Measuring and explaining the volatility of capital flows to emerging countries

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ABSTRACT

This paper analyzes the determinants of the volatility of the various types of capital inflows into emerging countries. After calculating a proxy of the volatility of FDI, portfolio and bank inflows, we use a panel data model to study their relationship with a broad set of explanatory variables. Our results highlight the difficulties policy-makers face in stabilizing capital flows. Thus, we show that since 2000 global factors beyond the control of emerging economies have become increasingly significant relative to country-specific drivers. However, we identify some domestic macroeconomic and financial factors that appear to reduce the volatility of certain capital flows without increasing that of others.

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1. Introduction

Over the last three decades the emerging economies have become more fully integrated in international financial markets as a result of the process of capital account liberalization. This development has prompted empirical literature aimed at identifying the drivers of the international allocation of capital. While most of these contributions study the determinants of the level of capital flows,[1] relatively few of them focus on the sources of volatility of those flows. This might seem surprising, given the positive link between the stability of capital flows and economic growth (Easterly et al., 2000; Ramey and Ramey, 1995). Besides, managing volatile international flows is especially challenging for emerging countries, where inflows are more volatile than in developed ones. This fact makes policies aimed at encouraging stable capital flows particularly important, especially given that inflows into emerging economies are a major source of economic financing. Our paper contributes to this literature by proposing an accurate measure of the volatility of capital flows, identifying the main determinants of total inflows and their three components (foreign direct investment—FDI hereaf-

ter—, portfolio and bank inflows) and suggesting some policy recommendations on the basis of our findings.

The existing empirical literature can be broadly classified into two strands.[2] First, some papers focus on analyzing the difference in volatility between the capital flows to emerging and advanced economies. For instance, the cross-country regressions of Broner and Rigobon (2005) show that the higher volatility in emerging markets is primarily due to these economies' propensity to build up mismatches, which generates more persistent shocks and a higher likelihood of international contagion. In a similar vein, Alfaro et al. (2007) emphasize the importance of domestic factors, such as institutional quality and the soundness of macroeconomic policies, in explaining these volatility differences. This distinct behavior of capital flow volatility in emerging counties can also be characterized by type of investment. For instance, the gap between the volatility of FDI and portfolio flows is found to be smaller in advanced economies (Goldstein and Razin, 2006), whereas in emerging countries the share of FDI in total capital inflows is higher (Albuquerque, 2003), as is the volatility of their portfolio flows (Tesar and Werner, 1995).

Other contributions use instead panel data models to analyze the impact of financial integration on volatility. This is the case of Neumann et al. (2009), who show that financial integration tends to increase the volatility of FDI in emerging economies, while

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[1] These empirical papers often distinguish between country-specific or 'pull' factors and global or 'push' factors. See Calvo et al. (1996).

[2] Previous theoretical contributions focus on the role of incomplete information (Bacchetta and van Wincoop, 1998), financial development (Aghion et al., 2004) and trade liberalization (Martin and Rey, 2006).

reducing that of other debt flows in mature economies. In turn, the IMF's 2007 Global Financial Stability Report concludes that financial openness and institutional quality are associated with more stable inflows both in developed and in emerging economies. Finally, Bekaert and Harvey (1997), Lagoarde-Segot (2009) and Umutlu et al. (2010), focusing on prices rather than volumes, conclude that financial liberalization reduces the volatility of stock market returns in emerging economies.[3]

However, most of these contributions present serious drawbacks rooted in the methodology used to approximate volatility and the lack of disaggregation between types of flows. This paper overcomes both limitations. First, regarding the approximation of volatility, we propose a new measure based on Engle and Gonzalo Rangel (2008), which is the dependent variable of our model specification. We demonstrate that this approximation is more appropriate for characterizing annual volatilities than previous proposals, which were mostly based on the standard deviation of capital flows over a rolling window or the estimated volatilities of a GARCH (1, 1) model. Thus, for instance, our measure generates volatilities with a lower serial correlation than the other proposals, which marks an advantage when characterizing the uncertainty of flows during times of crisis.

Second, in addition to analyzing total flows, we draw a clear distinction between the three different categories of capital flows. The literature on capital flows notes that FDI, portfolio and bank inflows have different drivers. Thus, FDI has a rather long-term nature, tends to be associated with increased domestic investment and growth (Bank for International Settlements (BIS), 2009), and, in general, is less volatile and more persistent than non-FDI inflows.[4] Consequently, FDI is more resilient during financial crises and contributes to the economic stability of the host country; see, for instance, Sarno and Taylor (1999) or Lipsey (2001). By contrast, the volatility of portfolio and bank inflows is considered to be higher, perhaps because of the sensitivity of these investments to domestic conditions in both emerging and developed countries.[5]

This different nature of capital flows across types also holds for their volatility dynamics. This may pose dilemmas for policy-makers seeking to attain a virtuous cycle of stable flows, as volatility dynamics differ depending on the type of flow (Bank for International Settlements (BIS), 2009). Nevertheless, most of the previous contributions do not disentangle these different drivers across components and analyze total inflows (Broner and Rigobon, 2005 and IMF, 2007). Other authors concentrate on one investment type—for instance, (Bekaert and Harvey, 1997; Alfaro et al., 2007; Lagoarde-Segot, 2009 and Umutlu et al., 2010) focus exclusively on equity flows—or, even if they analyze disaggregated flows, leave total flow dynamics unexplored, as Neumann et al. (2009).

Besides resolving the aforementioned methodological limitations, our objective is twofold. First, we seek to identify the determinants of capital flow volatility in emerging countries by fitting a panel data model from 1980 to 2006. We also fit the subsample from 2000 to 2006 to account for possible structural breaks during the most recent wave of capital inflows into emerging markets. In contrast to previous studies, which considered a limited number of potential explanatory variables, we use a broad set of determinants including not only domestic macroeconomic and financial drivers,

but also global factors, which have received little attention in the literature.[6] Second, we attempt to infer policy recommendations from these results. Ideally, these policy options should allow emerging economies to hedge against the risks stemming from volatile capital inflows while maintaining their access to international finance. However, our results indicate that various explanatory variables have a differential and time-varying impact, which implies that few drivers appear to reduce the volatility of capital flows across the board.

Moreover, although the interpretation of the results is not always straightforward, the increasing importance of global factors as volatility determinants over the last decade is a robust result across the three types of flows, especially for FDI (as in Neumann et al., 2009). This outcome poses a challenge for policy-makers in emerging economies as it suggests that the scope for implementing policies that enhance the stability of flows is more limited than it used to be.

On the positive side, we identify a number of domestic macroeconomic and financial factors that are partly under the control of policy-makers and reduce the volatility of specific types of flows without increasing that of others. As regards domestic macroeconomic drivers, in line with Broner and Rigobon (2005) and contrary to IMF (2007), our analysis evidences their importance—especially GDP per capita and the degree of reserve accumulation—in determining the volatility of total flows. Their impact on overall flows is mostly driven by their effects on the volatility of FDI and bank inflows. Some domestic financial variables seem to play an important role in FDI, portfolio and bank inflows, as well as in total flows. Most of these links are stronger in the most recent subsample, particularly in portfolio flows. Although there are some conflicting results across flows, the development of the domestic financial system tends to reduce the volatility of the three categories.

The remainder of this paper is organized as follows. Section 2 introduces our data on capital flows and Section 3 compares previous approximations of capital flow volatility with our proposed measure. Section 4 presents the methodological approach used in this paper and Section 5 describes our set of explanatory variables. Finally, Section 6 summarizes the main results of our empirical analysis and Section 7 concludes.

2. Data on capital flows

Our data set focuses exclusively on *capital inflows*, defined as purchases by non-residents of domestic assets minus their sales of such assets (therefore, figures may be negative). We draw quarterly data on capital inflows from the IMF's International Financial Statistics (IFS) by component (FDI, portfolio flows—which include debt securities and equity—and bank inflows[7]), which will allow us to examine the different nature of these flows. Finally, we also analyze the volatility of total inflows to determine which factors dominate the dynamics of overall volatility, which is particularly relevant in the case of lack of consistency across components.[8]

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[3] Chuang et al. (2009) and Jinjarak et al. (2011) analyze the relationship between stock returns and volumes.

[4] According to Albuquerque (2003), since some emerging countries are financially constrained, they should borrow relatively more through FDI because the default premium is lower than that of non-FDI flows.

[5] Eichengreen (2001) relates this to the vulnerabilities of emerging countries with weak domestic financial systems after capital account liberalization.

[6] Only Neumann et al. (2009) and IMF (2007) include global factors as explanatory variables: the former uses world interest rates and industrial production growth, and the latter employs global liquidity and real interest rate spreads.

[7] IFS defines our bank flow category as "Other investment flows". This is a residual item that mostly consists of cross-border bank lending. Given that these transactions are not included elsewhere in the balance of payments statistics, we use in this paper the term "bank inflows".

[8] One alternative for analyzing volatility across components could be to disentangle the more unstable short-term loans and portfolio flows from the longer-term flows, although this distinction is not feasible with our data set. Nevertheless, as noted by Claessens et al. (1995), long-term flows are often as volatile as short-term ones, so that the property of being more or less volatile is not inherent in the type of flow.

Table 1
Capital flows over GDP by type of flow and region. Summary statistics.

		LA	AS	EU	AF	EMEs	LA	AS	EU	AF	EMEs
		FDI					*Portfolio*				
1980–2006	Mean	0.02	0.02	0.03	0.03	0.02	0.01	0.01	0.01	0.00	0.01
	SD	0.02	0.04	0.03	0.06	0.04	0.03	0.03	0.02	0.02	0.03
1980–1990	Mean	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
	SD	0.01	0.03	0.00	0.01	0.02	0.03	0.01	0.00	0.00	0.02
1991–2000	Mean	0.03	0.03	0.03	0.04	0.03	0.01	0.01	0.01	0.01	0.01
	SD	0.02	0.05	0.03	0.09	0.04	0.04	0.04	0.02	0.02	0.03
2001–2006	Mean	0.03	0.03	0.05	0.05	0.04	0.00	0.01	0.01	0.00	0.01
	SD	0.02	0.05	0.04	0.04	0.04	0.02	0.02	0.03	0.01	0.02
		Bank inflows					*Total*				
1980–2006	Mean	0.02	0.02	0.02	0.02	0.02	0.01	0.05	0.06	0.03	0.05
	SD	0.75	0.08	0.05	0.04	0.43	0.17	0.10	0.07	0.04	0.12
1980–1990	Mean	−0.03	0.03	0.00	0.03	0.01	−0.01	0.05	0.00	0.03	0.02
	SD	0.25	0.04	0.05	0.04	0.16	0.24	0.06	0.05	0.05	0.16
1991–2000	Mean	0.07	0.01	0.02	0.01	0.03	0.03	0.05	0.06	0.03	0.07
	SD	0.60	0.11	0.05	0.03	0.33	0.09	0.12	0.06	0.04	0.09
2001–2006	Mean	0.04	0.01	0.04	−0.01	0.03	0.04	0.05	0.11	0.03	0.07
	SD	1.46	0.07	0.05	0.02	0.77	0.07	0.12	0.07	0.03	0.09

Notes: SD: standard deviation; LA: Latin America; AS: Emerging Asia; EU: Emerging Europe; AF: Africa; EMEs: Aggregate of the four regions. Types of capital flows: FDI (foreign direct investment); Portfolio (portfolio flows); Bank inflows ("Other investment flows", according to IFS classification); Total (sum of the three types of flows). We calculate the descriptive statistics using the annual aggregate from IFS quarterly data of capital flows over GDP. See Appendix A for the complete country sample.

We obtain quarterly capital flows as a proportion of GDP for 48 emerging and less developed economies (see Appendix A for the complete country list and some summary statistics at country level).[9] The sample is limited to countries with information for the three types of capital flows for at least 10 years. We also include other emerging countries that do not meet these standards but which we consider relevant economies for the study, such as Singapore and South Africa, and four additional African countries to obtain a more geographically balanced panel. The sample period runs from 1980 to 2006 as prior information is scarce.

Table 1 reports some summary statistics by type of flow and region. Total capital flows as a proportion of GDP dried up during the 1980s debt crisis, and sharply recovered in the 1990s and thereafter, coinciding with the liberalization of the capital account in an increasing number of emerging countries. The developments in inflows in our sample differ depending on the type of investment. First, FDI represents around half of the total flows throughout the whole period. Regarding volatility, in line with Sarno and Taylor (1999) and with Lipsey (2001), the standard deviation of FDI and portfolio inflows is significantly lower than that of bank inflows. This points to the stability and resilience of FDI flows even during financial crises. Nevertheless, in line with Goldstein and Razin (2006), from 1990 onwards FDI is more volatile than portfolio flows. In fact, as shown in Fig. 1, which shows the share of each type of flow and region in total annual flows, the proportion of FDI in total capital inflows tends to increase during turbulent phases, as other sources of finance dry up. Portfolio flows become an important source of finance from the 1990s, coinciding with the opening-up of the capital accounts of most emerging countries. However, these flows quickly turn negative or insignificant in periods of financial turbulence such as the 1980s or the more recent crises. Finally, the largest swings correspond to bank inflows, which registered negative values during the second half of the 1980s, as a result of the debt crisis, and at the turn of the century during the wave of emerging market crises.[10] By region, Fig. 1 also shows that these swings affected especially Latin America and emerging Europe during the 1980s, and Latin America and emerging Asia during the late 1990s and early 2000s.

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[9] Capital inflows data released by IFS for China are only available on a half-yearly basis.
[10] See Smith and Valderrama (2009) for a recent theoretical contribution on the composition of capital flows to emerging markets.

3. How can we measure capital flow volatility?

Approximating capital flow volatility is not straightforward. Neumann et al. (2009) and IMF (2007) make use of the standard deviation of capital flows over a rolling window of annual data. This approximation of the volatility of capital inflows for country i in year t, σ_{it}, is given by this expression

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

where $\mu = \frac{1}{n} \sum_{k=t-(n-1)}^{t} flow_{ik}$, and $flow_{ik}$ denotes capital inflows in country i and period k. This measure is subject to at least three drawbacks. First, it entails a loss of observations at the beginning of the sample, which depends on the window's length. Second, σ_{it} is strongly persistent as it leans on previous periods, generating problems of endogeneity and serial correlation that may result in non-robust estimates. Finally, σ_{it} assigns the same weight to $flow_{it-1}$ and $flow_{it-(n-1)}$, which tends to overly smooth the volatility processes. As a result, volatility tends to be underestimated when a shock takes place, and overestimated thereafter.

A second alternative, in line with Bekaert and Harvey (1997) and Lagoarde-Segot (2009), is to use the estimated volatilities of a GARCH (1, 1) model (see Bollerslev, 1986). If we denote $y_t = \Delta flow_{it}$, the GARCH (1, 1) process is defined as

$$y_t = y_t^\dagger \sigma_t$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 y_{t-1}^2 + \alpha_2 \sigma_{t-1}^2, \quad (2)$$

where $y_t^\dagger$ is a Gaussian white noise process and σ_t^2 is the corresponding conditional variance, and parameters α_0, α_1 and α_2 satisfy the usual conditions to guarantee the positivity and stationarity of σ_t^2. In our context this second alternative also entails serious caveats, as the GARCH estimation procedure leads to convergence errors resulting from data scarcity, especially at the beginning of the sample and for portfolio flows. Besides, ML estimates for small samples contain considerable biases.

To overcome the drawbacks of these two methods, we propose a volatility measure based on Engle and Gonzalo Rangel (2008). To account for the uncertainty of macroeconomic variables, whose frequency is lower than that of financial variables, these authors model each variable and then obtain their measure of volatility from the residuals. Analogously, we first fit a suitable ARIMA
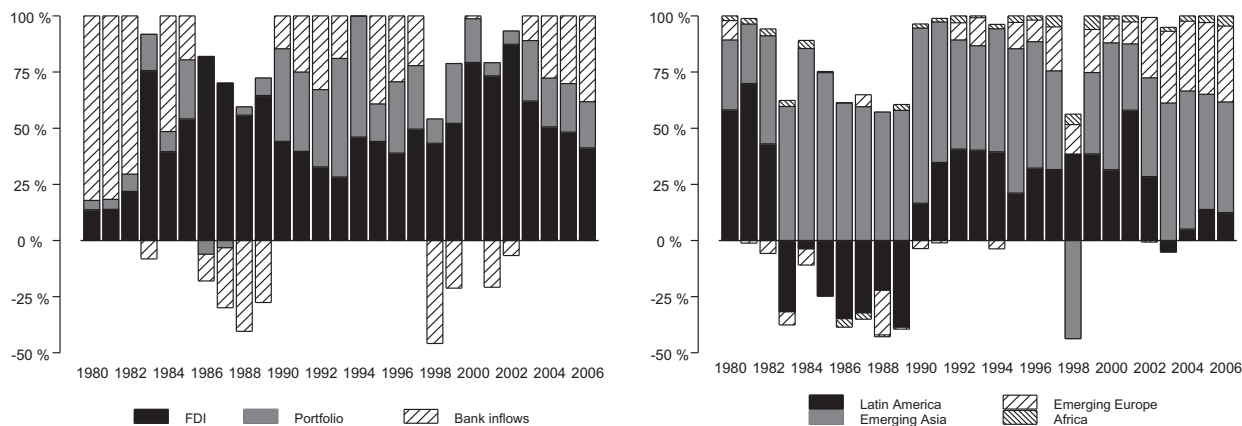
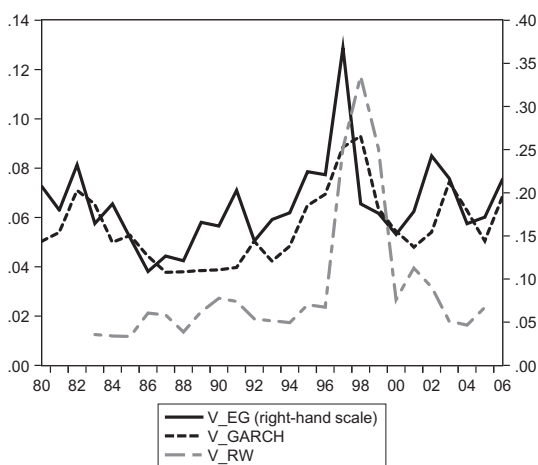Fig. 1. Breakdown of annual capital flows by type and region.

Fig. 2. Thailand: Volatility of banking inflows over GDP. Comparison of volatility measures based on Engle and Gonzalo Rangel (2008) (V_EG), on a quarterly GARCH (1, 1) model (V_GARCH) and on a rolling window (V_RW).

Table 2

Volatility of capital flows measured by three procedures (method based on Engle and Gonzalo Rangel (2008), annual rolling window and estimation of a GARCH (1, 1) model). Summary statistics.

	V_EG	V_RW	V_GARCH	V_EG	V_RW	V_GARCH
	FDI			*Portfolio*		
Mean	0.12	0.01	0.01	0.10	0.01	0.04
SD	0.25	0.01	0.01	0.08	0.02	0.05
SK	0.65	0.85	1.14	0.25	0.78	1.17
κ	3.03	2.92	3.93	2.45	2.74	3.79
$\rho(1)$	0.36	0.59	0.60	0.37	0.61	0.33
Minimum	0.00	0.00	0.00	0.00	0.00	0.00
Maximumn	2.80	0.14	0.06	0.47	0.17	0.47
	Bank inflows			*Total*		
Mean	0.22	0.05	0.06	0.26	0.03	0.05
SD	0.43	0.26	0.23	0.46	0.05	0.07
SK	0.55	0.69	1.19	0.58	0.79	1.40
κ	3.14	2.98	4.14	3.01	2.86	5.14
$\rho(1)$	0.27	0.55	0.45	0.26	0.52	0.39
Minimum	0.00	0.00	0.00	0.01	0.00	0.00
Maximumn	4.13	5.85	3.18	4.21	1.19	0.72

Notes: V_EG: Volatility measure based on Engle and Gonzalo Rangel (2008); V_RW: Volatility measure based on an annual rolling window; V_GARCH: Annual mean of the volatilities estimated by a quarterly GARCH (1, 1) model; SD: Standard Deviation; SK: Skewness; κ: Kurtosis; $\rho(1)$: Autocorrelation of order 1. SK, κ and $\rho(1)$ calculated as country average. We calculate GARCH volatilities only for those quarterly series where the GARCH (1, 1) model converges (see Footnote 12). Types of capital flows: FDI (foreign direct investment); Portfolio (portfolio flows); Bank inflows ("Other investment flows", according to IFS); Total (sum of the three types of flows). See Appendix A for the complete country sample.

model for every country i and type of capital flow on a quarterly basis.[11] We then approximate the annual variance of capital flows as the yearly average of the absolute value of quarterly residuals, v_{itj}, that is

$$\sigma_{it}^2 = \frac{1}{4}\sum_{j=1}^{4}|v_{itj}| \tag{3}$$

where $j = 1, \ldots, 4$ denotes each quarter of year t.

As an illustration, Fig. 2 compares the performance of the three alternative measures of volatility for bank inflows in Thailand. We chose this example for two reasons. For one thing, Thailand underwent a financial crisis in 1997 and, therefore, illustrates the dynamics of the three alternative measures during financial distress. For another, the convergence of the GARCH (1, 1) model allows for the availability of the three volatility approximations. This Figure shows that our proposed measure identifies crisis periods more precisely and the changes in it seem to be less smooth—that is, its autocorrelation could be lower—than the other two alternatives.

As a more formal comparison for the full panel data set, Table 2 reports some summary statistics of the three volatility measures.[12] Apart from the loss of data at the beginning of the sample, the approximation based on a rolling window masks the effects of the largest outliers, as shown by its lower kurtosis, except for portfolio. This means that in times of crisis our measure identifies volatile periods better. This drawback would not apply to the GARCH (1, 1) measure, as it generates the biggest kurtosis among the three approximations. The autocorrelations of order 1, $\rho(1)$, illustrate that in general the standard deviation over a rolling window and the GARCH (1, 1) measure generate a stronger correlation structure.

Table 3 presents summary statistics of the volatility of FDI, portfolio and bank inflows using our chosen volatility measure. In line with the summary statistics of Table 1, the mean volatility suggests that bank inflows display the highest volatility throughout the complete sample. However, volatility increases over time for all types of investments, with both FDI and portfolio flows showing larger increases than bank inflows since the early 90s. By region, emerging Asia displays the highest volatility for total flows from

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[11] We model each series by the automatic TSW procedure of Caporello and Maravall (2004).

[12] Table 2 only reports the summary statistics of those volatilities estimated from GARCH (1, 1) models with no convergence problems. We report them only for illustrative reasons, as they are not directly comparable. Thus, we only consider those volatilities estimated from models where $\hat{\alpha}_0, \hat{\alpha}_1$ and $\hat{\alpha}_2$ are greater than zero and $\hat{\alpha}_1 + \hat{\alpha}_2 < 1$. Of the 48 countries in our sample, these conditions are fulfilled only in 12 and 8 countries for FDI and portfolio flows, respectively, and in 16 countries for bank and total inflows. We estimate volatilities on a quarterly basis and transform them into annual figures using the yearly average of quarterly estimates of σ_{it}. GARCH (1, 1) estimates are available upon request.

Table 3
Mean volatility of FDI, portfolio, bank inflows and total inflows over GDP calculated using the measure based on Engle and Gonzalo Rangel (2008) by type of flow and region.

	LA	AS	EU	AF	EMEs	LA	AS	EU	AF	EMEs
	FDI					*Portfolio*				
1980–2006	0.07	0.16	0.12	0.06	0.12	0.08	0.11	0.13	0.08	0.10
1980–1990	0.05	0.04	0.04	0.04	0.04	0.03	0.06	0.09	0.06	0.05
1991–2000	0.07	0.19	0.11	0.05	0.13	0.09	0.11	0.13	0.07	0.11
2001–2006	0.09	0.23	0.14	0.07	0.15	0.09	0.14	0.14	0.10	0.12
	Bank inflows					*Total*				
1980–2006	0.19	0.31	0.22	0.07	0.22	0.21	0.36	0.23	0.09	0.26
1980–1990	0.14	0.21	0.13	0.07	0.16	0.14	0.23	0.13	0.08	0.18
1991–2000	0.20	0.33	0.23	0.07	0.24	0.22	0.40	0.25	0.10	0.27
2001–2006	0.20	0.42	0.21	0.07	0.26	0.24	0.47	0.21	0.10	0.29

Notes: LA: Latin America; AS: Emerging Asia; EU: Emerging Europe; AF: Africa; EMEs: Aggregate of the four regions. Types of capital flows: FDI (foreign direct investment); Portfolio (portfolio flows); Bank inflows ("Other investment flows", according to IFS classification); Total (sum of the three types of flows). See Appendix A for the complete country sample.

1980 to 2006, followed by emerging Europe, Latin America and Africa. FDI volatility increases over time in all regions, whereas portfolio uncertainty also grows over time in all regions but Latin America, where this flow stabilizes at the end of the sample. In turn, the volatility of bank inflows increases globally during the nineties and becomes more stable from the beginning of the century in all regions but emerging Asia, where it increases further. This last region shows the sharpest rise in volatility of total flows during the last decade.

4. Methodology

4.1. The model

Our approach is similar to Neumann et al. (2009) or IMF (2007) in that once we obtain the dynamic volatility measure for all countries and types of capital flows, we construct a panel data set to analyze which factors explain the observed volatility patterns. The estimated equation is

$$\sigma_{it} = x'_{it-1}\beta + \varepsilon_{it}, \quad \forall i = 1, \ldots, N, \quad t = 1, \ldots, T, \quad (4)$$

where x_{it-1} is a $(J+1) \times 1$ vector of independent variables and β is a $(J+1) \times 1$ vector of unknown coefficients, $\beta = (\beta_0, \ldots, \beta_J)'$. The estimation includes country fixed effects,

$$\varepsilon_{it} = \eta_i + \omega_{it} \quad (5)$$

where η_i is a country fixed effect and ω_{it} is an error term that can be serially and spatially correlated. The matrix $x_i = (x'_{i1}, \ldots, x'_{iT})'$ contains the volatility determinants. We include lagged explanatory variables in all estimations to minimize problems of endogeneity and meet the estimator requirement of exogeneity.

Most previous dynamic studies on the sources of volatility try to overcome the problems posed by the existence of serially correlated errors. As with the rolling window approach, our procedure for approximating volatility may give rise to residuals with a moving average component, that is $cov(\omega_{it}, \omega_{it-k}) \neq 0$ for some $k \neq 0$. That is why a correction of the standard errors is required. Also, due to contagion effects, the residuals could suffer from spatial (cross-sectional) correlation, $cov(\omega_{it}, \omega_{jt}) \neq 0$ for some $j \neq k$, which would again bias the estimated standard errors.[13] To cope with both drawbacks we use the Driscoll and Kraay (1998) correction for the covariance matrix estimator, which handles not only the usual serial correlation and heteroskedasticity problems, but also spatially correlated errors.[14]

4.2. Tests for the time-invariant and flow-specific impact of the volatility determinants

Apart from fitting model (4) by type of determinant, we also propose some tests to analyze the extent to which the three different types of factors have a time-variant and flow-specific impact on volatility. Section 6 interprets the most relevant statistics.[15]

On the one hand, to formally test whether certain volatility drivers have a different impact in the last years of the sample, we perform a set of hypothesis tests for all types of capital flows and explanatory variables categories. Specifically, we define a dummy variable, δ_t, which takes a value of 1 from 2000 onwards, that is, $\delta_t = I(t \geqslant 2000)$, where I is the indicator function.[16] If we denote $\beta^* = (\beta_0^*, \ldots, \beta_J^*)$ as the shift coefficients, we can test for the null hypothesis of structural break in 2000 by estimating the equation

$$\sigma_{it} = x'_{it-1}\beta^1 + (\delta_t x_{it-1})'\beta^* + \varepsilon_{it}, \quad \forall i = 1, \ldots, N, \quad t = 1, \ldots, T, \quad (6)$$

where $\forall j = 1, \ldots, J$, β_j^1 are the coefficients for the subsample from 1980 to 1999, and β_j^* are the shift coefficients, in such a way that $\beta_j^2 = \beta_j^1 + \beta_j^*$ denote the parameters of the second subsample. If the break in volatility determinants does not exist and the overall regressors are structurally stable over the sample period, that is, $\beta_j^* = 0$ for all the explanatory variables, expression (6) simplifies to (4). The null hypothesis of no structural break, $H_0: \beta^* = 0$, can be tested by a Wald-type F test of this restriction.[17]

On the other hand, we also perform a battery of tests to analyze whether the three categories of explanatory factors—global, macroeconomic or financial—have different effects on each type of flow. First, we compare the three types of flows pairwise. Then, we run the same regressions as in (4) but considering the difference in estimated volatilities as the dependent variable, that is

$$\sigma_{it}^j - \sigma_{it}^k = x'_{it-1}\alpha + v_{it}, \quad \forall i = 1, \ldots, N, \quad t = 1, \ldots, T, \quad j \neq k \quad (7)$$

where the super-index j and k in the volatility σ_{it} denotes the type of flow—FDI, portfolio or bank inflows—, so that a test for the null of $H_0: \alpha = 0$ is equivalent to a test for $H_0: \beta^j = \beta^k$. We also estimate a system of simultaneous equations, namely a SURE model, and perform Wald-type tests to jointly compare the coefficients of the three types of flows.[18]

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[13] We use a cross-section dependence test based on the errors obtained from standard fixed effects estimation. The results show that the errors are indeed spatially correlated so a correction is needed.

[14] We estimate the model using the Stata module `xtscc` (Hoechle, 2007). The estimator can identify the order of serial correlation.

[15] The full battery of stability tests and tests for the null hypothesis that the three categories of explanatory factors have a different effect on each type of flow is available upon request.

[16] To simplify the analysis, the breakpoint date is considered as exogenous.

[17] Joint test statistics for each category of explanatory variables and each type of flow, as well as statistics for the individual hypothesis of $H_0 : \beta_j^* = 0$ are available upon request.

[18] Estimation of SURE models does not allow for the standard error correction performed in the rest of the analysis, meaning that these last results should be interpreted with caution.

5. Volatility determinants

We use a large set of explanatory factors, which can be grouped in three categories: global, domestic macroeconomic and domestic financial variables.[19] See Appendix B for a summary of variables and sources.

We use five global factors: the rate of growth of world GDP, a measure of global liquidity and three variables that depict conditions in the US economy (inflation, the 3-month T-bill rate and the value of the Standard & Poor's 500 stock exchange index).[20] The relevant literature has identified most of these variables as 'push' determinants of the levels of capital flows in one or the other direction. However, their relationship with capital flow volatility is ambiguous. As global factors alter investors' risk aversion, they can affect capital flow volatility. For instance, a decrease in world GDP growth and global liquidity or a rise in the US T-bills rate is likely to spark a flight to quality.

The domestic macroeconomic variables considered are: per capita GDP and its rate of growth to capture both the level of economic development and the dynamism of our sample countries; inflation, to approximate the "quality" of macroeconomic policies; the stock of foreign exchange reserves in months of imports as a measure of vulnerability to balance of payment crises; and trade openness to assess their level of integration in global goods markets.

A priori, less developed countries are likely to display lower levels of volatility, as they rely primarily on official flows. However, this could also be expected from more stable advanced economies.[21] Consequently, we expect a non-linear relationship between economic development and capital flow volatility. In turn, we think that capital flows are more volatile in countries with higher inflation rates, as a result of erratic and distortionary monetary conditions. Following Martin and Rey (2006), we guess that trade openness correlates negatively with volatility. However, countries more reliant on international trade may be more vulnerable to changes in global conditions, especially if their export base is narrow, as in many of the commodity exporters in our sample. Hence, trade openness may be associated with higher volatility. The stock of foreign exchange reserves can affect the volatility of flows through various channels. On one hand, low reserves may lead to liquidity crises and, therefore, higher volatility. On the other, larger stocks of foreign exchange reserves may reflect precisely countries' need to self-insure. Consequently, countries with larger reserves may display higher volatility.

Finally, the greater availability of financial data allows us to include six variables related to our sample countries' financial systems. A first set of factors focuses on domestic banking systems: ratios of commercial banks' assets, private credit and financial system deposits relative to GDP, and interest rate spreads (the gap between the interest rates on deposits and loans). While higher asset, credit and deposit ratios should reflect more developed domestic banking systems, high levels of domestic credit could also signal

episodes of economic overheating and lead to an increase in volatility. In turn, lower interest rate spreads should reflect more competitive systems, but this higher competition could imply lower volatility, as a result of a deeper banking system, or higher volatility, as more competition could lead to more capital intermediated through banks. A second set of drivers focuses on equity markets: the ratio of stock market capitalization to GDP, and the stock market turnover ratio. A higher value for both variables should indicate more developed and liquid equity markets. Aghion et al. (2004) point to a non-linear relationship between the development of financial systems and capital flow volatility. According to them, only the economies at an intermediate stage of financial development display higher volatility.

6. Results and discussion

We describe here the main results by type of driver (global, domestic macroeconomic and domestic financial). Tables 4–6 report the estimates for the volatility of FDI, portfolio and bank inflows. We complete our study with an analysis of the determinants of volatility of total inflows, which is probably the most relevant variable for policy-makers (see Table 7).

6.1. Global factors

Global drivers seem to have gained weight in shaping the volatility of the three types of flows over recent years. Indeed, the stability tests based on (6) clearly reject the null hypothesis of no structural break after 2000 for the three types of flows, as well as for overall flows.[22] Moreover, once we fit Eq. (7), the joint tests for the null hypothesis that the effects of global drivers are equal across the three types of capital flows cannot be rejected.[23] That is, this higher relevance of global factors since 2000 is homogeneous across components, and even the volatility of the a priori more stable flow, FDI, reacts to these drivers in much the same way as that of portfolio or bank inflows does.

The increasing role of global variables from 2000 to 2006 is precisely one of the main characteristics of FDI volatility (see Table 4). The regressions show that global factors appear to have a limited role in determining FDI volatility for the full sample, whereas from 2000 to 2006 the significance of these variables increases. In this period higher US interest rates are associated with lower FDI volatility and US inflation is positively linked to FDI volatility, whereas volatility is negatively related to world GDP growth and global liquidity. Global factors also exhibit some correlation with the volatility of portfolio flows, especially US interest rates and the S&P index, see Table 5, and with the volatility of bank flows, especially the S&P index and US inflation, see Table 6. In general, the sign of the coefficients is consistent across flow types. However, there are contradictory effects in a few cases. For instance, US inflation is negatively linked to FDI volatility, but it has a positive relation with the volatility of bank inflows.

As shown in Table 7, the S&P index and US inflation are the global variables that seem more closely related to the volatility of total flows. Note that US inflation is negatively linked to the volatility of total flows, since the effect of the volatility of bank inflows predominates in the aggregate. This means that lower US inflation is associated with stronger bank inflows. Finally, contrary to IMF (2007), which finds a negative relation between the volatility of overall inflows and global liquidity, our estimates do not identify a robust relation between these two variables across regressions.

All in all, these results signal additional difficulties for policy-makers, since the effect of global drivers might limit the stabilizing

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[19] We also regress our volatility measure on a set of geopolitical and institutional factors that might be of relevance in explaining the behavior of international capital flows. Nevertheless, the small sample size of this data set (around 150 observations for 28 countries) prevents a comparable joint estimation with the remaining explanatory factors, so we use these variables in an alternative specification. The results are available upon request and show that institutional factors, such as economic and political stability (source: Freedom House) or quality of governance (source: International Country Risk Guide), have some explanatory power for the full sample, but not from 2000. However, given the relative time-invariant character of our indicators, we are confident that we already capture such variation with our country dummies. Neumann et al. (2009) also use this last finding as an argument for not including institutional quality variables in their analysis.

[20] We approximate global liquidity with an index representing developments in a GDP-weighted sum of M2 measures for more than 50 countries. See Erce (2008) for details.

[21] More dynamic countries might attract more stable capital flows. It may also be that volatile capital flows are a hindrance to growth, which means that we cannot rule out the possibility that causality is running in the opposite direction (see Ferreira and Laux, 2009).

[22] The F-test statistics obtained from (6) for the null hypothesis of no structural break in the global driver coefficients after 2000 are 36.3, 14.9, 7.4 and 8.0 for FDI, portfolio and bank inflows and total flows, respectively.

[23] The p-value associated with the joint Wald-type test is 0.072.

Table 4
Volatility of FDI flows over GDP. Regression results for the full sample and for 2000–2006.

	Global		Macro		Financial		Global-macro		Macro-financial		Global-domestic	
	1980–2006	2000–2006	1980–2006	2000–2006	1980–2006	2000–2006	1980–2006	2000–2006	1980–2006	2000–2006	1980–2006	2000–2006
US 3 month T-Bill$_{t-1}$	−0.0021	−0.0030					0.0003	−0.0081			−0.0016	−0.0099
	[1.19]	[2.84]***					[0.14]	[6.40]***			[0.99]	[3.53]**
S&P$_{t-1}$	−1.22E−05	4.45E−07					−7.30E−06	7.61E−07			1.09E−05	2.72E−05
	[1.79]*	[0.34]					[0.78]	[0.31]			[1.71]*	[9.45]**
US inflation$_{t-1}$	0.0025	0.006					−0.0026	0.0064			−0.0012	0.0047
	[1.07]	[5.93]***					[1.27]	[4.83]***			[0.50]	[1.55]
World GDP growth$_{t-1}$	0.0012	−0.008					−0.0032	−0.0089			−0.0070	−0.0115
	[0.26]	[8.51]***					[1.34]	[7.05]***			[2.63]**	[5.17]**
Global liquidity$_{t-1}$	0.0006	−0.0003					0.0006	−0.0013			0.0002	−0.0014
	[2.90]***	[1.62]					[2.97]***	[6.22]***			[0.73]	[3.52]**
GDP pc$_{t-1}$			2.99E−05	5.19E−05			1.67E−05	3.95E−05	1.51E−05	3.64E−05	1.62E−05	2.82E−05
			[3.87]***	[12.86]***			[3.02]***	[6.16]***	[2.02]*	[16.80]***	[5.79]***	[4.56]**
(GDP pc)$^2_{t-1}$			−1.42E−09	−1.67E−09			−7.37E−10	−1.37E−09	−5.07E−10	−9.63E−10	−4.72E−10	−7.46E−10
			[3.45]***	[3.70]***			[3.80]***	[8.07]***	[1.36]	[5.92]***	[3.29]***	[4.67]**
GDP pc growth$_{t-1}$			0.0002	0.0002			0.00072	0.0004	0.00013	0.0002	0.00097	0.001
			[0.62]	[0.43]			[1.90]*	[1.03]	[0.26]	[0.46]	[3.11]***	[2.18]*
Inflation$_{t-1}$			−1.37E−07	2.30E−06			6.69E−06	6.72E−06	−8.39E−06	1.88E−05	2.03E−06	2.46E−05
			[0.10]	[0.23]			[5.10]***	[0.68]	[1.10]	[1.61]	[1.21]	[2.79]**
Openness$_{t-1}$			0.0004	0.0010			0.00019	0.0009	0.00012	5.01E−05	0.00022	0.0009
			[2.61]**	[2.59]**			[1.07]	[2.60]**	[0.77]	[0.21]	[0.92]	[2.32]*
Reserves$_{t-1}$			0.0005	−0.0014			−0.00335	−0.0027	−0.00398	−0.0068	−0.00297	−0.0068
			[0.55]	[1.07]			[2.25]**	[2.74]***	[3.49]***	[4.31]***	[1.67]	[4.04]**
Bank assets$_{t-1}$					−0.106	−0.1275			−0.0391	−0.0690	−0.0672	−0.0626
					[2.88]***	[6.15]***			[1.47]	[1.40]	[2.51]**	[3.93]**
Bank credit$_{t-1}$					0.1478	0.1418			0.0805	0.0888	0.142	0.148
					[5.32]***	[7.48]***			[3.43]***	[2.35]**	[7.54]***	[14.76]***
Bank deposits$_{t-1}$					−0.0057	−0.0526			−0.0199	0.0280	−0.0770	−0.130
					[0.29]	[3.90]***			[0.92]	[1.40]	[2.19]**	[5.19]**
Interest rate spread$_{t-1}$					4.50E−05	−0.0003			6.19E−05	−0.0004	4.20E−05	0.0002
					[13.07]***	[2.81]***			[2.64]**	[4.01]***	[5.71]***	[1.74]
Capitalization$_{t-1}$					0.0559	0.0119			0.0460	0.0092		
					[3.43]***	[0.88]			[1.76]*	[0.63]		
(Capitalization)$^2_{t-1}$					−0.0115	−0.0121			−0.0108	−0.0048		
					[1.92]*	[2.37]**			[1.30]	[0.77]		
Constant	0.0748	0.213	0.0172	−0.0393	0.0926	0.1649	0.0246	0.256	0.0643	0.0332	0.105	0.317
	[2.23]**	[7.23]***	[1.32]	[1.55]	[11.54]***	[16.07]***	[1.03]	[5.84]***	[4.60]***	[1.83]*	[4.71]***	[4.68]**
Observations	549	308	557	247	333	212	472	286	324	208	353	232
Number of groups	47	47	44	42	33	33	45	45	33	33	38	38

Dependent variable: Volatility of capital inflows measured by the proposed procedure based on Engle and Gonzalo Rangel (2008). See Appendix B for a complete description of explanatory variables and data sources. Coefficients of "Turnover" not reported due to its lack of significance but included. Fixed country effects not reported but included. See Appendix A for the complete country sample. Standard errors have been corrected for serial correlation and heteroskedasticity using the Driscoll and Kraay (1998) procedure. *t*-statistics in square brackets.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

C. Broto et al./Journal of Banking & Finance 35 (2011) 1941–1953

Table 5
Volatility of portfolio flows over GDP. Regression results for the full sample and for 2000–2006.

	Global		Macro		Financial		Global-macro		Macro-financial		Global-domestic	
	1980–2006	2000–2006	1980–2006	2000–2006	1980–2006	2000–2006	1980–2006	2000–2006	1980–2006	2000–2006	1980–2006	2000–2006
US 3 month T-Bill$_{t-1}$	−0.0053	−0.0066					−0.0044	−0.0069			−0.0031	−0.0035
	[4.29]***	[2.92]***					[3.35]***	[2.33]**			[1.99]*	[1.22]
S&P$_{t-1}$	−2.70E−06	1.03E−05					2.25E−06	1.71E−05			1.35E−05	3.11E−05
	[0.34]	[3.07]***					[0.33]	[5.34]***			[2.43]**	[7.49]***
US inflation$_{t-1}$	0.0014	0.0051					0.0050	0.0040			−0.0010	0.0011
	[1.47]	[1.93]*					[3.59]*	[1.12]			[0.61]	[0.55]
World GDP growth$_{t-1}$	0.0033	−0.0008					0.0005	−0.0011			−0.0003	−0.0025
	[1.56]	[0.26]					[0.16]	[0.28]			[0.12]	[0.68]
Global liquidity$_{t-1}$	0.0002	−0.0004					2.31E−05	−0.0004			0.0002	0.0004
	[0.97]	[1.05]					[0.14]	[0.74]			[1.92]*	[1.36]
GDP pc$_{t-1}$			−2.74E−06	8.69E−06			5.68E−06	−3.43E−06	2.15E−06	1.64E−06	−2.27E−06	−2.11E−05
			[0.37]	[0.69]			[0.85]	[1.14]	[0.29]	[0.35]	[0.39]	[4.12]***
(GDP pc)$^2_{t-1}$			1.02E−09	1.07E−10			−1.48E−10	−1.05E−10	−2.15E−10	−1.84E−10	5.37E−11	5.29E−10
			[1.81]*	[0.11]			[0.82]	[0.81]	[0.56]	[0.57]	[0.16]	[2.39]**
GDP pc growth$_{t-1}$			−0.0004	−0.0010			−0.0006	−3.04E−06	0.0001	−0.0002	2.50E−05	0.0003
			[0.94]	[3.57]***			[3.18]***	[0.01]	[0.37]	[0.85]	[0.09]	[1.02]
Inflation$_{t-1}$			1.52E−05	−1.37E−05			9.39E−06	1.25E−05	−1.05E−05	−1.86E−05	9.69E−06	3.61E−06
			[4.10]***	[0.77]			[7.59]***	[0.83]	[2.48]**	[1.40]	[1.06]	[0.24]
Openness$_{t-1}$			0.0004	−0.0002			−0.0002	7.55E−05	−6.21E−05	0.0002	−0.0004	−0.0001
			[1.59]	[1.46]			[0.92]	[0.44]	[0.27]	[1.04]	[2.04]**	[0.70]
Reserves$_{t-1}$			0.0045	−0.0007			0.0015	−0.0019	−0.0005	−0.0009	0.0001	−0.0004
			[2.40]**	[0.46]			[1.13]	[0.92]	[0.30]	[0.24]	[0.07]	[0.11]
Bank assets$_{t-1}$					0.1279	0.1651			0.0445	0.102	−0.0221	−0.0019
					[1.29]	[2.76]***			[0.46]	[1.25]	[0.41]	[0.04]
Bank credit$_{t-1}$					−0.1519	−0.1926			−0.124	−0.146	−0.0252	−0.0266
					[2.01]*	[4.33]***			[2.04]*	[2.37]**	[0.78]	[0.68]
Bank deposits$_{t-1}$					0.0471	−0.1185			0.151	−0.0298	0.0187	−0.111
					[1.62]	[5.75]***			[2.83]***	[1.38]	[0.61]	[6.50]***
Interest rate spread$_{t-1}$					−5.20E−06	−1.27E−05			2.81E−05	7.13E−05	−3.25E−05	0.0006
					[0.86]	[0.06]			[1.86]*	[0.34]	[0.90]	[2.76]***
Capitalization$_{t-1}$					0.0966	−0.0421			0.0653	−0.0570	−0.0149	−0.0600
					[3.51]***	[8.25]***			[2.12]**	[10.49]***	[0.89]	[10.70]***
(Capitalization)$^2_{t-1}$					−0.0305	0.0025			−0.0180	0.0095	0.0007	0.0095
					[4.59]***	[1.07]			[2.14]**	[1.90]*	[0.13]	[1.72]*
Constant	0.114	0.201	0.0498	0.1121	0.077	0.2031	0.114	0.203	0.0741	0.159	0.150	0.194
	[5.41]***	[2.81]***	[2.18]**	[5.37]***	[5.08]***	[22.22]***	[4.55]***	[2.75]***	[3.43]***	[8.23]***	[8.51]***	[3.94]***
Observations	439	254	471	216	316	199	400	247	306	195	267	195
Number of groups	38	38	37	36	31	31	38	38	31	31	31	31

Dependent variable: Volatility of capital inflows measured by the proposed procedure based on Engle and Gonzalo Rangel (2008). See Appendix B for a complete description of explanatory variables and data sources. Coefficients of "Turnover" not reported due to its lack of significance but included. Fixed country effects not reported but included. See Appendix A for the complete country sample. Standard errors have been corrected for serial correlation and heteroskedasticity using the Driscoll and Kraay (1998) procedure. *t*-statistics in square brackets.

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 6
Volatility of bank inflows over GDP. Regression results for the full sample and for 2000–2006.

	Global		Macro		Financial		Global-macro		Macro-financial		Global-domestic	
	1980–2006	2000–2006	1980–2006	2000–2006	1980–2006	2000–2006	1980–2006	2000–2006	1980–2006	2000–2006	1980–2006	2000–2006
US 3 month T-Bill$_{t-1}$	0.0132 [3.63]***	−0.0020 [0.33]					0.00387 [1.16]	−0.0028 [0.42]			0.0019 [0.41]	−0.0042 [0.39]
S&P$_{t-1}$	2.84E−05 [1.33]	7.14E−05 [6.67]***					3.85E−05 [2.07]**	7.71E−05 [7.01]***			5.34E−05 [2.42]**	8.86E−05 [3.03]***
US inflation$_{t-1}$	−0.0172 [3.46]***	−0.026 [2.84]***					−0.0162 [4.32]***	−0.0229 [3.16]***			−0.0238 [5.78]***	−0.0296 [2.67]**
World GDP growth$_{t-1}$	0.0005 [0.09]	0.0093 [0.84]					0.0016 [0.28]	0.0059 [0.56]			−0.0004 [0.05]	0.0070 [0.40]
Global liquidity$_{t-1}$	−0.0005 [0.94]	−0.0013 [0.91]					−0.0011 [2.29]**	−0.0015 [0.88]			−0.0019 [3.76]***	−0.0020 [1.01]
GDP pc$_{t-1}$			−0.0001 [3.25]***	−8.77E−06 [0.18]			−7.23E−06 [1.18]	3.46E−06 [0.22]	−1.20E−05 [2.37]**	4.54E−06 [0.76]	−1.11E−05 [0.96]	−3.79E−06 [0.09]
(GDP pc)$^2_{t-1}$			1.26E−08 [3.54]***	2.53E−09 [0.37]			1.03E−09 [4.39]***	8.03E−10 [2.46]**	1.07E−09 [4.08]***	7.06E−10 [1.79]*	1.15E−09 [3.58]***	9.01E−10 [0.88]
GDP pc growth$_{t-1}$			8.16E−05 [0.11]	0.0025 [2.83]***			0.0008 [1.25]	0.0026 [3.64]***	0.0012 [3.05]***	0.0005 [0.65]	0.0023 [2.62]**	0.0034 [1.95]*
Inflation$_{t-1}$			2.88E−06 [1.37]	7.46E−05 [3.37]***			6.65E−06 [1.48]	9.07E−05 [3.76]***	1.44E−05 [1.85]*	7.30E−05 [6.43]***	9.95E−06 [1.73]*	0.0001 [4.59]***
Openness$_{t-1}$			0.0004 [0.85]	−0.0008 [0.46]			−0.0004 [0.87]	−0.0008 [0.55]	5.89E−05 [0.39]	−0.0003 [1.70]*	−0.0008 [0.92]	−0.0011 [0.63]
Reserves$_{t-1}$			0.0027 [1.05]	0.0055 [1.45]			−0.0058 [2.72]***	0.0015 [0.98]	−0.0002 [0.12]	−0.0001 [0.06]	−0.0028 [1.04]	0.0009 [0.21]
Bank assets$_{t-1}$					−0.1557 [2.06]**	−0.2618 [5.20]***			−0.0915 [2.43]**	−0.192 [3.09]***	0.0253 [0.39]	−0.0395 [0.89]
Bank credit$_{t-1}$					0.1476 [3.29]***	0.2378 [8.40]***			0.170 [7.45]***	0.210 [8.51]***	0.0301 [0.83]	0.0468 [0.38]
Bank deposits$_{t-1}$					0.0058 [0.12]	0.1511 [3.61]***			−0.0346 [1.10]	0.0385 [1.37]	0.0265 [0.27]	0.0938 [0.32]
Interest rate spread$_{t-1}$					−9.67E−06 [2.14]**	−0.0008 [7.93]***			−4.64E−05 [2.12]**	−0.0012 [6.26]***	−3.10E−05 [1.47]	−0.0009 [0.54]
Capitalization$_{t-1}$					−0.0099 [0.23]	−0.1107 [3.80]***			−0.0032 [0.09]	−0.104 [3.25]***		
(Capitalization)$^2_{t-1}$					0.0027 [0.23]	0.0254 [2.90]***			−0.0053 [0.54]	1.38E−02 [1.07]		
Constant	0.290 [3.22]***	0.427 [1.74]*	0.2935 [8.82]***	0.2239 [1.35]	0.1855 [16.60]***	0.1828 [14.14]***	0.431 [6.98]***	0.463 [1.74]*	0.173 [9.32]***	0.208 [9.15]***	0.560 [8.93]***	0.588 [1.67]
Observations	577	312	629	252	342	210	495	291	332	206	368	236
Number of groups	48	47	45	43	33	33	46	45	33	33	39	38

Dependent variable: Volatility of capital inflows measured by the proposed procedure based on Engle and Gonzalo Rangel (2008). See Appendix B for a complete description of explanatory variables and data sources. Coefficients of "Turnover" not reported due to its lack of significance but included. Fixed country effects not reported but included. See Appendix A for the complete country sample. Standard errors have been corrected for serial correlation and heteroskedasticity using the Driscoll and Kraay (1998) procedure. *t*-statistics in square brackets.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 7
Volatility of total inflows over GDP. Regression results for the full sample and for 2000–2006.

	Global		Macro		Financial		Global-macro		Macro-financial		Global-domestic	
	1980–2006	2000–2006	1980–2006	2000–2006	1980–2006	2000–2006	1980–2006	2000–2006	1980–2006	2000–2006	1980–2006	2000–2006
US 3 month T-Bill$_{t-1}$	0.0078 [2.01]*	−0.0025 [1.30]					−0.0025 [1.22]	0.0023 [1.26]			−0.0025 [1.22]	0.0094 [7.17]***
S&P$_{t-1}$	4.00E−05 [2.98]***	5.56E−05 [11.61]***					3.28E−05 [3.66]***	3.6E−05 [7.20]***			3.28E−05 [3.66]***	6.80E−06 [2.78]***
US inflation$_{t-1}$	−0.0088 [3.07]***	−0.0149 [3.43]***					−0.0082 [2.29]**	−0.0113 [4.15]***			−0.0082 [2.29]**	−0.0037 [6.29]***
World GDP growth$_{t-1}$	−0.0061 [1.22]	−0.0008 [0.16]					0.0034 [0.82]	−0.0011 [0.24]			0.0034 [0.82]	−0.0095 [21.48]***
Global liquidity$_{t-1}$	−0.0009 [2.61]**	−0.0011 [1.68]*					−0.0007 [1.97]*	−0.0005 [0.71]			−0.0007 [1.97]*	0.0001 [0.72]
GDP pc$_{t-1}$			−1.24E−04 [3.00]***	3.90E−05 [1.72]*			−1.77E−05 [3.20]***	−1.34E−05 [1.63]	−1.81E−05 [3.79]***	9.50E−06 [1.70]*	−1.78E−05 [2.78]***	1.38E−05 [2.68]**
(GDP pc)$^2_{t-1}$			1.19E−08 [3.39]***	−3.16E−09 [1.40]			1.13E−09 [5.11]***	7.76E−10 [2.54]**	5.98E−10 [3.27]***	2.19E−10 [0.93]	8.43E−10 [4.57]***	1.04E−10 [0.52]
GDP pc growth$_{t-1}$			3.28E−04 [0.36]	0.0023 [3.19]***			0.0012 [2.63]**	0.0017 [3.44]***	0.0018 [2.92]***	−0.0002 [0.66]	0.0018 [2.81]**	7.36E−05 [0.16]
Inflation$_{t-1}$			2.96E−06 [0.57]	−4.89E−06 [0.41]			1.46E−05 [9.42]***	−1.22E−05 [1.66]	7.51E−06 [1.30]	−3.13E−05 [3.34]***	1.61E−05 [1.03]	−3.16E−05 [2.42]**
Openness$_{t-1}$			0.0006 [1.54]	0.0008 [0.81]			−8.28E−05 [0.25]	0.0011 [1.57]	−2.83E−04 [0.87]	−0.0004 [0.98]	−0.0004 [1.32]	−0.0004 [0.83]
Reserves$_{t-1}$			0.0035 [1.93]*	0.0051 [1.38]			−0.0051 [2.80]***	0.0016 [1.43]	−0.0039 [2.09]**	−0.0007 [0.45]	−0.0054 [2.76]***	−0.0008 [0.49]
Bank assets$_{t-1}$					−0.239 [3.20]***	−0.3077 [3.48]***			−0.207 [3.87]***	−0.289 [4.03]***	−0.219 [4.61]***	−0.251 [2.70]**
Bank credit$_{t-1}$					0.1632 [2.78]***	0.1441 [2.24]**			0.150 [3.38]***	0.105 [1.99]*	0.122 [2.44]**	0.0620 [0.88]
Bank deposits$_{t-1}$					0.1528 [5.36]***	0.2128 [6.85]***			0.226 [5.29]***	0.205 [2.03]*	0.192 [3.45]***	0.231 [2.27]**
Interest rate spread$_{t-1}$					2.95E−05 [6.02]***	0.0011 [7.60]***			8.69E−06 [0.43]	9.03E−04 [10.09]***	−2.19E−05 [0.42]	0.0009 [10.41]***
Capitalization$_{t-1}$					0.0257 [1.00]	−0.017 [1.64]			0.0345 [1.45]	−0.001 [0.10]		
(Capitalization)$^2_{t-1}$					−0.0063 [1.10]	−0.0038 [0.73]			−0.0101 [1.26]	0.0045 [0.82]		
Constant	0.390 [8.17]***	0.462 [3.97]***	0.2938 [7.86]***	0.0921 [1.28]	0.1959 [21.00]***	0.2324 [13.97]***	0.404 [9.20]***	0.263 [2.57]**	0.228 [10.47]***	0.225 [25.10]***	0.404 [9.20]***	0.174 [7.03]***
Observations	577	312	586	250	333	211	476	290	323	207	280	207
Number of groups	48	47	45	43	33	33	46	45	33	33	33	38

Dependent variable: Volatility of capital inflows measured by the proposed procedure based on Engle and Gonzalo Rangel (2008). See Appendix B for a complete description of explanatory variables and data sources. Coefficients of "Turnover" not reported due to its lack of significance but included. Fixed country effects not reported but included. See Appendix A for the complete country sample. Standard errors have been corrected for serial correlation and heteroskedasticity using the Driscoll and Kraay (1998) procedure. t-statistics in square brackets.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

potential of emerging economies' domestic policies. This increasing importance of global drivers for all types of capital flows indicates that the forces triggered by globalization have intensified in recent years.

6.2. Domestic macroeconomic drivers

Unlike global variables, macroeconomic drivers have a different impact on each type of flow, as we confirm in the joint and individual tests based on (7). The test statistics reject the null hypothesis that these drivers have similar effects across flows for the three types of flows. For instance, Tables 4 and 6 show that some of these variables exhibit a high degree of association with the volatility of FDI and bank inflows, whereas the volatility of portfolio flows is weakly correlated with them. Indeed, according to Table 5 on portfolio volatility regressions, few macroeconomic variables are significant across specifications. This feature seems to be a robust characteristic of portfolio flows throughout the sample period, as we verify in the stability tests built from (6).[24]

We also find that some macroeconomic drivers affect the volatility of FDI inflows differently from that of bank inflows. This blurs the interpretation of the estimates, leading to rather complex policy recommendations. In general, where there is a different impact across types, depending on which effect predominates in the overall volatility of inflows, we discern three possible outcomes. First, the effects of macroeconomic drivers on the two variables could be significant and of opposite sign, but one effect might outweigh the other in the aggregate flows. For instance, this is the case of economic development as measured by GDP per capita. We find a significant and non-linear relation between economic development and FDI volatility (see Table 4). This inverted U-shaped relationship between the two variables means that lower FDI volatility levels are associated with both the less developed and the more advanced emerging economies. This finding is consistent with Aghion et al. (2004) and contrary to IMF (2007). On the other hand, there is also evidence of a non-linear relation between GDP per capita and the volatility of bank flows (see Table 6). However, unlike in the case of FDI, this is a U-shaped relationship, that is, the quadratic term is positive. This result indicates that more dynamic economies display more volatile bank inflows. Table 7 shows that this second effect predominates in the dynamics of total flows, but only for the whole sample period, since after 2000 both effects seem to offset one another.

Second, certain macroeconomic variables may be associated only with the volatility of one specific type of flow and this effect might predominate in the dynamics of total flows. For instance, reserves and FDI volatility are negatively related, especially since 2000 (see Table 4). This negative link also holds for total flows (see Table 7), particularly for the whole sample, but it is not present in the other two types of flows. This outcome argues in favor of the use of foreign reserves as a tool for self-insurance against volatile FDI flows. However, this policy recommendation would be useless for stabilizing portfolio and bank inflows.

Finally, certain macroeconomic variables might be significant in determining the volatility of a particular flow type but this effect might be masked in total flows. In those cases, any analysis limited to total flows—as in Broner and Rigobon (2005) or IMF (2007)—would gloss over some significant links. For instance, trade openness is positively linked to FDI volatility, mostly after 2000, although this effect disappears in the aggregate.

6.3. Domestic financial drivers

The volatilities of the three types of flows also respond differently to domestic financial drivers, as we illustrate with the tests based on (7).[25] This finding, as in the case of domestic macroeconomic variables, might entail policy dilemmas depending on which effect predominates.[26] Moreover, some relevant results may be masked when there is a strict focus on the volatility of aggregate flows, which adds difficulty to the analysis of these drivers. For instance, the effects of domestic financial factors on portfolio volatility constitute a clear example of the limitations of strictly analyzing overall flows without considering the relevant decomposition (see Table 5). Thus, although domestic financial factors are particularly important in shaping portfolio volatility, as shown by the significance of the coefficients, these effects are completely masked when analyzing the aggregate. Indeed, only the positive association of interest rate spreads with portfolio volatility, while not quite robust, predominates in total flows. Unfortunately, the coefficient is negative for the volatility of FDI (especially after 2000) and bank inflows, which suggests that higher banking competition could be an element of destabilization for these two flows.

In principle, these discrepancies across types of flows do not necessarily imply bad news for policy-makers in their attempt to stabilize portfolio flows. Nevertheless, to make an accurate assessment they should take into account the peculiarities of this flow as compared with FDI and bank inflows. For instance, in line with Aghion et al. (2004), we find that the volatility of portfolio flows has a non-linear relationship with the development of stock markets but, interestingly, it reverses from 2000 to 2006 (the quadratic term becomes positive); see Table 5. That is, while relatively small stock markets seem to be synonymous with higher volatility, portfolio flows become more stable as they develop. This variable is not significant for aggregate flows, which demonstrates that an aggregated analysis can be misleading; see Table 7.[27] Furthermore, from 2000 to 2006, higher levels of credit and deposits turn out to be associated with more stable portfolio flows,[28] whereas financial system deposits do not exhibit any kind of link either with other types of flows or with the aggregate. This outcome also argues in favor of the development of domestic banking sectors to achieve more stable portfolio flows.

Conversely, the effects of domestic financial variables on bank inflows and FDI volatilities seem to shape the dynamics of the aggregate; see Tables 4, 6 and 7. For instance, this is the case of the ratio of banks' assets and private credit to GDP, which are, respectively, negatively and positively associated with the volatility of these three flows.[29] Again, the negative coefficient for banks' assets suggests the benefits of developing banking systems to achieve stable flows, whereas the positive coefficient of bank credit could reflect the instability linked to overheating processes.[30]

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[24] For portfolio flows, we cannot reject the null hypothesis of no structural break in the coefficients of macroeconomic drivers after 2000, where the F-test statistic of the test based on (6) is 1.80. On the contrary, we reject the null of no structural break for FDI and bank flows, which means that the importance of macroeconomic factors changed in the last part of the sample.

[25] We reject the test for the null hypothesis that domestic financial variables have a similar effect on the volatilities of the different categories of flows for the three individual tests (with a p-value of 0.000).

[26] As in the case of global factors, the importance of financial variables has changed in recent years for all types of flows as well as for the aggregate, as inferred from the stability tests built from (6). Given the estimates from Tables 4–7, the effect of these drivers seems to be higher from 2000. Note that our results for domestic financial drivers contrast with those of Neumann et al. (2009), who do not find any significant correlation, with the exception of their indicator of financial liberalization.

[27] This last result disagrees with Broner and Rigobon (2005) and IMF (2007). Also note that from 2000 to 2006 the quadratic relationship between stock market development and the volatility of bank inflows is also significant and positive across regressions (see Table 6).

[28] This negative link between credit and portfolio volatility is contrary to Alfaro et al. (2007), who argue that financial liberalization, when not followed by proper regulation and supervision, can raise equity flows intermediated through banks as well as increase bank credit.

[29] The positive sign of bank credit for the volatility of total flows is contrary to the results of Broner and Rigobon (2005).

[30] Festić et al. (2011) study the relationship between credit growth, foreign flows and economic overheating for a sample of Central and Eastern European countries.

7. Conclusions

This paper presents evidence on the factors underlying the observed pattern of volatility for FDI, portfolio and bank inflows into emerging economies. From a methodological point of view this work builds on the existing literature in two ways. First, we propose a proxy for capital flow volatility based on the measure developed by Engle and Gonzalo Rangel (2008) for macroeconomic variables. This enables us to overcome some serious weighting problems associated with other measures of volatility used in this literature. Second, for the sake of completeness, we analyze capital flow volatility at both disaggregated and aggregated levels. The different dynamics of FDI, portfolio and bank inflows justify this decomposition, while the study of total flows allows us to determine the predominating effect when there is a mix of effects across types.

The conclusions reached in our empirical analysis illustrate some of the challenges facing policy-makers in their attempt to overcome the difficulties posed by volatile capital flows, given their different behavior across types. For instance, our results show that global drivers, which are beyond the control of emerging economies, have gained in importance as determinants of capital flow volatility in recent years.

This growing significance of global determinants in all types of flows is compounded by the conflicting impact of various domestic factors on the volatility of the different types of capital flows. Some of these domestic factors may be targeted by policy-makers acting on findings reported in the literature. For instance, higher competition in domestic banking systems reduces the volatility of FDI and bank inflows to the detriment of that of portfolio inflows, although it would increase the volatility of total flows. That is, the impact of a given factor on an specific flow might be masked or might dominate the dynamics of the volatility of total flows, which hampers analysis. Hence, it is not easy to identify a single policy track to reduce volatility across the board, which, together with the increasing importance of global factors, could explain why some emerging economies have opted to "hedge" against the risk posed by the effects of volatility rather than addressing its roots.

On a more positive note, due precisely to the different dynamics of the three types of capital flows, our paper does identify some domestic determinants that can reduce the volatility of a given category of capital flows without increasing that of others. For instance, we find that domestic macroeconomic fundamentals are relevant in shaping the volatility of FDI. Thus, reserve accumulation seems to be a good measure to stabilize FDI flows, whereas this policy recipe would not affect the volatility of portfolio and banking inflows. Although the results for the domestic financial factors were mixed, i.e. their impact on portfolio volatility differs from that on the other two flows, our results highlight the importance of achieving deeper domestic financial sectors to stabilize flows. In the search for financial and macroeconomic stability, when trying to foster the stability of the capital account, policy-makers should try to take advantage of these findings.

Appendix A. Quarterly capital flows by country

Summary statistics of quarterly data on capital inflows over GDP expressed on a per unit basis by country and flow type.

Country	FDI Mean	SD	Portfolio Mean	SD	Bank Mean	SD	Country	FDI Mean	SD	Portfolio Mean	SD	Bank Mean	SD
Albania	0.01	0.00	0.00	0.00	0.00	0.03	Lithuania	0.03	0.03	0.02	0.04	0.05	0.06
Argentina	0.01	0.01	0.00	0.01	−0.01	0.03	Malaysia	0.11	0.06	0.02	0.17	0.00	0.16
Bahamas	0.01	0.01	0.00	0.00	0.09	1.52	Mexico	0.01	0.00	0.00	0.01	0.00	0.01
Bangladesh	0.48	0.89	0.00	0.31	5.42	3.87	Moldova	0.01	0.01	0.00	0.01	0.01	0.02
Bolivia	0.04	0.05	0.00	0.00	0.02	0.04	Morocco	0.04	0.04	0.00	0.01	−0.03	0.03
Brazil	0.02	0.01	0.01	0.06	−0.01	0.06	Myanmar	0.00	0.00	0.00	0.00	0.00	0.01
Bulgaria	0.06	0.06	0.01	0.04	0.02	0.09	Nepal	0.00	0.00	0.00	0.00	0.01	0.01
Cambodia	11.99	6.34	0.00	0.00	8.54	14.15	Nicaragua	0.01	0.01	0.00	0.00	−0.02	0.04
Chile	0.05	0.04	0.02	0.02	0.02	0.04	Pakistan	0.00	0.00	0.00	0.00	0.00	0.01
China	0.09	0.02	0.01	0.01	0.02	0.03	Peru	0.03	0.03	0.01	0.02	0.00	0.03
Colombia	0.04	0.03	0.01	0.02	0.00	0.03	Philippines	0.01	0.01	0.01	0.03	0.02	0.05
Croatia	0.05	0.04	0.02	0.04	0.06	0.09	Poland	0.04	0.02	0.02	0.03	0.01	0.03
Ecuador	0.04	0.02	−0.03	0.19	0.01	0.07	Czech Republic	0.06	0.05	0.02	0.03	0.04	0.07
Estonia	0.08	0.07	0.02	0.09	0.08	0.08	Romania	0.03	0.03	0.00	0.02	0.04	0.04
Ethiopia	0.00	0.01	0.00	0.00	0.00	0.01	Russia	0.01	0.01	0.00	0.03	0.00	0.05
Guatemala	0.00	0.01	0.00	0.01	0.00	0.01	Singapore	0.14	0.08	0.02	0.03	0.12	0.21
Hong Kong	0.16	0.14	0.10	0.17	−0.05	0.44	South Africa	0.00	0.07	0.00	0.01	0.00	0.01
Hungary	0.06	0.05	0.03	0.06	0.01	0.05	Sri Lanka	0.00	0.00	0.00	0.00	0.01	0.01
India	0.00	0.01	0.00	0.01	0.01	0.01	Sudan	0.01	0.01	0.00	0.00	0.00	0.01
Indonesia	0.01	0.01	0.00	0.03	0.01	0.04	Thailand	0.02	0.02	0.01	0.02	0.01	0.08
Korea	0.01	0.01	0.01	0.02	0.01	0.04	Turkey	0.01	0.02	0.01	0.03	0.02	0.05
Lao PDR	0.01	0.01	0.00	0.00	0.00	0.01	Ukraine	0.19	0.76	0.00	0.04	0.90	2.93
Latvia	0.05	0.03	0.01	0.02	0.12	0.10	Uruguay	0.01	0.01	0.01	0.02	−0.01	0.06
Lesotho	0.03	0.03	0.00	0.00	0.01	0.02	Venezuela	0.01	0.01	0.00	0.01	−0.01	0.07

SD: Standard deviation; Bank: Bank inflows.

Appendix B. Variables and data sources

Capital inflows: Purchases by non-residents of domestic assets minus their sales of such assets. Source: International Financial Statistics (IFS), IMF. The series correspond to codes 78bed (Direct investment in reporting economy n.i.e.); 78bmd (Equity securities liabilities); 78bnd (Debt securities liabilities) and 78bid (Other investment liabilities); *GDP:* Annual percentage growth rate of GDP at market prices based on constant local currency. Source: IFS, IMF; *GDP pc:* GDP per capita (constant 2000 US$). Source: World Development Indicators (WDI), World Bank; *Inflation:* National consumer prices, (annual %). Source: WDI, World Bank; *Openness:* Degree of trade openness measured by the ratio of total trade to GDP. Total trade volume is the sum of goods exports (f.o.b.) and goods imports (c.i.f.). Source: WDI, World Bank; *Reserves:* Reserves in months of imports. Source: WDI, World Bank; *Bank Assets:* Deposit Money Bank Assets to GDP. Source: Financial Structure Database (FSD), World Bank; *Bank Credit:* Private Credit by Deposit Money Banks to GDP. Source: FSD, World Bank; *Bank Deposits:* Financial System Deposits to GDP. Source: FSD, World Bank; *Interest rate spread:* Lending rate minus deposit rate (%). WDI, World Bank; *Capitalization:* Stock Market Capitalization. Source: FSD, World Bank; *Turnover Ratio:* Stock Market Turnover Ratio. Source: FSD, World Bank; *3 months US T-Bill rate:* Source: Datastream; *S&P:* S&P 500 Index. Source: Datastream; *US Inflation:* US Inflation rate (annual %). Source: WDI, World Bank; *World GDP growth:* Source: WDI, World Bank; *Global Liquidity:* Index based on the aggregation of money and quasi-money (M2) over GDP for over 50 countries. Source: Erce (2008).

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