flows is nowhere near the levels predicted in With-QE scenario. Furthermore, as it was discussed in the previous section, the episode identification methodology identified two surge episodes in portfolio flows, one in early 90s and the other in 2009-10. Results in this section indicate that the observed surge in 2009 would certainly not have happened without the QE.

4.5 Conclusion

Following on from the previous chapter, this chapter contributes to the existing literature on international capital flows by examining the time-varying drivers of international PCFs to emerging markets in the last decades.

First, findings presented in the chapter indicate that there is notable time-variation in the importance of different global fundamentals for PCFs. Similar to the recently growing literature focusing on identifying episodes in capital flows across decades, I identified episodes in PCFs. Results indicate that, episodes across time have different characteristics with notable time-variation in their underlying drivers. This finding casts doubt on the methodology and the results in the literature, that pool together episodes across decades.

Second, in line with the results from the previous chapter and the literature, US interest rates and output gap have been found to be important drivers of capital flows. However, their importance changes across time with time-variation in their coefficients. For instance, the sensitivity of flows to US short interest rates have increased with the recent global financial crisis and peaked in the last sample period here, in 2013Q1. Similarly, VIX index that represents risk aversion became ever more important in driving flows during the last decades and its importance seems to have peaked during the crisis.

Third, for the role of the improvements/deteriorations in EM-specific fundamentals[20], results clearly indicate that the sensitivity of flows to these factors have increased dramatically in the last decades. Concerning the debate about the relative importance of developed-world versus EM factors, during the early 90s, results point towards the role of global push factors of the developed world rather than EM specific factors to be the main drivers of flows. Starting with the end-of-90s, EM specific factors gained importance in driving flows to EMs. However, relative contributions indicate that flows are mostly driven by US interest rates and global risk appetite in the last decades.

Regarding the recent debate about the possible implications of rising interest rates and the termination of the QE program in the US for EMs, results indicate that flows in the aftermath of the crisis are mostly driven by low US short interest rates and improved risk appetite. Hence, an increase in the interest rates will possibly have considerable affect for PCFs to EMs. But, to the degree that the market sentiment improves along with lower unemployment and higher growth in US, the negative effect of an increase in the short rate may be countered with a higher risk appetite.

Finally, linked to the debate about the termination of the QE program in the US, I performed a counterfactual analysis to find out whether the observed surge in PCFs in 2009 would have still be present in the absence of the application of the US QE program. Results clearly indicate that the US QE program had a major role in driving flows to EMs and in the absence of the QE, observed surge in PCFs would not be present in 2009. On the other hand, this result may not directly imply that the termination of the QE program in the US will lead to a sudden stop in PCFs in near future. The analysis presented in here show that the channel through which QE led to a surge in PCFs in 2009 was mainly through a fall in global uncertainty and a rise in risk appetite. On the other hand, given that the termination of the QE program in the US will happen if the global uncertainty disappears and the US economy recovers, this channel may not be relevant for PCFs.

[20]For instance the rise of BRICS in 2000s.

Appendix A

A.1 Theoretical Appendix

Defining the steady-state as the state in which no adjustment is need for the arbitrage condition (3.1) to hold with equality, then there would be many (possibly infinite) states with different values for g, c, v, f, S_{-1}. In order to track the cumulative impact of shocks in the underlying fundamentals on the flows, assume the shocks occur in period t and in $t-1$ we were in the old steady-state. Then,

$$F_{t-1} = \Delta S_{t-1} = 0$$

$$\overbrace{\Delta F_t}^{=F_t} = F_1 \Delta g_t + F_2 \Delta c_t + F_3 \Delta v_t + F_4 \Delta f_t + F_5 \overbrace{\Delta S_{-1}}^{=0}$$

$$F_t = F_1 \Delta g_t + F_2 \Delta c_t + F_3 \Delta v_t + F_4 \Delta f_t,$$

where F_i' s are the contemporaneous impact coefficients. In $t+1$,

$$\Delta F_{t+1} = F_5 \Delta S_t$$

$$F_{t+1} = (1 + F_5) F_t$$

$$F_{t+s} = \phi^s \left(\sum_{i=1}^{4} F_i \Delta f_i \right), \tag{A.1}$$

where $\phi = (1+F_5)$. By construction F_5 is assumed to be $-1 < F_5 < 0$, hence $0 < \phi < 1$. So, according to (A.1), effect of a shock in the fundamentals on required flows decay over time depending on F_5.

Cumulated flows until the arrival to the new steady-state is then given by,

$$F^* = \sum_{j=0}^{\infty} \phi^j \left(\sum_{i=1}^{4} F_i \Delta f_i \right) = \frac{1}{1-\phi} \left(\sum_{i=1}^{4} F_i \Delta f_i \right).$$

If at t', $\phi^{t'} \cong 0$, then,

$$F^* = \frac{1}{1-\phi}\left(\sum_{i=1}^{4} F_i \Delta f_i\right) \cong \frac{1-\phi^{t'-t+1}}{1-\phi}\left(\sum_{i=1}^{4} F_i \Delta f_i\right).$$

The expressions for the multipliers then read,

$$F_i^m \cong \frac{1}{1-\phi} \cdot F_i \cdot \Delta f_i \cong \frac{1-\phi^{t'-t+1}}{1-\phi} \cdot F_i \cdot \Delta f_i.$$

Assuming the adjustment takes place quickly with F_5 being small enough and hence the implied cumulative adjustments by the changes in the fundamentals between sample observations do approximately occur, we arrive at equation (3.4)

$$F^* = F_1^m \Delta g + F_2^m \Delta c + F_3^m \Delta v + F_4^m \Delta f.$$

A.2 Data

A.2.1 Portfolio Capital Flows

For all countries, the main source for portfolio equity and debt flows data used is IMF International Financial Statistics (IMF-IFS) except for Taiwan, flows data has been obtained from Datastream (Central Bank of China).

Interpolation procedure of Chow & Lin [1971] has been employed in several cases to obtain missing quarterly flows data from existing yearly series by using quarterly related-indicator series from US portfolio capital flows dataset of US Treasury International Capital System (TIC).

For China, Chile, Colombia, Egypt, Hungary, Peru, Poland, Romania and Singapore missing quarterly observations in portfolio equity inflows have been interpolated using Chow & Lin [1971] as described. In case of China, World Bank World Development Indicators (WB-WDI) database has been used to obtain yearly data partly. For Colombia, IMF International Investment Position (IMF-IIP) database has been used to obtain yearly data partly. For Egypt and Peru, database provided by Lane & Milesi-Ferretti [2007] has been used to obtain yearly data partly. For Pakistan, 1D Interpolation procedure has been used to interpolate a single observation.

For China, Chile, Colombia, Egypt, Hungary, Morocco, Peru, Poland, Romania and Singapore missing quarterly observations in portfolio debt inflows have been interpolated using Chow & Lin [1971] as described. For Egypt and Peru, database provided by Lane & Milesi-Ferretti [2007] has been used to obtain yearly data partly.

A.2.2 Real GDP

Main source for real GDP data is IMF-IFS, except for Argentina Datastream (Ministerio de Economia y Production, Republica Argentina), for Lebanon Datastream (Statistical, Economic and Social Research and Training Centre for Islamic Countries), for Taiwan Datastream (Directorate-General of Budget, Accounting and Statistics, Taiwan) have been used.

In order to obtain some of the missing quarterly real GDP data, Dées et al. [2007b] employ an interpolation procedure for which "The objective is to estimate a relatively smooth set of observations...". Even though in some cases their procedure has been employed here as well, a rather more accurate option is to use Chow & Lin [1971]. In fact, Chow & Lin [1971] procedure has been implemented in here by using Industrial Production (IP) as quarterly related-indicator series to obtain quarterly real GDP.

Chow & Lin [1971] with IP as indicator series has been used for Brazil (with IP data from Organisation for Economic Co-operation and Development (OECD)), for China (with IP data from Data Service & Information (DSI) - WB), for Colombia (with IP data from DSI-WB), for Hungary (with IP data from IMF), for Indonesia (with IP data from OECD), for Malaysia (with IP data from IMF), for Pakistan (with IP data from DSI-WB), for Poland (with IP data from OECD), for Romania (with IP data from IMF), for Saudi Arabia (with IP data from DSI-WB). Comparing the relative RMSE values of resulting interpolated series using Chow & Lin [1971] and Dées et al. [2007b] indicated the superior performance of Chow & Lin [1971] with respect to the latter.

Interpolation procedure of Dées et al. [2007b] has been used for Argentina, China, Colombia, Egypt, India, Morocco, Pakistan, Saudi Arabia, Singapore, Thailand.[1]

Seasonally unadjusted series have been seasonally adjusted in Eviews by US Census Bureau' s X12 seasonal adjustment program.

[1]Both interpolation procedures have been employed for different time periods in missing data for any country mentioned twice in both procedures.

A.2.3 Nominal GDP

IMF-IFS is the source of Nominal GDP for all countries except for Canada OECD, for Japan Datastream (Cabinet Office, Japan), for Korea OECD, for Lebanon Datastream (Statistical, Economic and Social Research and Training Centre for Islamic Countries), for Mexico OECD, for Norway OECD, for Pakistan Datastream (State Bank of Pakistan), for South Africa OECD, for Taiwan Bloomberg (Taiwan Directorate General of Budget Accounting & Statistics) and for USA OECD have been used.

Dées et al. [2007b] interpolation method has been used to obtain quarterly series for Argentina, Brazil (with WB data), China, Chile, Colombia, Egypt, Hungary, India, Indonesia, Malaysia, Morocco, New Zealand, Pakistan, Peru (with WB data), Poland, Romania, Saudi Arabia, Singapore, Thailand.

Seasonally unadjusted series have been seasonally adjusted in Eviews by US Census Bureau' s X12 seasonal adjustment program.

Nominal GDP in local currency has been converted to US Dollars using nominal exchange rate data from IMF-IFS for all countries, except for Romania, exchange rate data has been obtained from Bloomberg.

GDP-PPP (international US Dollars) data has been obtained from WB, except for Taiwan Datastream (IMF WEO) has been used.

A.2.4 Short Interest Rates

IMF-IFS database is the main source for the short interest rate variable used here, except for Hong Kong IMF series are complemented with Datastream (interbank rate, Hong Kong Monetary Authority), for Morocco IMF data has been complemented with interpolated (1D and Boot et al. [1967]) yearly data from Datastream (short rate, Oxford Economics), for Norway IMF data has been complemented with Datastream (short rate, Oxford Economics), for Saudi Arabia yearly interpolated (Boot et al. [1967]) Datastream series (deposit rate, WB; short rate, Oxford Economics), for Poland Datastream (short rate, Oxford Economics), for Romania Datastream (short rate, Oxford Economics), for Taiwan Datastream (commercial paper rate, Central Bank of the Republic of China (Taiwan)) have been used.

Money market rate has been used for Argentina, Australia, Austria, Brazil, Canada, Finland, France, Germany, Hong Kong, Indonesia, Italy, Japan, Korea, Malaysia, Mexico, Morocco, Netherlands, Norway, New Zealand, Pakistan, Philippines, South Africa, Singapore, Spain, Sweden, Switzerland, Thailand, Turkey, UK and US. Deposit Rate has been used for China, Chile, Colombia, Egypt, Hungary. Discount rate has been used for India and Peru. Treasury bill rate has been used for Lebanon. Similar to Dées et al. [2007b], Euro Overnight Index Average (EONIA) from European Central Bank has been used for Austria, Finland, France, Germany, Italy, Netherlands and Spain for 1999Q1-2010Q4.

A.2.5 Consumer Price Index

Main source for consumer price index used here is IMF-IFS except for Romania IMF series has been complemented with Datastream (Wiener Institut fur Internationale Wirtschaftsvergleiche), Lebanon 1D interpolated Datastream (IMF World Economic Outlook (WEO)), for China Datastream (National Bureau of Statistics, China), for Taiwan Datastream (Directorate-General of Budget, Accounting and Statistics, Taiwan), for UK Datastream (OECD) have been used.

Seasonally unadjusted series have been seasonally adjusted in Eviews by US Census Bureau' s X12 seasonal adjustment program.

A.2.6 Real Effective Exchange Rates

For Australia, Austria, Brazil, Canada, China, Chile, Colombia, Finland, France, Germany, Hong Kong, Hungary, Italy, Japan, Korea, Malaysia, Morocco, Netherlands, Norway, New Zealand, Pakistan, Philippines, Poland, Romania, South Africa, Saudi Arabia, Singapore, Spain, Sweden, Switzerland, UK and US IMF-IFS data have been used.

For Argentina, Egypt, Peru, Taiwan and Thailand Datastream (JPMorgan) has been used, whereas the source for India, Indonesia, Mexico and Turkey is OECD. Finally, data for Egypt has been 1D interpolated using yearly Datastream (The Economist Intelligence Unit) data.

A.2.7 Real Equity Prices

Main source for nominal equity prices data used here is IMF-IFS except for Argentina IMF data has been complemented with Datastream (S&P IFCG Argentina), for Brazil

Datastream (Bovespa), for Chile Datastream (Santiago SE General), for Hong Kong Datastream (Hang Seng), for Indonesia Datastream (IDX Composite), for Philippines Datastream (Philippine SE I), for Switzerland OECD, for Taiwan Datastream (Taiwan SE Weighted), for Thailand Datastream (Bangkok SET) and for Turkey OECD have been used.

Once nominal series have been obtained, real equity prices have later been calculated using consumer price index series, as described in Section 3.5.

A.2.8 Credit Ratings

The source of the credit ratings data for all countries is Institutional Investor Magazine's semi-annual Credit Ratings from March and September issues. For all countries, 2010Q1 has been 1D interpolated.

A.2.9 Current Account

IMF-IFS is the source of current account data for all countries except for Singapore Datastream (Statistics Singapore) and for Taiwan Datastream (Central Bank of the Republic of China (Taiwan)) have been used.

Interpolation procedure of Boot et al. [1967] has been employed for China, Chile, Colombia, Egypt, Hong Kong (IMF data complemented with Datastream, IMF-WEO), Hungary, Lebanon (IMF data complemented with Datastream, IMF-WEO), Malaysia, Morocco, Norway, Peru, Poland, Romania, Saudi Arabia, Switzerland.

Seasonally unadjusted series have been seasonally adjusted in Eviews by US Census Bureau' s X12 seasonal adjustment program.

A.2.10 Reserves

Reserves variable is obtained from IMF-IFS for all countries, except for Hong Kong Datastream (Oxford Economics) and in Taiwan Datastream (Central Bank of the Republic of China (Taiwan)) have been used.

A.2.11 Short Term Debt

For all emerging market countries except Hong Kong, international bank claims, consolidated, up to one year has been obtained from Bank for International Settlements (BIS). Existing semi-annual data for 1987Q3-1999Q4 has been 1D interpolated to obtain quarterly data.

A.2.12 VXO Index

CBOE (Chicago Board Options Exchange) S&P 100 Volatility Index has been obtained from Datastream.

A.3 Tables and Figures

Table A.1: Comparison of Different Interpolation Procedures

	Real GDP							
	Bra	Col	Hu	Ind	Indo	Mal	Pol	Rom
rmse_cl	1.44	0.18	0.12	1.12	0.57	0.28	0.36	3.57
rmse_wn	0.87	0.65	0.22	0.35	0.88	0.47	0.61	3.91
rmse_dees	1.75	0.42	0.81	0.37	0.91	1.27	0.57	5.43
rmse_bfl	0.88	0.21	0.10	0.24	0.58	0.38	0.29	3.67
corr_cl	0.38	0.77	0.80	-0.28	0.77	0.60	0.44	0.20
corr_wn	0.31	0.31	0.54	0.29	0.55	0.52	0.41	0.20
corr_dees	0.23	0.48	0.48	0.31	0.66	0.56	0.37	0.14
corr_bfl	0.34	0.60	0.80	0.47	0.77	0.72	0.37	0.18

	Portfolio Equity Flows						
	Chl	Col	Hu	Mor	Per	Pol	Rom
rmse_cl	0.0043	0.0024	0.011	0.0136	0.0025	0.0075	0.0001
rmse_wn	0.0098	0.0022	0.0111	0.0159	0.0022	0.0094	0.0001
rmse_dees	-	-	-	-	-	-	-
rmse_bfl	0.0093	0.002	0.0108	0.0136	0.002	0.0092	0.0001
corr_cl	0.8646	0.5561	0.5717	0.523	0.675	0.6315	0.7793
corr_wn	0.6826	0.5335	0.563	0.3708	0.6641	0.5094	0.7775
corr_dees	-	-	-	-	-	-	-
corr_bfl	0.6855	0.603	0.5762	0.5254	0.6913	0.5321	0.7819

	Portfolio Debt Flows					
	Chl	Col	Hu	Per	Pol	Rom
rmse_cl	0.0287	0.018	0.1962	0.001	0.5081	0.0056
rmse_wn	0.0183	0.0242	0.0828	0.001	0.5292	0.0057
rmse_dees	-	-	-	-	-	-
rmse_bfl	0.0152	0.0249	0.0748	0.0011	0.5078	0.0058
corr_cl	0.4476	0.8114	0.3946	0.4633	0.278	0.5431
corr_wn	0.5769	0.5938	0.6615	0.3587	0.187	0.5339
corr_dees	-	-	-	-	-	-
corr_bfl	0.6489	0.5759	0.6974	0.3451	0.2806	0.5318

rmse_x: Root mean square error of interpolated series with interpolation procedure x.
corr_x: Correlation of the actual and interpolated series that is interpolated with procedure x. For Real GDP, growth rates of respective series are used.
cl: Chow & Lin [1971] procedure with industrial production as related indicator.
wn: Chow & Lin [1971] procedure with white noise as related indicator.
dees: Dées et al. [2007b] procedure. bfl: Boot et al. [1967] procedure.

Table A.2: Country Specific Models - Domestic Variables

Country	Variables										
	EF	DF	Y	SR	$Dcpi$	$Reer$	SM	CR	CA	RSD	VIX
DC	-	-	√	√	√	√	√	-	-	-	√
Arg	√	√	√	√	√	√	√	√	√	√	-
Bra	√	√	√	√	√	√	√	√	√	√	-
China	-	-	√	√	√	√	-	√	√	√	-
Chl	√	√	√	√	√	√	√	√	√	√	-
Col	√	√	√	√	√	√	√	√	√	√	-
Egy	√	√	√	√	√	√	-	√	√	√	-
Hk	-	-	√	√	√	√	√	√	√	-	-
Hu	√	√	√	√	√	√	-	√	√	√	-
India	√	-	√	√	√	√	√	√	√	√	-
Indns	√	√	√	√	√	√	√	√	√	√	-
Kor	√	√	√	√	√	√	√	√	√	√	-
Leb	-	-	√	√	√	-	-	√	√	√	-
Mal	-	-	√	√	√	√	√	√	√	√	-
Mex	√	√	√	√	√	√	√	√	√	√	-
Mor	√	-	√	√	√	√	-	√	√	√	-
Pak	√	√	√	√	√	√	√	√	√	√	-
Per	√	√	√	√	√	√	-	√	√	√	-
Phlp	-	√	√	√	√	√	√	√	√	√	-
Pol	√	√	√	√	√	√	-	√	√	√	-
Rom	√	√	√	√	√	√	-	√	√	√	-
Safrc	√	√	√	√	√	√	√	√	√	√	-
Sing	-	-	√	√	√	√	√	√	√	√	-
Taiw	√	√	√	√	√	√	√	√	√	√	-
Thai	√	√	√	√	√	√	√	√	√	√	-
Turk	√	√	√	√	√	√	√	√	√	√	-

√: Variable Included

- : Variable Not Included

Table A.3: Results of Unit Root Tests

Country	*EF* ADF_1	*EF* ADF_1 (WS)	*EF* ADF_2	*EF* ADF_2 (WS)	*DF* ADF_1	*DF* ADF_1 (WS)	*DF* ADF_2	*DF* ADF_2 (WS)
DC	-	-	-	-	-	-	-	-
Arg	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Bra	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
China	-	-	-	-	-	-	-	-
Chl	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Col	I(1)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)
Egy	I(0)	I(0)	I(0)	I(0)	I(1)	I(1)	I(1)	I(0)
Hk	-	-	-	-	-	-	-	-
Hu	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
India	I(0)	I(0)	I(0)	I(0)	-	-	-	-
Indns	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Kor	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Leb	-	-	-	-	-	-	-	-
Mal	-	-	-	-	-	-	-	-
Mex	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Mor	I(0)	I(0)	I(0)	I(0)	-	-	-	-
Pak	I(0)	I(0)	I(0)	I(0)	I(1)	I(0)	I(0)	I(0)
Per	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(1)	I(0)
Phlp	-	-	-	-	I(0)	I(0)	I(0)	I(0)
Pol	I(1)	I(1)	I(1)	I(0)	I(0)	I(0)	I(1)	I(1)
Rom	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Safrc	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Sing	-	-	-	-	-	-	-	-
Taiw	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Thai	I(0)	I(0)	I(0)	I(0)	I(1)	I(1)	I(1)	I(0)
Turk	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)

5% critical values are used for both tests

^{1} : With a trend, ^{2} : Without a trend

Table A.4: Results of Cointegration Rank Tests for GVAR Models

Country	CI Rank[1]	GVAR - EF CI Rank[2]	GVAR - EF CI Rank[3]	GVAR - DF CI Rank[2]	GVAR - DF CI Rank[3]	Final CI Rank
DC	1	1	1	1	1	1
Arg	2	2	4	5	4	1
Bra	4	5	6	4	5	2
China	5	5	5	5	5	2
Chl	4	7	7	6	6	2
Col	3	6	6	6	5	1
Egy	6	6	6	7	6	2
Hk	3	3	3	4	4	2
Hu	4	5	5	5	5	3
India	1	2	3	3	3	1
Indns	4	8	8	4	5	3
Kor	4	6	5	6	5	3
Leb	4	5	5	5	5	2
Mal	2	2	2	3	3	1
Mex	4	7	6	5	5	2
Mor	2	4	4	4	4	1
Pak	3	5	6	5	5	1
Per	4	6	6	5	5	2
Phlp	5	7	7	6	6	2
Pol	5	6	6	5	6	2
Rom	4	6	5	5	6	2
Safrc	1	4	2	2	2	1
Sing	3	5	5	5	5	1
Taiw	5	9	8	6	6	3
Thai	1	4	3	4	5	1
Turk	3	3	4	5	5	2

[1] : With $I(1)$ endogenous and $I(1)$ exogenous variables only

[2] : With $I(1)$ and cum. $I(0)$ endogenous variables as endogenous; $I(1)$ and cum. $I(0)$ exogenous variables as weakly exogenous

[3] : With $I(1)$ endogenous variables as endogenous; $I(1)$ and $I(0)$ exogenous as well as $I(0)$ cum. endogenous variables as weakly exogenous

Table A.5: Results of LR Tests for Exclusion of Cumulated Variables from CIVs GVAR-*EF* Model

Country	LR Test				
	Test Stat	χ^2 95%[1]	χ^2 99%[1]	Bootstrap 95%[2]	Bootstrap 99%[2]
DC	–	–	–	–	–
Arg	1.16	5.99	9.21	14.34	20.81
Bra	11.04	9.49	13.28	22.67	28.61
China	0.22	5.99	9.21	13.19	22.36
Chl	23.18	9.49	13.28	27.27	38.5
Col	1.98	5.99	9.21	14.99	21.2
Egy	19.16	9.49	13.28	23.95	32.56
Hk	0.87	5.99	9.21	13.45	22.24
Hu	22.95	12.59	16.81	34.06	45.05
India	3.95	5.99	9.21	15.44	22.69
Indns	41.75	12.59	16.81	29.66	41.61
Kor	19.52	12.59	16.81	34.17	45.88
Leb	2.35	5.99	9.21	11.6	20.36
Mal	0.02	3.84	6.63	7.59	13.85
Mex	25.6	9.49	13.28	26.43	37.91
Mor	6.15	5.99	9.21	16.54	24.62
Pak	21.75	5.99	9.21	15.1	23.96
Per	15.52	9.49	13.28	22.79	31.33
Phlp	2.59	5.99	9.21	13.25	20.18
Pol	19.25	9.49	13.28	20.17	27.61
Rom	7.76	9.49	13.28	21.92	31.97
Safrc	0.43	5.99	9.21	16.26	23.73
Sing	1.66	3.84	6.63	8.28	13.37
Taiw	20.16	12.59	16.81	32.11	41.69
Thai	0.56	5.99	9.21	15.07	20.98
Turk	21.79	9.49	13.28	23.2	36.04

[1] : Degrees of freedom equal to CI Rank times the total number of cumulated variables

[2] : Obtained with 250 draws

Table A.6: Results of F-Tests for Weak Exogeneity for GVAR-*EF* Model

		F-Test Statistic									
Country	C.V.	EF	EF⋆	Y⋆	SR⋆	Dcpi⋆	SM⋆	CR⋆	CA⋆	RSD⋆	VIX
DC	3.97	–	–	2.05	–	–	–	–	–	–	–
Arg	3.99	0.00	1.67	1.42	3.89	6.28	0.21	0.02	0.62	0.45	0.02
Bra	3.15	0.12	0.61	0.34	7.25	0.68	0.43	0.26	4.12	1.06	0.86
China	3.14	–	0.22	0.32	1.97	0.96	0.37	0.90	0.27	0.24	0.51
Chl	3.15	1.18	0.07	0.01	2.30	0.01	0.02	0.56	1.68	1.14	0.53
Col	3.99	0.96	2.11	0.01	0.25	0.68	0.17	2.30	0.14	3.62	0.01
Egy	3.14	3.16	0.40	2.29	2.27	1.55	0.08	0.69	3.53	0.50	0.70
Hk	3.14	–	1.23	0.80	4.88	2.56	0.72	2.62	0.09	0.92	0.87
Hu	2.75	0.46	0.66	0.95	0.42	1.38	0.71	0.32	0.52	1.06	0.37
India	3.99	0.22	0.03	0.26	0.00	0.74	1.30	1.17	2.25	0.12	4.62
Indns	2.76	7.06	0.58	0.28	0.85	2.49	1.27	1.82	0.13	1.50	1.62
Kor	2.76	1.66	2.35	0.46	0.23	2.79	3.36	0.36	1.19	1.73	4.11
Leb	3.13	–	0.03	1.37	4.26	3.18	0.15	0.20	1.10	0.39	0.97
Mal	3.99	–	2.78	0.41	0.57	0.23	0.68	0.14	0.69	0.35	0.10
Mex	3.15	0.30	0.07	0.33	2.04	1.20	1.07	0.81	0.56	0.52	0.22
Mor	3.99	0.21	0.22	1.81	0.08	0.11	0.03	0.09	0.93	0.29	0.26
Pak	3.99	0.64	0.02	4.11	0.09	0.03	0.00	0.44	2.98	1.01	2.07
Per	3.14	0.71	0.20	0.62	11.15	0.58	1.73	0.17	2.58	0.53	0.47
Phlp	3.14	–	0.46	0.12	0.44	0.92	0.30	0.97	1.61	1.27	0.47
Pol	3.14	0.06	0.58	1.66	9.11	0.81	1.11	0.27	1.10	0.36	0.99
Rom	3.14	1.03	0.88	1.58	0.91	0.53	0.71	0.08	4.69	0.21	1.47
Safrc	3.99	0.00	0.17	1.09	0.91	0.31	0.13	0.69	0.00	1.77	0.08
Sing	3.99	–	6.77	0.27	0.80	3.24	6.63	2.29	1.58	5.71	0.82
Taiw	2.76	1.00	1.00	0.23	5.65	1.07	0.14	2.04	0.28	1.16	0.37
Thai	3.99	0.75	2.23	2.37	0.18	6.98	3.99	0.62	0.47	10.41	0.99
Turk	3.15	2.03	0.74	0.67	0.79	0.17	0.01	0.20	0.00	1.86	0.17

C.V. : Critical Value

Table A.7: Average Pair-Wise Cross-Section Correlations

	EF		DF		Y		SM	
Country	Lev.	Res.	Lev.	Res.	1st Diff.	Res.	1st Diff.	Res.
DC	–	–	–	–	0.20	-0.07	0.48	-0.07
Arg	0.01	0.01	0.04	-0.03	0.10	0.03	0.33	0.03
Bra	0.22	0.01	0.07	-0.02	0.06	0.03	0.47	0.01
China	–	–	–	–	0.14	0.02	–	–
Chl	0.10	0.00	0.03	0.00	0.11	0.00	0.40	0.06
Col	0.14	-0.04	0.03	0.00	0.14	0.07	0.34	0.07
Egy	0.10	0.00	0.17	0.02	0.04	0.01	–	–
Hk	–	–	–	–	0.23	-0.03	0.44	-0.01
Hu	0.06	0.01	0.14	-0.02	0.11	-0.01	–	–
India	0.22	0.02	–	–	0.03	0.01	0.42	0.09
Indns	0.00	0.02	0.17	0.00	0.10	0.01	0.36	0.02
Kor	0.12	-0.01	0.17	-0.02	0.15	0.01	0.44	0.04
Leb	–	–	–	–	-0.04	0.06	–	–
Mal	–	–	–	–	0.20	0.02	0.47	0.06
Mex	0.11	-0.01	0.13	0.01	0.07	0.01	0.52	0.12
Mor	0.12	-0.01	–	–	0.00	0.00	–	–
Pak	0.13	0.04	0.06	0.00	0.05	-0.03	0.41	0.08
Per	0.16	-0.02	0.11	0.00	0.07	0.07	–	–
Phlp	–	–	0.15	-0.10	0.08	0.02	0.38	0.04
Pol	0.09	0.03	0.11	-0.02	0.04	0.01	–	–
Rom	0.08	0.00	0.03	0.00	0.08	0.02	–	–
Safrc	0.08	0.01	0.14	0.02	0.16	0.05	0.32	0.00
Sing	–	–	–	–	0.19	-0.02	0.55	0.00
Taiw	0.14	-0.07	0.08	-0.01	0.16	-0.01	0.27	-0.03
Thai	0.16	-0.01	0.11	0.01	0.17	0.01	0.36	-0.02
Turk	0.17	0.00	0.14	-0.03	0.11	0.03	0.24	0.05

Note: Results for fundamentals are obtained from GVAR-EF Model.

Lev.: Levels of the variable

1st Diff.: 1st Difference of the variable

Res.: Residuals from respective country models

Table A.8: Contemporaneous Impact Coeff. of Foreign on Domestic Variables

Country	Variables				
	EF	DF	Y	SM	CR
DC	–	–	0.20***	–	–
Arg	0.01*	0.41***	0.16	1.99***	1.57***
Bra	0.61***	0.63***	1.22***	1.16***	0.40***
China	–	–	0.08	–	0.66***
Chl	1.04***	0.22***	0.44*	0.62***	0.31***
Col	0.34***	0.31***	-0.12	0.65	0.88***
Egy	0.12**	0.11***	-0.21	–	0.70***
Hk	–	–	0.55**	0.94***	0.77***
Hu	0.46***	2.49***	0.44*	–	0.19*
India	0.37**	–	0.40**	0.35	0.93***
Indns	0.00	0.60***	-0.06	1.95***	0.61***
Kor	0.41***	0.22	1.05***	0.95***	0.57***
Leb	–	–	-0.35	–	0.99***
Mal	–	–	0.87***	1.02***	1.03***
Mex	0.65***	0.58***	-0.13	1.24***	0.44***
Mor	0.20***	–	-0.47	–	0.34***
Pak	0.41***	0.03	0.40	0.71**	2.17***
Per	0.48***	0.53***	0.4	–	1.20***
Phlp	–	1.08***	1.20***	1.83***	0.74***
Pol	0.08	0.36***	0.29	–	0.72***
Rom	0.04***	0.15**	1.79***	–	0.82***
Safrc	0.21	0.39*	0.13	1.27***	0.90***
Sing	–	–	0.93***	1.19***	0.27***
Taiw	0.69	0.06	1.59***	0.91***	0.33***
Thai	0.38	0.20**	1.03***	2.69***	1.05***
Turk	0.25***	0.39***	1.13**	1.40***	1.16***

Note: White Heteroskedasticity Consistent Standard Errors are used in models without I(0) endogenous variables. Coeffs of fundamentals are obtained from GVAR-EF Model.

*, **, *** denote significance at 10%, 5% and 1% levels respectively.

Table A.9: Long Run Relations

Country	r	Fisher	PPP	UIP	LR(df)	CV 99%
Brazil	2	$\surd$	$\surd$		170.01(30)	139.49
Colombia	1	$\surd$			70.26(16)	85.64
India	1	$\surd$			61.87(16)	70.66
Indonesia	3	$\surd$	$\surd$	$\surd$	71.61(16)	81.60
Korea	3	$\surd$	$\surd$	$\surd$	191.27(42)	167.78
Mexico	2	$\surd$		$\surd$	246.97(42)	175.42
Philippines	2	$\surd$		$\surd$	138.42(30)	120.57
South Africa	1		$\surd$		224.95(30)	124.47
Thailand	1			$\surd$	107.69(30)	120.17
Turkey	2	$\surd$		$\surd$	104.55(16)	101.13

Table A.10: EM-F Shock Robustness - 4Q-Ahead GIRFs Correlations

	Y	SM	Reer	Dcpi	CA
rGVAR-EF	0.92	0.99	0.95	0.83	0.99
sGVAR-EF	0.88	0.92	0.92	0.91	0.92
rGVAR-DF	0.91	0.93	0.89	0.65	0.75
sGVAR-DF	0.91	0.87	0.88	0.56	0.85

Table A.11: VIX Shock Robustness - 4Q-cum SGIRFs Correlations

	EF	DF
rGVAR	0.99	0.96
sGVAR	0.98	0.95

Table A.12: GFEVDs Robustness - Average Contributions Correlations

	EF				DF			
0Q	EF	Dom.	DC	EFs	DF	Dom.	DC	DFs
rGVAR	0.97	0.87	0.98	0.99	0.97	0.93	0.97	0.96
sGVAR	0.82	0.65	0.95	0.94	0.85	0.53	0.97	0.81

	EF				DF			
4Q	EF	Dom.	DC	EFs	DF	Dom.	DC	DFs
rGVAR	0.98	0.93	0.98	0.99	0.99	0.96	0.97	0.97
sGVAR	0.81	0.85	0.97	0.97	0.95	0.68	0.97	0.86

Table A.13: Capital Controls - During and After the Crisis

	PCFs	Y-Growth	Dcpi	ΔReer	ΔCC
2007	0.4	5.7	5.6	0.4	-19.8
2008	-2.2	3.9	8.5	-2.8	53.6
2009	3.1	-0.5	4.3	1.0	-20.1
2010	3.2	6.9	5.9	1.2	-10.1

Values are cross-sectional averages of Argentina, Brazil, Chile, Egypt, Indonesia, S. Korea, Mexico, Thailand and Turkey. PCFs are normalized by NGDP in $, in percentage points, include equity and debt. Y column has been calculated using the IMF change in country GDP volume series, in percentage points. Dcpi and Reer are from the dataset constructed in the paper and they are the yearly percentage change (points) in the average of countries. CC is calculatedusing yearly change in the Chinn-Ito capital account openness measure.

Table A.14: *EF* Responses to Capital Control Shocks - Edison-Warnock Measure

	0Q - *EF* Response				1Q - *EF* Response							
Shock	Arg	Chl	Col	Per	Arg	Col	Hu	Kor	Safr	Taiw	Thai	Turk
Arg								+*				
Bra			+*		+*							
Chl		-**										
Egy												
India												
Indn												
Kor									-*			
Mex		+*		+*								
Taiw	+*				+**	+**	-*		-*	-**	-*	
Thai												
Turk												+*

*, ** denote significance using 10-90 and 5-95 quantiles of bootstrap GIRFs respectively.
Blue: robustness with respect to alternative model specifications, rGVAR and sGVAR.

Table A.15: *DF* Responses to Capital Control Shocks - Edison-Warnock Measure

	0Q - *DF* Response							1Q - *DF* Response				
Shock	Bra	Chl	Indn	Per	Rom	Safr	Turk	Egy	Per	Phlp	Taiw	Turk
Arg												
Bra	-**		-*	+*								
Chl												
Egy												
Indn		-*				+*						
Kor							+*		+**	+*		
Mex					+*							
Phlp								+*				
Taiw											+**	
Thai												
Turk												+**

*, ** denote significance using 10-90 and 5-95 quantiles of bootstrap GIRFs respectively.
Blue: robustness with respect to alternative model specifications, rGVAR and sGVAR.

TABLE A.16: *EF* and *DF* Responses to Capital Control Shocks - Chinn-Ito Measure

	0Q - EF Response								1Q - EF Response							
Shock	Arg	Chl	Col	Ind	Kor	Mor	Pak	Per	Arg	Chl	Col	Ind	Kor	Mor	Pak	Per
Arg									-*							
Bra				+**		+*										
Chl						+*										
Kor					+*											
Mex	+*	+*					+*	+**		+**	+**				+*	+**

	0Q - DF Response								
Shock	Bra	Chl	Col	Indn	Pak	Pol	Rom	Safr	Thai
Bra	-*		+**						
Chl		-**							
Egy			-*		-*	-*			
Mex							+*	+*	
Thai				-**					-**
Turk					-*				

	1Q - DF Response						
Shock	Arg	Bra	Col	Hu	Kor	Pol	Turk
Arg	+**				+*	-**	
Bra		+*	+**				
Kor				-*			-*
Mex				-*		-*	

*, ** denote significance using 10-90 and 5-95 quantiles of bootstrap GIRFs respectively.
Blue: robustness with respect to the interpolation procedure employed to get quarterly Chinn-Ito Measure.

Table A.17: *EF* and *DF* Responses to *CC* Shocks - Triangular Identification

	0Q - EF Response			1Q - EF Response	
Shock	Chl	Col	Per	Arg	Col
Bra		+*		+*	
Mex	+*		+*		
Taiw					+*

	0Q - DF Response	1Q - DF Response			
Shock	Per	Bra	Egy	Per	Taiw
Bra	+*	-*			
Kor				+*	
Phlp			+*		
Taiw					+**

*, ** denote significance using 10-90 and 5-95 quantiles of bootstrap GIRFs respectively.
Results are from the model in which *CC* is ordered the last for identification.
Blue indicates robustness with respect to alternative ordering of variables for identification, with both block diagonal and unrestricted estimated sample variance-covariance matrices.

Table A.18: *CC* Shocks Robustness - Sign Restrictions

	Response						
Shock	Y	SR	$Dcpi$	$Reer$	SM	F	CC
Supply	$>$		$<$				
Demand	$>$		$>$				
Monetary Policy	$<$	$>$	$<$	$>$	$<$		
Inflows	$>$		$>$	$>$	$>$	$>$	
Capital Controls					$<$	$<$	$>$

Figure A.1: Persistence Profiles of the CI Relations - GVAR-EF

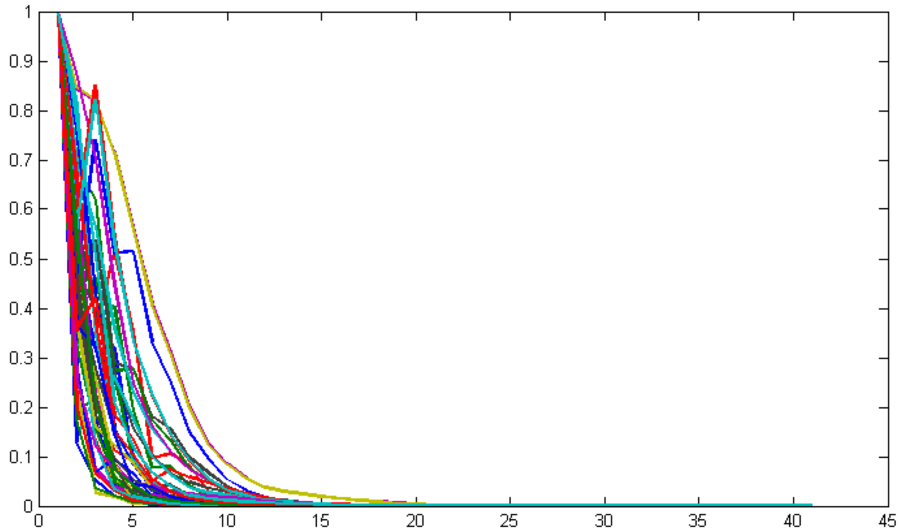
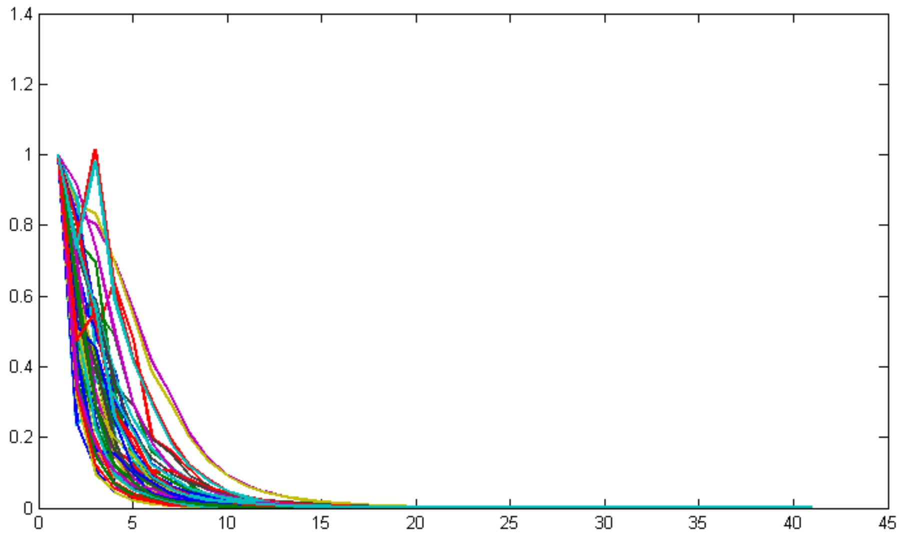


Figure A.2: Persistence Profiles of the CI Relations - GVAR-EF (Bootstrap)



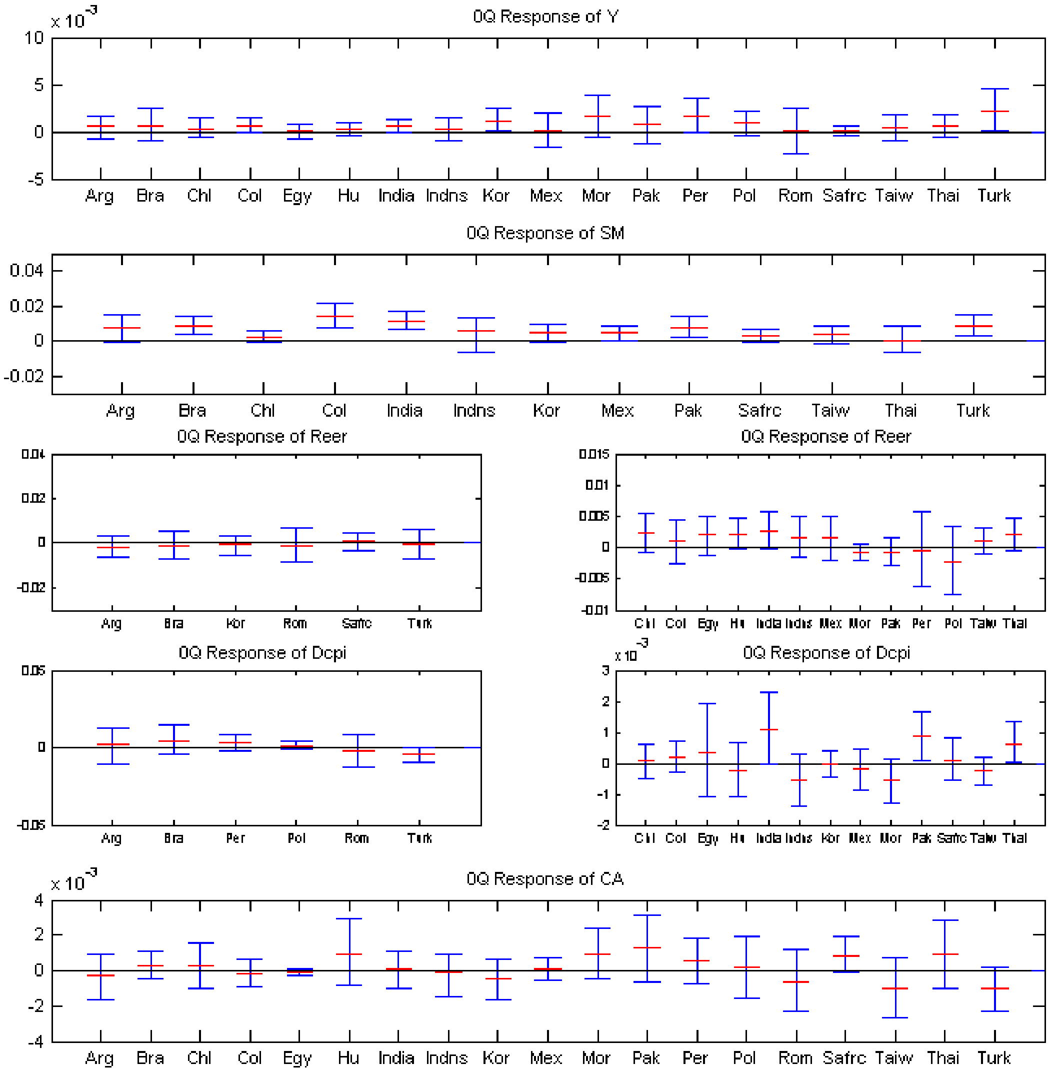


Figure A.3: GIRFs: 1 std err Global Positive Shock to EM - EF - Contemp.

FIGURE A.4: GIRFs: 1 std err Global Positive Shock to EM - EF - 1 Quarter

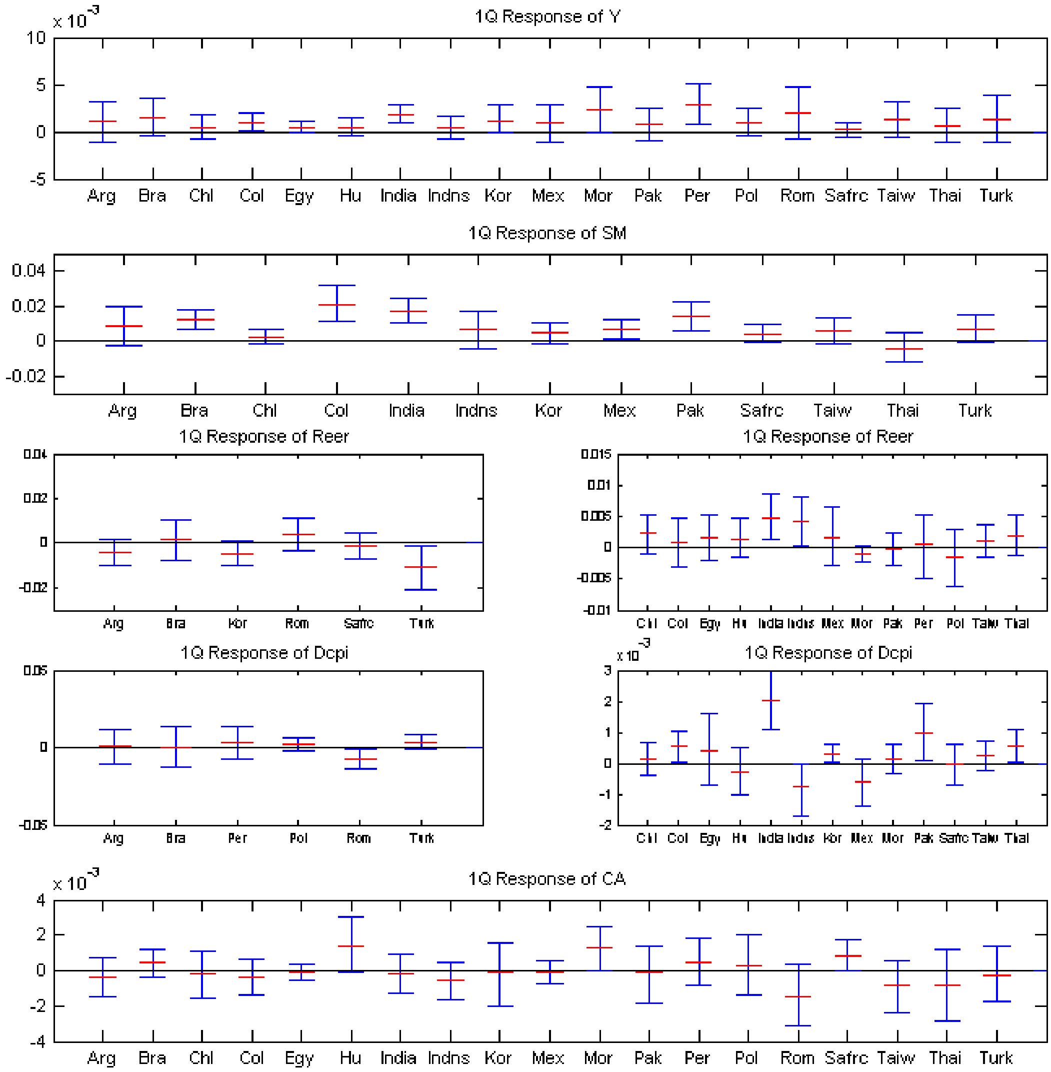


Figure A.5: GIRFs: 1 std err Global Positive Shock to EM - EF - 4 Quarters

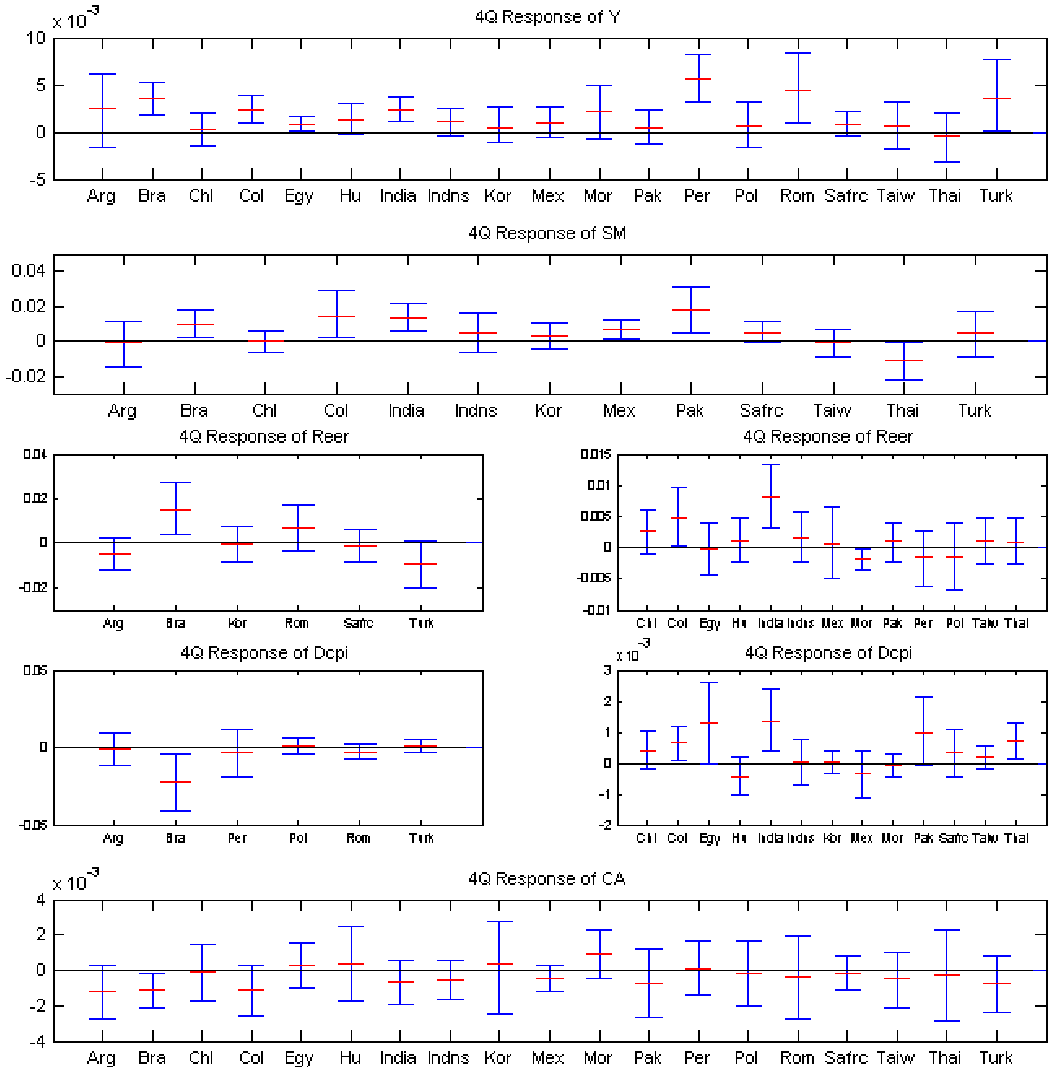


Figure A.6: GIRFs: 1 std err Global Positive Shock to EM - DF - Contemp.

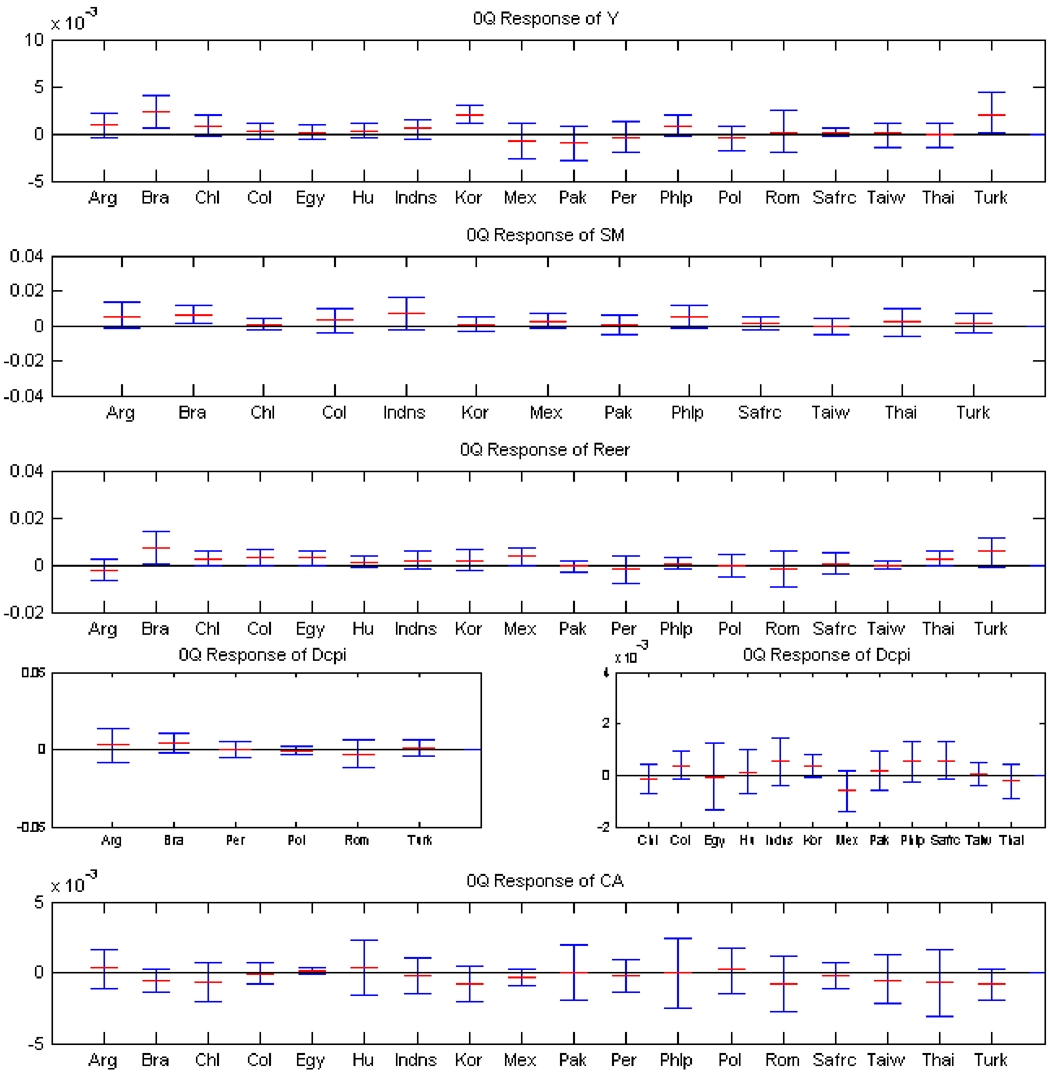


Figure A.7: GIRFs: 1 std err Global Positive Shock to EM - DF - 1 Quarter

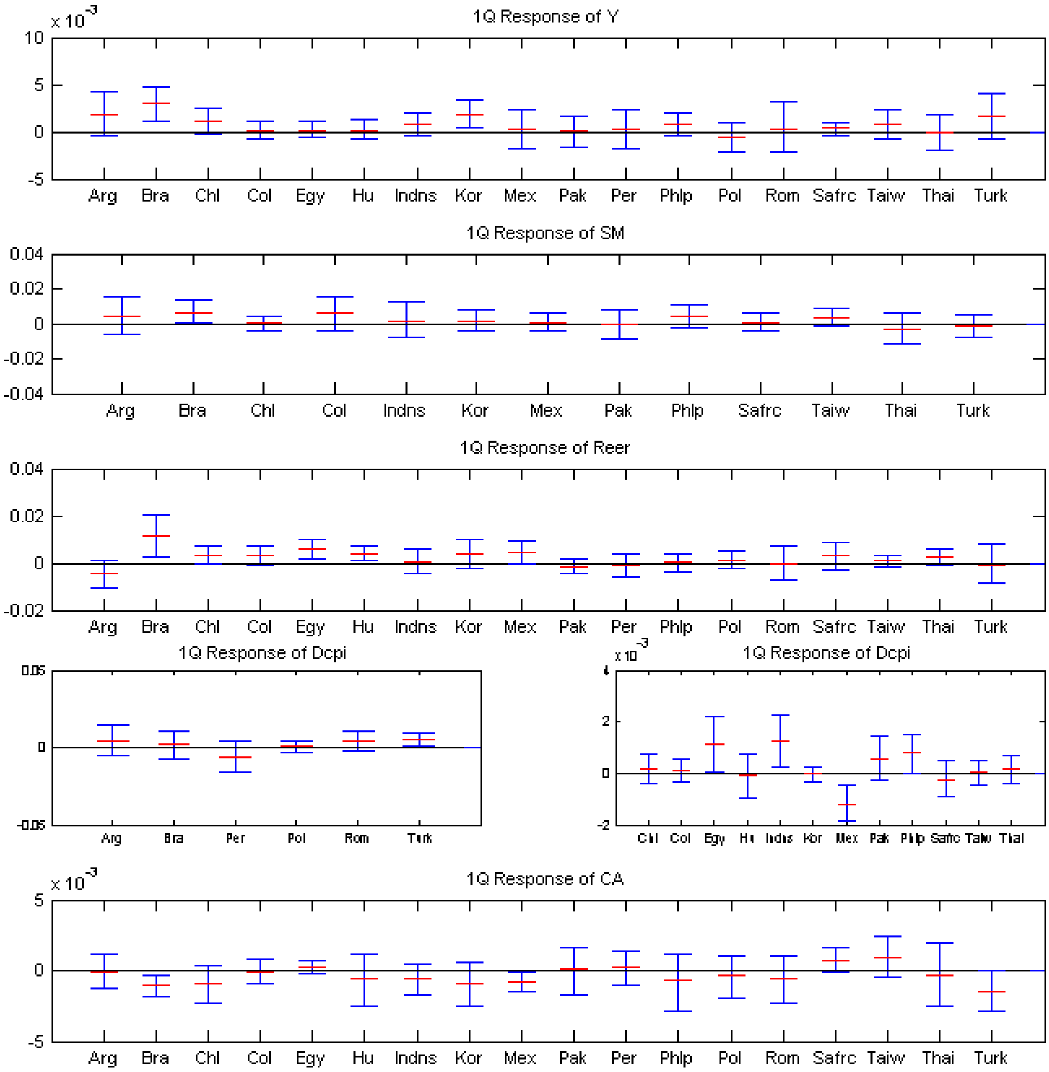


FIGURE A.8: GIRFs: 1 std err Global Positive Shock to EM - DF - 4 Quarters

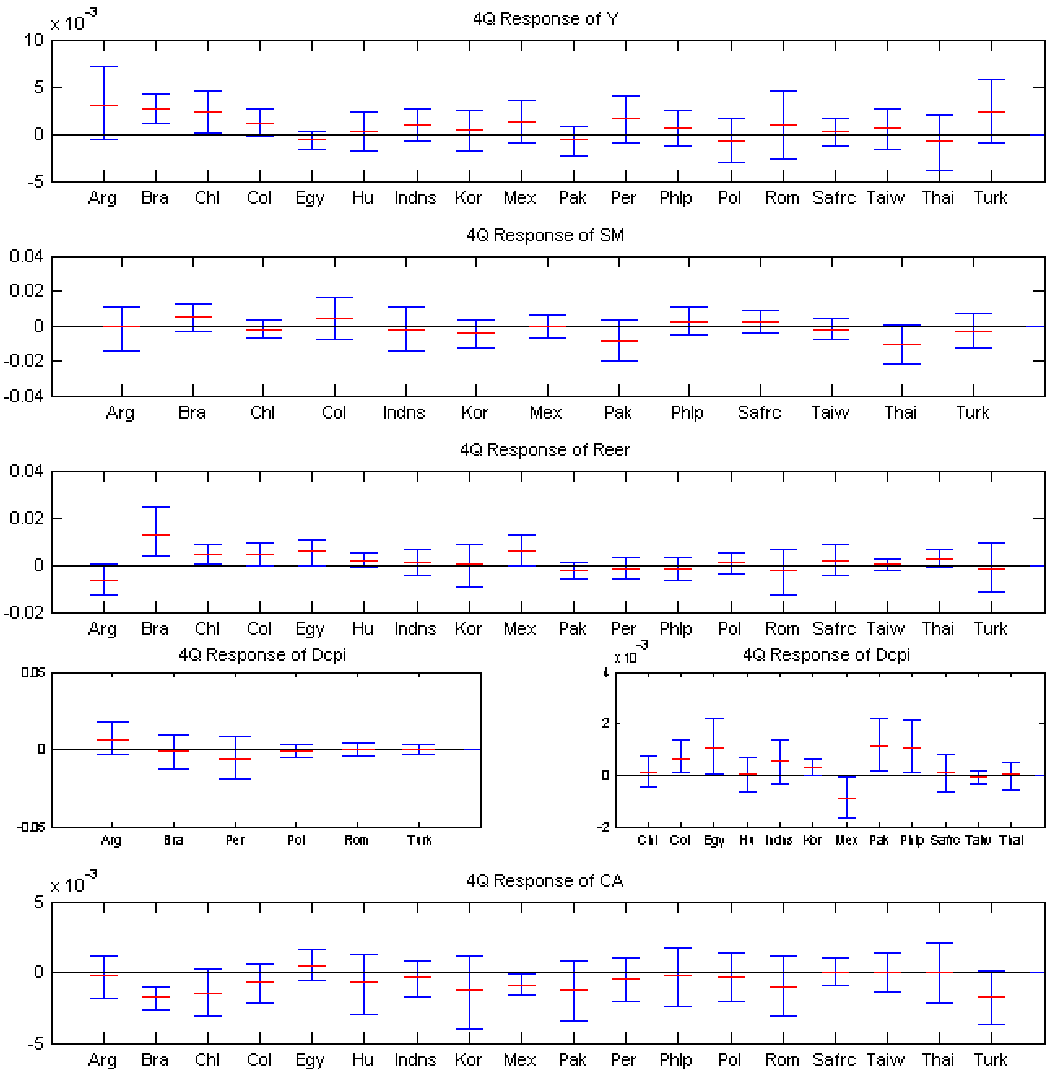


FIGURE A.9: GIRFs: 1 std err Global Positive Shock to EM - EF

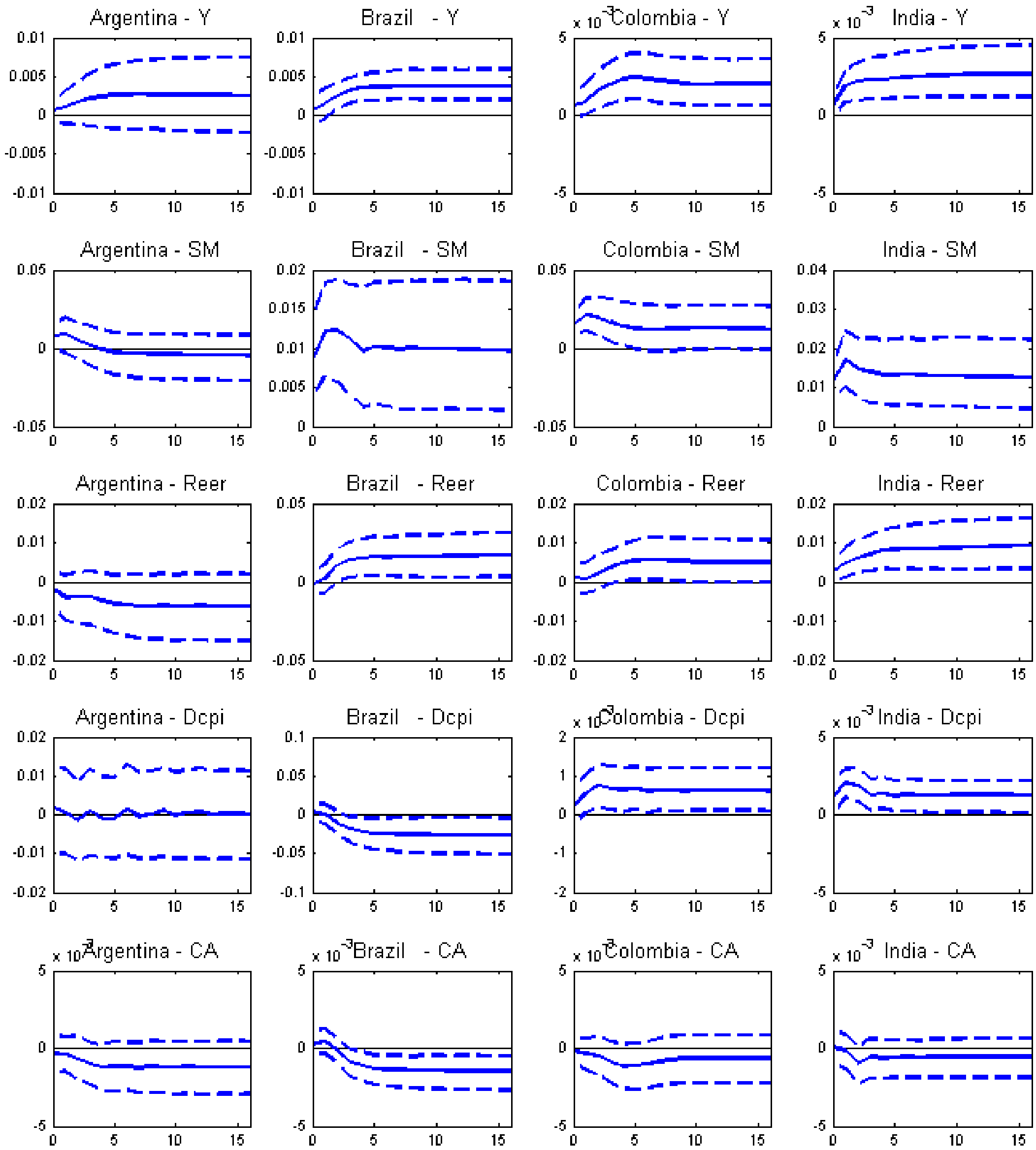


FIGURE A.10: GIRFs: 1 std err Global Positive Shock to EM - EF

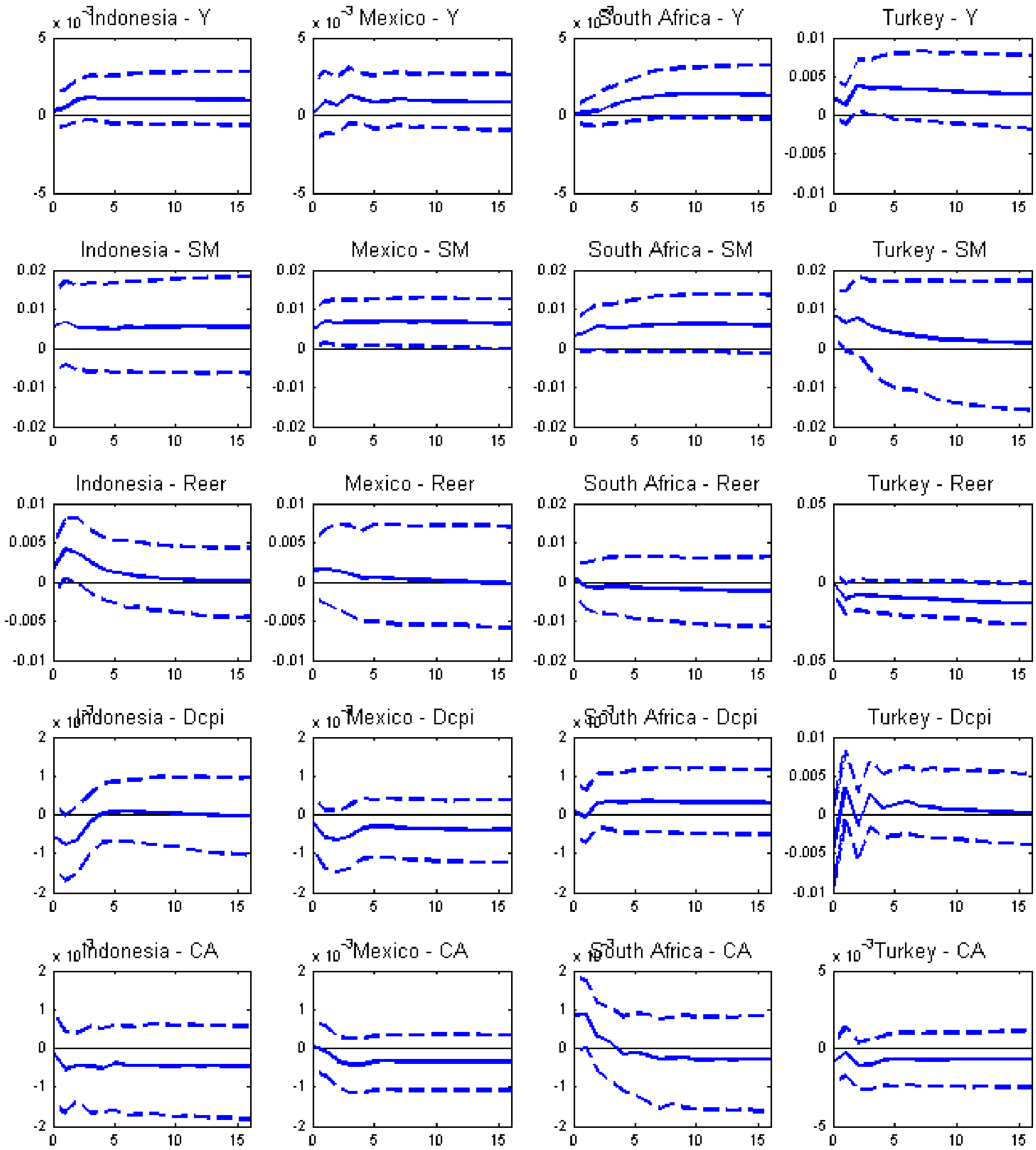


Figure A.11: GIRFs: 1 std err Global Positive Shock to EM - DF

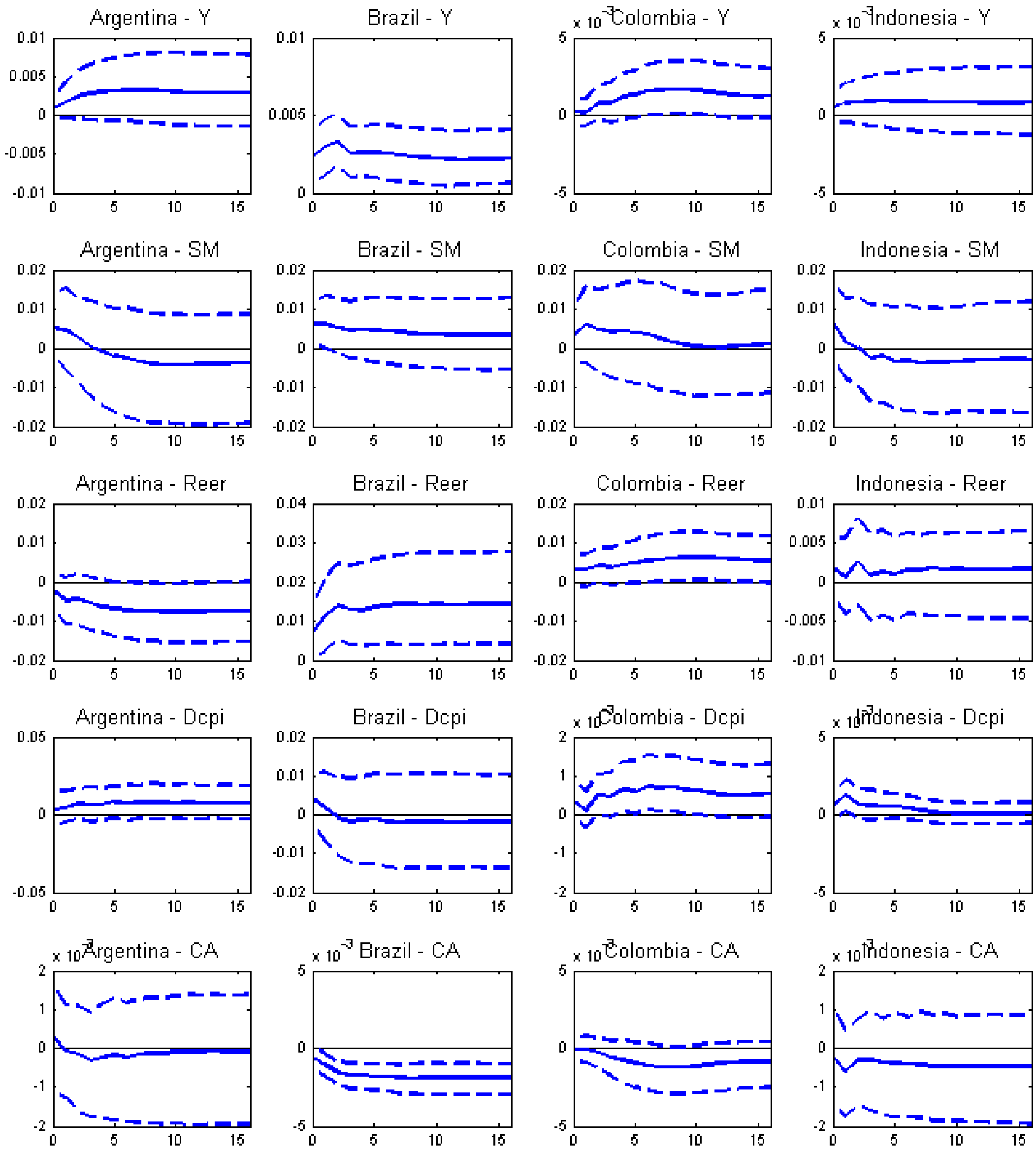


Figure A.12: GIRFs: 1 std err Global Positive Shock to EM - DF

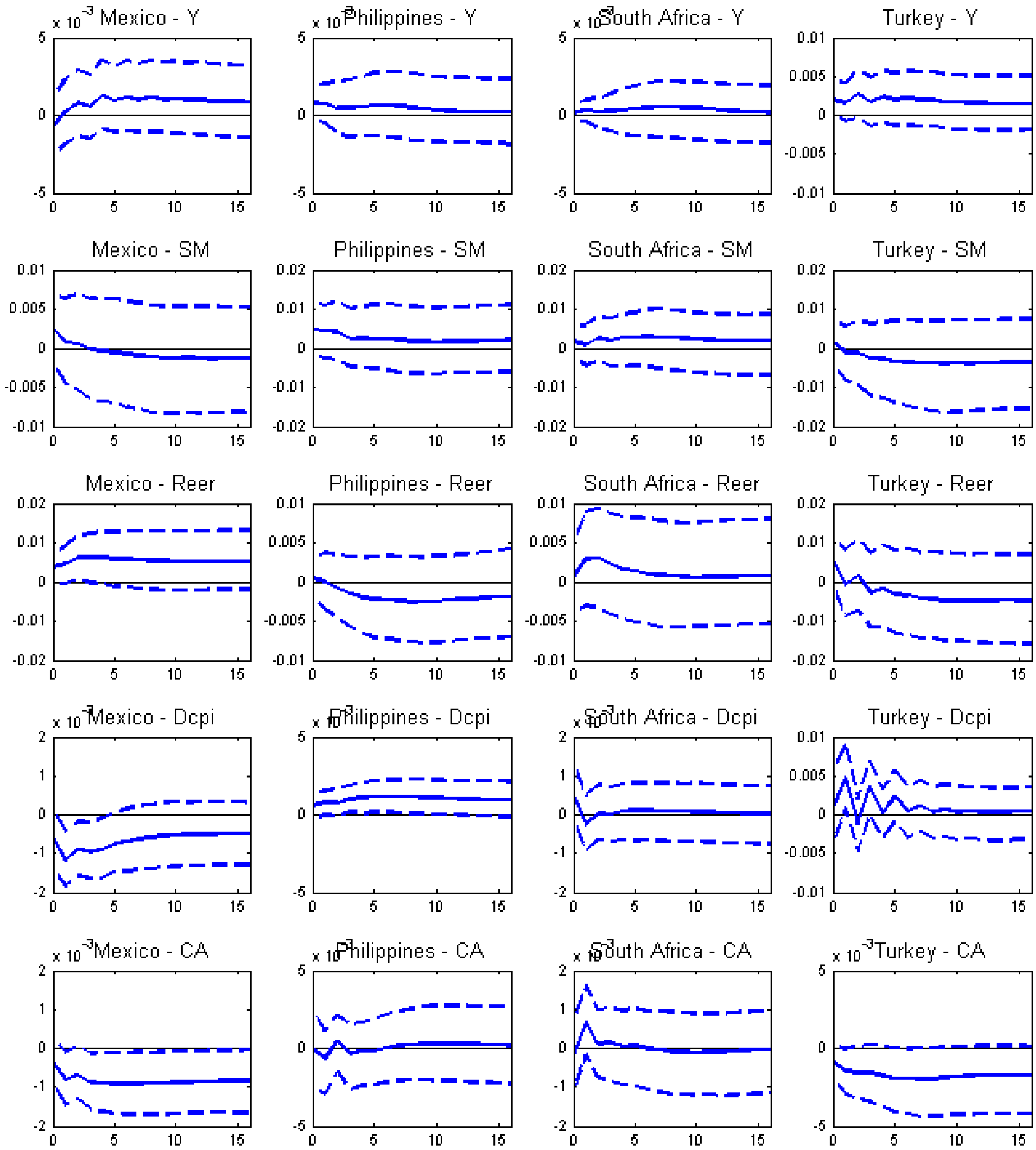


FIGURE A.13: S-GIRFs: 1 std-dev Positive Shock to VIX on DF (4Q-Cum.)

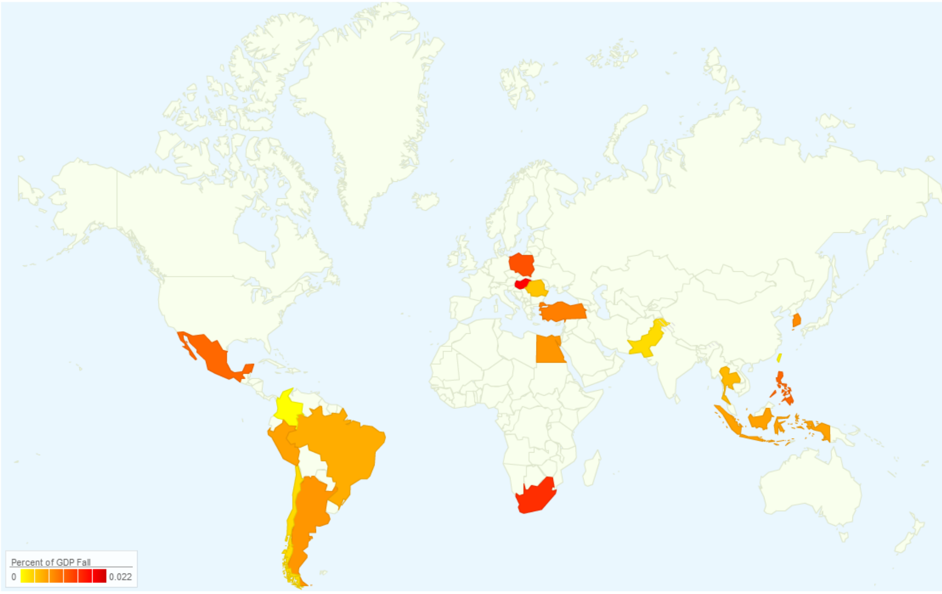


FIGURE A.14: S-GIRFs: 1 std-dev Positive Shock to VIX on EF (4Q-Cum.)

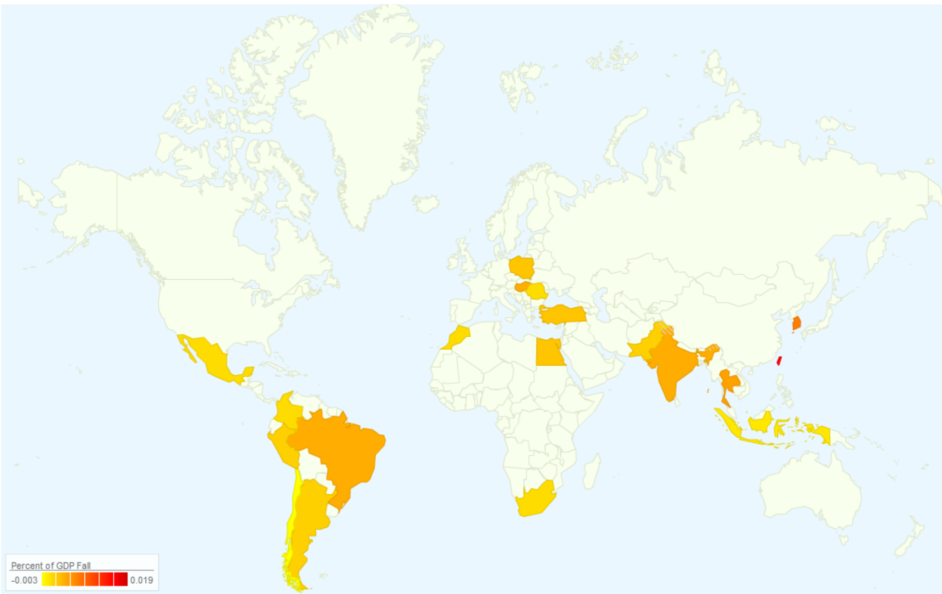


Figure A.15: GFEVDs: Average Normalized Contributions Across EMs - EF

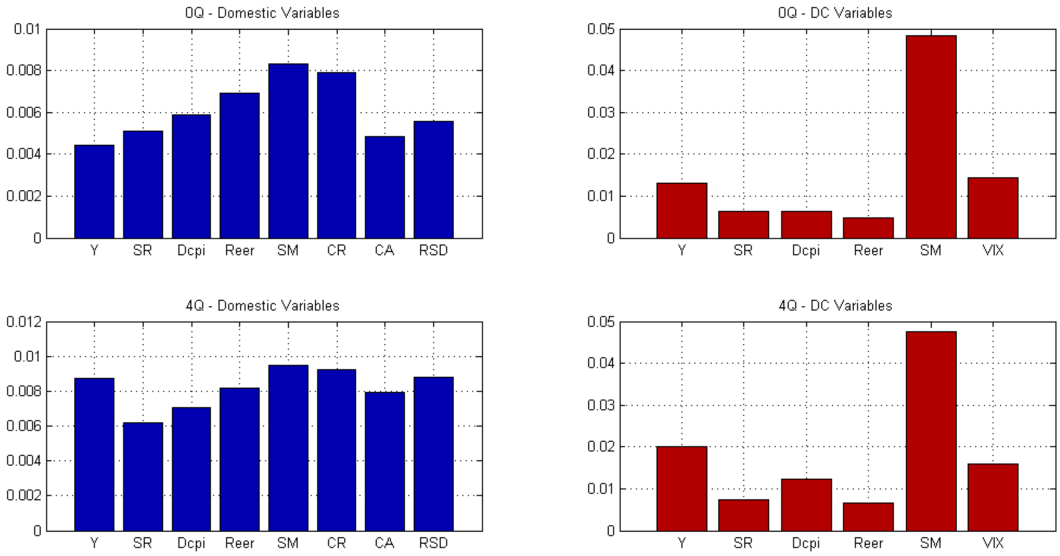


Figure A.16: GFEVDs: Average Normalized Contributions Across EMs - DF

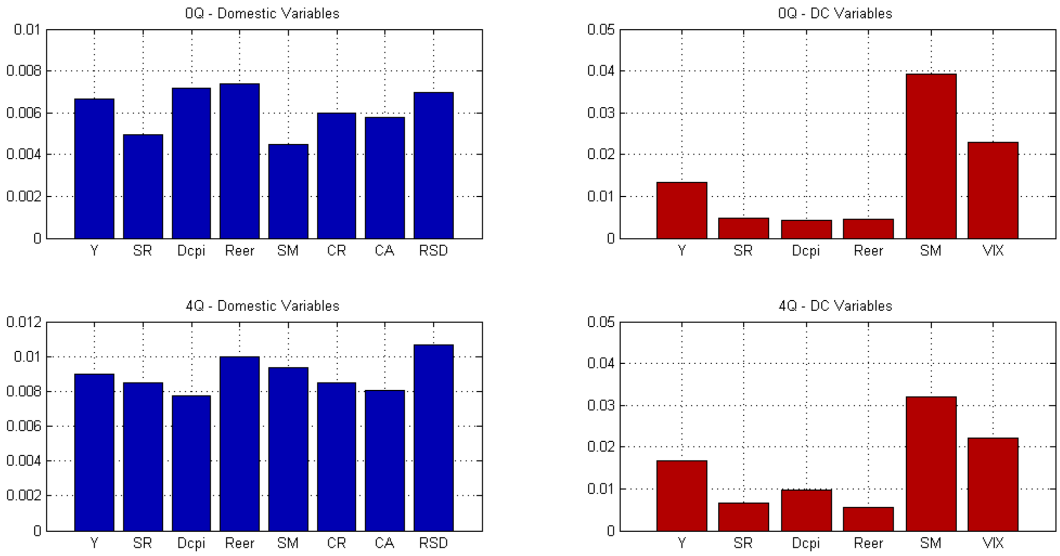


Figure A.17: GFEVDs: Rankings of Fundamentals in Contributions towards EF (y-axis: total # times a given rank is observed *among* countries)

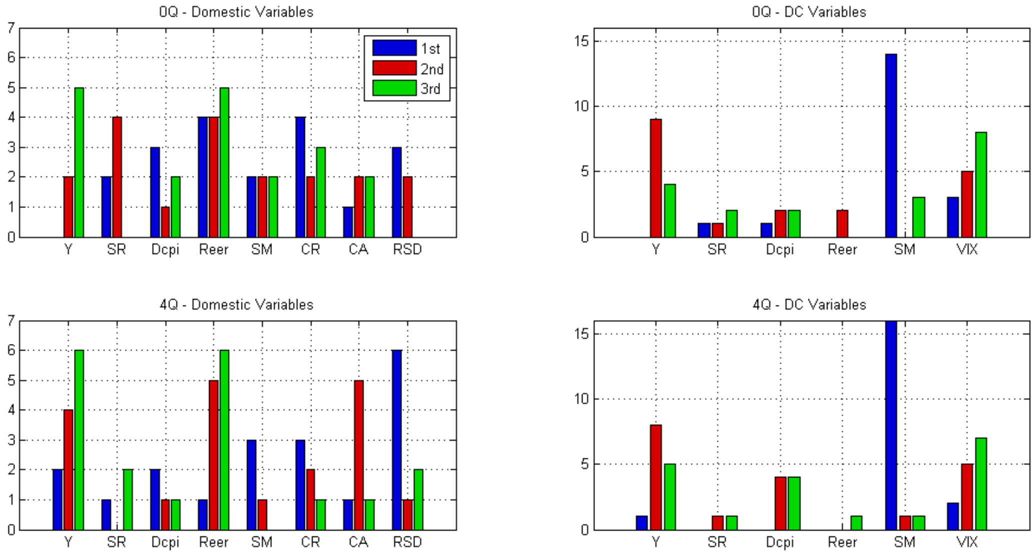


Figure A.18: GFEVDs: Rankings of Fundamentals in Contributions towards DF (y-axis: total # times a given rank is observed *among* countries)

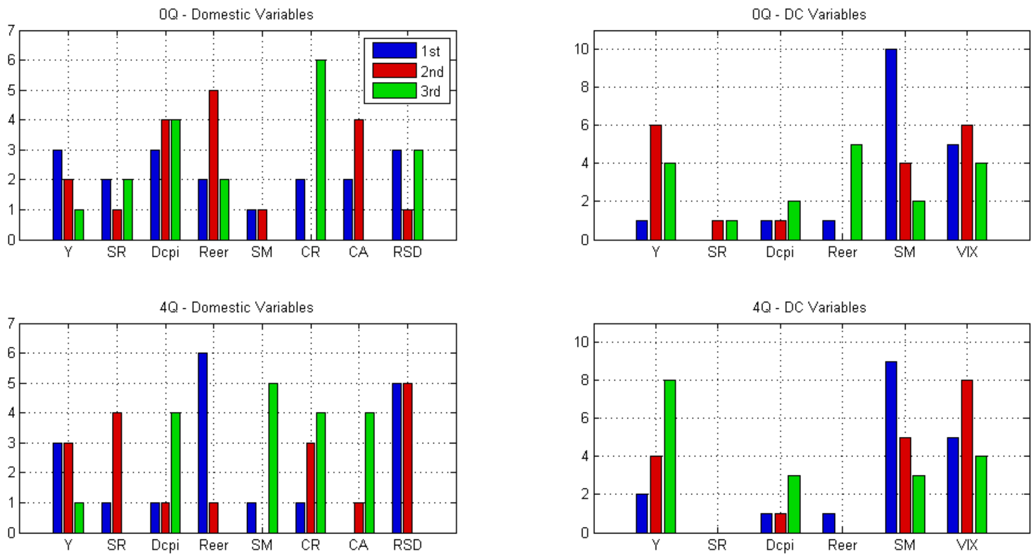


Figure A.19: GFEVDs: Total Contributions of Pull vs Push Factors

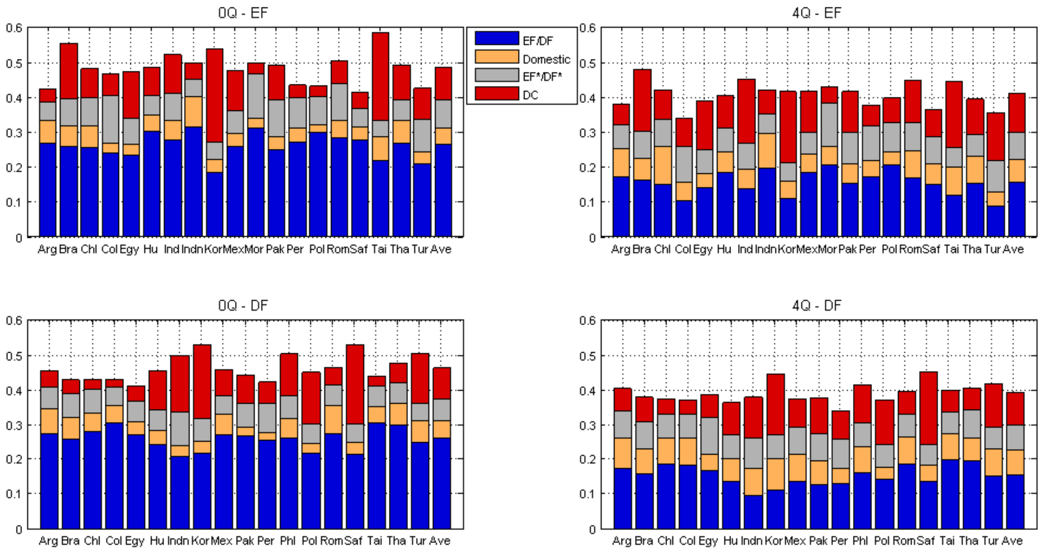
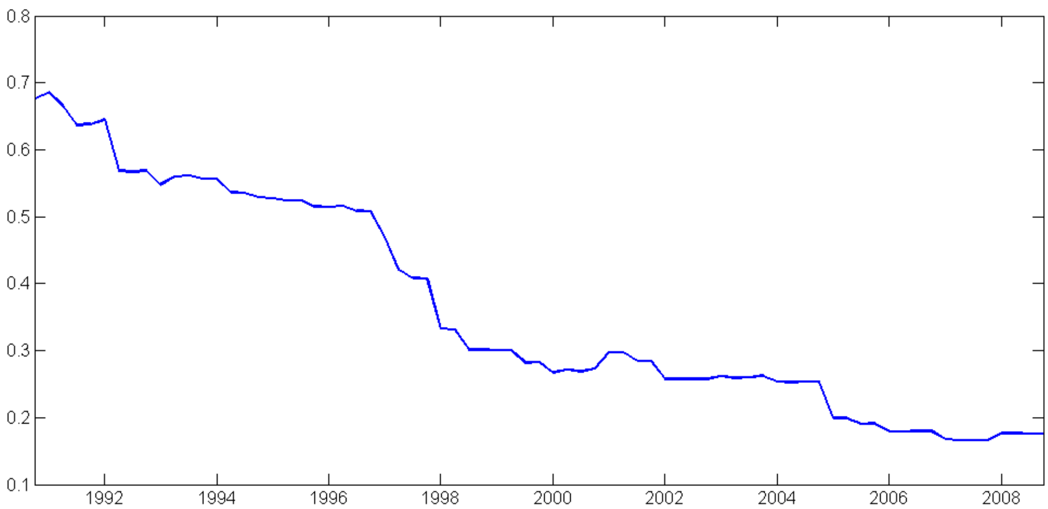


Figure A.20: Edison-Warnock Controls Measure - Average across Sample Countries



Appendix B

Figure B.1: Contributions of Fundamentals - With a TV Constant

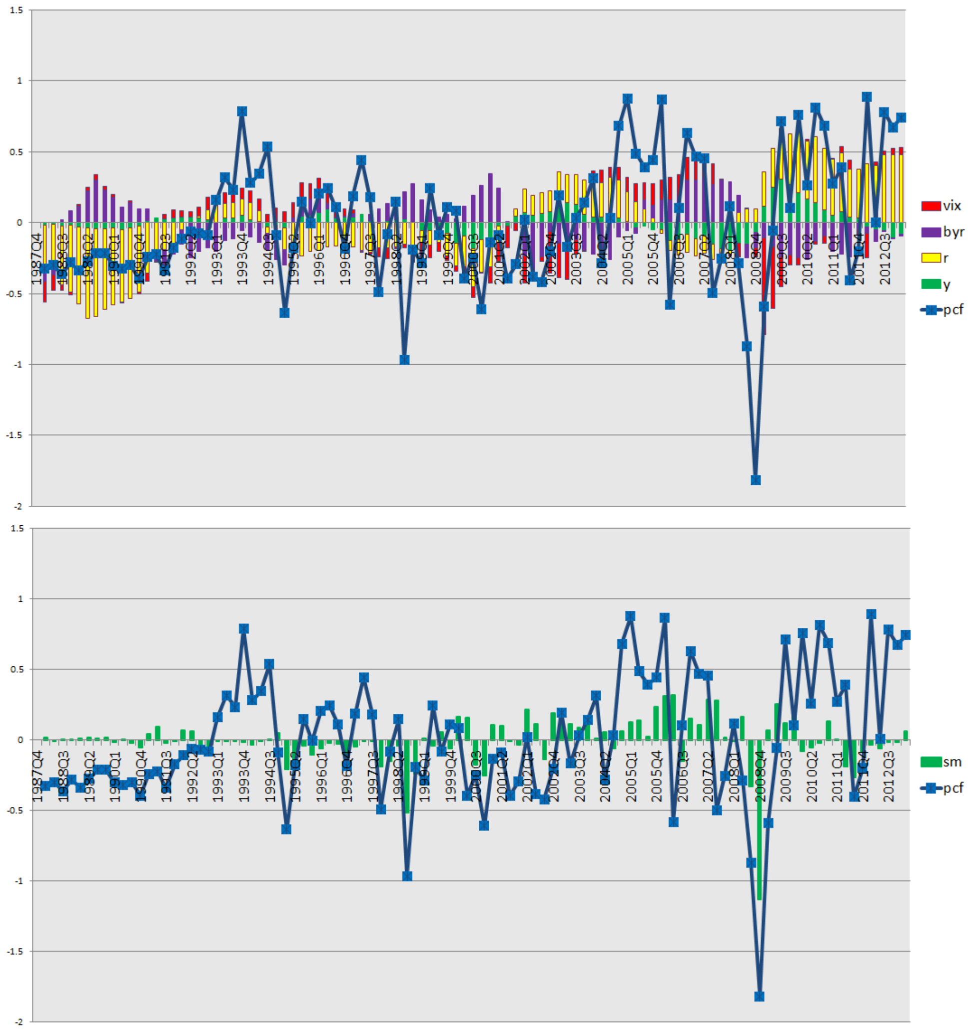
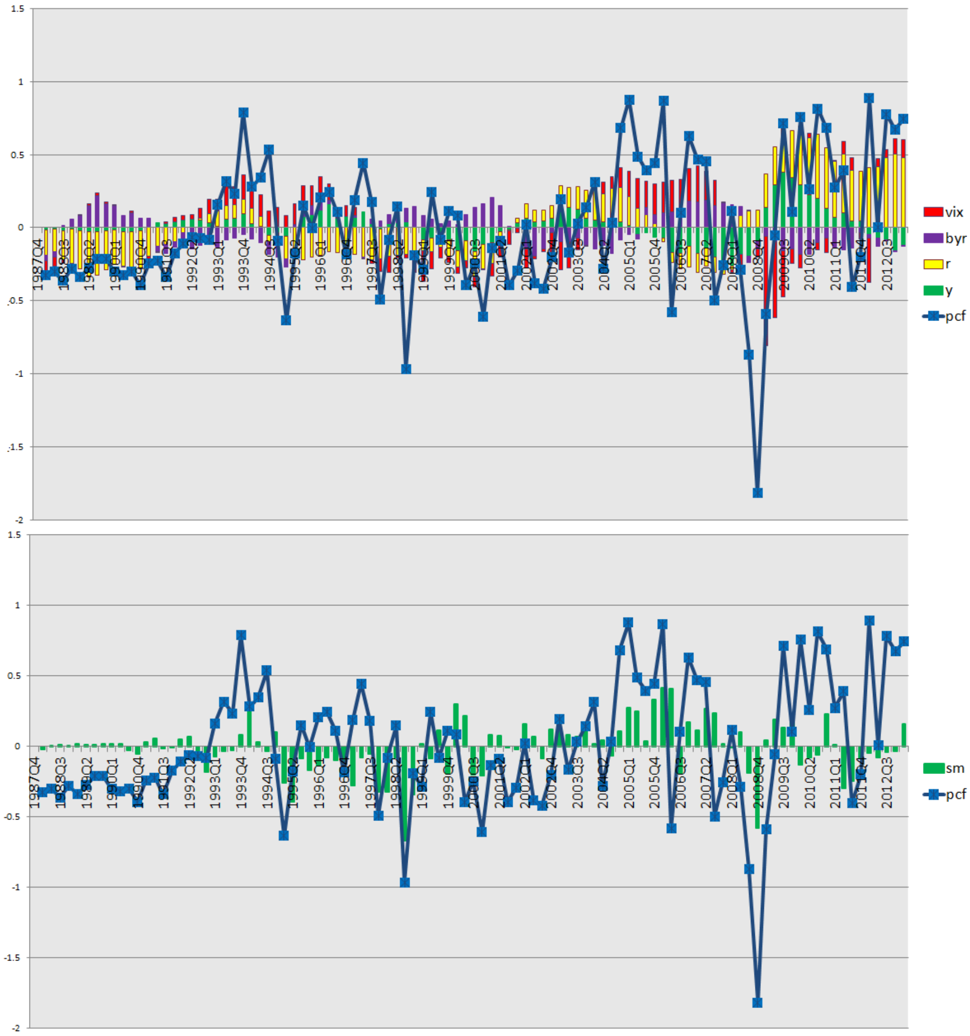


Figure B.2: Contributions of Fundamentals - With a TV Const. and Lagged *pcf*



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