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The Volatility of Capital Flows in Emerging Markets: Measures and Determinants

Maria Sole Pagliari¹ and Swarnali Ahmed Hannan²

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Abstract

Capital flow volatility is a concern for macroeconomic and financial stability. Nonetheless, literature is scarce in this topic. Our paper sheds light on this issue in two dimensions. First, using quarterly data for 33 emerging markets and developing economies over the period 1970Q1-2016Q4, we construct three measures of volatility, for total capital flows and key instruments. Second, we perform panel regressions to understand the determinants of volatility. The measures show that, after a period of sharp rise during the Global Financial Crisis, the volatility of most instruments is back to pre-crisis levels but are prone to bouts, having increased significantly during global shocks like the taper tantrum episode. Capital flow volatility thus remains a challenge for policy makers. The regression results suggest that push (external) factors are generally more important than pull (domestic) factors in explaining the volatility of capital flows. However, certain pull factors have become relevant since the Global Financial Crisis.

JEL Classification Numbers: C13, C33, C58, F32, F36, F40.

Keywords: Volatility Estimation, International Flows, Push vs Pull Factors

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I. INTRODUCTION³

Capital flow volatility is a major source of concern for macroeconomic and financial stability in emerging market and developing economies (EMDEs). Over the last three decades, the emerging economies have liberalized their capital accounts and have become more integrated in international financial markets. However, as the Global Financial Crisis (GFC) has shown, reaping the benefits of capital account liberalization while containing the associated risks remains a key challenge for many countries for several reasons.

First, EMDEs tend to receive capital flows that, even in net terms, are large relative to their domestic economies and overall absorptive capacity in terms of the size and depth of their financial systems. By looking at data over the last 20 years, international capital gross inflows to EMDEs have experienced a remarkable rise from the mid-1990s to the first half of 2000s, reaching a peak of, on average, 12% of GDP for gross inflows and 6% for net inflows in 2007. Within this broader trend, the patterns of net inflows to EMDEs is mainly determined by gross inflows, as capital flows to EMDEs have been generally driven by foreign investments into domestic assets, while the amount of domestic investments abroad have played a smaller role.⁴

Second, EMDEs are more vulnerable to shocks, partly because their economies are smaller and less diversified, and because they have less domestic economic and political stability. In addition, shocks of any kind—positive or negative, domestic or external—are exacerbated and propagated more easily in EMDEs because of structural and institutional characteristics. Indeed, following the GFC in 2008, inflows to EMDEs dropped sharply in 2008 to an average of -6% of GDP (for both gross and net inflows) and regained their upward momentum in 2009, only to fall again in late 2011, as the peripheral Euro Area sovereign debt crisis intensified, getting to another slowdown over the period 2014-2016.

Finally, in light of what mentioned above, the GFC has prompted new concerns that flows to EMDEs are overly sensitive to some global (push) factors that are beyond the influence of domestic policies.

Given all this, financial integration poses serious challenges to economic and financial sector stability in EMDEs.⁵ To the extent that there exists a positive link between the stability of capital

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⁴ In the last decade, however, EMDEs have started to increasingly invest abroad as well (see Obstfeld (2012b)).

⁵ For instance, Broner and Ventura (2016) point out that financial globalization has sometimes led to capital flows that are volatile and procyclical.

flows and economic growth (see Easterly, Islam, and Stiglitz 2001 and Ramey and Ramey 1995), maintaining a steady stream of capital flows is a policy priority in most EMDEs.

In this regard, the composition of the financial account is another crucial aspect to consider⁶. While FDI represent the majority of capital inflows for EMDEs, the surge and the subsequent collapse in inflows during the GFC was mainly driven by shorter-term instruments like other investment flows, and, among the latter, bank flows. Even the post crisis pick-up in capital flows was led by debt-creating (bank and portfolio debt) instruments, with some reversals between 2014 and 2016. Therefore, policymakers should also pay particular attention to the potential portfolio rebalancing effects, when evaluating different policies aimed at increasing financial stability.

The existing empirical literature on the volatility of capital flows can be classified into two strands.⁷ The first strand focuses on analyzing the difference in volatility between the capital flows to emerging and advanced economies. For instance, Rigobon and Broner (2005) show that the higher volatility in EMDEs is primarily due to these economies' propensity to build up imbalances, which generates more persistent shocks and a higher likelihood of international contagion. Similarly, Alfaro et al. (2007) emphasize the importance of domestic factors, such as institutional quality and the soundness of macroeconomic policies, in explaining volatility differences.

The second strand focuses on the impact of financial integration on volatility. Neumann et al. (2009) show that financial integration tends to increase the volatility of FDI in emerging economies, while reducing that of other debt flows in mature economies. Bekaert and Harvey (1997), Lagoarde-Segot (2009) and Umutlu et al. (2010), by focusing on prices rather than quantities, conclude that financial liberalization reduces the volatility of stock market returns in emerging economies.⁸ Broto et al. (2011) analyze the determinants of the volatility of various types of net capital inflows to EMDEs, by using annual data over the period 1980-2006. Their main finding is that, since 2000, global factors have become increasingly significant relative to country-specific drivers. However, they also identify some domestic macroeconomic and financial factors that appear to reduce the volatility of certain instruments without increasing that of the others. In another study, Byrne and Fiess (2016), using data until 2008Q4, show how the volatility of capital inflows to emerging markets is mainly driven by the US long-term interest rates and the real commodity prices. Despite being a focus of policymakers, capital flow volatility is usually quantified in policy and academic discussions using a crude measure of standard deviation of flows

⁶ The three instruments that are usually closely monitored are: 1) Foreign Direct Investments (FDI), "a category of cross-border investments associated with a resident in one economy having control or a significant degree of influence on the management of an enterprise that is resident in another economy"; 2) Portfolio flows, "defined as cross-border transactions and positions involving debt or equity securities, other than those included in direct investment or reserve assets"; 3) Other flows, "a residual category that includes positions and transactions other than those included in direct investment, portfolio investment, financial derivatives and employee stock options, and reserve assets", classified in government-related flows and private flows (bank and non-bank flows). Definitions are taken from the sixth edition of the Balance of Payments and International Investment Position Manual (BPM6).

⁷ Previous theoretical contributions include Bacchetta and Van Wincoop (1998), Aghion et al. (2004) and Martin and Rey (2006).

⁸ See Chuang et al. (2009) and Jinjark et al. (2011) for an analysis of the relationship between stock returns and volumes.

over a specified period. Given the importance of this issue, a better understanding of volatility in capital flows is warranted.

This paper aims to provide a deeper understanding of volatility of capital flows by contributing to the existing literature along three important dimensions:

1) **Measurements:** The first step of this study consists of deriving measures that can accurately describe volatility. Our paper provides capital flow volatility measures using three methodologies: rolling window standard deviation, GARCH(1,1) conditional variance and ARIMA(1,1,0) estimates. Our approach is similar to Engle et al. (2005) and Broto et al. (2011) but we make some methodological modifications.

2) **Determinants:** In order to pursue policies to increase resilience and help manage capital flow volatility, it is important to understand the drivers of capital flow volatility. We perform panel regressions to understand what are the key variables driving volatility, by disentangling between, on the one hand, global or push factors and, on the other hand, domestic or pull factors. The approach adopted here is built upon the theoretical model provided by Devereux and Sutherland (2009) who, using a two-country DSGE model with portfolio choice, derive a linear relationship between gross capital flows, productivity, measures of monetary policy, price levels, excess returns and valuation risks in both home and foreign economies.

3) **Components:** Compared to Broto et al. (2011), we analyze the evolution of volatility across a larger number of instruments. In particular, the high level of granularity of our dataset allows us to achieve a greater precision in the study of particular categories of flows.

Using quarterly data over the period 1970Q1-2016Q4, we build three measures of volatility to document its evolution over time. Our computed measures for gross inflows in EMDEs suggest that portfolio and other investments are respectively around two and four times more volatile than FDI. In addition, amongst portfolio flows, portfolio debt is more volatile than portfolio equity. For other investment flows, private flows are much more volatile than the official sector ones. Within private flows, bank flows usually tend to be more volatile than non-bank flows, but there are periods where this does not hold.

For policymakers, it is not only the level of volatility but also the changes in volatility over time that matter. Our computed measures suggest that, after a spike during the GFC, capital flow volatility in EMDEs is now back to pre-crisis levels. However, volatility has sharply risen in response to some after-crisis global shocks, particularly during the taper tantrum episode. There exists, however, a degree of heterogeneity in the results, depending on the type of flows targeted. The volatility estimates for FDI present an upward trend before the GFC and a downward (and steadier) trend afterwards. The volatility estimates for portfolio tend to hover around the long-run averages, while that of other investments display the highest volatility among all instruments.

One of the major contributions of our paper is that we produce capital flow volatility estimates, both for total flows and different instruments, for 33 individual countries across four regions.⁹ We

⁹ See Appendix A for a list of countries and regions.

then use the volatility estimates at the country level to run panel regressions with the aim of understanding the determinants of volatility. Our regression analysis shows that push factors like the US monetary policy stance, US economic performance, and global risk aversion have influenced the volatility of capital flows in EMDEs to a greater extent than domestic and structural variables. However, certain pull factors have become relevant since the Global Financial Crisis.

The remainder of this paper is structured as follows: Section II contains an overview of the methodological approaches adopted and analyzes the evolution of volatility of capital flows over time, across instruments and countries; Section III identifies the main drivers of volatility via panel regressions; Section IV concludes.

II. VOLATILITY MEASURES

The first way to expand the existing literature is to build a dataset with broader coverage, in terms of time period, frequency and instruments. The empirical papers previously cited use *annual* data and do not cover all the different categories included in the balance of payments. Our paper uses quarterly data, spanning from 1970Q1 to 2016Q4, and encompasses a wider set of capital flow instruments.¹⁰ These features allow us to carry on a more in-depth analysis of how volatility has evolved both over time, across countries and across instruments.

A. Methodology

In order to produce reliable estimates of capital flow volatility, we consider three approaches, building on Engle and Gonzalo Rangel (2008) and Broto et al. (2011):

I. Standard deviations over a rolling window (RW)

This consists of the standard deviation of capital flows computed over a rolling window as follows:

$$\sigma_{it} = \left(\frac{1}{n} \sum_{k=t-(n-1)}^t (flow_{ik} - \mu)^2 \right)^{1/2},$$

where $\mu = \frac{1}{n} \sum_{k=t-(n-1)}^t flow_{ik}$ and $flow_{ik}$ denotes capital flows in country i in period k . In these computations, $n = 4$ quarters.

As mentioned in Broto et al. (2011), there are some caveats associated with this measure:

- a) there is a loss of data at the beginning of the sample, whose entity depends on the window length (n);
- b) σ_{it} is strongly persistent and this might entail problems of endogeneity and serial correlation;
- c) the same weights are assigned to $flow_{i(t-1)}$ and $flow_{i(t-n)}$, which overly smooths volatility. As a result, volatility might be underestimated when a shock takes place and overestimated thereafter, compared to other measures.

¹⁰Refer to Appendix B for a list of the variables with time coverage and sources.

II. *Estimated standard deviations produced by a GARCH(1,1) model*

The second alternative measure makes use of estimated conditional volatilities of a GARCH(1,1) model. The process is defined as follows:

$$y_{it} = \varepsilon_{it}\sigma_{it}$$
$$\sigma_{it}^2 = \alpha_0 + \alpha_1 y_{i(t-1)}^2 + \alpha_2 \sigma_{i(t-1)}^2,$$

where $y_{it} \equiv \Delta flow_{it}$, ε_{it} is a Gaussian white noise process and σ_{it}^2 is the corresponding conditional variance.

This measure, however, has its own drawbacks. Notably:

- a) data scarcity might lead to convergence errors;
- b) Maximum-Likelihood estimates for small samples contain biases;
- c) stationarity and positivity of estimates require that $\widehat{\alpha}_1 + \widehat{\alpha}_2 < 1$, $\widehat{\alpha}_0 > 0$, $\widehat{\alpha}_1 > 0$ and $\widehat{\alpha}_2 > 0$. If these conditions are violated for some country i , then the model fails to produce valid estimates for that country;
- d) in some cases, the residuals do not present ARCH effects and that makes the GARCH model not suitable.

III. *Estimated standard deviations produced by an ARIMA(p,1,0) model*

The third measure is given by the standard deviation of the residuals obtained after fitting an ARIMA(p,1,0) to the data.¹¹ Notably, we first estimate the residuals from the following AR(p) process:

$$\Delta flow_{it} = c + \sum_{k=1}^p \beta_k \Delta flow_{i(t-k)} + v_{it}$$

Then, a test is performed to detect the presence of any ARCH effects in the residuals. If the null hypothesis of heteroscedasticity is rejected:

$$\sigma_{it}^2 = \frac{1}{4} \sum_{j=t-(n-3)}^{t+(n-2)} (v_{ij})^2$$

otherwise conditional volatility is estimated by fitting a GARCH(1,1) model to the residuals.

The heteroscedasticity checks on the ARIMA residuals constitute a contribution to the reference literature (e.g. Broto et al. 2011), as we deem this further step to be helpful in improving the robustness of the resulting estimates vis-à-vis possible misspecifications. Moreover, this procedure is useful in addressing the shortcomings related to the GARCH(1,1) approach explained above. For these reasons, we prefer the ARIMA estimates and use it as the benchmark measure in our regression analysis.

¹¹ The choice of the AR lag length is based on the Schwartz information criterion (SIC), while the MA lag order is suggested by the relevant literature. The degree of differencing is set equal to 1 as some of the data series of interest are integrated of order one ($\sim I(1)$) as confirmed by unit root tests (results are available upon request).

B. Evolution of Volatility over Time

Using the volatility estimates from the three approaches, this section considers how the volatility of capital flows has evolved over time. We first look at the aggregate flows for EMDEs,¹² and, then, we study the evolution of volatility for the single components of gross inflows.

Total Flows

Figure 1 shows the evolution of capital flow volatility using the three different measures. The charts clearly show that RW underestimated the spike in volatility at the onset of the crisis and overestimated the fall in volatility following the end of the crisis. This underscores the need for going beyond the crude RW measure. Comparing the three measures, the GARCH estimates tend to lag slightly behind the RW and the ARIMA, and are on average higher than the estimates produced by the other two approaches. However, broadly speaking, the three estimates show similar results.

Looking at the volatility of gross inflows and gross outflows in EMDEs separately, the volatility of inflows is on average higher than outflows, thereby driving up the volatility of net flows. An interesting question is how the volatility has fared since the GFC¹³, especially in EMDEs. The charts show that, barring several spikes, the biggest one corresponding to the GFC, the current level of volatility is comparable to the pre-crisis average. However, EMDEs volatility has been prone to bouts, as it has risen during global risk off episodes. In particular, the volatility spiked up during the taper tantrum episode. These bouts of increase in volatility thus remain a policy challenge for EMDEs, particularly in the current context of capital flow slowdown (IMF 2016a,b), where even small swings in flows can lead to substantial net outflows or sudden stops¹⁴.

¹² In this section, the aggregates represent total capital flows divided by total GDP. As a robustness check, volatility estimates have been computed for weighted aggregate capital flows series, using two different sets of weights. Notably, the first set is given by domestic GDP as a share of group GDP, while the second consists of each country's International Investment Position (IIP), measured as the sum of assets and liabilities, divided by the group's IIP. The series are available upon request. The final results are not qualitatively different from the outcomes observed for unweighted data.

¹³ For the purpose of this paper, we identify the GFC with the period 2007Q3-2009Q2, which corresponds to the business cycle dates of the NBER.

¹⁴ For instance, given its size, China could have an impact in the overall capital flow volatility of EMDEs. We rerun the estimation of capital flow volatility, excluding China from our sample. Broadly speaking, the evolution is not very different. However, the increases in volatility observed more recently are not as pronounced. In particular, this discrepancy is associated with the volatility of other investments.

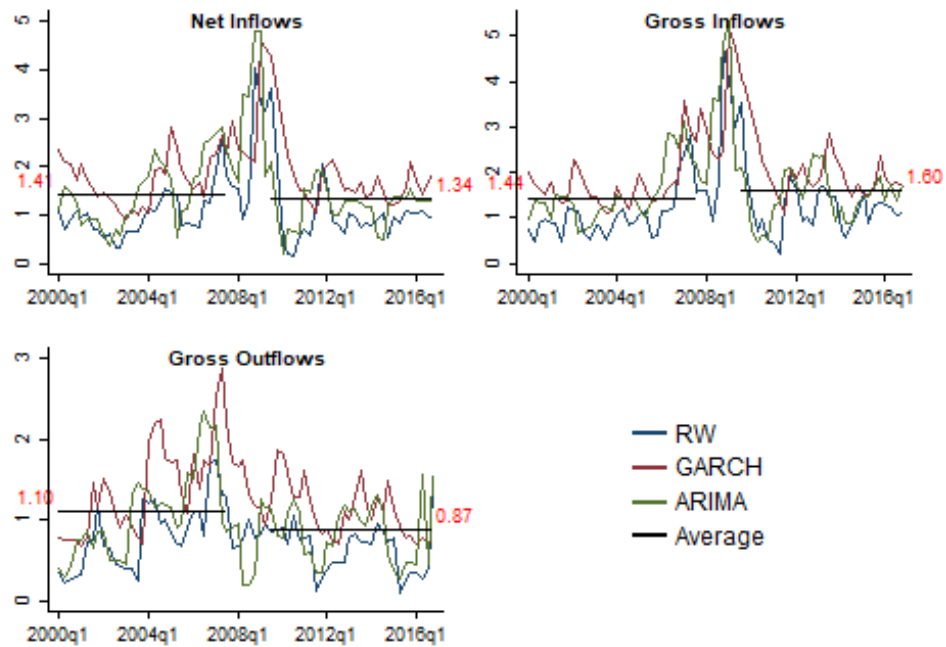


Figure 1: Evolution of the volatility of capital flows in EMDEs. *Notes:* Measures are expressed as % share of total GDP. Source: IMF, *International Financial Statistics*, authors' computations.

To check for the presence of any effective difference, we perform some tests to detect whether the mean value of the estimates has significantly changed after the GFC compared to the pre-crisis period. Table 1 reports the results for the Geweke's separated partial means test performed over the three different measures.¹⁵

As it can be noticed, there is no statistically significant difference in volatility means before and after the GFC and this result is consistent across flow types and methodologies¹⁶. Nonetheless, as already highlighted in the previous section, there exist some fundamental divergences in the dynamics of individual components (or instruments) of the financial account. It is therefore necessary to extend the analysis to single instruments as well.

¹⁵ Refer to Geweke (2005). We prefer this test as it allows us to control for autocorrelation of the volatility estimates.

¹⁶ With the notable exception of GARCH estimates for gross outflows.

| | RW | | | GARCH | | | ARIMA | | |
|--------------|------|------|------|-------|------|------|-------|------|------|
| | GIs | GOs | NIs | GIs | GOs | NIs | GIs | GOs | NIs |
| <i>EMDEs</i> | | | | | | | | | |
| Statistic | 0.27 | 0.62 | 0.01 | 0.64 | 0.01 | 1.46 | 0.27 | 5.85 | 0.09 |
| P-value | 0.60 | 0.43 | 0.92 | 0.42 | 0.94 | 0.23 | 0.60 | 0.02 | 0.77 |

Table 1: statistics and p-values of the Geweke's separated partial means test for the volatility estimates (RW, GARCH and ARIMA) of EMDEs capital flow aggregates. *Notes:* GIs: Gross Inflows; GOs: Gross Outflows; NIs: Net Inflows. Statistics are based on two separate means ($p=2$) and covariance functions are tapered at 2%; the limiting distribution is $\chi^2(1)$; H_0 : means are equal, H_1 : means are different.

Individual Components

Even if EMDEs are moving towards a greater financial integration, they still attract inflows from foreign investors that more than outweigh investments of domestic agents abroad.¹⁷ Our paper focuses primarily on the analysis of the volatility and its determinants for gross inflows, as evidence suggests these are of greater importance for EMDEs.¹⁸ Figure 2 shows the evolution of volatility for individual components of EMDEs gross inflows. Portfolio and other investment flows are around two and four times, respectively, more volatile than FDI. Among portfolio flows, portfolio debt is more volatile than portfolio equity. These results are in line with literature showing that equity flows, both FDI and portfolio equity, are generally less volatile.

Looking at the evolution of each instrument, the volatility estimates for FDI present an upward trend before the GFC and a downward (and steadier) trend afterwards. However, volatility has been picking up after 2015. For portfolio, GARCH and ARIMA estimates are higher than RW, in particular as far as portfolio equity instruments are concerned. Broadly speaking, there is not a defined trend and estimates tend to hover around the long-run averages. However, the volatility for these instruments is slightly lower in the subsample 2009-2016. As to portfolio equity, the ARIMA and RW estimates highlight a slight upward trend for volatility until the GFC and a downward trend thereafter. What is more interesting to notice, anyways, is the behavior of volatility of portfolio debt flows, as there is a break point in estimates at the end of 2009. After this date, indeed, volatility has drastically dropped, in particular during the period 2014-2015, and has been subjected to fewer and less ample swings than before¹⁹.

¹⁷ The differences in the behavior of net flows between AEs and EMDEs is also due to the fact that, while in AEs capital flows are used for both risk-sharing and portfolio diversification, in EMDEs, by contrast, capital flows are not only instrumental for risk-sharing, but also to have access to greater external financing (see Canuto and Ghosh (2013), Ch. 3).

¹⁸ Measures for gross outflows and net inflows, however, are available upon request. Broadly speaking, the volatility measures for gross inflows and net inflows are similar, but those of gross outflows are different.

¹⁹ Even if, in certain cases, volatility seems to have declined over time, the results can be different when estimates are adjusted by the levels (the idea is very similar to computing the coefficient of variation). In particular, though FDI volatility has gone down significantly, it is rising when adjusted for the levels. Similarly, portfolio adjusted volatility has also increased in more recent periods. These results are available upon request.

Finally, other investments display the highest volatility estimates among all instruments. Even in this case, GARCH produces higher values than the other approaches.

The volatility of individual components can help track down the dynamics underlying the evolution of volatility of total capital flows. With this purpose, Figure 3 plots the ARIMA estimates of total inflows together with the individual components. Positive changes in volatility are, broadly speaking, driven primarily by increases in the volatility of other investments, followed by the volatility of portfolio inflows (debt primarily).

Table 2 reports the partial means test results for gross inflows in EMDEs, broken down by instruments. While the null hypothesis of equal means is rejected for portfolio, portfolio debt and portfolio equity across all the estimators, the volatility of other inflows (GARCH) and the volatility of FDI (RW and GARCH) have means that are not statistically different before and after the GFC. Using ARIMA estimates, we can conclude that, in the aftermath of the financial crisis, EMDEs have experienced a change in the volatility of FDI, portfolio and other investments, on average, by -0.027%, -0.068% and 0.235% of GDP respectively.

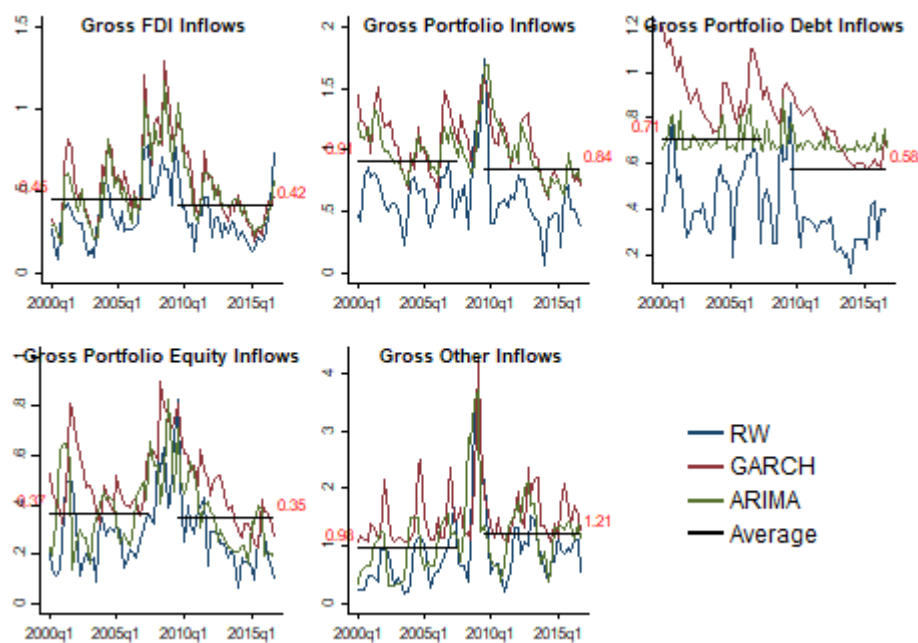


Figure 2: Evolution of the volatility of gross capital inflows for EMDEs by *components*. *Notes:* measures are expressed as % of group GDP. Source: IMF, *International Financial Statistics*, authors' computations.

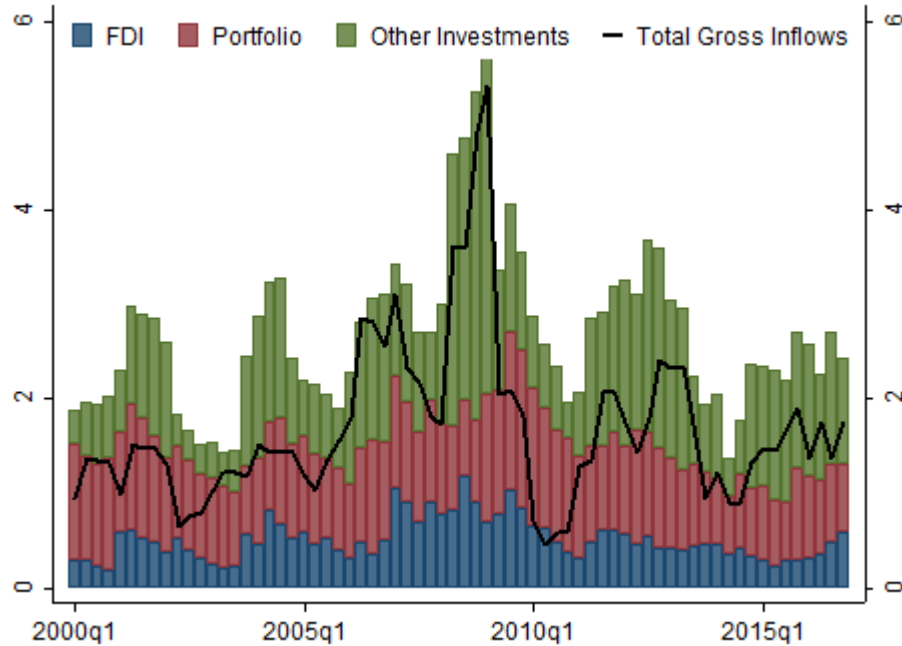


Figure 3 Evolution of the ARIMA volatility estimates of aggregate gross capital inflows and their components in EMDEs. *Notes:* measures are expressed as % of group GDP. Source: IMF, *International Financial Statistics*, authors' computations.

| | Total | FDI | Portfolio | Port. Debt | Port. equity | Other |
|--------------|-------|-------|-----------|---------------|--------------|----------|
| <i>RW</i> | 0.27 | 1.28 | 5.58** | 18.29*** | 3.76* | 6.48** |
| <i>GARCH</i> | 0.64 | 0.35 | 22.36*** | 117.53*** | 4.85** | 0.70 |
| <i>ARIMA</i> | 0.27 | 3.39* | 32.7*** | 4.66** | 6.73*** | 10.99*** |

Table 2: statistics of the Geweke's separated partial means test for the volatility estimates (*RW*, *GARCH* and *ARIMA*) of EMDEs gross inflows. *Notes:* *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Statistics are based on two separate means ($p=2$) and covariance functions are tapered at 2%; the limiting distribution is $\chi^2(1)$; H_0 : means are equal, H_1 : means are different.

In addition to the distinction across the instruments considered above, other investment flows can be classified in: i) bank flows; ii) private non-bank flows; iii) official sector flows. Even though other investments are, on average, smaller in levels than equity instruments like FDI, previous findings and stylized facts show that they are very relevant in determining the volatility developments for capital inflows to EMDEs. Therefore, it is necessary to conduct an in-depth analysis of the evolution of volatility for each subcomponent of the other investments category. Figure 4 below shows the evolution of volatility estimates for other gross inflows²⁰. It can be noticed that the volatility of private flows is much higher than the volatility of flows through the

²⁰ Estimates for net inflows and gross outflows are available upon request.

official sector. The latter, indeed, after a spike during the crisis, has stabilized around a level which is below 1% of group GDP.

In the private sector, flows to banks display a gradual decrease in volatility from December 2011 onwards. This could be motivated by two recent developments: i) since the onset of GFC, banks have been constantly reducing their exposure towards international investors, thus decreasing their activity on international markets²¹; ii) international investors have become more and more risk adverse and this has led to the capital flow slowdown observed in EMDEs.

On the other hand, the non-banking sector has followed a more cyclical path after the GFC, while stabilizing around a mid-term average which is lower than in the pre-crisis period. All in all, we can say that the volatility of other investments is almost completely driven by the volatility of private flows and, for these latter ones, volatility is around equally distributed across the banking and non-banking sectors.

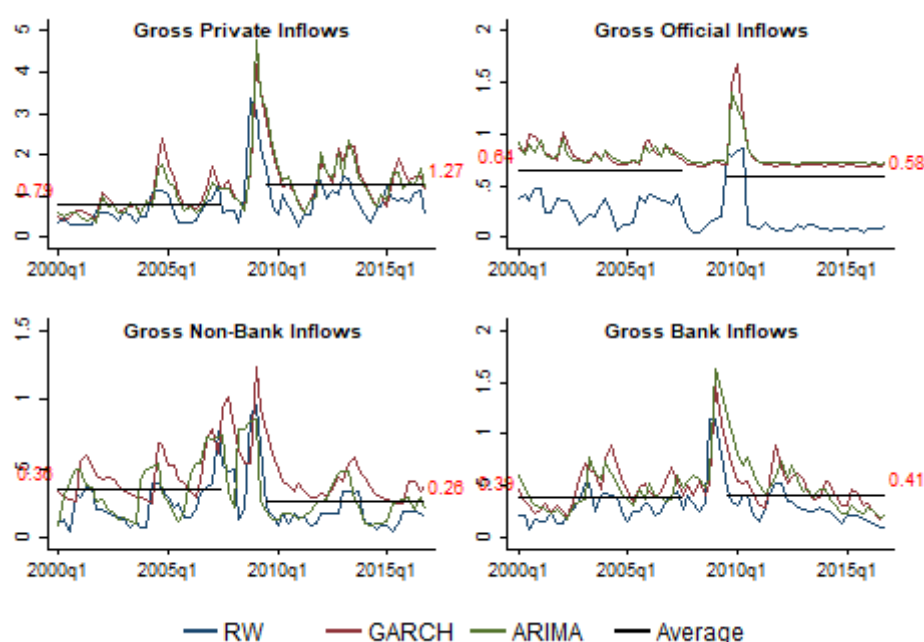


Figure 4: Volatility estimates for other gross capital inflows in EMDEs *by components*. *Notes:* measures are expressed as % share of group GDP; aggregates for flows to the banking and non-banking sector do not include non-reporting countries. Source: IMF, *International Financial Statistics*, authors' computations.

C. Cross-regional and Cross-country Comparisons

Apart from computing volatility of aggregate series, we also estimate capital flow volatility for the individual EMDE countries as well as for different geographic regions²². The volatility measures

²¹ A phenomenon that is referred to as the “deglobalisation” of financial markets (see, for instance, Forbes et al. (2016)).

²² Given that the three methodologies produce very similar estimates across different types of flows and instruments, the analysis carried out in the remainder of the paper will be based on our preferred ARIMA estimates only.

of single countries are useful for several reasons. First, they can be important tools in policy discussions related to understanding and mitigating undesirably high volatility in a particular country. Second, the volatility measures of single components will inform policymakers about which instruments they should monitor more closely. Third, these measures can be extremely useful in studies and research geared towards understanding and comparing volatility across countries and regions, as they can shed light on the instruments responsible for possible shifts in volatility. Fourth, as shown in our subsequent analysis, the estimates of individual countries can help understand the determinants of EMDEs capital flow volatility.

Figure 5 compares the ARIMA estimates of total, FDI, portfolio and other gross inflows across different regions. By looking at the aggregate inflows, the onset of the GFC entailed a jump in volatility for all the groups considered. However, there are discrepancies that are worth mentioning, in terms of both magnitude and timing.

Among the countries included in the sample, European developing economies have experienced the earliest and most marked increase in capital inflow volatility, with some sudden swings that are roughly coinciding with known episodes of regional financial turmoil²³. In addition, such increase presents a higher degree of persistence compared to other regions, as volatility estimates at the end of the time period considered are substantially greater than in 2000Q1. For other regions, while the GFC period is characterized by bouts in volatility, on the other hand the post-crisis estimates show levels that are comparable to the pre-crisis quarters.

As far as instruments are concerned, shorter-term flows like portfolio or other investments seem to be more volatile than FDI for most of the regions considered. Yet, emerging Europe once again constitutes an exception to this trend, since the volatility of FDI in this region tends to be decidedly higher than portfolio inflow volatility and, in some periods, even somewhat comparable to that of other investments. Broadly speaking, volatility dynamics for FDI are more stable and persistent than those of portfolio and other investments. For these latter, however, volatility estimates show a decreasing and smoother trend in the aftermath of the GFC for Asia, Latin America and Middle East and Africa. This is not the case for emerging Europe, whose other inflow volatility estimates show a sudden jump in the third quarter of 2014.

Generally speaking, while the behavior of volatility estimates for aggregate portfolio inflows is mainly driven by portfolio debt inflows, the volatility of other investments, on the other hand, is influenced by private sector inflows, and, notably, in bank inflows (see Figure 6).

Portfolio equity inflows, after episodes of heightened exuberance in the period 2005-2010, show volatility levels that are decidedly lower than 10 years ago for all regions but Latin America. As to portfolio debt instruments, although the path is slightly more diversified across groups, it can be noticed how volatility levels are generally higher in the latest part of the time span considered, compared to the pre-2008 period. The cases of Latin America and Europe, however, stand out, as the volatility of debt inflows decreased in 2007-2009 and bounced back to unprecedented levels in the first quarters of 2010.

²³ See for instance Lane (2013), Lane and Milesi-Ferretti (2017).

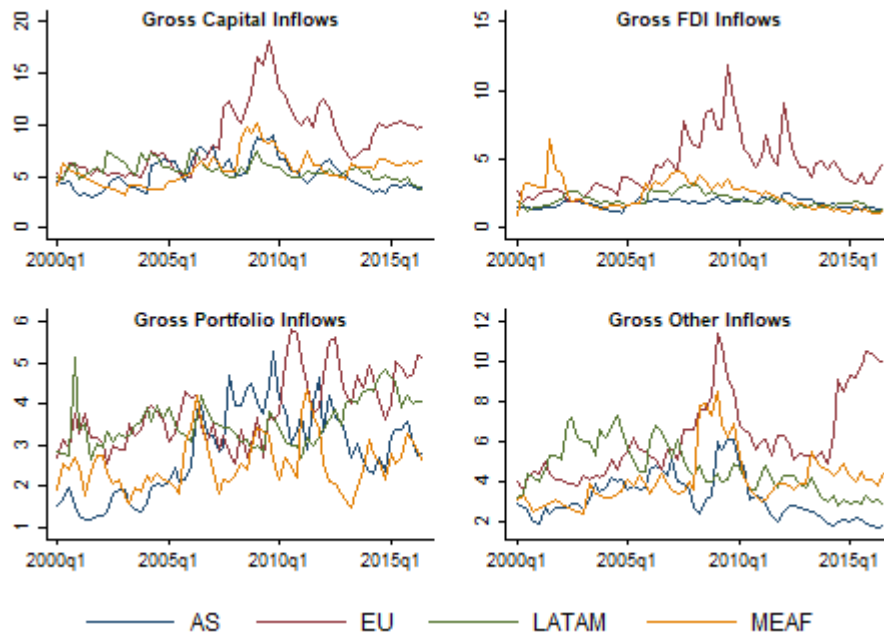


Figure 5: ARIMA volatility estimates for gross capital inflows in EMDEs by *regions* and *instruments*. Notes: AS=Asia, EU=Europe, LATAM=Latin America, MEAF=Middle East and Africa; measures are computed as average across countries and expressed as % share of GDP. Source: IMF, *International Financial Statistics*, authors' computations.

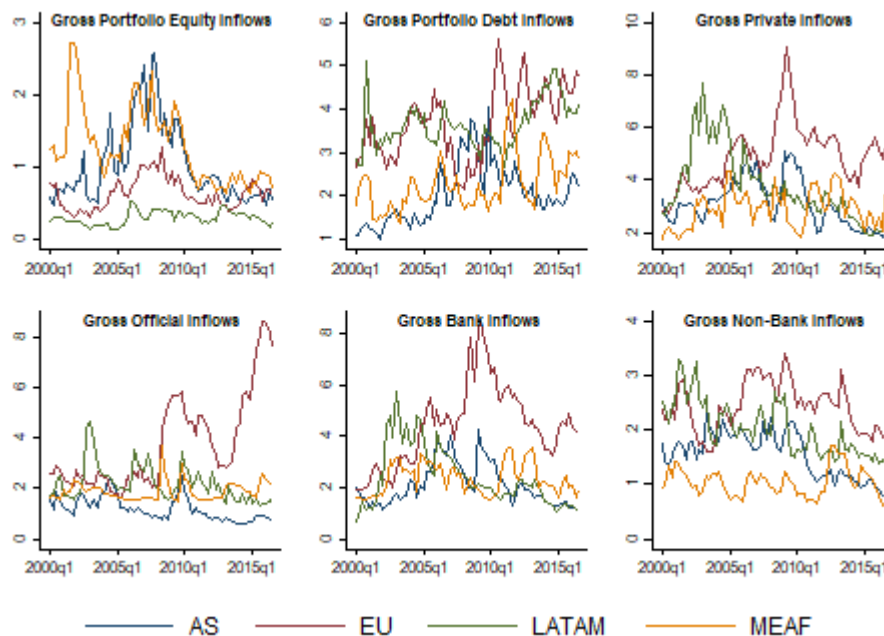


Figure 6: ARIMA volatility estimates for gross capital inflows in EMDEs by *regions* and *instruments* - *subcomponents*. Notes: AS=Asia, EU=Europe, LATAM=Latin America, MEAF=Middle East and Africa; measures are computed as average across countries and expressed as % share of GDP. Source: IMF, *International Financial Statistics*, authors' computations.

III. EXPLAINING VOLATILITY – PANEL REGRESSIONS

A. Regression framework

To understand the determinants of the volatility of gross inflows in EMDEs over the period 1980Q1-2016Q4, we construct some panel regressions. In line with literature on the determinants of capital flows, our starting point is the framework based on the principles of portfolio choice theory, whereby expected returns, risk premia and risk preference play a major role²⁴. In this paper, we extend this theoretical framework to understand the determinants of the volatility of capital flows, rather than their level. The approach adopted here is built upon the theoretical model provided by Devereux and Sutherland (2009) who, using a two-country DSGE model with portfolio choice, derive a linear relationship between gross capital flows, productivity, measures of monetary policy, price levels, excess returns and valuation risks in both home and foreign economies²⁵. This model is particularly useful in explaining the dynamics of portfolio holdings across EMDEs (home) and advanced economies (AEs, foreign). We model capital flows using the following structural equation:

$$flow_{it} = \beta' X_t \quad (1)$$

where $flow_{it}$ are gross inflows to country i (home) at time t (in GDP terms), β are coefficients and X_t is a vector of home and foreign variables.

Notably, $X_t = (y_t^i, y_t^*, m_t^*, v_t^*, r_t^i, r_t^*, p_t^i, p_t^*, e_t^i, nfa_t^*)$, where a star denotes foreign-country variables, y stands for real GDP, m is money supply, v represents equity value, r is the short-term interest rate, p represents the price level, e is the exchange rate between home and foreign currencies and nfa is the foreign-country net foreign asset position. All variables are expressed in deviations from the steady state.

By applying the variance operator on both sides of equation (1), one gets:

$$\sigma_{it}^2 = \sum_{q=1}^k \beta_q^2 V(x_{qt}) + 2 \sum_{q=1}^k \sum_{j>q} \beta_q \beta_j Cov(x_{qt}, x_{jt}) \quad (2)$$

where k is the number of elements in vector X_t and x_{qt} represents the q th element of the same vector.

Using a first-order Taylor expansion, equation (2) can be approximated as:

$$\sigma_{it}^2 = Var(\beta' X_t) \approx \beta' J(X_t) |_{\bar{x}} V(X_t) \beta \quad (3)$$

²⁴ See, for instance, Ahmed and Zlate (2014).

²⁵ Notably, in equation (28), Devereux and Sutherland (2009) show how home-country holdings of foreign equities and bonds depend on a set of domestic and foreign indicators. As we mainly focus on gross inflows (so changes in foreign holdings of domestic assets), we can flip the interpretation of this relationship so to derive a direct link between foreign-country holdings of domestic equities and bonds and the same set of domestic and foreign indicators.

where $J(X_t)|_{\bar{x}}$ is the Jacobian of X_t evaluated at the steady state and $V(X_t)$ is the variance-covariance matrix. Therefore, capital flow volatility can be proxied with a linear function of the rate of change of the variables in X_t around the steady state.

Equations (2) and (3) provide the baseline setup for our panel regressions, where the dependent variables are the ARIMA volatility estimates of both total flows and different types of instruments, computed at the country-level for EMDEs. In addition, in line with some of the existing literature²⁶, we choose the US as our AE of reference, and also as a proxy for global economic stance.

The independent variables consist of a set of regressors²⁷, grouped in two categories: global (US) factors and domestic factors²⁸. Global variables include the US shadow rate²⁹, the US real GDP, S&P 500 realized returns³⁰, the US CPI and the US M2 aggregate. The domestic variables include the real GDP, CPI, short-term interest rates, and the nominal domestic exchange rate vis-à-vis the USD. Moreover, since $NFA_t^* \approx CA_t^* + r'_x a_{t-1}$, where CA_t^* is the current account of the foreign economy (US) and $r'_x a_{t-1}$ represents the unanticipated valuation effect arising from gross asset positions held in the home country (EMDE), we also include the US current account³¹ and the lagged dependent variable (capital inflow volatility estimate) in the right-hand side of the regression.

Therefore, given the $N=33$ EMDEs in our sample, the baseline dynamic panel regression model is:

$$\sigma_{it}^2 = \gamma_1 \sigma_{it-1}^2 + \sum_{q=1}^k \vartheta_q g_{iqt} + \varepsilon_{it}, \quad i = 1, \dots, N,$$

where g_{iqt} are growth rates of the regressors and $\varepsilon_{it} = \eta_i + \delta_t + \omega_{it}$, so that we control for the presence of both country and time fixed-effects.

²⁶ See, for instance, Broto et al. (2011) and Rey (2013,2016).

²⁷ In our specification, we don't include proxies for covariances among the regressors. This does not generate endogeneity issues, as explained below.

²⁸ Since in equation (3) the variance is linearized around the steady state, we demean the regressors, using the trend estimated via HP filtering as a proxy for the steady state. Moreover, in order to identify the coefficients, we standardize the series so that variables have unit variance. All variables are in log-terms, except for the shadow rate and short-term interest rates, which are included in levels.

²⁹ The use of the shadow rate instead of the policy rate (Fed Fund rate) is preferred as it allows to capture changes in US monetary policy even when the official rate is at the ZLB. Following most of the literature, we consider short-term interest rates as the only relevant factors. However, there is a strand of the literature arguing that long-run interest rates may be at least as important for capital flows as short-run rates, if investors prefer to diversify assets with short maturities and assets of different maturity are imperfect substitutes (see Bernanke et al. (2011)). As a robustness check, we ran regressions using long-term interest rates, but the key results were substantially unchanged.

³⁰ In this case, we follow Ghosh et al. (2014) and Ghosh, Ostry and Qureshi (2016) and we use changes in the S&P 500 realized returns volatility as an index for global risk aversion. Ideally, VIX would be a better indicator, but data are available only from 1990 onwards.

³¹ The US current account balance is used here as a counterpart for the country's net flows and it can be seen as a proxy for the stability of the international financial markets. For a discussion about the relationship between a country's Net International Investment Position (NIIP) and its current account balance, as well as the risk associated to the build-up of persistent current account imbalances, refer to Obstfeld (2012b) and Lane (2013).

Following Broto et al. (2011), we correct the covariance matrix as suggested by Driscoll and Kraay (1998), to account for both serial and spatial (cross-sectional) correlations.³² In addition, we run two sets of diagnostic checks to detect whether this framework is capable of addressing the issues of endogeneity in regressors and cross-sectional dependence in the residuals³³. Endogeneity in our model can arise for two reasons: i) we are focusing just on the diagonal elements of the Jacobian and the variance-covariance matrix in the right-hand side of equation (3), thus leaving cross-variables covariances in the error term; ii) our volatility measures for capital flows are estimates of actual variance, and, as such, are subject to measurement errors, which are included in the regression residuals. Both these factors could lead to an omitted variable bias problem, which would produce biased estimates. The test results suggest that both endogeneity and spatial correlation can be ruled out for all regressions (see Appendix C).

B. Results

Baseline

Table 3 below summarizes the effects of each factor over the volatility of each instrument, as produced by the regression estimation. Table 4 reports the complete estimation outcomes. The results suggest that the volatility of capital flows is a somewhat persistent process, with autocorrelation coefficient estimates ranging from 0.20 for government sector investments to 0.83 for total inflows. This points at the presence of substantial valuation risks stemming from the holding of assets in EMDEs.

Global factors

As expected, global factors are important drivers of capital flow volatility, but their effects vary across instruments. For instance, changes in the US shadow rate have a positive impact on the volatility of most of the instruments considered, with the exception of FDI and portfolio equity inflow volatility. The overall effect, however, is positive, with a 100-basis-points increase in the shadow rate leading to an increase in the volatility of total inflows by 5.14% of GDP. This result is mainly driven by other investment flows (+7.17% of GDP) and, among the latter, by bank inflows (+2.45% of GDP).

An increase in the S&P realized returns has a negative impact for almost all the instruments, with the exception of FDI, whose volatility positively responds to increases in global uncertainty (+2.77% of GDP). The effect on overall inflows, however, is negative (-3.25% of GDP), due to the negative impact on the volatility of other investments (-4.37% of GDP), and, more specifically, of bank inflows (-2.20%). These results seem counterintuitive to the expectation that global risk aversion should increase capital flow volatility. Indeed, the results from the next section suggest that the baseline regressions may be missing some dynamics (both across countries and over time) that need to be further explored.

³² To do so, we used the `xtscc` command in Stata (see Hoechle (2007)).

³³ In the former case, we use the Durbin-Wu-Hausman test, while in the latter we perform the test for weak cross-sectional dependence proposed by Pesaran (2015).

Indicators of the US economic stance (US real GDP and US CPI) generally have a negative effect over the volatility of EMDEs capital inflows, except for FDI and portfolio equity inflows. All in all, a 1% increase either in the US real GDP or in the US CPI decreases the volatility of gross capital inflows by 6.31% and 2.17% of GDP respectively. These findings seem in line with the common belief that, in general and all else equal, an acceleration in the US economic activity implies greater stability in the global financial system and, consequently, lower uncertainty.

The US monetary policy stance also matters for capital flow volatility. An increase in the US M2, a proxy for the implementation of accommodative monetary policies, raises the volatility of all the instruments considered (but FDI), with particularly remarkable effects for other investments and bank inflows (+23.11% of GDP and +8.31% of GDP respectively). Finally, movements in the US current account increase the volatility of FDI and other investments (both bank and non-bank inflows), with an overall positive effect on the volatility of total inflows (+5.69% of GDP)

| | Total | FDI | Portfolio | Port. Debt | Port. Equity | Other | Banks | Official | Non- banks | Total private |
|--------------------------|-------|-----|-----------|---------------|-----------------|-------|-------|----------|---------------|------------------|
| $\sigma^2_{(t-1)}$ | + | + | + | + | + | + | + | + | + | + |
| US shadow rate | + | - | + | + | - | + | + | + | + | |
| Real. returns volatility | - | + | | | + | - | - | | - | |
| US Real GDP | - | + | - | - | + | - | - | | - | |
| US CPI | - | + | | | + | | - | | - | + |
| US M2 | + | | + | + | + | + | + | + | + | + |
| US Current Account | + | | | | | + | + | | + | - |
| Real GDP | | | | | | | | | | |
| CPI | | | | + | | | | | | |
| Short-term int. rate | | | | | | | | | | |
| Exchange rate vs USD | | | | | | | | | | |

Table 3: sign effects of global and domestic factors variance, as reported in the baseline regression results. *Notes:* + positive and significant (90%) impact; - negative and significant (90%) impact.

Domestic Factors

Tables 3 and 4 also show that domestic factors are not relevant drivers of capital flows volatility in EMDEs, thus implying a predominance of global factors influence. While this finding is in line with evidence provided by some of the existing literature (see, for instance, Broto et al (2011) and Byrne and Fiess (2016)), yet it has also been pointed out how these effects over capital flow levels are highly heterogenous across countries, due to differences in the quality of domestic institutions, country risk and the strength of domestic macroeconomic fundamentals (Fratzscher (2012), IMF (2016a)). Moreover, it has also been shown that these effects are characterized by a certain degree of variation over time, since the GFC has actually strengthen the role played by global factors in driving the level of capital flows. This evidence calls then for an extension of our baseline model to account for potential differences in the effects of domestic variables over the volatility of capital flows in the pre and post-crisis periods.

In order to get a sense of the contribution of each variable towards capital flow volatility over time, we compute the marginal effects (expressed as semi-elasticities) of changes in the variance of the regressors over capital inflow volatility.³⁴ Results for total inflows over the period 1990Q1-2016Q4 are reported in Figure 15.

Among the global factors, the negative impact of returns hits its lowest value between 2008 and 2009 (about -10%) and returns to positive values in the aftermath of the GFC. The effect of the shadow rate shows positive spikes in correspondence of financial turmoil (e.g., the Latin America debt crisis in the mid-1990s, the Asian crisis at the end of 1990s and the GFC), while it turns negative soon after. The marginal effect of the US GDP, on the other hand, plunged during the GFC (~-10%), after having reached a positive peak in 2007. In the last part of the sample, however, the semi-elasticity reached a new record-high (15%) around 2010. The exceptionality of the 2008-2009 recession is also shown by a negative spike (~-12%) in the semi-elasticity of total inflows volatility to the US CPI. Furthermore, the impact of changes in US M2 aggregate presents a hike and, soon after, a plunge (from 50% to -50%) over the period 2008-2010. Finally, the impact of the US current account presents a swing corresponding to the GFC, where it has soared to almost 2% and then, immediately after, decreased to values around -10% (which is the second-lowest value since the mid-1990s). All in all, the marginal effects of global factors seem to hover around a long-run zero mean, with, nonetheless, evident breaks at the onset and during the financial crisis.

As far as the goodness of fit is concerned, the within R^2 statistic shows how our baseline model is particularly suitable to explain the volatility of total inflows towards EMDEs (70%), as well as that of bank and non-bank inflows (60% and 56% respectively), while it is less so for portfolio debt inflows (13%) and other investments through the official sector (7%).

³⁴ For the domestic variables, marginal effects have been computed using the quarterly median value across countries.

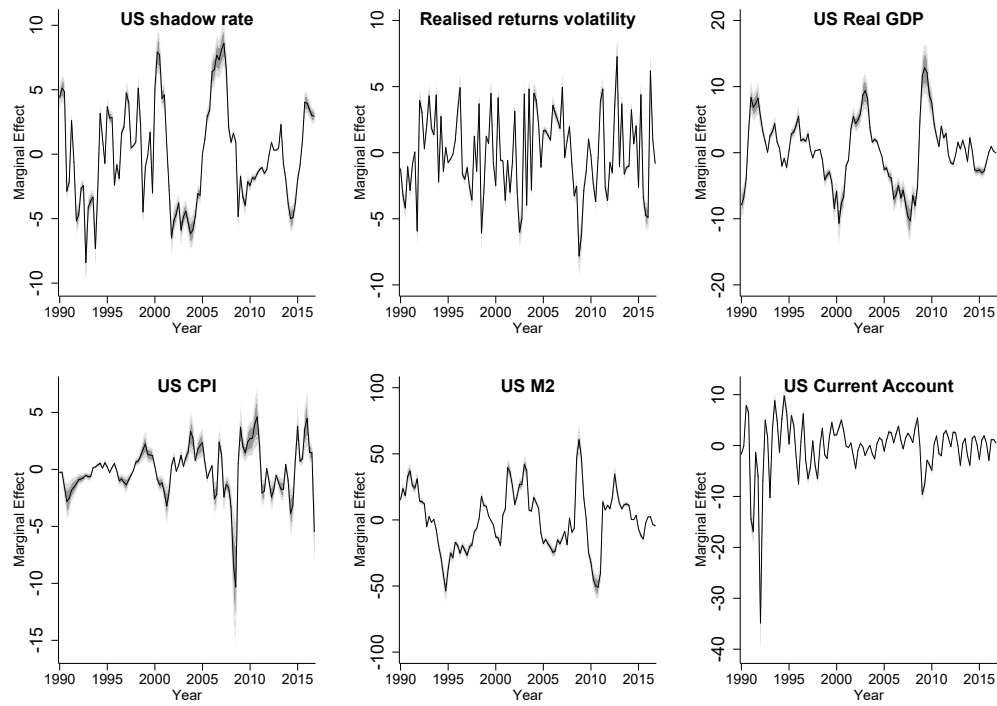


Figure 7: Baseline model, marginal effects on volatility of aggregate gross inflows in EMDEs, global factors. *Notes:* Grey shaded areas are confidence intervals at 90%, 80% and 70% confidence levels. Source: IMF, *International Financial Statistics*, authors' computations.

| VARIABLES | (1) Total | (2) FDI | (3) Portfolio | (4) Portfolio Debt | (5) Portfolio Equity | (6) Other | (7) Banks | (8) Official | (9) Non-banks | (10) Total private |
|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|--------------------------------|-----------------------------|-----------------------------|-----------------------------|------------------------------|------------------------------|
| $\sigma^2_{(t-1)}$ | 0.826*** (0.0497) | 0.658*** (0.0673) | 0.306*** (0.0197) | 0.317*** (0.0178) | 0.657*** (0.0705) | 0.241*** (0.0260) | 0.762*** (0.0545) | 0.202*** (0.0219) | 0.735*** (0.0411) | 0.741*** (0.0624) |
| US shadow rate | 5.143*** (0.644) | -1.133* (0.589) | 1.292*** (0.303) | 0.634** (0.296) | -0.00574** (0.00283) | 7.166*** (0.678) | 2.448*** (0.134) | 1.631*** (0.555) | 0.430*** (0.0338) | 0.0116 (0.0913) |
| Realized returns volatility | -3.255*** (0.419) | 2.772*** (0.413) | -0.242 (0.356) | -0.0291 (0.296) | 0.0464* (0.0242) | -4.368*** (0.609) | -2.206*** (0.132) | -0.317 (0.648) | -0.414*** (0.0274) | -0.0114 (0.107) |
| US Real GDP | -6.310*** (1.146) | 7.190*** (1.188) | -1.667*** (0.353) | -0.781** (0.359) | 0.0608* (0.0323) | -10.92*** (0.857) | -4.397*** (0.372) | -1.255 (0.808) | -0.804*** (0.0430) | 0.679 (0.439) |
| US CPI | -2.170*** (0.733) | 7.820*** (0.755) | 2.808 (3.034) | 3.473 (3.027) | 0.117*** (0.0413) | 0.487 (5.317) | -2.366*** (0.317) | 4.580 (5.271) | -0.415*** (0.0439) | 1.105*** (0.400) |
| US M2 | 21.26*** (2.339) | 2.542 (1.840) | 4.244*** (0.353) | 2.717*** (0.358) | 0.0591*** (0.0199) | 23.11*** (1.009) | 8.307*** (0.346) | 3.214*** (0.844) | 1.161*** (0.104) | 0.493** (0.225) |
| US Current Account | 5.686*** (0.570) | 0.463 (0.518) | 0.573 (0.560) | -0.198 (0.446) | -0.0112 (0.00960) | 5.153*** (0.850) | 1.734*** (0.0590) | 0.0359 (0.942) | 0.485*** (0.0360) | -0.214*** (0.0791) |
| RGDP | -1.336 (0.883) | -1.011 (1.024) | 1.112 (1.799) | 0.504 (1.553) | 0.0405 (0.0457) | 0.696 (3.368) | -0.798 (0.904) | 0.763 (3.648) | -0.0476 (0.187) | -0.869 (0.968) |
| CPI | 0.0939 (1.018) | -0.508 (0.729) | 2.338 (1.541) | 2.488* (1.458) | -0.0565 (0.0520) | 0.463 (3.068) | -0.517 (0.930) | -0.159 (2.387) | 0.0691 (0.154) | -0.405 (0.997) |
| Short-term int. rate | 0.981 (1.081) | 1.133 (1.054) | -3.960 (3.023) | -4.123 (3.173) | 0.102 (0.0998) | -2.172 (4.939) | 1.507 (1.459) | -1.358 (4.682) | 0.126 (0.179) | 1.650 (1.493) |
| Exchange rate vs USD | -2.344 (1.960) | -2.163 (1.969) | 10.45 (10.33) | 9.865 (10.09) | 0.177 (0.144) | 18.96 (17.96) | 0.675 (0.816) | 18.83 (18.00) | -0.136 (0.137) | 0.706 (0.903) |
| Constant | 14.03*** (1.811) | 5.915*** (1.672) | 3.389 (2.328) | 3.546 (2.160) | 0.0391 (0.0340) | 15.90*** (3.915) | 5.243*** (0.581) | 4.424 (3.889) | 1.210*** (0.137) | 1.769*** (0.600) |
| Observations | 4,498 | 4,499 | 4,488 | 4,311 | 4,277 | 4,498 | 4,497 | 4,498 | 4,498 | 4,483 |
| Number of groups | 33 | 33 | 33 | 32 | 32 | 33 | 33 | 33 | 33 | 33 |
| Within R ² | 0.703 | 0.453 | 0.123 | 0.132 | 0.475 | 0.0877 | 0.600 | 0.0718 | 0.563 | 0.573 |

Table 4: Baseline regression for volatility of capital inflows. *Notes:* Driscoll and Kraay (DK) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Some countries have been excluded from the pool due to lack of an adequate number of observations

Extended regression: the role of commodity prices

In this session, we expand the baseline regression to account for commodity prices, as they are deemed influential drivers for capital flows towards both exporting and importing economies (Byrne and Fiess (2016)). Notably, a positive shock to commodity prices increases bank investments to commodity exporting countries, whose financial institutions, in turn, reinvest their increased revenues into the international financial markets, to diversify their portfolios.³⁵ Nonetheless, changes in commodity prices are also positively correlated with capital inflows to commodity importers. This could be associated with the fact that these prices partly reflect global demand conditions and therefore global income³⁶. Results, reported in detail in Table 6, are summarized in Table 5.

An increase in commodity prices decreases the volatility of all the instruments considered and, therefore, of overall inflows as well. Notably, an increase in the commodity price index by 1% lowers the volatility of total inflows by 14.4% of GDP, with estimates ranging from -15.38% for other investments to -0.159% for portfolio equity inflows.

| | Total | FDI | Portfolio | Port. Debt | Port. Equity | Other | Banks | Official | Non- banks | Total private |
|--------------------------|-------|-----|-----------|---------------|-----------------|-------|-------|----------|---------------|------------------|
| $\sigma^2_{(t-1)}$ | + | + | + | + | + | + | + | + | + | + |
| US shadow rate | + | - | + | | | + | + | + | + | + |
| Real. returns volatility | + | + | + | + | + | + | + | | | + |
| US Real GDP | + | + | + | + | | + | | + | | |
| US CPI | + | + | | | + | + | + | | + | + |
| US M2 | + | - | + | | + | + | + | | + | + |
| US Current Account | + | - | | | | | + | | + | + |
| Commodity price index | - | - | - | - | - | - | - | - | - | - |
| Real GDP | | | | | | | | | | |
| CPI | | | | + | | | | | | |
| Short-term int. rate | | | | | | | | | | |
| Exchange rate vs USD | | | | | | | | | | |

Table 5: sign effects of global and domestic factors variance, as reported in the extended regression results. *Notes:* + positive and significant (90%) impact; - negative and significant (90%) impact.

In addition, in this augmented setting, most of the coefficients of global factors are positive. In particular, and more in line with expectations, an increase in S&P 500 realized returns volatility exerts a positive effect on the volatility of almost all the instruments, with estimates ranging from 0.48% for total private investments to 5.9% for FDI (with an overall effect of about 5% of GDP).

³⁵ See Arezki, Mazarej, and Prasad (2015) and Arezki, Obstfeld and Milesi-Ferretti (2016).

³⁶ See Ahmed, Curcuru and Warnock (2015).

| VARIABLES | (1) Total | (2) FDI | (3) Portfolio | (4) Portfolio Debt | (5) Portfolio Equity | (6) Other | (7) Banks | (8) Official | (9) Non-banks | (10) Total private |
|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|------------------------------|-----------------------------|-----------------------------|-----------------------------|------------------------------|-----------------------------|
| $\sigma^2_{(t-1)}$ | 0.825*** (0.0499) | 0.658*** (0.0675) | 0.306*** (0.0197) | 0.317*** (0.0178) | 0.657*** (0.0705) | 0.241*** (0.0258) | 0.762*** (0.0545) | 0.202*** (0.0216) | 0.735*** (0.0411) | 0.741*** (0.0625) |
| US shadow rate | 1.177*** (0.226) | -2.658*** (0.260) | 0.351* (0.178) | -0.0438 (0.182) | 0.00929 (0.00953) | 2.988*** (0.375) | 1.076*** (0.0914) | 0.705** (0.325) | 0.211*** (0.0190) | 1.014*** (0.0915) |
| Realized returns volatility | 4.953*** (0.522) | 5.909*** (0.339) | 1.724*** (0.616) | 1.395*** (0.526) | 0.0832* (0.0423) | 4.341*** (1.136) | 0.634*** (0.162) | 1.644 (1.102) | 0.0378 (0.0322) | 0.476** (0.183) |
| US Real GDP | 6.835*** (0.557) | 12.18*** (0.811) | 1.505*** (0.456) | 1.528*** (0.579) | 0.0852 (0.0601) | 3.117** (1.217) | 0.158 (0.536) | 1.969* (1.103) | -0.0811 (0.0603) | 0.178 (0.542) |
| US CPI | 9.124*** (1.201) | 12.07*** (0.764) | 5.531 (3.463) | 5.452 (3.402) | 0.157** (0.0644) | 12.62** (6.269) | 1.553*** (0.510) | 7.411 (6.052) | 0.207*** (0.0791) | 1.393*** (0.533) |
| US M2 | 8.997*** (1.031) | -2.132** (0.887) | 1.308** (0.562) | 0.590 (0.587) | 0.107** (0.0417) | 10.13*** (1.042) | 4.060*** (0.259) | 0.301 (1.168) | 0.486*** (0.0467) | 3.635*** (0.282) |
| US Current Account | 2.443*** (0.265) | -0.778*** (0.263) | -0.201 (0.673) | -0.756 (0.541) | -0.000442 (0.0162) | 1.700 (1.103) | 0.613*** (0.0860) | -0.764 (1.156) | 0.306*** (0.0252) | 0.548*** (0.0920) |
| Commodity price index | -14.43*** (1.584) | -5.489*** (1.233) | -3.469*** (0.566) | -2.519*** (0.493) | -0.159*** (0.0398) | -15.38*** (1.293) | -4.998*** (0.279) | -3.507*** (1.057) | -0.793*** (0.0753) | -4.403*** (0.353) |
| RGDP | -1.236 (0.888) | -0.854 (1.004) | 1.065 (1.781) | 0.429 (1.534) | 0.0427 (0.0467) | 0.513 (3.322) | -0.790 (0.917) | 0.560 (3.599) | -0.0417 (0.190) | -0.874 (0.982) |
| CPI | 0.101 (1.022) | -0.500 (0.735) | 2.349 (1.551) | 2.488* (1.466) | -0.0561 (0.0522) | 0.456 (3.086) | -0.515 (0.933) | -0.170 (2.400) | 0.0698 (0.154) | -0.407 (1.001) |
| Short-term int. rate | 0.986 (1.086) | 1.151 (1.062) | -3.961 (3.025) | -4.129 (3.178) | 0.102 (0.100) | -2.178 (4.936) | 1.511 (1.462) | -1.363 (4.683) | 0.127 (0.179) | 1.654 (1.496) |
| Exchange rate vs USD | -2.333 (1.970) | -2.165 (1.979) | 10.49 (10.36) | 9.901 (10.11) | 0.177 (0.144) | 19.16 (18.00) | 0.671 (0.819) | 19.05 (18.04) | -0.137 (0.138) | 0.706 (0.907) |
| Constant | 10.62*** (1.482) | 4.612*** (1.454) | 2.554 (2.457) | 2.940 (2.271) | 0.0828*** (0.0288) | 12.13*** (4.198) | 4.065*** (0.542) | 3.473 (4.126) | 1.022*** (0.124) | 3.801*** (0.633) |
| Observations | 4,465 | 4,466 | 4,455 | 4,279 | 4,245 | 4,465 | 4,464 | 4,465 | 4,465 | 4,450 |
| Number of groups | 33 | 33 | 33 | 32 | 32 | 33 | 33 | 33 | 33 | 33 |
| Within R ² | 0.703 | 0.453 | 0.123 | 0.132 | 0.475 | 0.0875 | 0.600 | 0.0716 | 0.563 | 0.573 |

Table 6: Extended regression for volatility of capital inflows. *Notes:* Driscoll and Kraay (DK) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Some countries have been excluded from the pool due to lack of an adequate number of observations.

Pre and Post Lehman collapse

Most of the estimated marginal effects present turning points over the period 2008-2010, which might signal the presence of structural breaks, something that might also hold for the effects of domestic variables, as previously mentioned. In this section, we modify the extended regression to investigate whether the effects of global and domestic variables are significantly different before and after the GFC. To do so, we first run Chow tests to detect whether certain dates effectively represent structural breaks in our empirical model. Results are reported in Table 7 below.

As it can be noticed, two natural candidates are 2008Q3 and 2008Q4, which roughly correspond to the collapse of Lehman Brothers. Since this event took place in September 2008, we deem that 2008Q4 is a more well-suited break date, something which is also confirmed by the lower Chow test p-values. Therefore, we construct a time dummy variable which equals one for dates after 2008Q4 and zero otherwise. We then rerun the regression from previous section by interacting such dummy with the relevant independent variables.

| Chow tests for structural breaks | | | | | | | | | | |
|----------------------------------|-------|------|-----------|------------|--------------|-------|-------|----------|-----------|---------------|
| Date | Total | FDI | Portfolio | Port. Debt | Port. Equity | Other | Banks | Official | Non-Banks | Total private |
| 2007Q1 | 0.00 | 0.00 | 0.01 | 0.21 | 0.66 | 0.00 | 0.00 | 0.00 | 0.01 | 0.05 |
| 2007Q2 | 0.00 | 0.00 | 0.01 | 0.21 | 0.14 | 0.00 | 0.00 | 0.00 | 0.02 | 0.02 |
| 2007Q3 | 0.00 | 0.00 | 0.01 | 0.22 | 0.09 | 0.00 | 0.00 | 0.00 | 0.03 | 0.02 |
| 2007Q4 | 0.00 | 0.00 | 0.01 | 0.25 | 0.00 | 0.00 | 0.01 | 0.00 | 0.05 | 0.01 |
| 2008Q1 | 0.00 | 0.00 | 0.01 | 0.24 | 0.00 | 0.00 | 0.00 | 0.00 | 0.05 | 0.00 |
| 2008Q2 | 0.00 | 0.00 | 0.00 | 0.21 | 0.00 | 0.00 | 0.01 | 0.00 | 0.06 | 0.02 |
| 2008Q3 | 0.00 | 0.00 | 0.00 | 0.06 | 0.01 | 0.00 | 0.08 | 0.00 | 0.00 | 0.03 |
| 2008Q4 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 |
| 2009Q1 | 0.00 | 0.00 | 0.01 | 0.09 | 0.00 | 0.00 | 0.35 | 0.00 | 0.00 | 0.48 |
| 2009Q2 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.31 | 0.00 | 0.00 | 0.71 |
| 2009Q3 | 0.00 | 0.00 | 0.04 | 0.01 | 0.00 | 0.00 | 0.34 | 0.00 | 0.01 | 0.78 |
| 2009Q4 | 0.00 | 0.32 | 0.06 | 0.01 | 0.00 | 0.00 | 0.46 | 0.00 | 0.02 | 0.77 |
| 2010Q1 | 0.00 | 0.54 | 0.03 | 0.00 | 0.00 | 0.00 | 0.34 | 0.00 | 0.03 | 0.73 |
| 2010Q2 | 0.00 | 0.28 | 0.03 | 0.00 | 0.01 | 0.00 | 0.44 | 0.00 | 0.00 | 0.58 |
| 2010Q3 | 0.00 | 0.53 | 0.09 | 0.01 | 0.03 | 0.00 | 0.36 | 0.00 | 0.00 | 0.72 |
| 2010Q4 | 0.00 | 0.02 | 0.10 | 0.01 | 0.04 | 0.00 | 0.32 | 0.00 | 0.00 | 0.75 |

Table 7: P-values of Chow test for structural breaks; H_0 : no break at selected date; H_1 : otherwise.

Tables 8a and 8b report the results for this modified regression. The effects of global factors are particularly pronounced after 2008Q4, while they get somewhat less significant in earlier quarters. In particular, global risk aversion has a significant and positive impact over the volatility of all the instruments only after the GFC. Generally speaking, while risk does not influence volatility in the pre-crisis period, this effect becomes large and positive in later periods, with estimates ranging from 0.05% of GDP for portfolio equity inflows to more than 29% of GDP for FDI. Therefore, results highlighted in previous sections were substantially driven by the post-crisis dynamics.

Figure 8 displays the different marginal effects of global factors over the volatility of total gross inflows across the pre and post-crisis periods. There is a striking difference in terms of both

statistical significance and magnitude. Global risk, for instance, has a decidedly significant effect onto the volatility of gross inflows after the onset of the GFC, with particularly remarked positive spikes (~30%) in the period 2008-2010, in line with the findings of existing literature, as well as expectations. The GFC, indeed, was a period of heightened risk aversion and uncertainty, which has led to sudden stops of capital inflows in EMDEs. Such a phenomenon holds also for volatility, as the 2008-2010 period is characterized by a much higher sensitivity of our estimates to movements in the S&P 500 realized returns volatility.

Another interesting finding concerns the effects of shocks in the US monetary policy, captured via changes in both the shadow rate and the aggregate money supply (M2). While the marginal effects of such variables are decidedly amplified in the post-Lehman collapse period, it is worth noticing how the elasticity of gross inflows volatility to an increase in the shadow rate has fallen in negative domain in two particular periods: in 2009 and in 2014. The former episode relates to the implementation of unconventional monetary policy to offset the negative effects of the GFC, something which is also confirmed by the drop in the marginal effect of changes in US M2 (~30%) over the same period. The latter one, on the other hand, can be identified with the taper tantrum episode, but it does not coincide with any significant change in the effects of US M2.

Finally, commodity price index seems to exert a significant effect on capital inflow volatility only in the pre-GFC period. This is a new finding compared to existing literature (Byrne and Fiess (2016)), as it shows how, in the last 10 years, the influence of commodity prices has been greatly reduced compared to that of other global factors.

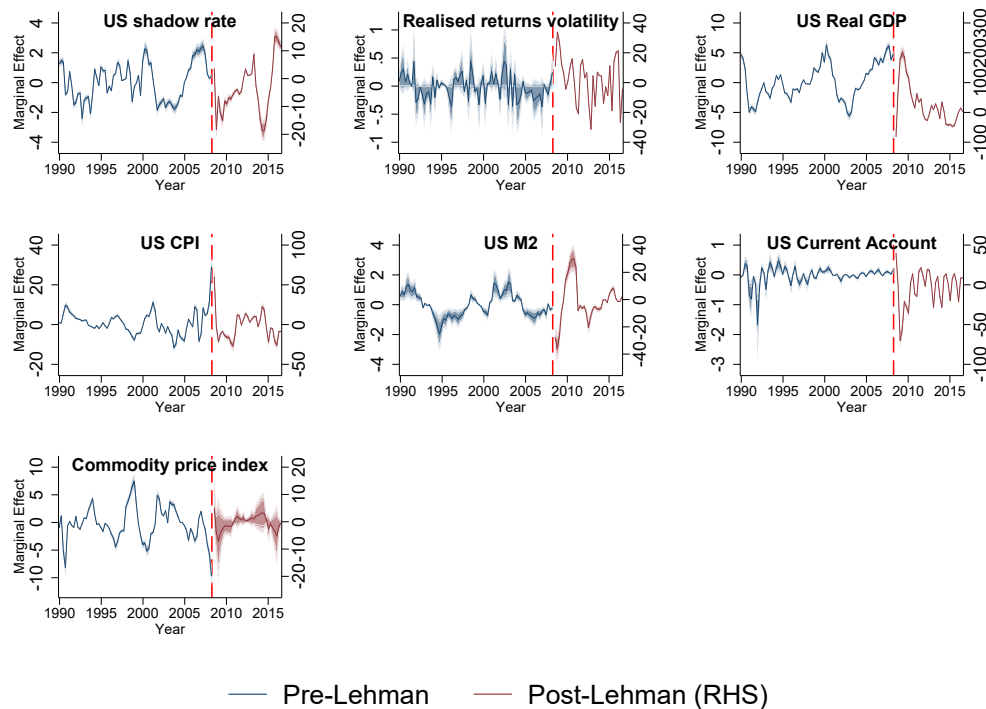


Figure 8: Extended model, marginal effects on volatility of aggregate gross inflows in EMDEs, global factors, pre and post-2008Q4. *Notes:* Shaded areas are confidence intervals at 90%, 80% and 70% confidence levels. Source: IMF, *International Financial Statistics*, authors' computations.

As to the effects of domestic factors, it can be noticed that, after the GFC, the volatility of certain types of inflows has become more sensitive to changes in some of the variables included. There is, moreover, a degree of heterogeneity across instruments, that is concealed when looking at the effects of the same variables over the aggregate gross inflows.

For instance, in the post-Lehman period, FDI volatility is positively affected by increases in domestic short-term interest rates (+30% of GDP for a 100-bp increase), while domestic production (real GDP) has a positive and significant effect over the volatility of other investments (+3.1% of GDP for 1% increase), and, in particular, the volatility of both private and government investments (+1.22% and +1.58% of GDP respectively). In addition, other investment volatility is also negatively affected by surges in the domestic exchange rate. Over the same period, portfolio inflow volatility positively reacts to increases in both the domestic CPI (+4.9% of GDP for a 1% increase) and the exchange rate vis-à-vis the USD (+2% of GDP for a 1% increase).

Figure 9 displays the marginal effects computed using the estimates reported above for some selected flows. As already mentioned, FDI inflows have started to react to changes in domestic short-term interest rates in the aftermath of the GFC; notably, there is a sharp decrease in the elasticity of FDI volatility over the period 2009-2010 (~-5%), followed then by a surge into positive domain in 2012. In the end of the time span considered, however, the effect hovers again around 0, a level which is comparable to the pre-crisis estimates.

Another interesting result concerns the reaction of portfolio and other investment volatility to changes in the exchange rate (notably, a 1%-depreciation) vis-à-vis the USD. While the marginal effect for the volatility of other investments shows two negative spikes (~-2%) in the aftermath of the GFC (2009) and in 2016, the marginal effect on portfolio volatility is exactly reversed, with positive peaks of around 1% in the same periods. This might be pointing at the presence of important portfolio rebalancing effects across these two types of instruments, which are particularly responsive to changes in exchange rate risks.

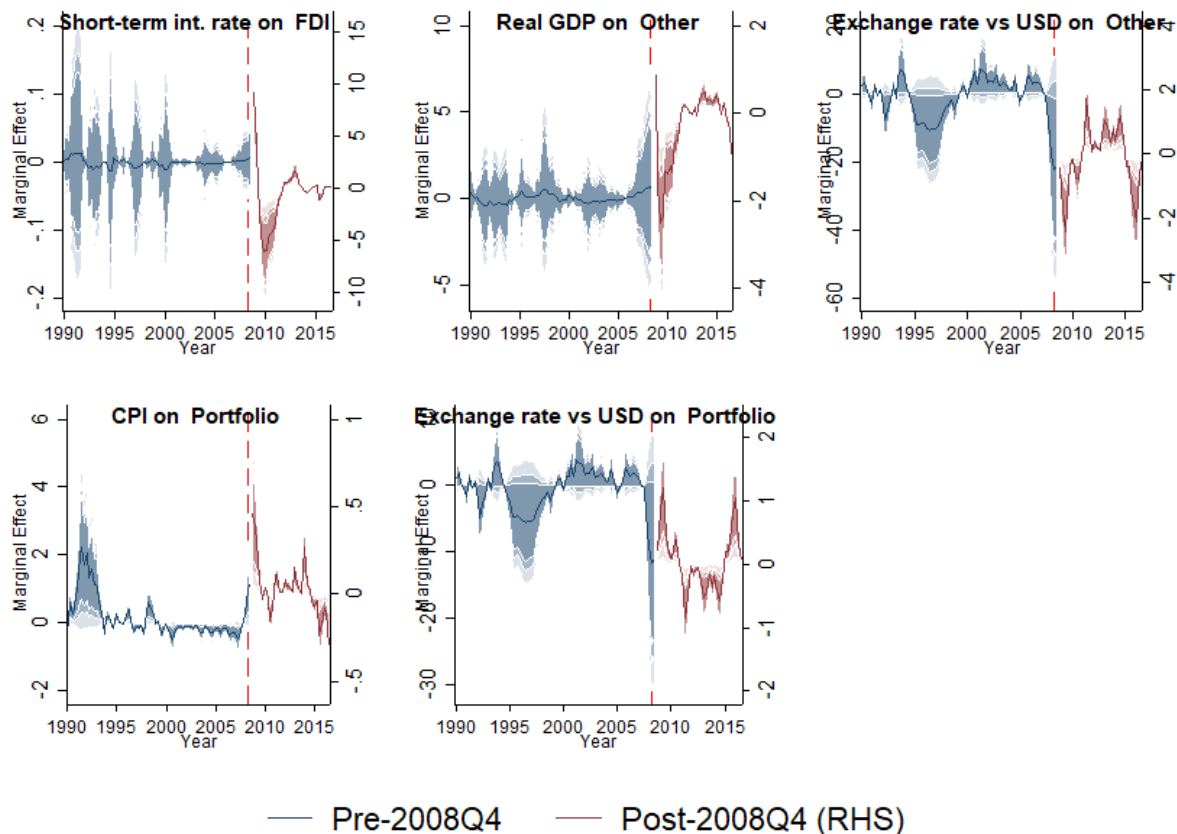


Figure 9: Extended model, marginal effects on volatility of aggregate gross inflows in EMDEs, by instrument, domestic factors, pre and post-2008Q4. Notes: Shaded areas are confidence intervals at 90%, 80% and 70% confidence levels; domestic factors are considered as median values across countries. Source: IMF, *International Financial Statistics*, authors' computations.

| VARIABLES | (1) | | (2) | | (3) | | (4) | | (5) | |
|-----------------------------|-----------------------------|-----------------------------|------------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-------------------------------|
| | Total | | FDI | | Portfolio | | Portfolio Debt | | Portfolio Equity | |
| | (i) | (ii) | (i) | (ii) | (i) | (ii) | (i) | (ii) | (i) | (ii) |
| $\sigma_2(t-1)$ | 0.828*** (0.0295) | 0.837*** (0.0614) | 0.691*** (0.0326) | 0.670*** (0.0747) | 0.307*** (0.0195) | 0.783*** (0.0428) | 0.319*** (0.0179) | 0.782*** (0.0579) | 0.667*** (0.0743) | 0.664*** (0.0680) |
| US shadow rate | 1.466*** (0.202) | 19.41*** (2.525) | -0.137 (0.101) | 55.66*** (2.595) | 0.712 (0.608) | 1.819*** (0.252) | 0.721 (0.520) | 1.860*** (0.615) | 0.0338 (0.0214) | 0.319*** (0.0326) |
| Realised returns volatility | 0.239 (0.221) | 14.02*** (0.633) | 0.128 (0.0987) | 29.53*** (1.239) | 0.226 (1.317) | 2.321*** (0.271) | 0.529 (1.156) | 1.963*** (0.321) | -0.00205 (0.0219) | -0.0487*** (0.0179) |
| US Real GDP | 3.747*** (0.332) | -97.80*** (8.251) | -0.202 (0.176) | -172.7*** (3.682) | 2.331* (1.353) | -13.69*** (0.837) | 1.372 (1.477) | -10.89*** (0.675) | 0.0936* (0.0515) | -0.633*** (0.123) |
| US CPI | 7.534*** (0.868) | 12.58*** (2.082) | -1.186* (0.608) | -16.13*** (2.739) | 7.905*** (2.990) | -2.632*** (0.283) | 7.094** (3.119) | -0.844*** (0.293) | 0.223** (0.102) | 0.345*** (0.0172) |
| US M2 | 0.780** (0.316) | -12.53*** (2.501) | 0.115 (0.107) | -7.913*** (2.917) | -0.858 (2.740) | 0.631 (0.513) | 0.0816 (2.481) | -0.0405 (0.701) | 0.00427 (0.0351) | -0.142*** (0.0280) |
| US Current Account | 0.270** (0.131) | 41.62*** (3.511) | -0.107*** (0.0382) | 124.5*** (2.419) | -0.522** (0.261) | 7.864*** (0.324) | -0.987*** (0.184) | 4.338*** (0.386) | -0.0153 (0.0134) | -0.234*** (0.0726) |
| Commodity price index | -3.247*** (0.392) | 1.979 (2.821) | 0.638** (0.294) | 45.11*** (2.695) | -2.206*** (0.179) | 5.735*** (0.230) | -2.019*** (0.270) | 4.674*** (0.338) | -0.0676 (0.0433) | -0.0219 (0.0315) |
| RGDP | -1.287* (0.751) | 0.794 (5.686) | -0.158 (0.145) | -3.316 (8.253) | 1.516 (1.965) | 0.444 (0.738) | 0.931 (1.628) | -0.388 (1.044) | 0.0393 (0.0497) | 0.0178 (0.0813) |
| CPI | -0.0739 (0.895) | 3.476 (8.779) | -0.0542 (0.194) | -6.731 (13.40) | 2.113 (1.540) | 4.914** (2.386) | 2.319 (1.426) | 4.376 (2.784) | -0.0773 (0.0546) | 0.334 (0.261) |
| Short-term int. rate | 0.370 (0.849) | 15.36 (9.559) | -0.105 (0.157) | 30.07** (11.68) | -4.008 (3.145) | -0.251 (0.992) | -4.204 (3.318) | -0.351 (1.180) | 0.105 (0.106) | -0.0280 (0.0745) |
| Exchange rate vs USD | 0.00994 (0.788) | -27.44** (12.36) | -0.243 (0.275) | -22.81 (18.09) | 11.21 (11.35) | 2.033** (0.958) | 10.60 (11.10) | 1.105 (0.896) | 0.172 (0.160) | 0.213 (0.129) |
| Constant | -0.111 (0.113) | 0.0588 (0.103) | -0.0383 (0.0365) | -0.0293 (0.132) | 0.716 (0.663) | 0.0255 (0.0325) | 0.736 (0.686) | 0.0279 (0.0361) | 0.00447 (0.0173) | -0.00163 (0.00157) |
| Observations | 4,465 | 4,465 | 4,466 | 4,466 | 4,455 | 4,455 | 4,279 | 4,279 | 4,245 | 4,245 |
| Number of groups | 33 | 33 | 33 | 33 | 33 | 33 | 32 | 32 | 32 | 32 |
| Within R2 | 0.702 | 0.734 | 0.494 | 0.473 | 0.124 | 0.713 | 0.134 | 0.699 | 0.478 | 0.729 |

Table 8a: extended regression in pre (columns (i)) and post (columns (ii)) 2008Q4; *Notes:* Driscoll and Kraay (DK) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Some countries have been excluded from the pool due to lack of an adequate number of observations.

| VARIABLES | (6) Other | | (7) Banks | | (8) Official | | (9) Non-banks | | (10) Total private | |
|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-------------------------------|------------------------------|-----------------------------|------------------------------|
| | (i) | (ii) | (i) | (ii) | (i) | (ii) | (i) | (ii) | (i) | (ii) |
| | $\sigma^2_{(t-1)}$ | 0.237*** (0.0239) | 0.899*** (0.0563) | 0.763*** (0.0608) | 0.822*** (0.0311) | 0.199*** (0.0203) | 0.954*** (0.0591) | 0.745*** (0.0454) | 0.762*** (0.0907) | 0.740*** (0.0654) |
| US shadow rate | 2.549** (1.014) | -15.74*** (0.838) | 1.155*** (0.173) | 0.709 (0.441) | 0.994 (1.049) | -16.03*** (0.386) | 0.279*** (0.0380) | -0.780*** (0.0446) | 1.188*** (0.194) | -3.341*** (0.447) |
| Realized returns volatility | -0.0198 (2.224) | -8.513*** (0.318) | 0.112 (0.188) | -4.194*** (0.142) | -0.181 (2.141) | -3.627*** (0.161) | 0.130* (0.0706) | -0.160*** (0.0219) | 0.141 (0.200) | -3.276*** (0.0857) |
| US Real GDP | 7.721*** (2.597) | 27.39*** (3.556) | 2.763*** (0.495) | 10.05*** (1.379) | 4.260* (2.343) | 10.88*** (0.817) | 0.165** (0.0634) | 1.186** (0.495) | 2.604*** (0.505) | 8.124*** (1.406) |
| US CPI | 21.63*** (5.213) | 19.65*** (0.445) | 6.770*** (0.586) | 13.14*** (0.238) | 12.31** (4.973) | 7.294*** (0.400) | 0.992*** (0.128) | 0.939*** (0.0918) | 6.404*** (0.646) | 8.098*** (0.161) |
| US M2 | -1.524 (4.865) | -4.175*** (0.546) | 0.542 (0.331) | -4.059*** (0.861) | -2.124 (4.832) | -3.494*** (0.319) | 0.0722 (0.0699) | 0.427* (0.216) | 0.707* (0.373) | -0.824 (0.655) |
| US Current Account | -1.081** (0.459) | -39.07*** (1.069) | -0.422*** (0.139) | -26.69*** (0.970) | -1.246** (0.493) | -8.539*** (0.534) | 0.0600* (0.0340) | -2.091*** (0.137) | -0.395** (0.166) | -17.47*** (0.846) |
| Commodity price index | -6.826*** (0.259) | -24.52*** (0.734) | -2.932*** (0.216) | -11.83*** (0.503) | -3.397*** (0.231) | -9.192*** (0.515) | -0.372*** (0.0645) | -0.840*** (0.108) | -2.780*** (0.242) | -8.453*** (0.489) |
| RGDP | 0.637 (3.672) | 3.080** (1.301) | -0.901 (0.981) | 0.426 (0.793) | 0.533 (4.040) | 1.580* (0.830) | -0.0110 (0.203) | -0.409* (0.230) | -1.057 (1.051) | 1.220* (0.644) |
| CPI | 0.372 (3.120) | 3.114 (2.715) | -0.575 (0.996) | 0.924 (1.043) | 0.0252 (2.449) | -1.502 (0.942) | 0.0882 (0.158) | -0.105 (0.156) | -0.496 (1.073) | 1.079 (0.785) |
| Short-term int. rate | -2.459 (5.006) | -1.626 (2.813) | 1.533 (1.526) | 1.547 (2.640) | -1.453 (4.746) | -0.838 (1.032) | 0.128 (0.186) | 0.0389 (0.253) | 1.750 (1.572) | -0.0203 (1.583) |
| Exchange rate vs USD | 21.77 (19.59) | -3.797** (1.620) | 0.835 (0.862) | -1.013 (1.689) | 20.55 (19.65) | 1.229 (2.861) | -0.157 (0.155) | 0.148 (0.135) | 0.769 (0.966) | 0.0565 (1.256) |
| Constant | 0.574 (1.118) | 0.0868 (0.115) | -0.126 (0.106) | 0.0425 (0.0561) | 0.859 (1.077) | 0.0444 (0.0625) | -0.0769*** (0.0285) | 0.00748 (0.00988) | -0.141 (0.0996) | 0.0308 (0.0396) |
| Observations | 4,465 | 4,465 | 4,464 | 4,464 | 4,465 | 4,465 | 4,465 | 4,465 | 4,450 | 4,450 |
| Number of groups | 33 | 33 | 33 | 33 | 33 | 33 | 33 | 33 | 33 | 33 |
| Within R2 | 0.0870 | 0.805 | 0.597 | 0.771 | 0.0712 | 0.794 | 0.587 | 0.750 | 0.574 | 0.832 |

Table 8b: extended regression in pre (columns (i)) and post (columns (ii)) 2008Q4; *Notes:* Driscoll and Kraay (DK) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Some countries have been excluded from the pool due to lack of an adequate number of observations.

IV. CONCLUDING THOUGHTS

This paper is an attempt to deepen our understanding of capital flow volatility. We start by quantifying volatility using three measures: rolling standard deviation, GARCH, and ARIMA estimates. We then document the evolution of volatility over time and compare the levels of volatility across instruments. After a period of sharp increase following the GFC, capital flow volatility is back to pre-crisis levels but is prone to bouts during episodes of global financial turmoil. We use our computed volatility estimates to perform panel regressions with the aim of understanding the determinants of volatility. Our results show that push factors are more important than pull factors, and this result holds under different specifications accounting for potential structural breaks due to the GFC and including factors like commodity prices.

Our findings add to the literature that attempts to understand the volatility of capital flows. Despite being a focus of policymakers, capital flow volatility is usually quantified in policy and academic discussions using a crude measure of standard deviation of flows over a specified period. Our computed volatility measures—across a large number of countries and encompassing detailed instruments of capital flows—is a step forward in having more rigorous estimates of volatility. We use our computed measures for the panel regressions, and it can be useful for future studies related to capital flow volatility.

One of our key findings—the push factors are more important than pull factors—is yet another reminder that the determinants of the level of capital flows can be very different from the determinants of the volatility of capital flows. However, we also show how certain domestic (pull) factors have started to play a relevant role after the GFC. This is even more interesting against the backdrop of recent studies (IMF 2016) that show how the recent capital flow slowdown can be predominantly attributed to the broader emerging markets economic growth slowdown. While this study is a reminder that the findings from the push vs pull factors literature do not always hold when it comes to the study of capital flow volatility, it is still possible to detect some commonalities in the effects of push and pull factors over both the levels and the volatility of certain types of flows. Therefore, the debate on the relative importance of push versus pull factors needs to continue also in terms of the determinants of capital flow volatility.

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VI. APPENDIX

A. Countries and Regions

Asia (AS): China, India, Indonesia, Kazakhstan, Malaysia, Philippines, Sri Lanka, Thailand;
Europe (EU): Albania, Bulgaria, Croatia, Hungary, Lithuania, Latvia, Poland, Romania, Russia;

Latin America (LATAM): Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Guatemala, Mexico, Peru, Paraguay, Uruguay;

Middle East and Africa (MEAF): Egypt, Jordan, Saudi Arabia, South Africa, Turkey.

B. Data

Capital flows: 1970Q1-2016Q4 from International Financial Statistics (IFS); missing quarterly data have been extrapolated from the annual series using the disaggregation technique of Boot et al. (1967).

Real GDP: 1970Q1-2016Q4 from IFS; missing quarterly data have been extrapolated from the annual series using the disaggregation technique of Boot et al. (1967); non-seasonally adjusted series have been adjusted using the US Census' X13 program; growth rates are y-o-y.

Nominal GDP: 1970Q1-2016Q4 from IFS; missing quarterly data have been extrapolated from the annual series using the disaggregation technique of Boot et al. (1967); non-seasonally adjusted series have been adjusted using the US Census' X13 program.

CPI: 1970Q1-2016Q4 from IFS; missing quarterly data have been extrapolated from the annual series using the disaggregation technique of Boot et al. (1967); 2010=100; inflation rates are y-o-y. Data for Albania (1990), Brazil, Chile, China, Costa Rica, Croatia, Hong Kong, Hungary, Kazakhstan, Poland and Russia, are taken from the Global Financial Data (GFD) database.

Population: 1970-2016 from World Bank's World Development Indicators (WDI) database; annual data have been converted to quarterly frequency via linear interpolation.

Short-term interest rate: 1970Q1-2016Q4, money market interest rate from IFS. For countries where this series is not available, we used the following data: deposit rate from IFS for Albania, China, Costa Rica, Egypt, Hungary, Jordan, Turkey; lending rate from IFS for Chile, Cyprus, Guatemala, Peru and Uruguay; central bank's policy rate from IFS for Ecuador and Saudi Arabia; repo rate from IFS for Kazakhstan. Short-term interest rate for El Salvador is given by the interbank interest rate as reported by the national central bank. Data over the period 1979-1991 for Ecuador were taken from GFD database. Rates are annualized.

Exchange rates, defined as national currency per USD: 1970Q1-2016Q4 from IFS. Data for Albania (1970-1991), Bulgaria (1970-1990), Croatia (1970-1992), Ecuador (1970-1998), Kazakhstan (1970-1992), Latvia (1970-1992), Lithuania (1970-1992), Russia (1970-1992) were taken from GFD (black market rate). Former Soviet Union members used Soviet ruble (SUR) as single currency until the end of 1991. In the period between 1992 and 1993 they all adopted temporary currencies to help transition towards permanent independent currencies in

1993. For Euro Area members (Latvia and Lithuania), national exchange rates after the adoption of Euro have been computed by multiplying the fixed national currency/EUR conversion rate, reported by Eurostat, times the EUR/USD exchange rate as reported by the European Central Bank (ECB). Exchange rates are included in the regressions in real terms, i.e.: $e_{it} = \left(\frac{E_{it}}{CPI_{it}} \right)$

Wu-Xia US Shadow Rate: 1970Q1:2016Q4 from the Federal Reserve Bank of Atlanta. When positive, the shadow rate coincides with the Fed Fund rate.

S&P 500 realized returns: 1970Q1:2016Q4 from the FRED database of the Federal Reserve Bank of St. Louis. The rate is annualized.

US real GDP: 1970Q1:2016Q4 from IFS.

US CPI: 1970Q1:2016Q4 from IFS; 2010=100.

US M2: 1970Q1:2016Q4 from the FRED database of the Federal Reserve Bank of St. Louis.

US Current Account: 1970Q1:2016Q4 from IFS.

Commodity price index: 1970Q1:2016Q4 from the Hamburg Institute of International Economics (HWWI); 2005=100.

C. Regression tests

Endogeneity

In order to check whether the right-end side variables are affected by endogeneity, we first run panel regressions with variables and specification as outlined in Section V.A. We then collect the residuals and regress them over the same independent variables used in the first stage. Finally, an F test is performed on the joint significance of the coefficients of the second-stage regression. We repeat the process using as dependent variables the ARIMA measures of volatility for each instrument.

Results are reported in Table F1. As it can be noticed, the null hypothesis of the test cannot be rejected, meaning that the regressors are not endogenous, for all the instruments considered.

| Instrument | Statistic | Distribution | P-value |
|---------------------------|-----------|--------------|-------------|
| Total | 5.91E-16 | F(11,146) | 1.00 |
| FDI | 3.35E-16 | F(11,146) | 1.00 |
| Portfolio | 7.66E-16 | F(11,146) | 1.00 |
| Portfolio Debt | 9.62E-16 | F(11,146) | 1.00 |
| Portfolio Equity | 2.12E-15 | F(11,146) | 1.00 |
| Other | 1.92E-15 | F(11,146) | 1.00 |
| Other - private | 6.30E-16 | F(11,146) | 1.00 |
| Other - government | 3.36E-16 | F(11,146) | 1.00 |
| Other - banks | 8.57E-16 | F(11,146) | 1.00 |
| Other - non-banks | 7.92E-16 | F(11,146) | 1.00 |

Table E1: Durbin-Wu-Hausman tests of endogeneity; the table reports the statistics, asymptotic distributions and p-values of the test *by instrument*. Notes: H_0 : no endogeneity (all coefficients in the second-stage regression are 0); H_1 : at least one of the coefficients is not 0.

Weak cross-sectional dependence

The second check we perform aims at assessing whether the covariance-matrix corrections outlined in Section V.A are enough to solve the problem of cross-sectional dependence in residuals. With this purpose, after running the regressions for each instrument, we test for weak cross-sectional dependence, using the approach proposed by Pesaran (2015). We find that this test is particularly indicated in our case, as we have a large panel, with the time dimension (T) greater than the cross-sectional one (N), and the most commonly used tests usually are more suitable in cases where $N > T$. Moreover, weak cross-sectional dependence is implied by strong cross-sectional dependence, while the contrary is not true. This test, therefore, allows us to detect forms of spatial correlation that could be disregarded by other, more traditional, tests. The test results are reported below. As it can be noticed, the null hypothesis of weak spatial dependence can be rejected at 1% for all instruments.

| Instrument | Statistic | P-value |
|----------------------------------|------------------|----------------|
| Total | 16.82 | 0.00 |
| FDI | 68.00 | 0.00 |
| Portfolio | 80.60 | 0.00 |
| <i>Portfolio Debt</i> | 83.55 | 0.00 |
| <i>Portfolio Equity</i> | 7.20 | 0.00 |
| Other | 75.05 | 0.00 |
| <i>Other - private</i> | 26.99 | 0.00 |
| <i>Other - government</i> | 88.41 | 0.00 |
| <i>Other - banks</i> | 35.36 | 0.00 |
| <i>Other - non-banks</i> | 8.65 | 0.00 |

Table E2: Pesaran’s weak cross-sectional dependence test; the table reports the statistics and p-values of the test *by instrument*. Notes: H_0 : regression residuals are weakly cross-sectional dependent; H_1 : regression residuals are not weakly cross-sectional dependent.