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Evolution of global factors in emerging market capital flows

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Abstract

This paper examines whether the role of global factors in driving capital inflows has changed structurally in the past decades for Emerging Market and Developing Economies (EMDEs) by decomposing the capital flows into global, regional, and country-specific components using a dynamic factor model (DFM). A block-structured DFM shows that Foreign Direct Investment (FDI) and Foreign Portfolio Investment (FPI) inflows respond differently to global economic and financial conditions, with FDI being associated with policy-uncertainty shocks and FPI with financial-market sentiment. Moreover, the contribution of the global factor to capital flow variance exhibits statistically significant structural breaks post the Global Financial Crisis (GFC), with a persistent decline in FPI and a partial recovery in FDI. The results indicate a structural shift in the dynamics of EMDE capital flows following the GFC, with distinct patterns across long-term (FDI) and short-term (FPI) flows.

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1. Introduction

International capital flows to emerging market and developing economies (EMDEs) have historically been shaped by both global and domestic factors. Calvo et al. (1996) and Forbes and Warnock (2012) emphasized the dominance of global *push* factors, such as international interest rates, global liquidity, and global risk aversion, in driving capital flows. More recently, Rey (2015) identifies the Global Financial Cycle (GFCy) as a common dynamic process extracted from the actual capital flows using factor models. This extracted global factor captures the commonality in capital flows across economies, empirically tested by various studies in the literature (Bruno & Shin, 2015; Cerruti et al., 2019; Dua & Verma, 2024).

However, the global trade and financial landscape is shifting rapidly amid pandemic shock, geopolitical tensions, increased global risk aversion, decelerating global growth, and unsustainable debt levels in low-income nations. This has heightened the complexities of supply chain disruptions, reshoring and friendshoring, geoeconomic fragmentation, and protectionism. Against this backdrop, the present study aims to examine how long- and short-term capital inflows to EMDEs respond to changing global dynamics and whether there is evidence of a reduced share of global factors in explaining fluctuations in capital flows. The focus on EMDEs is motivated by the volatile nature of capital flow cycles in these economies, with recurrent surges and stop episodes, indicating that EMDEs are disproportionately affected by GFCy.

The paper contributes to the literature by providing time-varying evidence on the extent to which EMDE capital flows remain tied to the GFCy, along with highlighting heterogeneity across capital flows. The dynamic factor model (DFM) with a block structure is used to decompose foreign direct investment (FDI) and foreign portfolio investment (FPI) inflows into EMDEs for the period from 2005Q1 to 2025Q1 into global, regional, and country-level factors. The global factor for FDI (FPI) inflows captures the common movement in the FDI (FPI) inflows to the sample economies. A rolling variance decomposition is employed to trace the evolution of the global factor's contribution for each type of inflows.

The results indicate that the global factor of FDI inflows is closely associated with the economic policy uncertainty index, while global commonality in FPI inflows across cross-sections is closely aligned with short-term financial market fluctuations. The contribution of the global factor to capital flow variance exhibits statistically significant structural breaks following the Global Financial Crisis (GFC), with a persistent decline in FPI and a partial recovery in FDI.

2. Data

The quarterly data on FDI and FPI inflows are measured as the net incurrence of liabilities and sourced from the International Monetary Fund's Balance of Payments Statistics (BOPS) for the period from 2005Q1 to 2025Q1. To facilitate easy comparison across economies and avoid any single economy affecting the results disproportionately, the FDI and FPI inflows are taken as a percentage of nominal GDP¹ in estimation. A total of thirty-three economies are included for examining FDI inflows, and twenty-eight economies for FPI inflows². The countries included in the sample are presented in Table I below.

¹ The data on Nominal GDP for the period is sourced from the CEIC database.

² For examining FPI inflows, the countries from the Middle East and Central Asia are not included in the estimation due to the unavailability of data.

Table 1: Country Coverage

Region	Countries
Emerging and Developing Asia	Cambodia, China, India, Indonesia, Malaysia, the Philippines, Sri Lanka, Thailand
Emerging and Developing Europe	Belarus, Bulgaria, Moldova, Poland, Russia, Turkey
Middle East & Central Asia	Armenia, Azerbaijan, Kazakhstan, Kyrgyzstan, Tajikistan, Uzbekistan
Latin America & Caribbean	Argentina, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Paraguay, Peru

3. Econometric Methodology

A dynamic factor model (DFM) with a block structure is used to extract unobservable global, regional, country-specific and idiosyncratic factors from the comovement of FDI and FPI inflows across cross-sections of economies. The DFM model is closely adopted from Banbura & Modugno (2014).

Assume that the data on international capital flows (FDI and FPI) are denoted by a $T \times N$ matrix X ($X \in \mathbb{R}^{T \times N}$), partitioned as

$$X = \begin{bmatrix} x_1' \\ x_2' \\ \vdots \\ x_T' \end{bmatrix} \quad (1)$$

where x_t' is a $1 \times N$ vector of observed data at time t . The DFM model is specified as follows

$$x_t = \Lambda_0 F_t + \Lambda_1 F_{t-1} + \dots + \Lambda_h F_{t-h} + v_t \quad (2)$$

F_t is the column vector of r latent factors at time t ($F_t \in \mathbb{R}^r$), Λ_j are the factor loading matrices for the factor lag j ($\Lambda_j \in \mathbb{R}^{N \times r}$) which capture the sensitivity of the capital flows to the latent factors and v_t is the idiosyncratic component ($v_t \in \mathbb{R}^N$). In the present model, the vector of latent factors includes global, regional and country-specific factors. Thus, $F_t = [F_t^G F_t^R F_t^C]'$ and the total number of factors (r) is the sum of the number of global, regional and country-specific factors in the model, ($r = r^G + r^R + r^C$). Each row of the factor loading matrix (Λ_j) corresponds to an economy in the sample, and each column of it relates to each of the latent factors.

The latent factors and the error term in equation (2) follow the autoregressive processes,

$$F_t = A_1 F_{t-1} + \dots + A_p F_{t-p} + u_t \quad (3)$$

$$v_t = D_1 v_{t-1} + \dots + D_s v_{t-s} + e_t \quad (4)$$

The number of lags in the factor autoregressive process is p , and the number of lags in the dynamics of the idiosyncratic term is s . $u_t \sim \text{iid}(0, \Omega)$ and $e_t \sim \text{iid}(0, \Psi)$, where Ω and Ψ are assumed to be block diagonal and diagonal, respectively. The block structure is imposed on the standard DFM model via zero restrictions on some of the elements of the factor loading matrix (Λ). The FDI and FPI series for all economies are allowed to load on the global factors, while the region-specific (or country-specific) series are allowed to load on the corresponding region-specific (or country-specific) factor.

The FDI and FPI series (as a percentage of nominal GDP) for each country are checked for unit roots and standardized to estimate the DFM. The eigenvalue scree plot is used to select the number of latent factors for each block. The lags in the autoregressive processes and in the observation equation (1) are chosen based on the minimum values of the information criterion (Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC)). The model is cast in state-space form and estimated using the Expectation-Maximisation (EM) algorithm (Banbura & Modugno, 2014; Dempster et al., 1977; Doz et al., 2006).

To examine the time-varying change in the share of variation in capital flows explained by global factors, the DFM with a block structure is estimated over a rolling time sample of 28 quarters, starting from the first quarter of the dataset and advancing by one quarter at a time. This yields fifty-four different estimates of the factor model, showing a time-varying share of global factors in the variance decomposition of FDI and FPI inflows. The Bai-Perron multiple structural break test is used to confirm the presence of a statistically significant break in the share of global factors (Bai & Perron, 1998) and to identify the regimes.

4. Results and Discussion

4.1 Preliminary Tests

The panel data series for FDI and FPI inflows (as a percentage of nominal GDP) are found to be stationary using both first- and second-generation panel unit root tests (Maddala & Wu, 1999; Pesaran, 2012). Moreover, the Pesaran (2015) test rejects cross-sectional independence in capital flows, thereby indicating the presence of a common factor structure in the data.³

Based on the preliminary tests under the DFM model, the factors (global, regional and country-specific) are assumed to affect the dependent variable only contemporaneously. However, the model is interpreted as dynamic, as the AR process lags (p) for the factors are set to 2. Moreover, the AR process for the idiosyncratic term (s) is allowed to have one lag, and the number of common factors per block (r) is also set to 1.⁴

4.2 Estimation of Global Factors

Figure 1 plots the extracted global factors for FDI and FPI inflows. The global factor for FDI (Figure 1(a)) exhibits a sharp and sustained decline following the GFC in 2008. The series is trend-stationary, with a first-order autocorrelation coefficient (persistence) of 0.97. This indicates persistent weakening in the global FDI cycle after the GFC, rather than a temporary fluctuation. Moreover, the factor has a high negative correlation with the global economic policy uncertainty index (GEPU)⁵ (-0.76) and a low correlation with the VIX⁶ (-0.04), further

³ The results for panel unit root tests and cross-sectional dependence tests are not included in the paper for the sake of brevity.

⁴ The number of factors in each block is selected using the Bayesian and Hannan-Quinn Information Criterion.

⁵ Global Economic Policy Uncertainty Index sourced from the FRED database based on Baker et al. (2016)

⁶ VIX refers to the Chicago Board Options Exchange Volatility Index retrieved from FRED.

suggesting that common FDI dynamics are primarily associated with broad macro-policy uncertainty rather than short-term financial market volatility.

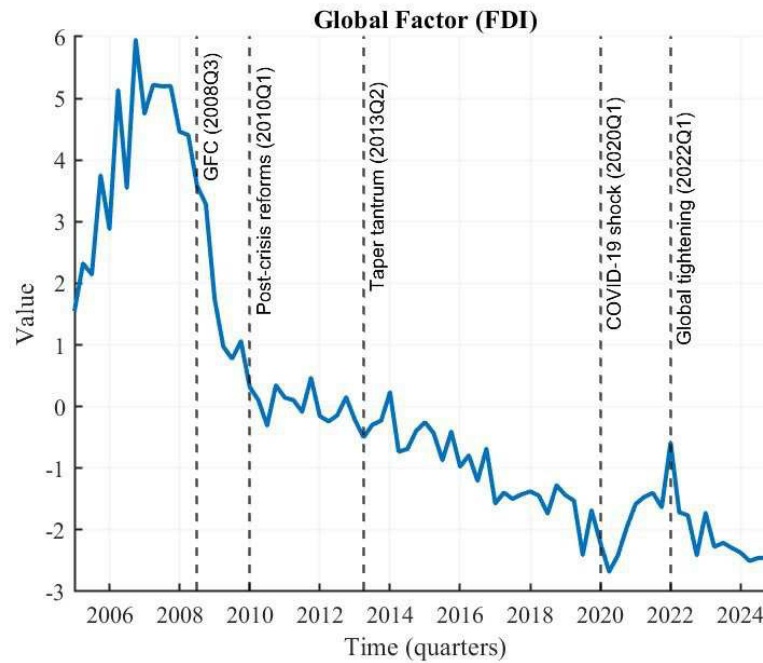


Figure 1(a)

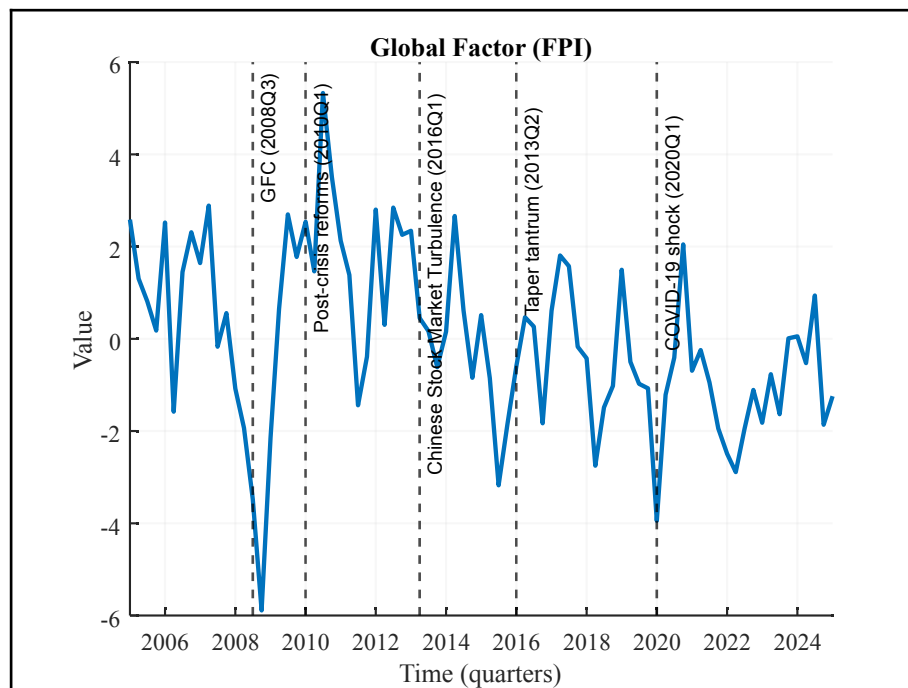


Figure 1(b)

Figure 1: Global Factors for FDI and FPI Inflows

Note: Vertical dashed lines denote major global events. The factor is standardized and reflects the common component driving cross-country fluctuations in capital flows. **Source:** Authors' calculations

On the other hand, the FPI global factor (Figure 1(b)) is stationary and moderately persistent, with an AR(1) coefficient of 0.58. This indicates a relatively rapid mean reversion of

common portfolio flow shocks. It has a strong negative correlation with the VIX (-0.50) and a weaker correlation with GEPU (-0.38), suggesting that common FPI movements for EMDEs are primarily associated with global risk sentiment rather than slow-moving structural conditions. The correlation between the two global factors is as low as 0.17, implying that different global shocks drive EMDE's FDI and FPI inflows.⁷

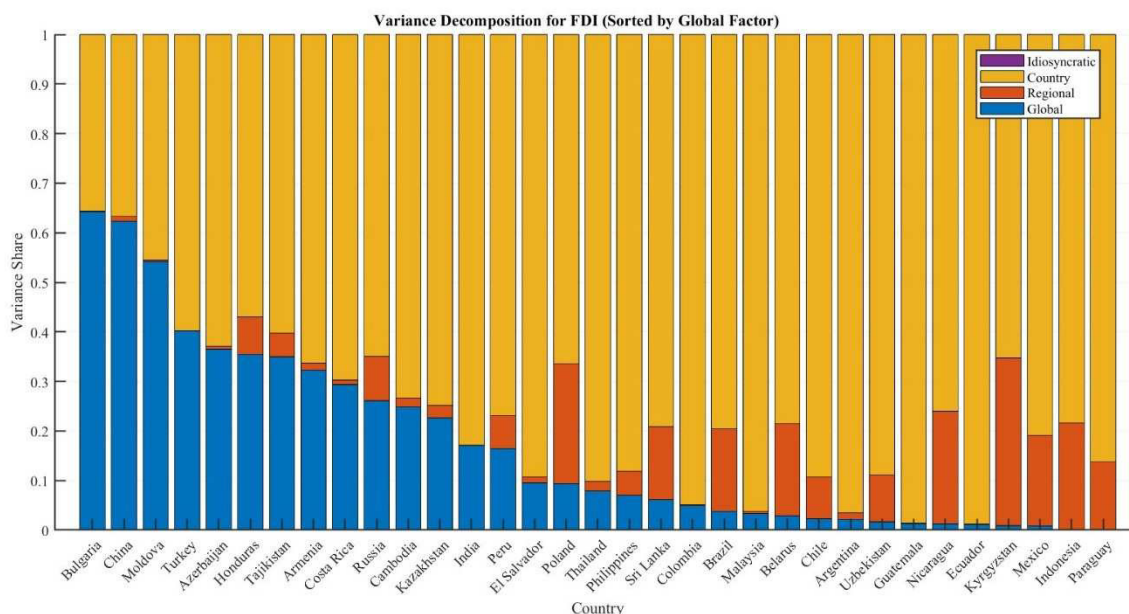


Figure 2(a)

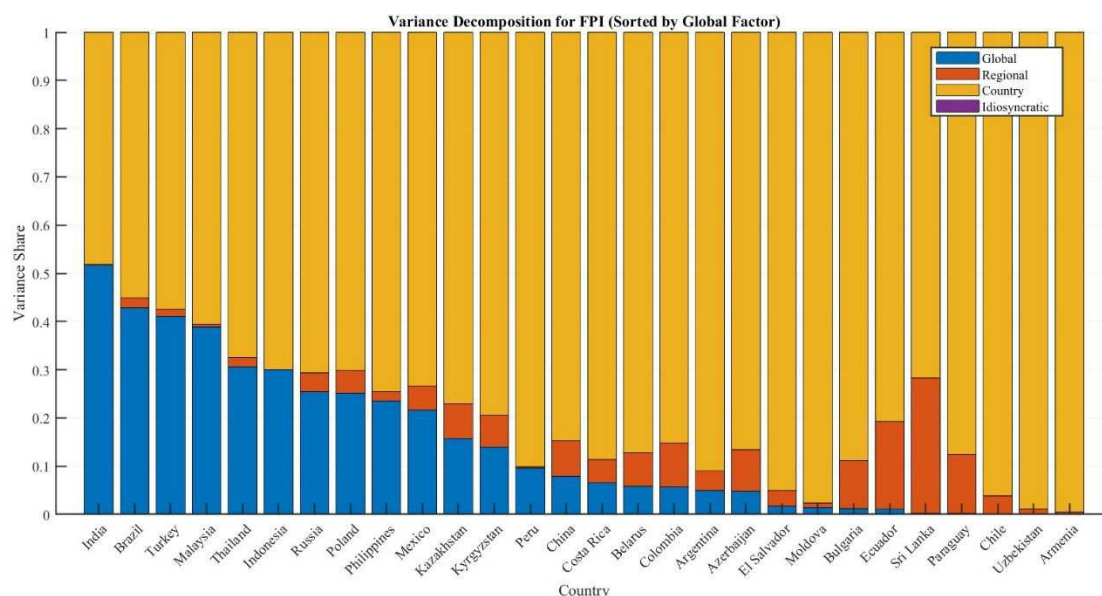


Figure 2(b)

Figure 2: Variance Decomposition of Capital Inflows

Source: Author's calculations

⁷ The cross-country analysis shows that the contribution of common factors (global, regional, and country-specific) to the observed variance in FDI and FPI inflows exhibits considerable heterogeneity across economies and regions. The country component dominates for most economies across both types of flows, while the share of regional factors is small but not negligible in some economies for FDI inflows. The results of the variance decomposition of common factors for DFM (2005Q1-2025Q1) are not shown here for the sake of brevity.

The contribution of common factors to the observed variance in FDI and FPI inflows shows considerable heterogeneity across economies and flow types, as evident in Figure 2. While economies such as Bulgaria, China, Moldova, and Turkey exhibit relatively high exposure to global shocks, country-specific factors dominate FDI dynamics in most economies, suggesting an association with country fundamentals such as market size, institutional quality, and infrastructure. Compared with FDI, global factors account for a larger share of the variance in portfolio inflows for several economies, including India, Brazil, Turkey, and Malaysia, supporting the short-term nature of portfolio investment, which correlates strongly with the global cycle. The share of regional factors is small for both types of flows, but it is not negligible in some economies. However, no clear regional pattern is emerging in the variance share of common factors.

4.3 Evolution of Global Factor Variance Share

To examine the change in the role of global factors in driving capital flows, time-varying variance decomposition is necessary. For this purpose, the DFM is estimated over a rolling time sample of twenty-eight quarters for each type of capital flows, yielding fifty-four estimates of the DFM model, and the share of the global factor in the explained variance is recorded for each sub-sample.⁸ Figure 3 plots the rolling or time-varying variance shares of global factors for FDI and FPI inflows to EMDEs.

Figure 3(a) shows that the global share for FDI inflows peaks around 2006-07, followed by a sharp drop after the onset of the GFC of 2008. The share of global factor has remained low for many years, presenting evidence for weakening global commonality after the GFC. The partial recovery post-2013 is evident, but not at pre-crisis levels. Thus, the global synchronization of FDI inflows weakens temporarily, followed by a statistically significant yet incomplete recovery.

However, for FPI, Figure 3(b) shows a larger share of the global factor in explaining the flows. The significant drop in the share post-GFC continued to further decline post-2014. Thus, the recovery in global factor share is not evident in FPI inflows. FPI exhibits a monotonic and statistically significant decline across regimes, consistent with the progressive weakening of global influence in driving these flows.⁹ The decline in the global variance share of FPI reduces the gap in the influence of global conditions between long-term (FDI) and short-term (FPI) capital flows.

⁸ For a robustness check, the DFM is estimated over a rolling time sample of 32 quarters and the results are same as the one reported in the paper. The technique closely follows the study by Barrot & Serven (2018).

⁹ Structural breaks are tested using the Bai-Perron (1998) test, and the number of breaks is based on the BIC criterion. Pairwise mean comparisons show statistically significant differences across all regimes ($p < 0.01$) for both FPI and FDI, indicating distinct structural shifts in the global variance share.

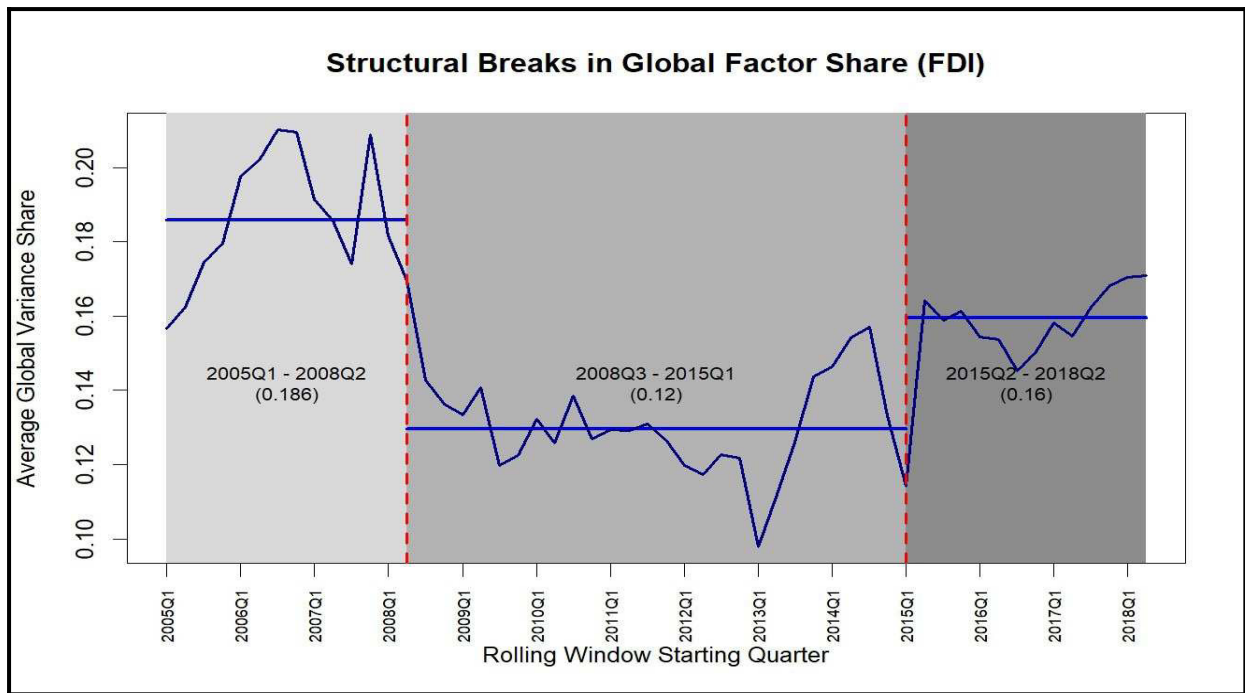


Figure 3(a)

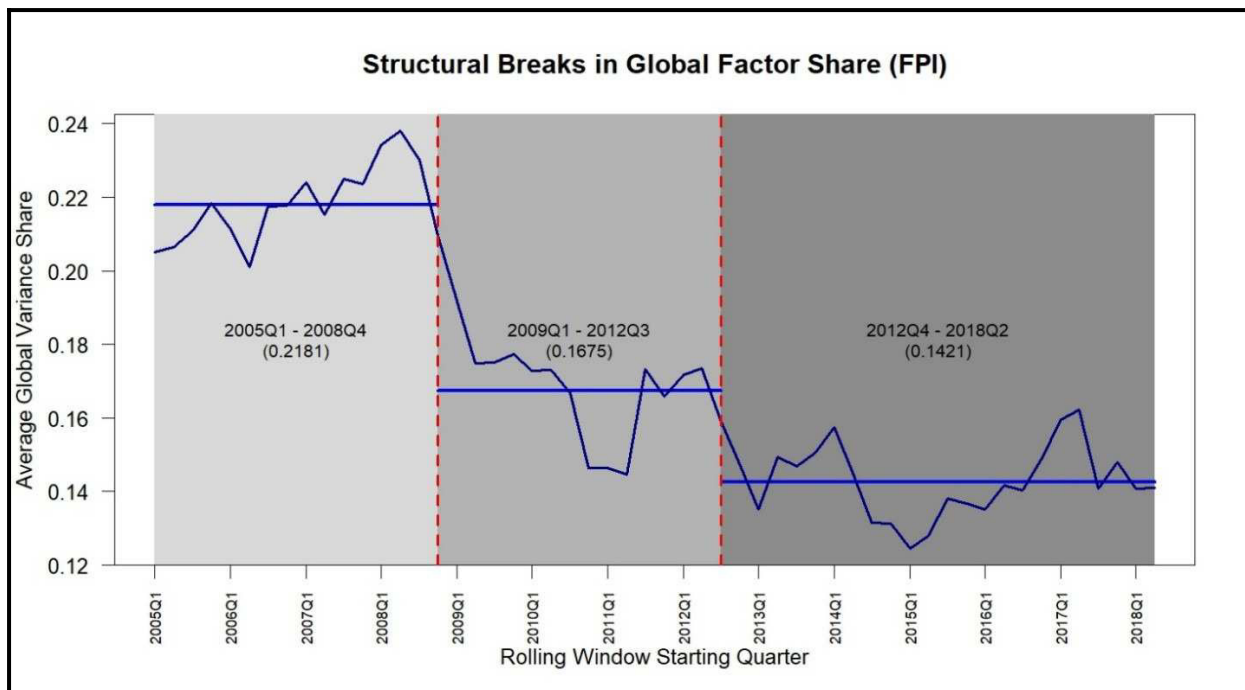


Figure 3(b)

Figure 3: Time-varying Share of Global Factor

Note: Red dashed lines denote break dates identified using the Bai–Perron multiple structural break test. Horizontal blue lines represent regime-specific mean global shares (numbers in parentheses). **Source:** Authors' calculations

5. Conclusion

The results indicate a clear structural shift in the dynamics of capital inflows to EMDEs post-GFC. The share of global factors in explaining FDI and FPI inflows decreased markedly after 2008, implying a reduced dominance of common global shocks in driving their fluctuations. The post-crisis trajectories of variance share differ across the flow types. There is a partial recovery in global factor share for FDI, whereas global synchronization for FPI inflows remains persistently low.

These contrasting post-GFC patterns highlight the heterogeneous nature of capital flow dynamics. The commonality in FDI inflows across countries is largely associated with global policy uncertainty, and in the contemporary period of heightened geopolitical and economic uncertainty, it is difficult for the host economy to remain insulated from global fluctuations.

On the other hand, FPI inflows are inherently sensitive to short-term fluctuations and market sentiments. In the aftermath of the GFC, the EMDEs have strengthened macroprudential frameworks and enhanced regulatory oversight in response to episodes of volatility. One plausible hypothesis is that this institutional strengthening has reduced the extent to which global financial shocks affect cross-country portfolio flows. The evidence does not suggest a full decoupling from global fluctuations, but rather a differentiated adjustment in which EMDEs exhibit greater resilience to global financial risk while remaining exposed to shifts in global policy uncertainty.

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