Global Economic Divergence and Portfolio Capital Flows to Emerging Markets

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Abstract

This paper studies the role of global and regional variations in economic activity and policy in developed world in driving portfolio capital flows (PCF) to emerging markets (EMs) in a Factor Augmented Vector Autoregressive (FAVAR) framework. Results suggest that PCFs to EMs depend mainly on economic activity at the global level and monetary policy in America and Asia, positively on the former and negatively on the latters. In contrast, economic activity and policy shocks in Europe contribute less to variations in PCFs to EMs. An important finding is, PCFs are pro-cyclical with respect to global activity, but counter-cyclical to regional activity. In aggregate, regional variations contribute more than global variations. Hence, PCFs are driven by not only common shocks across all developed countries, but also region specific variations. This implies that economic divergence in the developed world can have significant effects on EMs via PCFs.

Keywords: Portfolio Capital Flows; Bayesian Analysis, Factor Model, VAR, Emerging Markets.

JEL Classification: C11, C32, E30, E52, E58, F32.

1 Introduction

Divergence in economic activity and policy has been a widely debated topic across policy makers and academics. In particular, the issue has become more relevant in the aftermath of the global financial crisis. United States economy has experienced a stronger rebound than other developed economies in Europe and Asia. Hence, after three rounds of Quantitative Easing, the United States Federal Reserve (FED) terminated its asset purchasing programme in 2014, whereas in Asia and Europe, central banks scaled up their measures to further loose monetary policy in the face of possible deflation. As a result, FED has been raising its policy rate, whereas in Europe and Asia policy rates are expected to remain at historically low levels. In this current environment of economic divergence in the developed world, a great uncertainty for EMs is how capital flows will be affected. In this paper, we study the importance of variations in activity and policy at different global hierarchical levels to help shed light on the possible implications of economic divergence on PCFs to EMs.

Economic divergence implies that region specific variations in activity and policy become more prominent. Hence, the key question in the context of PCFs to EMs is how important global versus region specific variations for PCFs are. On other hand, existing literature on PCFs does not provide a formal treatment and answer for this question. Previous studies suggest that interest rates and activity in the developed world are relevant drivers of PCFs.[1] However, a common drawback of these studies is that they do not account for the fact that variations in key variables are increasingly due to factors that originate at the global or regional level rather than at national level, considering the increasing level of international real and financial linkages.[2] For instance, Kose et al. (2012) study global business cycle synchronization in a dynamic factor model and find convergence in business cycles of industrial countries. They argue that country specific variations have become less important over time. So, before examining the role of a particular variable of a country in driving PCFs to EMs, one has to account for the fact that variations in the given variable may be due to variations at a higher hierarchical level. Hence, one has to decompose the variations in country specific variables into variations at different hierarchical levels. Clearly, this is especially important if the objective is to study the implications of economic divergence in developed countries on EMs, via the impact of global and region specific shocks on PCFs as in here.

To study the global and regional variations in economic activity and policy in the developed world on PCFs to EMs, this paper employs a Factor-Augmented Vector Autoregressive (FAVAR) Model. Variations in countries in North America, Europe and Asia Pacific are decomposed into global, regional and idiosyncratic levels, and incorporated in a VAR, together with a factor representing common variations in PCFs to different EMs, to study the role of shocks at different hierarchical levels in driving flows.[3]

Results indicate, global activity shocks are important drivers of PCFs. Adverse global activity shocks have significant negative effects on PCFs. Hence, PCFs are found to be pro-cyclical with respect to global economic activity. In contrast, at the regional level, PCFs are found to be counter-cyclical with respect to economic activity. Contractionary American and Asian monetary policy shocks have significant negative impact on PCFs. Furthermore, forecast error variance and historical decompositions indicate that global activity, American and Asian monetary policy shocks are key drivers of PCFs. Also, there is heterogeneity in the importance of variations at different levels and regions. Overall, region-specific variations in aggregate dominate the role of global variations. Given the importance of regional variations, economic divergence have implications for PCFs and hence EMs. In particular, since one of the most important drivers of PCFs among the regional variables is American interest rates, a respective increase may have significant negative effects on PCFs. However, since PCFs are pro-cyclical with respect to global activity, a rebound in global growth may help rebalance the possible fall in PCFs.

The following section describes the econometric model and the estimation; Section 3 presents the dataset; Section 4 illustrates the results and Section 5 concludes.

2 Econometric Model

Theoretically, the literature categorize the drivers of capital flows as global push factors and country-specific pull factors. For instance, Fernandez-Arias & Montiel (1996) argues

[1] See for instance, Chuhan et al. (1998), Taylor & Sarno (1997), Forbes & Warnock (2012).

[2] See for instance, Hirata et al. (2013b), Diebold et al. (2008), Thorsrud (2013).

[3] During the paper, we use America and North America, Asia and Asia Pacific interchangeably.

that capital flows constitute the adjustment mechanism for an international arbitrage condition to hold for the recipient emerging market country. The condition implies that the risk adjusted expected return from investing in an emerging market should be equal to the opportunity cost. The authors argue that positive capital inflows increase the total liabilities of the recipient country; as liabilities increase creditworthiness falls, and opportunity cost of investing in the recipient country rises resulting from foreign investor's diversification concerns.

Following on from the theoretical framework of Fernandez-Arias & Montiel (1996), the empirical literature commonly categorize the drivers of capital flows as foreign push and domestic pull factors.[4]. For instance, Mody et al. (2001) and Boero et al. (2016) solve the international arbitrage condition of Fernandez-Arias & Montiel (1996) to derive a linear equation for capital flows with respect to the underlying drivers. The equation states that capital flows are equal to the sum of foreign push factors that push capital towards emerging market countries, and domestic pull factors that pull capital towards the recipient emerging market country. Note that, the literature considers the foreign push factors as the same for all emerging market countries, whereas domestic pull factors to be different naturally.

In line with the existing literature, we consider the following representation for PCFs,

$$pcf_{it} = \beta_i F_t^{pcf} + e_{it}, \qquad e_{it} \sim N(0, R_i)$$

where F_t^{pcf} represent the common component driven by foreign push factors across flows to different countries; and e_{it} denotes the country-specific idiosyncratic pull component for country i respectively. Push factors include activity and policy variables at global and regional levels. Push factors and the common component of capital flows are assumed to have the following FAVAR representation,

$$\begin{bmatrix} vix_t \\ F_t^y \\ F_t^p \\ F_t^r \\ F_t^{pcf} \end{bmatrix} = c + B(L) \begin{bmatrix} vix_t \\ F_t^y \\ F_t^p \\ F_t^r \\ F_t^{pcf} \end{bmatrix} + u_t \tag{1}$$

$$\begin{bmatrix} vix_t \\ X_t^y \\ X_t^p \\ X_t^r \\ pcf_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & \Lambda^y & 0 & 0 & 0 \\ 0 & 0 & \Lambda^p & 0 & 0 \\ 0 & 0 & 0 & \Lambda^r & 0 \\ 0 & 0 & 0 & 0 & \Lambda^{pcf} \end{bmatrix} \begin{bmatrix} vix_t \\ F_t^y \\ F_t^p \\ F_t^r \\ F_t^{pcf} \end{bmatrix} + e_t \tag{2}$$

where $u_t \sim N(0, A^{-1}Q(A^{-1})')$, $e_t \sim N(0, R)$, R is a diagonal matrix, X represents data vectors on which different factors load, pcf_t collects data on PCFs to different countries, F_t^{pcf} represents the common component of capital flows across countries, and vix_t represents the VIX index as a known driver. y, p and r represent real growth, inflation and short interest rates respectively. For y, p and r, we extract factors at global and regional levels; North America, Europe and Asia Pacific. For instance for y,

[4] See for instance, Boero et al. (2016), Fernandez-Arias (1996), Edison & Warnock (2008), Chuhan et al. (1998), Calvo et al. (1993)

$$X_t^y = \Lambda^y F_t^y + e_t^y = \begin{bmatrix} \Lambda_{11}^y & D_1^{America,y} & D_1^{Europe,y} & D_1^{Asia,y} \\ \Lambda_{21}^y & D_2^{America,y} & D_2^{Europe,y} & D_2^{Asia,y} \\ \vdots & \vdots & \vdots & \vdots \\ \Lambda_{.1}^y & D_.^{America,y} & D_.^{Europe,y} & D_.^{Asia,y} \end{bmatrix} \begin{bmatrix} F_t^{Global,y} \\ F_t^{America,y} \\ F_t^{Europe,y} \\ F_t^{Asia,y} \end{bmatrix} + e_t^y$$

$$D_i^{Location,y} = \left\{ \begin{array}{ll} \Lambda_i & \text{if country i is in } Location \\ 0 & \text{if country i is not in } Location \end{array} \right\}$$

Notice that the global factor loads on all growth variables in all regions, whereas regional factors load only on the variables in their respective regions. Similar to Mumtaz & Surico (2009), the loading of each factor on the first variable at the respective region is set to 1 and that variable is only allowed to load on the respective factor for identification.[5]

The identification of the structural shocks is carried out by imposing a specific ordering on the FAVAR variables.[6] For all regions we order the factors as F^y, F^p, F^r, which identifies monetary policy shocks within each region, similar to Christiano et al. (1999) and Primiceri (2005). We order capital flows factor last following the common convention in the FAVAR literature regarding the ordering of the fast-moving variables like flows.[7] [8] We order *vix* first, assuming that it represents uncertainty shocks, similar to Leduc & Liu (2015).[9] Regions are ordered with respect to their economic size; Global, North America, Europe and Asia Pacific. Overall, we identify regional monetary policy shocks, as well as uncertainty and portfolio capital flows shocks. We interpret structural shocks to growth and inflation factors as activity shocks, given that the existing literature consider and decompose the variation in these indicators as supply and demand shocks.[10] To obtain the contemporaneous impact matrix A^{-1}, we apply cholesky decomposition on the variance covariance matrix of FAVAR residuals.

The identification strategy involves identifying the common factors as well as the structural shocks, and it has certain advantages. Firstly, it allows to distinguish between global and regional factors in a parsimonious way. Identification of factors is carried out in a similar manner to Hirata et al. (2013a) and Kose et al. (2003), where global factors load on all relevant variables across the world, whereas regional factors load only on the regional variables. However, the dynamic factor models commonly employed in the literature rests on the assumption that the identified factors are orthogonal to each other. Hence, the FAVAR framework employed in here can capture richer temporal dependencies across identified factors. On the other hand, FAVAR methodology requires identifying the structural shocks, involving a specific ordering of factors. This paper follows the

[5]See Bai & Wang (2015) for a detailed discussion of identification and estimation of multi-level factor models.

[6]We use the codes provided by Binning (2013) for identification of shocks under the block exogeneity assumption since the authors' implementation allows for variety of exclusion restrictions to be in a straightforward fashion.

[7]We have tested for the number of common factors in *pcf* following Bai & Ng (2002), and concluded that a single factor is adequate.

[8]See for instance, Bernanke et al. (2005).

[9]We have also experimented by ordering *vix* last and observed that the role of uncertainty shocks decreases, but the main findings presented with IRFs and for aggregate contributions of regional vs global shocks does not change.

[10]See for instance, Bayoumi (1992) and Bayoumi & Eichengreen (1994).

common practice in the literature and order the factors according to the region size.[11] Nevertheless, alternative ordering of factors is also considered as a robustness check here.

We set the FAVAR lag length to 2. Estimation has been carried out by Markov Chain Monte Carlo (MCMC) methods, Gibbs Sampling similar to Mumtaz & Surico (2009) and Liu et al. (2014). Minnesota priors for FAVAR parameters[12] and uninformative priors for other parameters have been implemented. Furthermore, we use principle component estimates to obtain the autoregressive coefficients and starting values for the factors and FAVAR coefficients.

The estimation steps start with setting the priors and starting values, then respectively drawing factor loadings, factors following Carter & Kohn (1994), FAVAR coefficients, FAVAR variance covariance matrix, variable/country specific component variances. We repeat sampling steps until convergence, with 50000 replications and 48000 as burn in.

3 Dataset

Table 1: List of Emerging Market Countries

			pcf			
Argentina	China	Hungary	Malaysia	Peru	Romania	Taiwan
Brazil	Colombia	India	Mexico	Philippines	S. Afica	Thailand
Chile	Egypt	Indonesia	Pakistan	Poland	S. Korea	Turkey

Table 2: List of Developed Countries

		Fundamentals	
Europe		North America	Asia Pacific
Austria	Norway	Canada	New Zealand
Finland	Spain	United States	Australia
France	Sweden		Japan
Germany	Switzerland		
Italy	U. Kingdom		
Netherlands			

Table 1 and 2 outline the list of countries included in the model for PCFs and Fundamentals. In total 21 emerging market countries are included for PCFs, and 16 developed countries for fundamentals. The countries are selected on the basis of data availability. In line with the existing literature on capital flows and the specification of the econometric model employed, the common (push) factor is extracted from capital flows to all emerging market countries across the globe, whereas the underlying global and regional fundamental factors are extracted from the developed countries. The sample period is 1988Q1 - 2014Q3. The data for the fundamentals are from Datastream, The Organization for Economic Co-operation and Development (OECD), International Monetary Fund International Financial Statistics (IFS), World Bank (WB). Existing data from mentioned

[11] See for instance, Thorsrud (2013).

[12] Using dummy observations as in Bańbura et al. (2007) and Bańbura et al. (2010).

Table 3: Summary Statistics for Portfolio Capital Flows

	Mean	Stddev	Average Correlation	Minimum Correlation	Maximum Correlation
Argentina	0.7%	0.06	5%	-17%	24%
Brazil	1.7%	0.04	13%	0%	26%
China	0.5%	0.01	11%	-8%	33%
Chile	2.0%	0.03	11%	-22%	35%
Colombia	1.1%	0.02	11%	-13%	35%
Egypt	0.1%	0.03	16%	-3%	31%
Hungary	2.2%	0.06	15%	-6%	28%
India	0.8%	0.01	29%	-2%	49%
Indonesia	0.8%	0.03	18%	4%	29%
S. Korea	1.9%	0.03	27%	6%	49%
Malaysia	0.9%	0.07	27%	0%	44%
Mexico	1.9%	0.03	19%	0%	42%
Pakistan	0.3%	0.01	15%	-3%	29%
Peru	1.1%	0.02	18%	-3%	43%
Philippines	1.5%	0.03	19%	-8%	36%
Poland	1.4%	0.03	23%	-17%	45%
Romania	0.7%	0.02	13%	-3%	29%
S. Afica	2.6%	0.04	16%	-1%	31%
Taiwan	1.6%	0.05	16%	-22%	40%
Thailand	1.2%	0.02	20%	-2%	37%
Turkey	1.3%	0.03	24%	4%	42%
Average	1.2%	0.03	17%	5%	28%

Stddev denotes standard deviation; Average, Minimum and Maximum Correlations denote the average, minimum, maximum correlation of PCFs to respective EM and flows to other EMs; Average denotes the average across EMs.

sources is supplemented with the dataset from Mandalinci (2014) who uses various data sources and interpolation procedures to interpolate missing quarterly observations, in particular to construct quarterly PCFs variables.[13] Final pcf variables reflect the net purchases of portfolio equity and debt instruments of non-residents from residents.[14] We normalize flows by nominal gdp for each country.

For growth indicators, we use real gdp, composite leading indicators and industrial production. For inflation, we include consumer price index, producer price index, gdp deflator and core consumer price index for each country depending on the data availability. For short term interest rates, policy rates, deposit rates and 3 month Treasury-bill rates have been used. As a robustness check, we also augment the benchmark model with real equity prices of national stock markets. Yearly percentage changes are used for growth and price measures, whereas quarterly growth rates are for stock prices. Growth and inflation indicators are seasonally adjusted; and all variables are standardized.

[13]We interpolate three outliers in PCFs by linear interpolation.

[14]Note that, in addition to portfolio flows, direct investment and bank lending flows are also sizable components of aggregate capital flows to EMs. We focus only on portfolio flows for several reasons. The literature argues that the dynamics of direct investment and bank lending are significantly different than portfolio flows, which necessitates inclusion of different sets of variables in the model. Also, banking flows data is available from Bank of International Settlements, but for most EMs sample begins in early 2000s.

Figure 1: Estimated Factors

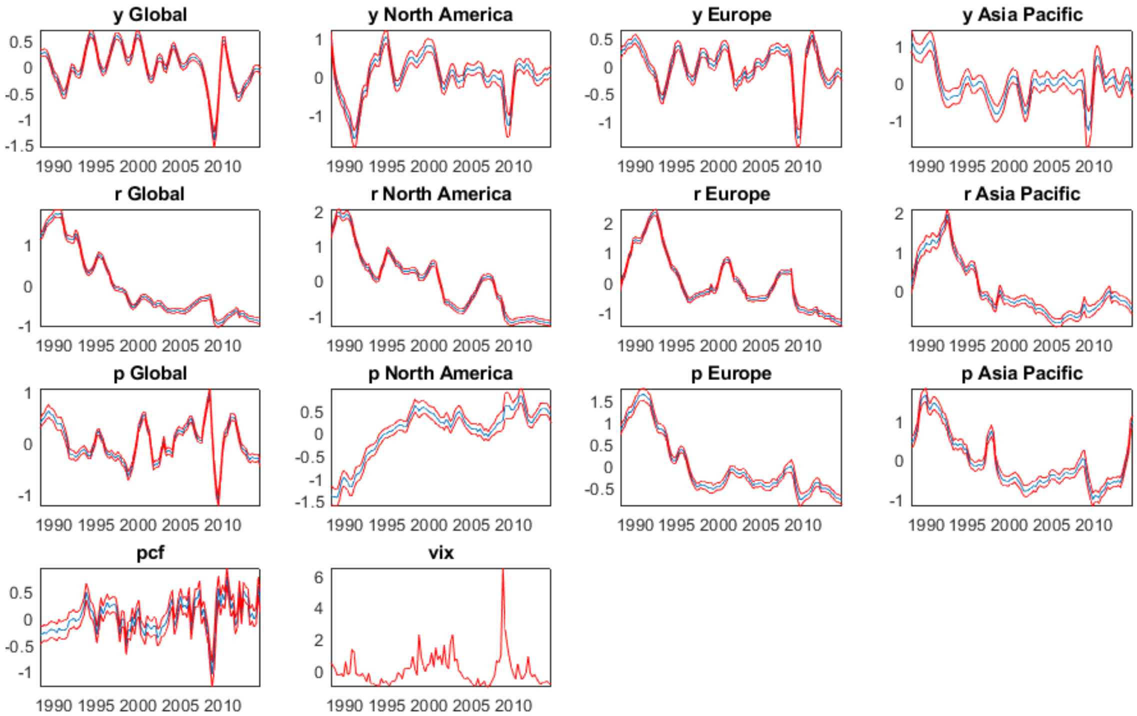


Table 3 presents summary statistics for unstandardized portfolio capital flows to nominal gdp ratios to emerging market countries. One can observe that the level of portfolio capital flows have been on average 1.2% of their respective gdp's. However, both the mean and the volatility of flows have been notably different across emerging markets. Correlations indicate that portfolio capital flows are positively correlated across emerging markets. This indicates preliminary evidence of the existence of the common push factor across flows to emerging markets. However, there are notable differences across correlation of flows among sample countries. For instance, capital flows to Argentina share less common variability with flows to other countries, whereas flows to India, South Korea and Malaysia seems to share more.

4 Results

Figure 1 presents the estimated factors with 16%-84% quantiles from their posterior distributions. Overall, the factors portray variations that are in line with prior expectations for all regions. For instance, the dramatic fall in economic growth and inflation during the recent global financial crisis, as well as historically low interest rates in the aftermath are visible in the dynamics of the factors. Evidence of the early 90s slowdown in the America and the late 90s East Asian crisis are present in the regional growth factors. Also, the European activity factor portrays the impact of European sovereign debt crisis, as expected. Regarding capital flows, we observe significant falls in 1995 Mexican and 1997-8 East Asian Crisis and Russian default; but they have been much smaller in absolute terms than the fall during the recent global financial crisis. Moreover, the rebound in capital flows to EMs in the aftermath of the crisis is captured by the common factor.

Figure 2: Selected Impulse Response Functions

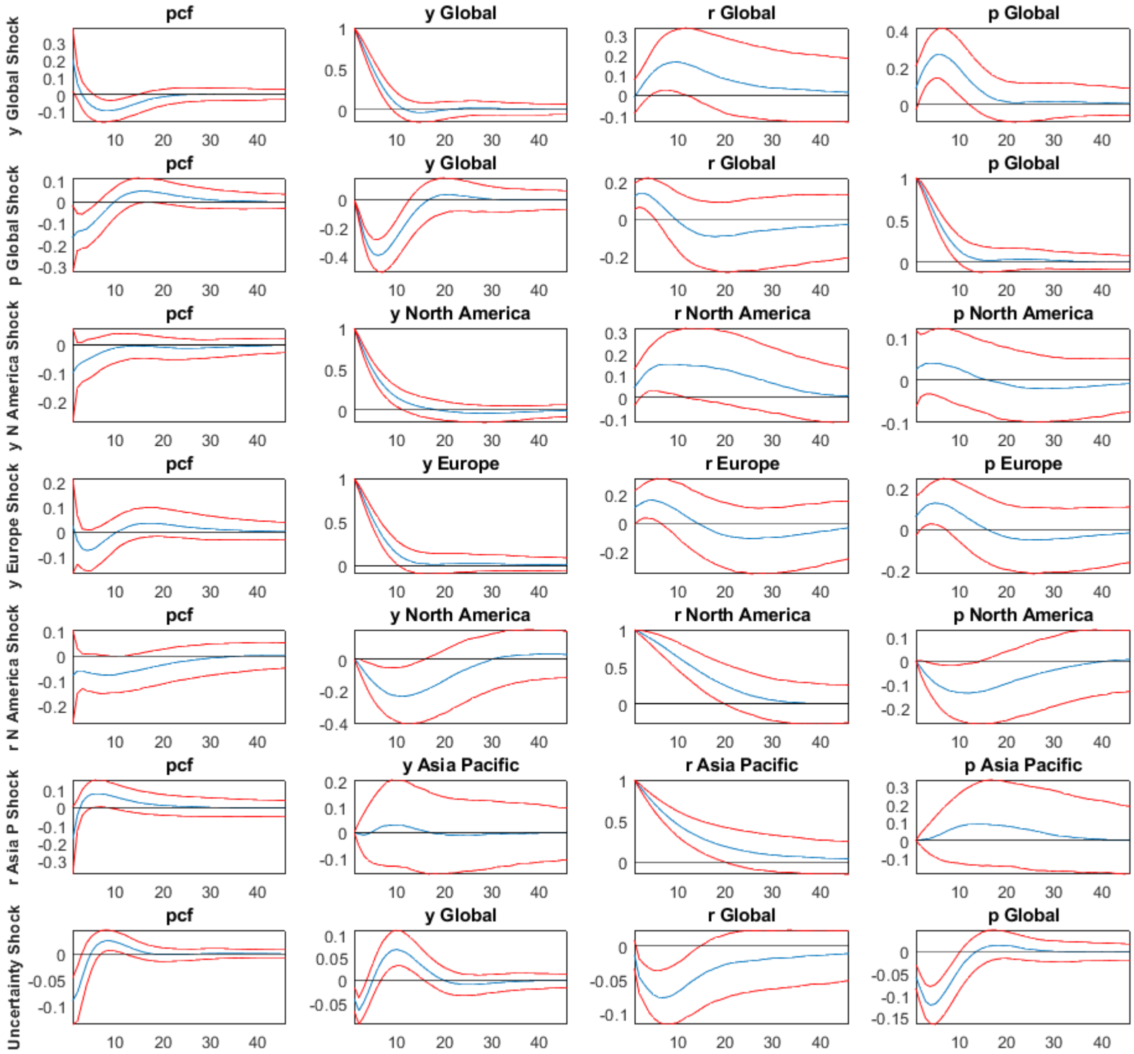


Figure 2 presents the Impulse Response Functions (IRFs) following global activity, American and Asian monetary policy and uncertainty shocks. Depicted shocks are the ones that PCFs respond strongest among all structural shocks. Starting with the global activity shocks, from the responses of PCFs one can argue that PCFs are pro-cyclical with respect to the global activity. In other words, adverse activity shocks, which affect global growth negatively, result in significant falls in PCFs. In contrast, IRFs reveal that regional positive activity shocks to y lead to a fall in PCFs. This suggests that there exist positive and negative relationship between global and regional activity and PCFs respectively. Examining the regional inflation and interest rates responses to regional y, in most of the cases the shocks lead to higher interest rates and inflation. A rise in interest rates in North America causes growth and inflation to go down, in line with the expectations, and also cause a significant fall in PCFs. Similarly, a rise in short interest rates in Asia Pacific results in a significant fall in PCFs, but growth and prices are not affected significantly. This may reflect the fact that currencies of the countries in this region are widely considered to be the short side of the carry trade activity, like Australia and Japan. Hence a rise in short rates may reduce flows to EMs as borrowing costs rise. Turning to the uncertainty shock, the responses of all model variables except interest

Table 4: FEVD of pcf - Global and Regional Aggregates

	Global			North America		
Horizon	Activity	Int. Rates	Inflation	Activity	Int. Rates	Inflation
0Q	1.56%	0.72%	1.37%	0.97%	0.57%	0.62%
1Q	1.44%	0.74%	1.91%	1.12%	0.62%	0.66%
4Q	1.95%	1.04%	3.73%	1.86%	1.08%	0.93%
8Q	2.91%	1.34%	4.3%	2.22%	1.7%	1.09%
20Q	3.87%	1.9%	5.4%	2.62%	2.69%	1.41%
40Q	3.93%	2.64%	5.81%	3.03%	3.33%	1.6%

	Europe			Asia Pacific		
Horizon	Activity	Int. Rates	Inflation	Activity	Int. Rates	Inflation
0Q	0.5%	0.51%	0.69%	0.75%	1.07%	0.53%
1Q	0.61%	0.57%	0.73%	0.83%	0.99%	0.62%
4Q	1.23%	1.13%	0.97%	1.33%	1.51%	1.16%
8Q	1.51%	1.44%	1.21%	1.62%	2.05%	1.53%
20Q	2.12%	1.92%	1.49%	2.14%	2.5%	2.21%
40Q	2.43%	2.25%	1.76%	2.51%	2.93%	2.84%

Table 5: FEVD of pcf - Regional Variables

Horizon	Global	North America	Europe	Asia Pacific	Uncertainty
0Q	3.65%	2.15%	1.7%	2.35%	6.26%
1Q	4.09%	2.4%	1.91%	2.44%	9.7%
4Q	6.72%	3.87%	3.33%	4%	11.55%
8Q	8.55%	5.02%	4.16%	5.2%	12.69%
20Q	11.18%	6.72%	5.53%	6.85%	12.81%
40Q	12.39%	7.95%	6.43%	8.28%	12.22%

rates in Asia, are significant and negative, including PCFs.

To examine whether variations at global or regional levels are the major driving forces behind PCFs, we calculate Forecast Error Variance Decomposition (FEVD) of PCFs. Table 4 illustrates the contribution of structural shocks originating at global and regional variables to PCFs at different horizons. Table 5 presents the contributions aggregated within different hierarchical levels, together with the contribution of uncertainty shocks. Starting with the individual variables, global activity shocks overall are the most important drivers of PCFs. On the other hand, American and Asian monetary policy shocks appear as other important drivers, as expected from the results presented for IRFs. Table 5 suggests that flows are driven mainly by the global variations, but on aggregate regional contributions are greater than global. Also, uncertainty shocks play a significant role in driving flows, in particular contemporaneously and in one quarter relatively.

Figure 3 plots the historical contributions (HDs) of idiosyncratic, uncertainty and aggregate global and regional shocks' contributions to PCFs; whereas Table 6 presents the average normalized (to 100%) HDs for different periods in the sample. Although FEVDs indicate the relative contribution of variations at global and regional level, HDs provide

Figure 3: HD of pcf - Global and Regional Aggregates

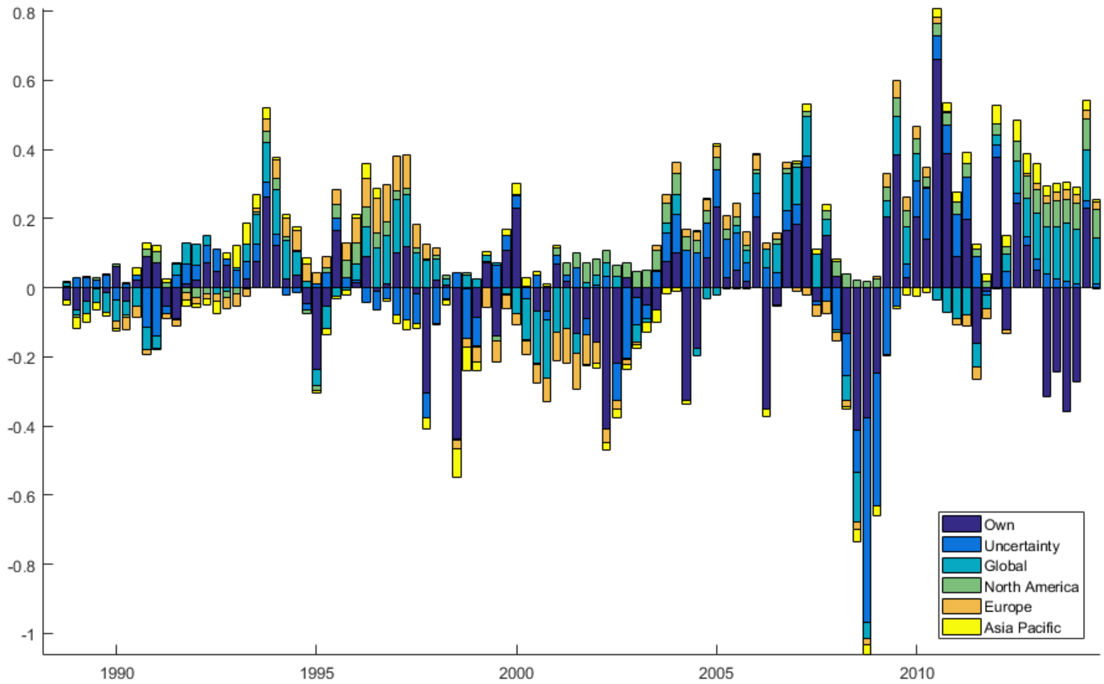


Table 6: Average HD of pcf - Global and Regional Aggregates

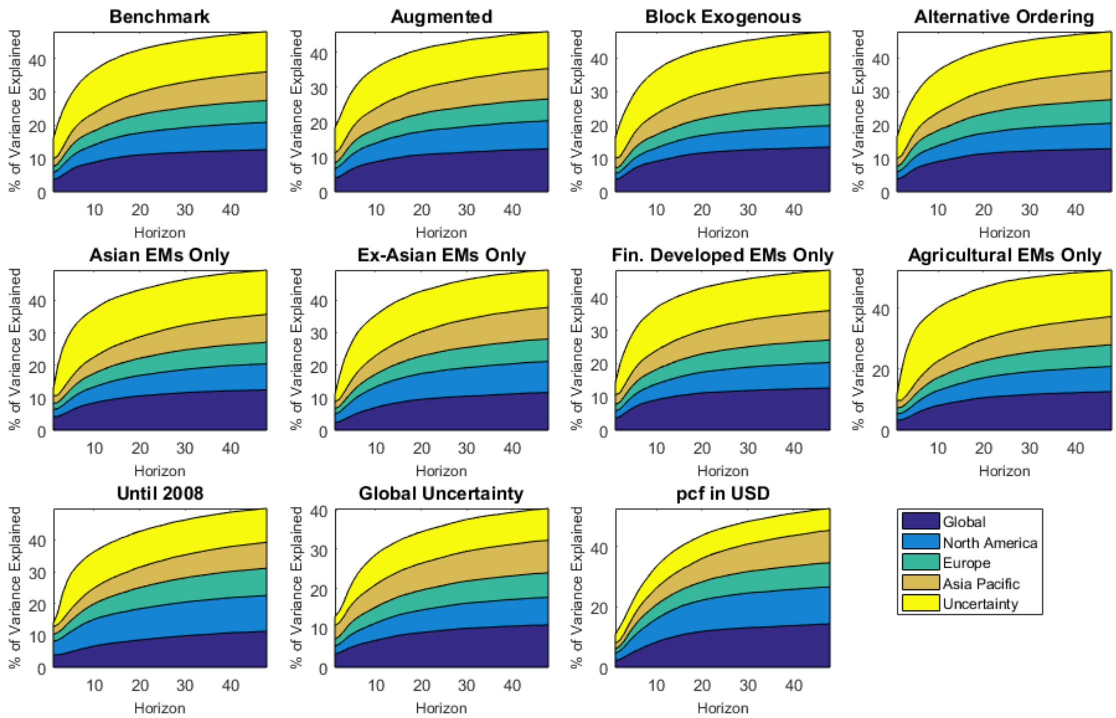
Date	Own	Uncertainty	Global	N. America	Europe	Asia Pacific
1990-2000	7.5%	-13.1%	46.4%	13.6%	19.4%	0.1%
2000-2008	-23.8%	16.6%	-8%	32.7%	-15.4%	-3.5%
2008-2009	-35.4%	-55.5%	-2.7%	2.5%	-0.5%	-3.4%
2009-2014	31.2%	8.2%	24.8%	21.8%	5.2%	8.8%

HDs shocks are normalized such that they sum to 100% in each period for ease of exposition.

further information about the importance of these contributions during the specific periods of interest. In line with the FEVDs, HDs indicate that global shocks have contributed most towards PCFs during the sample period considered here.

Historical decompositions indicate that, similar to FEVDs, variations in activity and interest rates in Europe have contributed the least towards PCFs overall, except from mid 1990s until early 2000s. Table 6 indicate that EM-specific "own" shocks contributed less towards PCFs in 1990s than in 2000s. North American fundamentals contributed towards the surge in capital flows in the early 2000s until the global financial crisis. During 2008-2009 crisis, uncertainty shocks have been the key driver of the sudden stop in capital flows to EMs. Results indicate that the significant rebound in PCFs to EMs following the global financial crisis was mostly due to uncertainty, Global and American fundamentals, as well as idiosyncratic (own) shocks which may partly reflect common improvement in EM specific fundamentals. On the other hand, during the period following the "Tapering Tantrum" of 2013, Global and American variations have contributed positively, but idiosyncratic shocks have contributed negatively towards PCFs. Considering the results discussed earlier, rising short interest rates in America may cause a significant fall in PCFs. However, Table 6 indicate that the idiosyncratic component overall contributed more than American fundamentals towards PCFs. Hence, one may argue that possi-

Figure 4: Sensitivity Analysis: FEVD of pcf - Global and Regional Aggregates



ble improvements in EM specific fundamentals, for instance structural reforms that may boost productivity, can constitute a balancing effect in against rising interest rates.

4.1 Sensitivity Analysis

In order to check whether the results obtained under the benchmark model are robust with respect to model specification and identification, we made changes to the benchmark model and examined the sensitivity of results. Figure 4 presents the contributions of activity and policy shocks to forecast error variance of PCFs under the benchmark and alternative cases considered. First, we considered an augmented model with additional variables; real stock market prices (sm). Stock prices can capture developments in underlying countries that may not be fully reflected in our benchmark activity and interest rate indicators.[15] Secondly, we experimented with a different identification scheme in which we restrict the contemporaneous impact of shocks between regions North America, Europe and Asia Pacific to be zero (block exogenous). Under this alternative identification scheme, global shocks can affect regions contemporaneously, but region-specific shocks are assumed not to have an impact on other regions instantaneously. We considered an alternative ordering of the regions and placed North America after Europe. Then we checked whether there are any differences between Asian vs ex-Asian EMs, and between financially developed vs agricultural EMs. For financially developed EMs, we used top 10 EMs with highest stock market capitalization of domestic stocks to gdp ratios. Similarly, we picked top 10 EMs with highest agricultural value added in their gdp. Furthermore, to examine whether results are sensitive to global financial crisis, we have re-estimated the model until 2008. Also, given that vix index is complied from US markets, we have used

[15] Since stock prices are fast moving financial variables, we order them after activity and policy variables of all regions, just before PCFs. The regional order is the same as other variables, Global, America, Europe and Asia.

the global uncertainty measure by Mumtaz & Theodoridis (2017). Finally, to illustrate whether the normalization of pcf by gdp have any impact on the key findings, we have estimated the model without normalization (pcf in USD).

Figure 4 illustrates that there are no major changes in the relative importance of regional drivers in models augmented with stocks prices, asian, ex-asian, financially developed, or agricultural EMs. Considering the case with a block exogenous contemporaneous impact matrix, Asia Pacific gains more importance and variations originating in North America slightly less. But relative contributions of global vs regional shocks are still very similar. When we reverse the ordering of North America and Europe, importance of European fundamentals become only marginally higher. With data until 2008, global variations and uncertainty become slightly less important and North America region becomes marginally more important. Replacing vix with global uncertainty results in a slight fall in its contribution, emphasizing the importance of US based uncertainty. Finally, with pcf in USD, importance of uncertainty shocks seems to fall. But, this may be due to the fact that un-normalized flows have risen sharply despite the moderation of uncertainty following 2009. For this reason the estimation may pay attention to the latter parts of the sample more than the rest, which may result in overall lower contribution towards pcf forecast errors throughout the sample period. Apart from uncertainty shocks, relative importance of regional drivers are very similar. Overall, results are found to be robust with respect to changes in model specification and identification assumptions.

5 Conclusion

This paper contributes to the literature by examining the role of global and regional activity and monetary policy shocks in driving PCFs to EMs. We have constructed a FAVAR model with PCFs and fundamentals that reflect activity and monetary policy shocks at different hierarchical levels, as well as uncertainty shocks. In the light of the on-going debate about economic divergence in developed countries and its possible implications for EMs, our motivation has been to lay evidence on the importance of global and regional economic variations for PCFs to EMs.

Results from the IRFs indicate that adverse Global activity and contractionary American monetary policy shocks lead to significant falls in PCFs, as well as adverse uncertainty shocks and positive regional growth shocks. Hence, results suggest that PCFs are procyclical with respect to global economic activity, but counter-cyclical to regional activity. Given the sensitivity of capital flows to global fundamentals, findings are in line with the literature on "push and pull" hypothesis of capital flows. FEVDs indicate that American and Asian monetary policy shocks are the most important regional drivers. Regarding the possible implications of economic divergence in developed countries, even though global variations are more important than variations in any single region, aggregate regional variations dominate global. This implies that economic divergence is in fact relevant for PCFs to EMs. But, historical decompositions indicate that a large amount of the variation in PCFs is driven by its own idiosyncratic shocks. Also, idiosyncratic shocks have played an important role in 2009-11 surge and 2013-onwards fall in PCFs. Considering that a portion of the common idiosyncratic shocks of PCFs to different countries reflect common improvement or worsening of EM specific fundamentals, from the results obtained here, one can argue that the possible impact of rising interest rates or divergence in economic activity in the developed world can be countered by structural reforms pursued in EMs.

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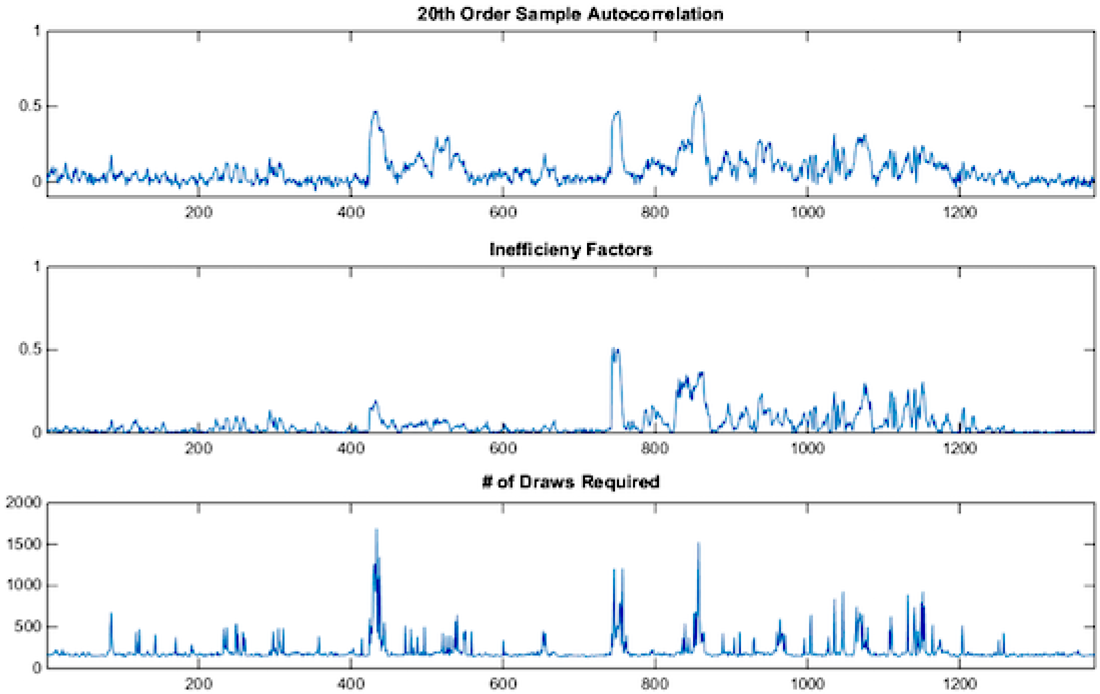
Figure 5: MCMC Convergence Diagnostics



6 Appendix

6.1 MCMC Convergence

Similar to Primiceri (2005), we have checked for the convergence of the MCMC algorithm by first examining the 20^{th} order autocorrelation of stored draws, as presented in the top panel of Figure 5. Apart from a few observations draws portray notably low autocorrelations, indicating convergence. As in Baumeister & Benati (2013), the middle panel of Figure 5 portray the inefficiency factors (IFs) for MCMC draws, which is the inverse of the relative numerical efficiency of Geweke (1992).[16] Primiceri (2005) and Baumeister & Benati (2013) argue that IFs below twenty are considered as an indication of convergence. In our case IFs are below 1 for all observations. Finally, lower panel of Figure 5 presents the total number of draws required for convergence for each observation following Raftery & Lewis (1992).[17] [18] In all cases required number of draws is far below the total replications carried out in here. Overall convergence diagnostics suggest the convergence of the MCMC algorithm.

6.2 Monte Carlo Experiment

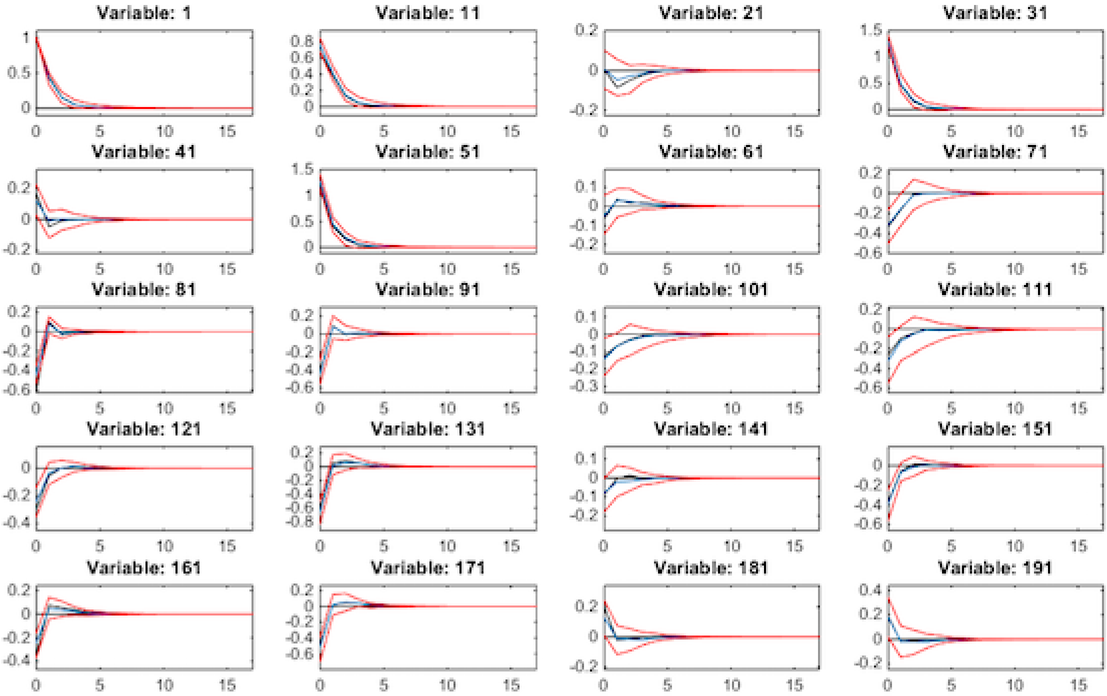
In order to assess the adequacy of the estimation methodology, we have conducted a monte carlo exercise. We have set the sample size to 110, lag length to 2, region number to 3, variable number per region to 20, number of factors for each region and capital flows to 1 and the number of known variables to 1. First, we generated random sets of parameters for the coefficient matrices and keep them fixed when we generate new

[16] Codes provided by Baumeister & Peersman (2013) have been used.

[17] Precision parameter has been set to 2.5%, quantile to 2.5%, and probability associated with the precision to 95%.

[18] Codes provided by LeSage (2005) have been used.

Figure 6: Monte Carlo Experiment: True vs Estimated IRFs for Selected Variables



variables by simulating different vectors of error terms in next steps. 100 simulations have been performed and the estimation methodology have been implemented for each of the simulations with 5000 gibbs replications, 4000 as burn-in. Exact specifications of parameters are depicted below.

$$
\begin{array}{rcl}
B & \sim & \left\{ \begin{array}{cc} N(0.3, 0.2) & \text{for } 1^{st} \text{ Own Lag} \\ N(0, 0.05) & \text{for } 1^{st} \text{ Lags of Other Variables} \\ N(0, 0.01) & \text{for } 2^{nd} \text{ Lags} \end{array} \right\} \\
A & \sim & N(0, 0.3) \qquad \text{for all non-zero elements} \\
\Lambda & \sim & N(1, 0.2) \qquad \text{for all non-zero elements} \\
c & \sim & N(0, 0.05), \quad Q = I_N, \quad R = 0.05
\end{array}
$$

Figure 6 presents the IRFs for 20 randomly selected variables out of the total of 201 following a shock to the first factor. Black lines denote the true IRFs, blue lines denote the estimated median IRFs and the red band represent the 16%-84% intervals from the simulations. Results indicate that the empirical methodology successfully captures the dynamics in the data.