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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, positively on the former and negatively on the latter. In contrast, economic activity and policy shocks in Europe and Asia contribute significantly less to variations in PCFs to EMs. Hence, PCFs are driven by not only common shocks across all developed countries, but also variations in specific regions. 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 have 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 is expected to raise its policy rate in late 2015, 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.

Existing Literature on PCFs suggest that interest rates and activity in the developed world are relevant drivers of PCFs.[1] However, considering the increasing level of international real and financial linkages, a common drawback of previous studies is that they

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

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.[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 variations at global, regional and idiosyncratic levels, and incorporated in a VAR, together with a factor representing common variations in PCFs to different countries, to study the role of shocks originating at different hierarchical levels in driving flows.[3]

Results indicate, global activity shocks are important drivers for 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. At the regional level, contractionary American and Asian monetary policy shocks have significant negative impact on PCFs. Furthermore, forecast error variance and historical decompositions indicate that the most important drivers are global activity shocks and American monetary policy shocks. Overall, since there is heterogeneity in the importance of variations at different levels and regions, economic divergence have implications for PCFs and hence EMs. In particular, since the single most important driver of PCFs is American interest rates, a respective increase may have significant negative effects on PCFs. However, since PCFs are procyclical with respect to global economic activity, a rebound in global economic 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

Early literature categorize the drivers of capital flows as global push factors and country-specific pull factors.[4] Similarly, we consider the following representation for PCFs,

$$pcf_{it} = \beta_i F_t^{pcf} + v_{it}, \qquad v_{it} = \rho_{it}(L) v_{it} + e_{it}, \qquad e_{it} \sim N(0, \sigma_{v_i}^2)$$

where $F_t^{pcf}$ and $v_{it}$ represent the common component driven by push factors across flows to different countries, and country-specific component driven by pull factors of country i respectively. Push factors include activity and policy variables at global and

[2] See for instance, Hirata et al. (2012), Diebold et al. (2008), Thorsrud (2013).

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

[4] See for instance, Fernandez-Arias & Montiel (1996), Fernandez-Arias (1996), Mody et al. (2001), Edison & Warnock (2008).

regional levels. Push factors and the common component of capital flows are assumed to have the following FAVAR representation,

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

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

where $u_t \sim N(0, A^{-1}Q(A^{-1})')$, $v_t = \rho(L)v_t + e_{vt}$ with $e_{vt} \sim N(0, R)$, $X$ represent 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 $y$,

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

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

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. 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.[6] [7] We order $vix$ first, assuming that it represents uncertainty shocks, similar to Leduc & Liu (2015).[8] Regions are ordered with respect to their economic size; Global, 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

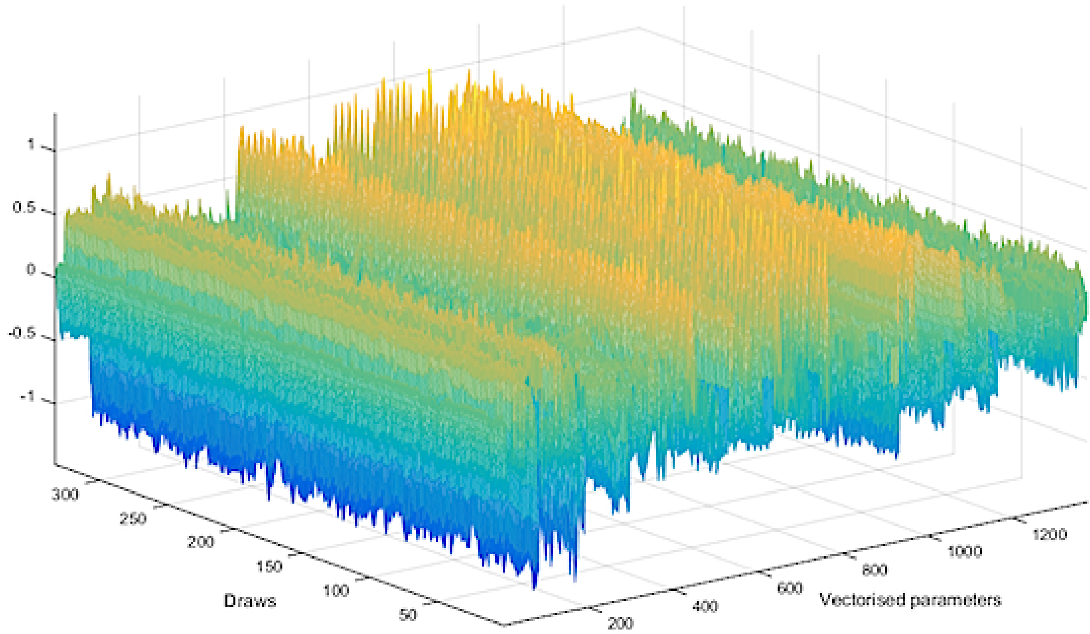
[5] We use the codes provided by Binning (2013) for identification.

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

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

[8] We have also experimented by ordering $vix$ last and observed that the findings do not change.

Figure 1: Convergence: Recursive Means of Factors




decompose the variation in these indicators as supply and demand shocks.[9] To obtain the contemporaneous impact matrix $A^{-1}$, we apply cholesky decomposition on the variance covariance matrix of FAVAR residuals.

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[10] and uninformative priors for other parameters have been implemented. Furthermore, we use principle component estimates to obtain the starting values for the FAVAR coefficients and the factors.

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 autoregressive coefficients, variable/country specific component variances. We repeat sampling steps until convergence, with 50000 replications and 40000 as burn in.

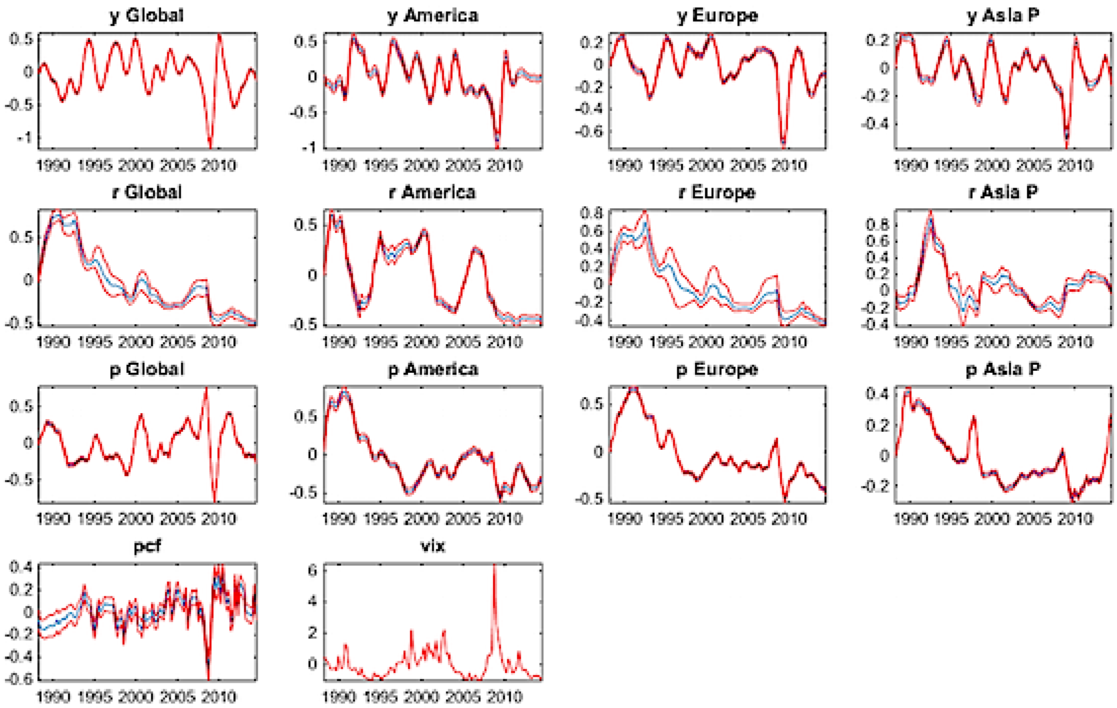
## 3 Dataset

Table 1 outlines 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 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). Existing data from mentioned 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. Final constructed

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

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

Figure 2: Estimated Factors




*pcf* variables reflect the net purchases of portfolio equity and debt instruments of non-residents from residents. 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.

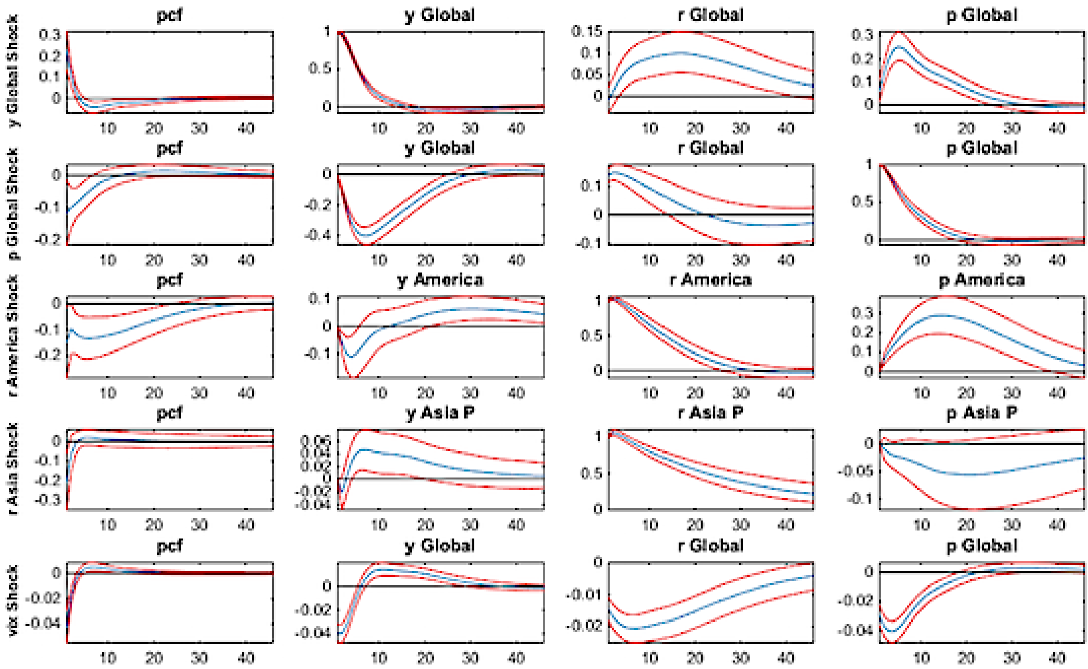
Table 1: List of Countries

| *pcf* | | | | *Fundamentals* | | |
|---|---|---|---|---|---|---|
| Argentine | Hungary | Pakistan | Taiwan | U.States | Italy | U.Kingdom |
| Brazil | India | Peru | Thailand | Canada | Netherlands | Japan |
| China | Indonesia | Philippines | Turkey | Austria | Norway | Australia |
| Chile | Korea | Poland | | Germany | Spain | N.Zealand |
| Colombia | Malaysia | Romania | | France | Sweden | |
| Egypt | Mexico | S.Africa | | Finland | Switzerland | |

## 4 Results

Figure 1 depicts the recursive means of estimated factors. Draws obtained from the simulations do not portray any shifts, indicating convergence of the MCMC algorithm. Figure 2 presents the estimated factors with 68% quantiles from their posterior distributions. Overall, the factors portray variations that are in line with prior expectations for all

Figure 3: Selected Impulse Response Functions

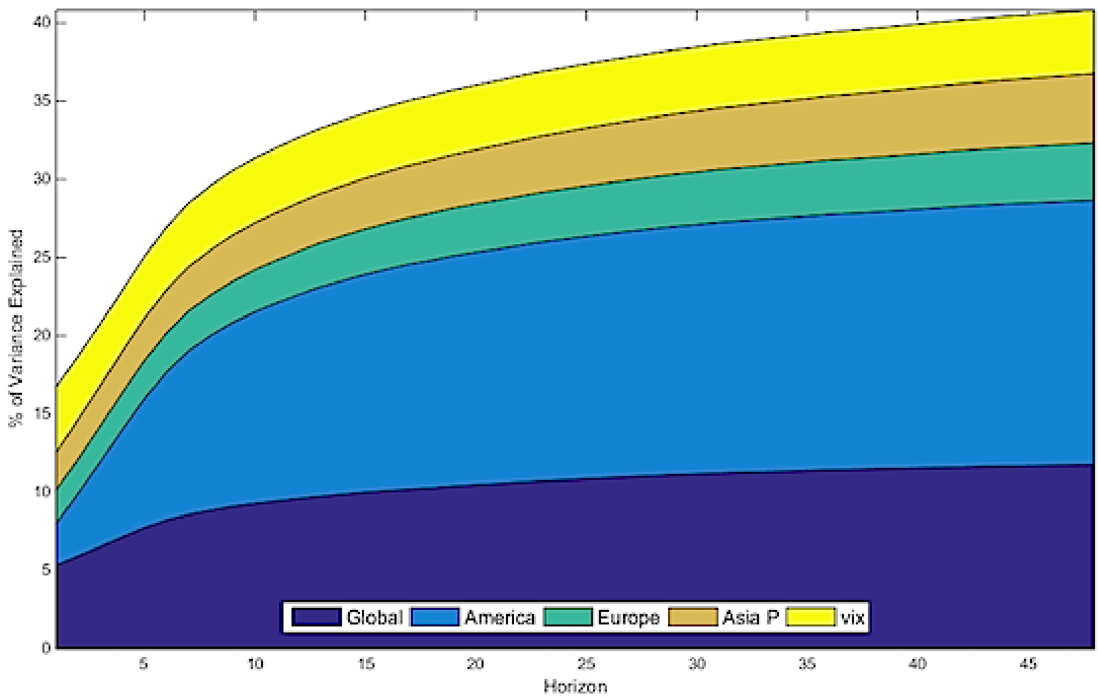



regions. For instance, they indicate the dramatic fall in economic growth and inflation during the recent global financial crisis, as well as historically low interest rates in the aftermath. Evidence of the early 90s slowdown in the America and the late 90s East Asian crisis are present in the regional growth factors. Also, the factors suggest that the rebound in growth has been stronger in America compared to a much weaker rebound in Europe and to a lesser extend Asia Pacific, which is not surprising given the European sovereign debt crisis. 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 3 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. Also, one can see that a rise in interest rates in North America causes a brief fall in growth and also cause a significant fall in PCFs. The long debated price puzzle[11] appear for America, as prices increase. In the fourth row, a rise in short interest rates in Asia Pacific causes growth and prices to go down in the short run as expected, and also results in a significant fall in PCFs. 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 for carry traders. Turning to the uncertainty shock, the responses of all model variables except interest rates in Asia,

[11] As discussed in Sims (1992) and Bernanke et al. (2005).

Figure 4: FEVD of $pcf$ - Global and Regional Aggregates



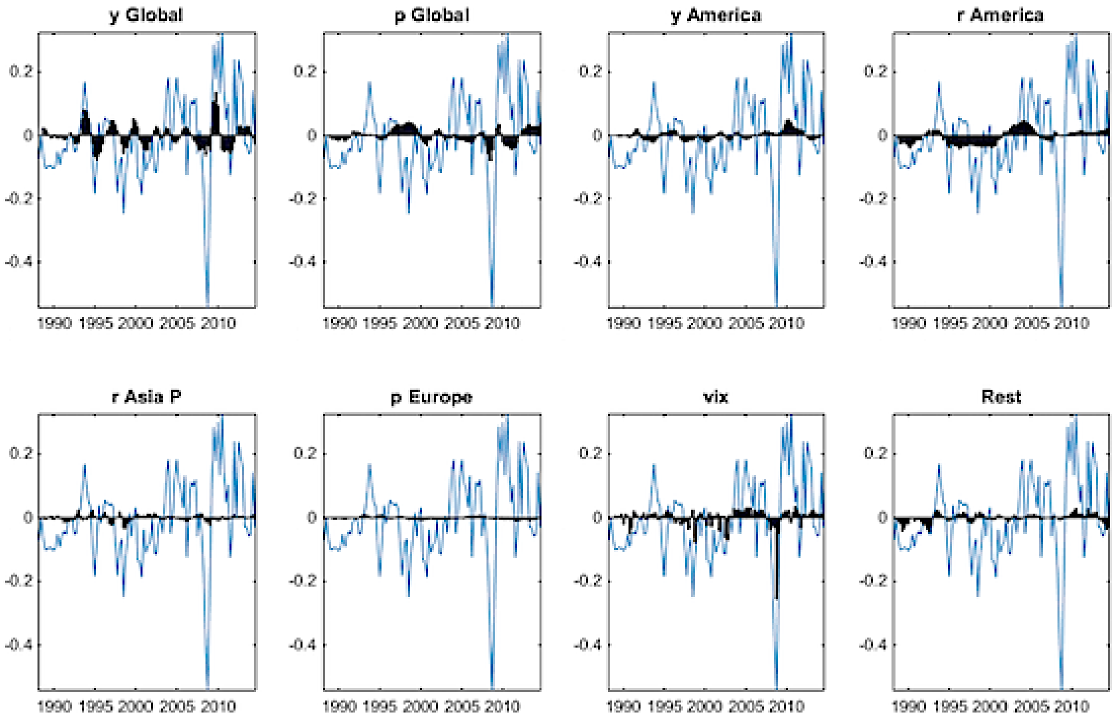

are significant and negative, including PCFs.

To examine whether variations at the global or regional levels are the major driving forces behind PCFs, we calculate Forecast Error Variance Decomposition (FEVD) of PCFs. Figure 4 presents the contribution of structural shocks, aggregated within different hierarchical levels, on PCFs at different horizons, together with the contribution of uncertainty shocks. One can clearly see that flows are driven mainly by the variation in America and Globe, whereas contemporaneously and in one quarter uncertainty shocks play a significant role.

Figure 5 presents the Historical Decomposition (HD) of PCFs to selected fundamentals, to better understand the contributions of different variables to PCFs during the sample period. As expected from the earlier results, shocks to Global activity and American short interest rates seem to have contributed the most towards PCFs. Even though IRFs indicate that Asian interest rates shock significantly affect PCFs, its contribution had been minimal over the sample period. Results indicate that uncertainty shocks have contributed significantly to the fall in PCFs in 1998 Russian default and 2008 global financial crisis episodes. Also, reduced uncertainty during 2003-2007 period seem to have played an important role in the notable surge in PCFs to EMs.

Figure 6 plots the historical contributions of idiosyncratic, uncertainty and aggregate global and regional shocks' contributions to PCFs. Results indicate that Global and American shocks have contributed most towards PCFs during the sample period considered here. As expected from the results of the FEVDs, variations in activity and interest rates in Europe and Asia have contributed little towards PCFs overall. Towards the end of the sample period, results indicate that the significant rebound in PCFs to EMs following the global financial crisis was mostly due to Global and American fundamentals, but

Figure 5: HD of $pcf$ - Selected Fundamentals




also due to idiosyncratic shocks which may also be partly due to 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 and hence the positive contribution from America may as well reverse. However, Figure 6 indicate that the idiosyncratic component overall contributed more than both American and Global fundamentals towards PCFs. Hence, one may as well argue that possible improvements in EM specific fundamentals, for instance involving structural reforms that may boost productivity, can constitute a balancing effect in the case of a rise in 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. 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.[12] 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). Finally, we considered an alternative ordering of the regions and placed North America after Europe.

[12] 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.

Figure 6: HD of $pcf$ - Global and Regional Aggregates

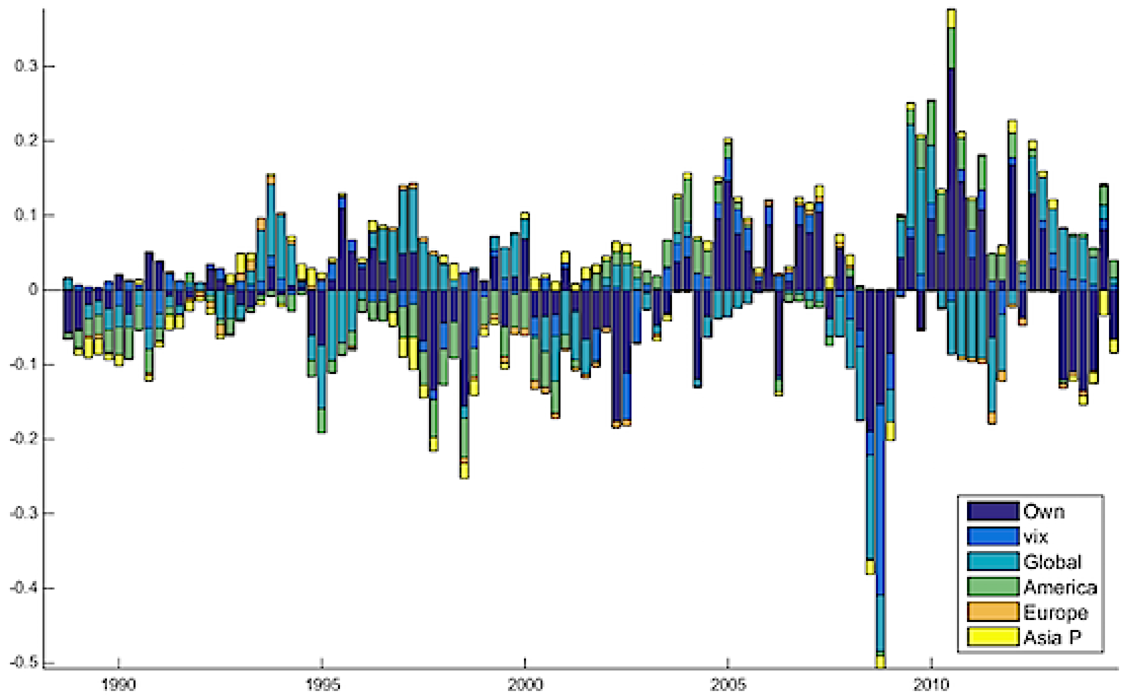



Table 2 presents the correlation of estimated factors in the benchmark model with the ones obtained in the augmented model with real stock prices. The factors are essentially identical, except a slight difference for the growth factor of Asia Pacific. In this case, the augmented model factor suggests slightly stronger real growth in Asia Pacific during 1996-1999. Figure 7 presents the FEVDs for PCFs under the benchmark and alternative cases considered. With stock prices, there is little change in the importance of fundamentals. Only notable difference is that the importance of uncertainty shocks increases slightly. Considering the case with a block exogenous contemporaneous impact matrix, Asia Pacific gains more importance and variations originating in North America slightly less. But the order of importance is still very similar, with American and Global fundamentals being the most important followed by Asia and Europe. Finally, when we reverse the ordering of North America and Europe, the importance of European fundamentals become higher, but again much lower than Global and North America. Overall, results are found to be robust with respect to changes in the model specification and identification assumptions.

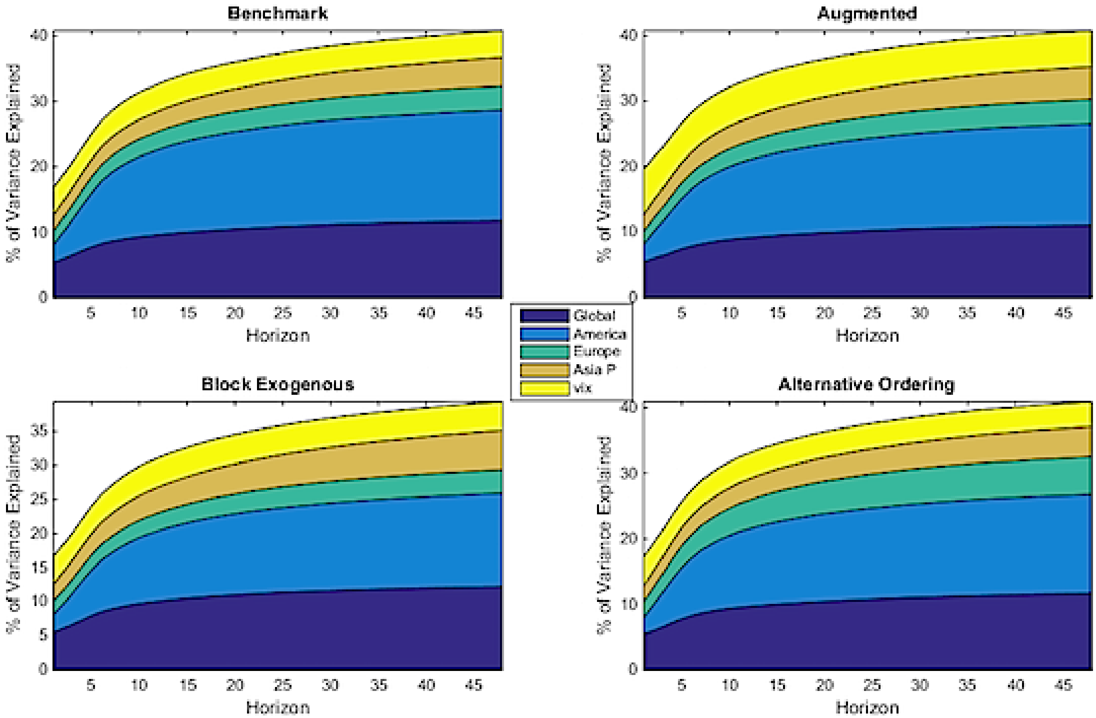
Table 2: Correlation of Estimated Factors under Benchmark and Augmented Model

| y Global | y Amer. | y Europe | y Asia P | r Global | r Amer. | r Europe |
|---|---|---|---|---|---|---|
| 0.9994 | 0.9952 | 0.9995 | 0.7549 | 0.9985 | 0.9977 | 0.9977 |
| r Asia P | p Global | p Amer. | p Europe | p Asia P | pcf | |
| 0.9900 | 0.9991 | 0.9996 | 0.9985 | 0.9994 | 0.9840 | |

## 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

Figure 7: Sensitivity Analysis: FEVD of $pcf$ - Global and Regional Aggregates




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. Hence, PCFs are pro-cyclical with respect to global economic activity. FEVDs indicate that American monetary policy shocks are the single most important driver of flows. Regarding the possible implications of economic divergence in the developed countries, there is heterogeneity in the importance of developments across different regions, which implies that economic divergence is in fact relevant for PCFs to EMs. But, historical decompositions indicate that a large amount of 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.

## References


Bai, J., & Ng, S. (2002). Determining the number of factors in approximate factor models. *Econometrica*, *70*(1), 191–221.

Bańbura, M., Giannone, D., & Reichlin, L. (2007). Bayesian vars with large panels. CEPR Discussion Paper No. DP6326, Centre for Economic Policy Research.

Bańbura, M., Giannone, D., & Reichlin, L. (2010). Large bayesian vector auto regressions. *Journal of Applied Econometrics*, *25*(1), 71–92.

Bayoumi, T. (1992). The effect of the erm on participating economies. *Staff Papers-International Monetary Fund*, (pp. 330–356).

Bayoumi, T., & Eichengreen, B. (1994). *One money or many?: Analyzing the prospects for monetary unification in various parts of the world*, vol. 76. International Finance Section, Department of Economics, Princeton University Princeton.

Bernanke, B. S., Boivin, J., & Eliasz, P. (2005). Measuring the effects of monetary policy: a factor-augmented vector autoregressive (favar) approach. *The Quarterly Journal of Economics*, *120*(1), 387–422.

Binning, A. (2013). Underidentified svar models: A framework for combining short and long-run restrictions with sign-restrictions. Working Papers 14, Norges Bank.

Carter, C. K., & Kohn, R. (1994). On gibbs sampling for state space models. *Biometrika*, *81*(3), 541–553.

Christiano, L., Eichenbaum, M., & Evans, C. (1999). Monetary policy shocks: What have we learned and to what end? *Handbook of macroeconomics*, *1*, 65–148.

Chuhan, P., Claessens, S., & Mamingi, N. (1998). Equity and Bond Flows to Latin America and Asia: The Role of Global and Country Specific Factors. *Journal of Development Economics*, *55*(2), 439–463.

Diebold, F., Li, C., & Yue, V. (2008). Global yield curve dynamics and interactions: A dynamic nelson–siegel approach. *Journal of Econometrics*, *146*(2), 351–363.

Edison, H., & Warnock, F. (2008). Cross-Border Listings, Capital Controls, and Equity Flows to Emerging Markets. *Journal of International Money and Finance*, *27*(6), 1013–1027.

Fernandez-Arias, E. (1996). The new wave of private capital inflows: push or pull? *Journal of development economics*, *48*(2), 389–418.

Fernandez-Arias, E., & Montiel, P. J. (1996). The Surge in Capital Inflows to Developing Countries: an Analytical Overview. *The World Bank Economic Review*, *10*(1), 51–77.

Forbes, K., & Warnock, F. (2012). Capital Flow Waves: Surges, Stops, Flight, and Retrenchment. *Journal of International Economics*, *88*(2), 235–251.

Hirata, H., Kose, M., Otrok, C., & Terrones, M. (2012). Global House Price Fluctuations: Synchronization and Determinants. NBER Working Papers 18362, National Bureau of Economic Research, Inc.

Kose, M., Otrok, C., & Prasad, E. (2012). Global business cycles: Convergence or decoupling?*. *International Economic Review*, *53*(2), 511–538.

Leduc, S., & Liu, Z. (2015). Uncertainty shocks are aggregate demand shocks. Working Paper Series 12/10, Federal Reserve Bank of San Francisco.

Liu, P., Mumtaz, H., & Theophilopoulou, A. (2014). The transmission of international shocks to the uk. estimates based on a time-varying factor augmented var. *Journal of International Money and Finance*, *46*, 1–15.

Mandalinci, Z. (2014). *Determinants, Dynamics and Implications of International Portfolio Capital Flows*. Ph.D. thesis, University of Warwick, Coventry, UK.

Mody, A., Taylor, M. P., & Kim, J. Y. (2001). Modelling Fundamentals for Forecasting Capital Flows to Emerging Markets. *International Journal of Finance & Economics*, *6*(3), 201–216.

Mumtaz, H., & Surico, P. (2009). The transmission of international shocks: A factor-augmented var approach. *Journal of Money, Credit and Banking*, *41*(s1), 71–100.

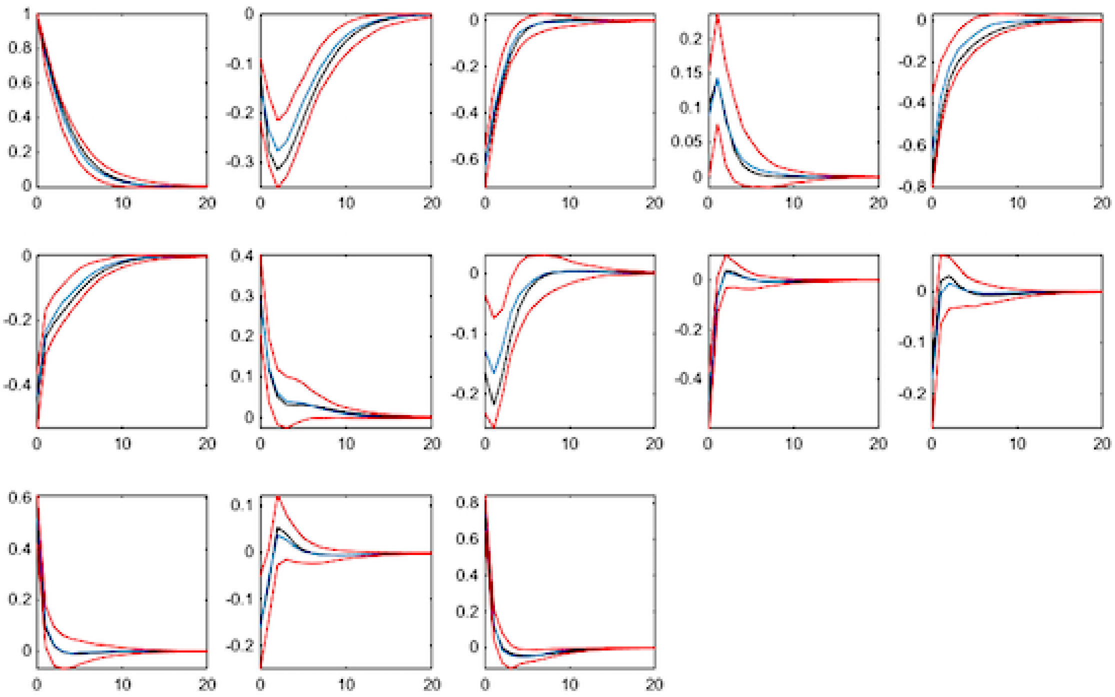
Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies*, *72*(3), 821–852.

Sims, C. (1992). Interpreting the macroeconomic time series facts: The effects of monetary policy. *European Economic Review*, *36*(5), 975–1000.

Taylor, M., & Sarno, L. (1997). Capital flows to developing countries: long-and short-term determinants. *The World Bank Economic Review*, *11*(3), 451–470.

Thorsrud, L. (2013). Global and regional business cycles-shocks and propagations. Norges Bank Working Papers 2013/08, Norges Bank.

Figure 8: Monte Carlo Experiment: True vs Estimated IRFs of Factors



# 6 Appendix

## 6.1 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 200, 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 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.

$$
\begin{array}{rcl}
B & \sim & \left\{ \begin{array}{c} N(0.5, 0.2) \qquad \text{for } 1^{st} \text{ Own Lag} \\ N(0, 0.05) \qquad \text{for } 1^{st} \text{ Lags of Other Variables} \\ N(0, 0.01) \qquad \text{for } 2^{nd} \text{ Lags} \end{array} \right\} \\
A & \sim & N(0, 0.4) \qquad \text{for all non-zero elements} \\
\Lambda & \sim & N(0.5, 0.1) \qquad \text{for all non-zero elements} \\
c & \sim & N(0, 0.05), \quad \rho \sim N(0, 0.1), \quad Q = I_N, \quad R = 0.05
\end{array}
$$

Figure 8 presents the IRFs for the factors 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 10-90 intervals from the simulations. Results indicate that the empirical methodology successfully captures the dynamics in the data.

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