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Portfolio Flows, Global Risk Aversion and Asset Prices in Emerging Markets

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Asia and Pacific Department

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Authorized for distribution by Romain Duval

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Abstract

In recent years, portfolio flows to emerging markets have become increasingly large and volatile. Using weekly portfolio fund flows data, the paper finds that their short-run dynamics are driven mostly by global “push” factors. To what extent do these cross-border flows and global risk aversion drive asset volatility in emerging markets? We use a Dynamic Conditional Correlation (DCC) Multivariate GARCH framework to estimate the impact of portfolio flows and the VIX index on three asset prices, namely equity returns, bond yields and exchange rates, in 17 emerging economies. The analysis shows that global risk aversion has a significant impact on the *volatility* of asset prices, while the magnitude of that impact correlates with country characteristics, including financial openness, the exchange rate regime, as well as macroeconomic fundamentals such as inflation and the current account balance. In line with earlier literature, portfolio flows to emerging markets are also found to affect the *level* of asset prices, as was the case in particular during the global financial crisis.

JEL Classification Numbers: G11, G14, F37

Keywords: portfolio flows; global risk aversion; asset prices, exchange rate

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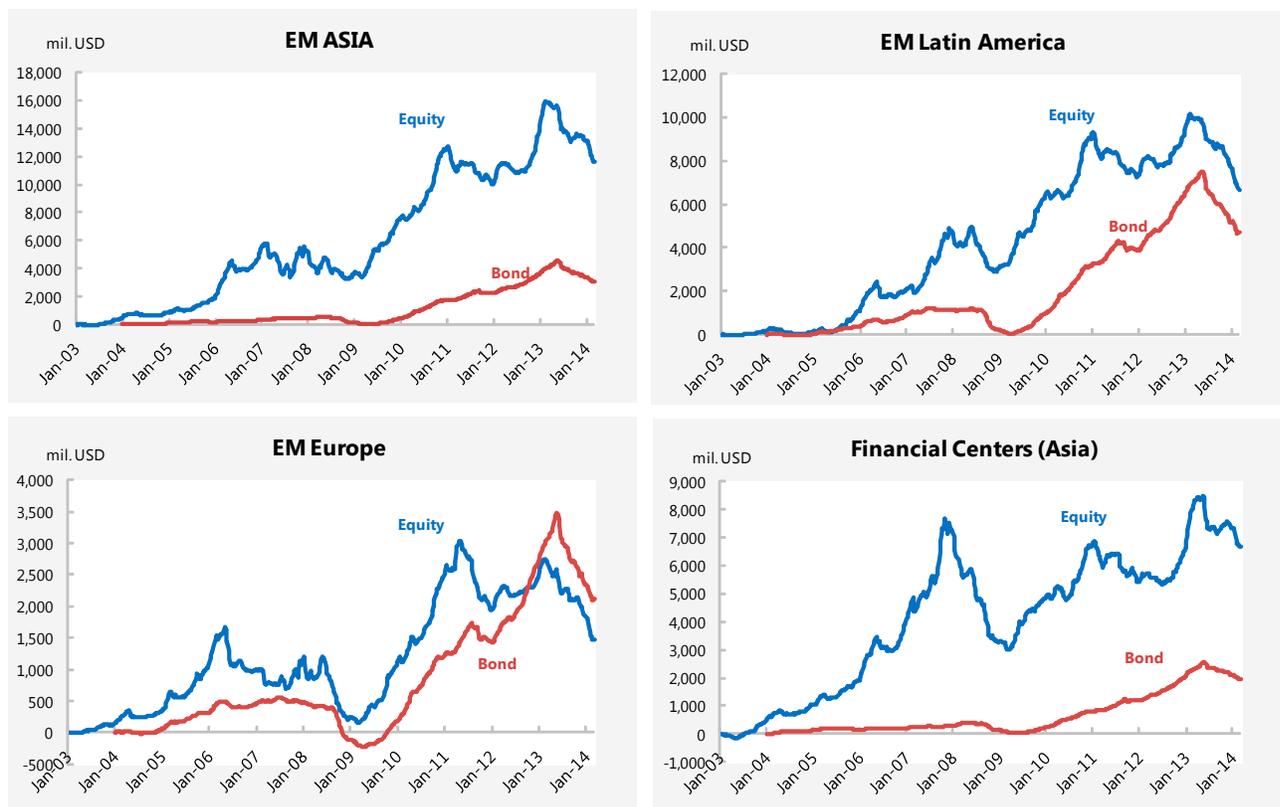
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Contents	Page
I. Introduction	3
II. Stylized facts on EPFR Portfolio Flows.....	6
A. Data	6
B. Stylized Facts	6
C. Drivers of EPFR Flows—Pull vs. Push Factors.....	8
III. Methodology	12
IV. Empirical results	15
A. Impact of Capital Flows on the Level of Asset Returns	15
B. Impact of Global Risk Aversion on the Volatility of Asset Returns.....	16
C. Spillovers across Asset Markets.....	20
V. Conclusions.....	22
Figures	
1. Cumulative Portfolio.....	3
2. Asset Prices in Emerging Markets	4
3. Weekly Portfolio Flows to Emerging Markets during 2007–09.....	7
4. Variance Decomposition of Weekly Fund Flows	10
5. Historical Decomposition of Weekly EFPR Flows in Selected Countries	11
6. Historical Decomposition of Total Fund Flows Deviation Pull vs. Push Drivers	12
7. Impact of Equity Flows on Stock Returns	15
8. Impact of Bond Flows on Bond Yields.....	16
9. Impact of Portfolio Flows on Exchange Rate	16
10. Impact of VIX on Asset Volatility Cross Regions.....	16
11. VIX and Conditional Volatility of Asset Returns in Emerging Markets.....	17
12. Impact of VIX on Stock Volatility vs. Financial Openness.....	18
13. Impact of VIX on Bond Yields Volatility vs. Inflation	18
14. Impact of VIX on Bond Yields Volatility vs CA Balance	18
15. Impact of VIX on Exchange Rate Volatility vs. Exchange Rate Regime	19
16. Impact of VIX on Bond Yields Volatility vs. Exchange Rate Regime	19
17. Correlation between Equity Returns and Exchange Rate Returns.....	20
18. Correlation between Change in Bond Yields and Exchange Rate Returns	20
19. Time-Varying Conditional Correlations of Asset Markets (Selected Countries).....	21
Appendices	
I. Summary Statistics of EPFR Flows.....	25
II. Impulse Responses of Total Fund Flows to Global and Domestic Factors	26
III. Country-Specific DCC-MGARCH Estimates	27
References.....	23

I. INTRODUCTION

Since the mid-2000s, capital flows to emerging markets (EMs) have become increasingly large and volatile². After the boom-bust cycle in 2005–08, portfolio flows to EMs recuperated to unprecedented high levels (Figure 1), partly driven by extremely accommodative monetary policies in advanced economies. Net inflows turned into net outflows as global risk aversion spiked around the peak of the euro area crisis in 2011–12, before recovering in 2013. More recently, as market expectations of an exit from quantitative easing by the U.S. Federal Reserve firmed up and uncertainties about growth prospects in EMs increased, EMs experienced episodes of capital flow reversals, in particular during the May 2013 and January 2014 episodes. Going forward, there will likely be further bouts of capital flow volatility in EMs.

Figure 1. Cumulative Portfolio Flows to Emerging Markets and Financial Centers



Source: EPFR database, IMF staff calculations.

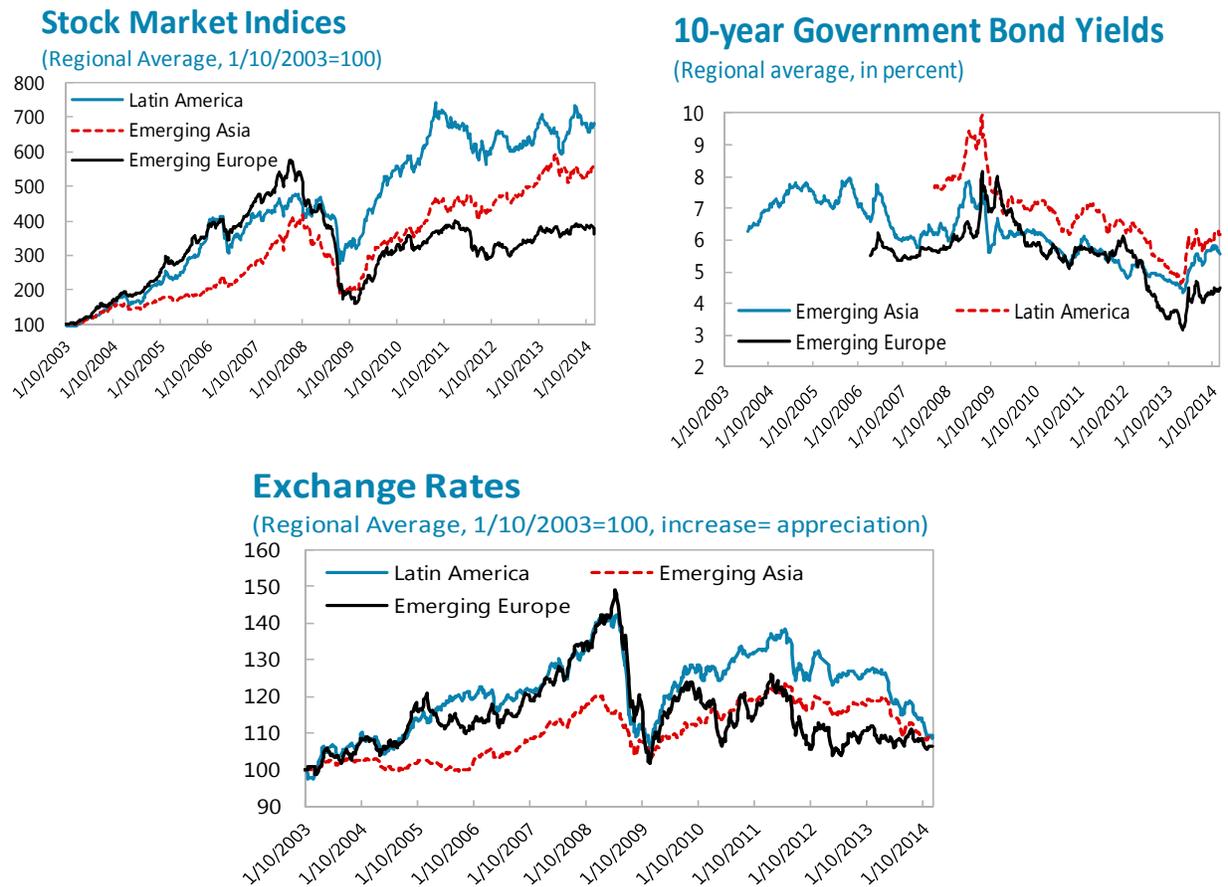
Note: The figure shows regional averages of cumulative weekly EPFR equity and bond flows since 2003 (equity) or 2004 (bond) through February 2014.

At the same time, asset prices in EMs have experienced large swings, in many instances coinciding with episodes of capital flow surges and reversals. Figure 2 shows asset price developments in three asset markets across regions. Despite some regional heterogeneity, there seems to be very strong co-movement of asset prices, especially in stock and bond markets. Concomitant with capital flow reversals at the onset of the global financial crisis (GFC), stock market indexes fell sharply across EMs and bond yields rose to historical highs. Both markets then

² See IMF (2011) for details.

recovered strongly, with some corrections coinciding with the events mentioned above. Exchange rates followed broadly similar patterns across regions, with Asian currencies displaying much less volatility through the cycles, likely reflecting the managed exchange rate regime in many economies.

Figure 2. Asset Prices in Emerging Markets



In the VAR analysis below, we find that global factors including the degree of global risk aversion and asset returns in advanced economies have been key drivers of capital flows to EMs, and particularly so at high frequency. This stresses the importance of capital flows as a transmission channel through which developments or shocks in global financial markets impact financial markets in other economies.

To what extent are capital flows and global risk aversion³ driving asset price volatility in EMs? There has been a large literature studying the effect of capital flows on asset prices.⁴ This

³ As stated above, global risk aversion is one of the key drivers of capital flows which in turn may have an impact on asset prices in emerging markets. However, global risk aversion can also affect asset prices via non-flow channels, for instance, through psychological effects on domestic investors. Thus, in our model we allow for capital flows and global risk aversion to affect the level of asset returns separately.

⁴ See Kim and Yang (2009), Olaberria (2012), Tillmann (2012), for example.

paper complements the literature in two important ways. *First*, most of the existing literature examines the *level* impact of capital flows on asset prices, using analytical frameworks such as VAR or panel regressions. In this paper, the use of a Multi-variate GARCH model allows us to study not only the level impact, but also the (asset price) volatility impact of global risk aversion. In addition, previous studies typically focus on one particular asset price, while here studying the three asset prices together allows us to control for cross-asset market spillovers when estimating the impact of capital flows. *Second*, previous literature uses balance of payments data, which are only available at quarterly frequency for most emerging economies. In this paper, we use a dataset based on net equity and bond inflows to EMs for registered funds from Emerging Portfolio Fund Research (EPFR). Because it is available at a weekly frequency,⁵ it enables us to study the high-frequency impact of capital flows and global risk aversion. Our work is also related to the literature on microstructure theory that considers the effect of order flows (signed transaction) on asset market volatility on a daily basis. Although there the focus is on the effect of flows on conditional variance of asset prices, in this paper we emphasize the effect on volatility of global risk aversion, with the level of capital flows assumed to affect mainly the level of asset prices.

We find that global risk aversion (proxied by VIX) has a significant impact on the volatility of asset prices in EMs, while the magnitude of the impact varies with country characteristics.

The impact of the VIX on stock market volatility is closely correlated with the financial openness of the country, as measured by total foreign liabilities in percent of GDP. The more exposed a country is to external fund flows, the greater the spillover from higher global risk aversion to the domestic equity market appears to be. No similar pattern is observed for bond markets. Instead it appears that the bond market's sensitivity to the VIX correlates better with domestic macro-economic fundamentals such as inflation and the current account balance. The impact is also most pronounced at the longer end of the yield curve. Regarding exchange rates, the effect of the VIX unsurprisingly depends on the exchange rate regime, with more managed currencies showing much less sensitivity to global risk aversion. By contrast, the impact of the VIX on bond yield volatility seems to be amplified in these economies, possibly reflecting the inability of exchange rate to serve as a shock absorber.

Our analysis also shows significant effect of (EPFR) portfolio flows on asset price levels, especially during the GFC. The impact of foreign equity and bond flows on the three asset prices is typically small in "normal" times, but was amplified 5–10 times during the crisis. As a caveat, however, this finding might reflect omitted factors, such as domestic investors selling off at the same time as foreign investors during the crisis, or shrinking market liquidity leading to a larger price impact of a given capital outflow.

The paper is organized as follows. Section II presents stylized facts of EPFR data and the drivers of flows in terms of pull vs. push factors; Section III describes the methodology and data used in the Multivariate-GARCH analysis; Section IV presents the empirical findings on the impact of capital flows and global risk aversion on asset prices, and relates it to country characteristics; Section V concludes.

⁵ This EPFR database is also available at daily frequency but with shorter time coverage and it may not be more suited for the purpose of our study which focuses on macroeconomic events and implications.

II. STYLIZED FACTS ON EPFR PORTFOLIO FLOWS

A. Data

To study high-frequency dynamics of international capital flows to EMs, we use a dataset on weekly portfolio flows provided by EPFR Global. Given that EPFR only covers mutual funds and Exchange Traded Funds (ETF), the flow data represents a subset of total portfolio flows as measured in the Balance of Payment statistics.⁶ However, despite the smaller coverage, fluctuations in EPFR flows are shown to match those in BOP data rather closely⁷ and have the advantage of being available at much higher frequency. Weekly frequency, as opposed to annual or quarterly frequency often used in previous literature, offers the valuable advantage of allowing us to better isolate specific shocks and crisis events on capital flows, and to better identify the effect of capital flows on asset prices. It also enables us to look more closely at the short-run dynamics of capital flows, which may differ from their long-run behavior.

In this paper, the fund-level data provided by the EPFR are aggregated at the level of each recipient country, for the 17 emerging markets and 2 financial centers in our sample. The sample period starts from the beginning of 2003 for equity flows, and mid-2004 for debt flows, through the end of February 2014. For cross-country comparability, z-scores of individual country's weekly flows are calculated and used throughout the analysis.⁸

B. Stylized Facts

It is worth highlighting some key features and stylized facts of the EPFR portfolio flows before delving into the main analysis. Figure 3 plots the z-scores of weekly equity and bond flows in different regions, with the top panel covering the global financial crisis of 2008 and the bottom panel showing most recent developments over 2012–14. Several interesting stylized facts can be drawn from these figures:

- **First, portfolio flows into different regional EMs are highly synchronized, especially following the global financial crisis (GFC).**⁹ After a large retrenchment in late 2008 and early 2009 due to the GFC, equity flows to EMs across the three regions saw their first peak in 2011 and the second peak during the first half of 2013 before starting to decline until the end of our sample period. The pickup in bond flows was particularly strong in EM Europe and EM Latin America, but less so in EM Asia and the financial centers. The strong

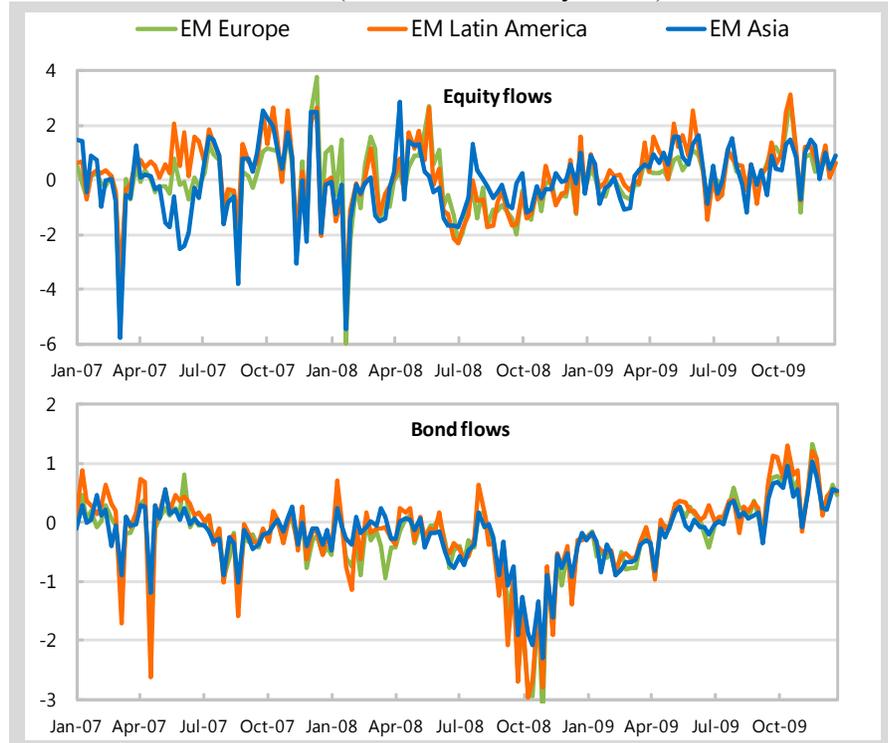
⁶ On average EPFR funds accounted for more than one fourth of total foreign portfolio investments at the country level. See Puy (2013) and Fratzscher (2011) for a more comprehensive overview of EPFR portfolio flow data. Further details on fund coverage can be found at <https://www.epfr.com/>.

⁷ See Miao and Plant (2012) and Jotikasthira, et al. (2010).

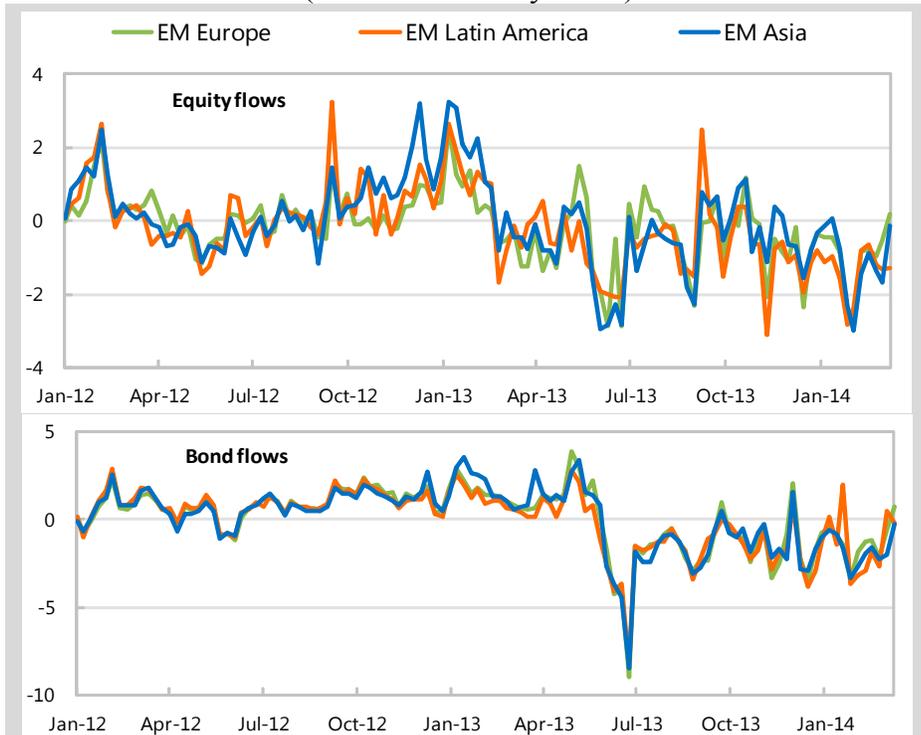
⁸ As standard, the z-scores are calculated by subtracting the mean from the weekly flows, then dividing by the standard deviation.

⁹ It should be noted that these overall regional trends may mask heterogeneity across individual countries at different points in time. Thus, subsequent analysis below will be performed mostly on a country-specific basis to allow for idiosyncratic behavior of portfolio flows, although in some cases regional averages will be reported to capture any meaningful cross-region differences.

Figure 3. Weekly Portfolio Flows to Emerging Markets during 2007–09
(Z-score of weekly flows)



Weekly Portfolio Flows to Emerging Markets during 2012–14 (Mar)
(Z-score of weekly flows)



Source: EPFR database, IMF staff calculations.

co-movement of capital flows to EMs across regions underscores the role of common factors in driving short-term dynamics of portfolio flows.

- **Second, extreme events are more frequent on equity flows than on bond flows.** Extreme observations above two standard deviations are not atypical in the case of equity flows. But in the case of bond flows extreme events are much less frequently observed, with the exceptions of a few events, such as the Lehman crisis and the unexpected “Fed tapering” talk in May 2013.¹⁰
- **Third, high-frequency equity and bond flows respond to extreme events somewhat differently.** For example, while equity flows to EMs declined sharply prior to the Bear Sterns event in mid-March 2008, bond flows appeared unscratched during that episode. In contrast, after the Lehman collapse, bond flows reversed sharply while equity flows remained relatively stable. In the May 2013 “QE tapering” event, however, investors retrenched from EM bond and equity markets to similar degrees. This underlines the importance of understanding both the common and differing forces behind the two types of portfolio investment flows.

C. Drivers of EPFR Flows—Pull vs. Push Factors

Recently, what drives cross-border capital flows has become a hotly debated topic in international policy forums. As policy makers in EMs stressed the role of ultra-easy monetary policies in advanced economies in “pushing” capital toward EMs, others have emphasized the growth and return attractiveness of EM economies as “pull” factors drawing capital from abroad.

This debate regarding “push” versus “pull” factors is not new; an earlier literature had focused on a surge of capital inflows to EMs in the late 1980s and early 1990s. Most recent literature has studied more specifically the behavior of capital flows around the GFC.¹¹ The overall findings seem to suggest that both push and pull factors matter, but their relative importance varies across recipient countries, types of flows, and time.¹² Fratzscher (2011), for instance, finds global factors to be the main drivers of capital flows during the crisis, while country-specific pull factors have been more important in explaining the dynamics of global flows after the crisis particularly for EMs.¹³

Most of the vast literature on push and pull factors has relied on low-frequency (quarter or annual) balance-of-payments data on capital flows. Thus far, little has been learned about what drives cross-border flows at a higher frequency, which yet is crucial for monitoring short-run developments of capital flows such as their sudden surges or reversals. To fill this gap in the literature, in this subsection we estimate country-by-country vector auto regressions (VARs) to

¹⁰ As for the size of volatility, equity flows are more volatile than bond flows for most countries in the sample, but there is a large heterogeneity across countries in this regard. (See summary statistics in Appendix I).

¹¹ See Forbes and Warnock (2011) for a review of recent literature on the determinants of international capital flows.

¹² See Chuhan et al. (1993); Taylor and Sarno (1997); Fratzscher (2011); Ahmed and Zlate (2013).

¹³ Along the same line, Mondino, et al. (2014) find that while country fundamentals such as growth and the level of public debt matters for capital flows in normal times, during the crisis the VIX becomes the dominant driver of capital flows, along with interest rate differentials.

analyze the dynamic interaction for each EM economy between weekly portfolio flows, macroeconomic fundamentals, and global financial factors.

We select a set of push and pull variables based on the existing literature. The push factors consist of (1) the VIX index as a measure of global risk sentiment, (2) S&P 500 excess returns to proxy for global stock performance and global growth prospects, and (3) the 10-year U.S. Treasury bond yield to reflect global interest rate conditions. The pull factors include (1) the GDP growth forecast for the recipient economy considered, (2) inflation, (3) the domestic short-term interest rate, and (4) the change in the domestic exchange rate vis-à-vis the U.S. dollar. The capital flow variables are the standardized weekly EPFR equity and bond flows to each recipient economy. We estimate the VARs separately for each type of flows and use the Cholesky decomposition for impulse response and variance decomposition calculations. Weekly EPFR flows are entered in the VAR in levels of their z-scores as standard unit root tests indicate stationarity.¹⁴ The order of the variables entering the VAR is as follows:¹⁵

{VIX, SP500, US10Y yield, Growth, Inflation, ST rate, EPFR flows, FX return}

Figure 4 shows the variance decomposition implied by our VAR results for selected countries in our sample.¹⁶ The variance of each type of portfolio flows appears to be mostly due to own shocks—about 80 percent for equity flows and slightly higher for bond flows.¹⁷ This could reflect the importance of idiosyncratic factors at high frequency or other factors such as the fund manager decision-making behavior that are not captured in this model. For the rest of the variance, **global factors, particularly the VIX and S&P 500 excess returns, are much more important contributors than domestic factors.**¹⁸ Among the domestic factors, exchange rate returns of the recipient country are generally a more important driver of portfolio flows, especially bond flows. As shown in the figure, there is also some cross-country heterogeneity in terms of the contribution of each shock.¹⁹

¹⁴ Based on the Augmented Dickey-Fuller test, the unit root null is rejected at the 5 percent significance level.

¹⁵ With this ordering, we assume that global factors and country-specific variables except for the exchange rate return may have contemporaneous effects on capital flows. The main results are robust to alternative ordering of the variables. Other robustness checks include replacing the growth consensus variable with stock market returns, adding other global factors such as high-yield corporate bond returns and Ted spread to capture credit risks, and using the first differences instead of levels for the interest rate variables.

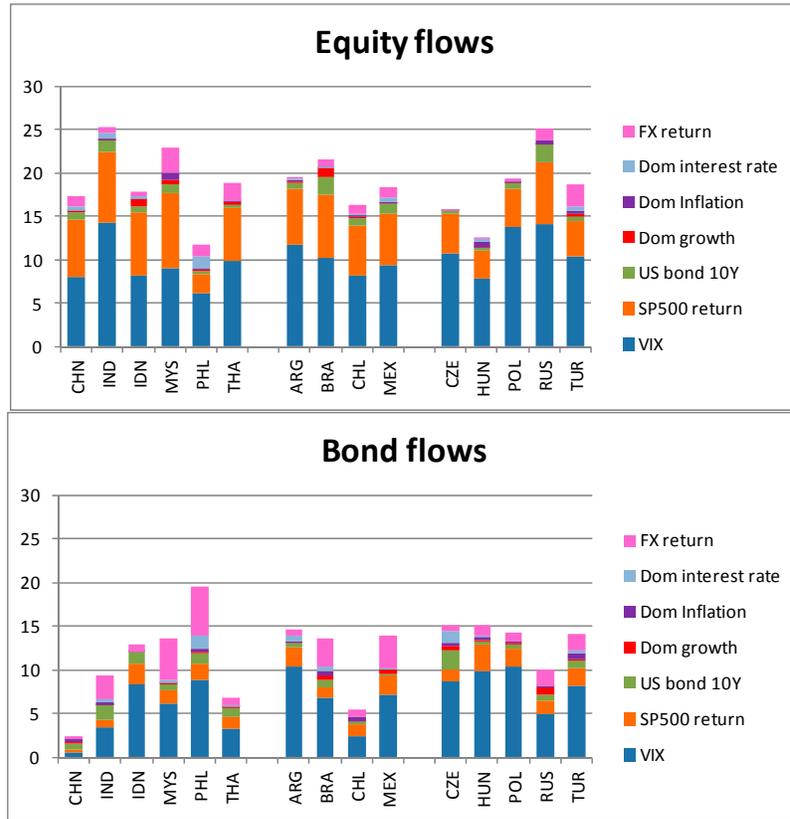
¹⁶ Impulse responses of EPFR flows to global and domestic shocks are presented in Appendix II.

¹⁷ A closer look at the impulse response reveals that the effect of its own shock generally lasts for about four–five weeks.

¹⁸ The finding that U.S. interest rates play a rather small role in driving portfolio flows is at odd with the Ghosh et al. (2014) and Ahmed and Zlate (2013). The use of portfolio *fund* flows here (dominated by institutional investors) as opposed to total portfolio flows used in the aforementioned studies could account to this discrepancy.

¹⁹ A single OLS regression would also yield similar results. For example, in [IMF's Regional Economic Issues for CESEE countries \(April 2014\)](#), portfolio flows are found to be highly volatile and the fit of the models of pull-push factors are modest at best. The mix of significant variables also tends to vary considerably across countries.

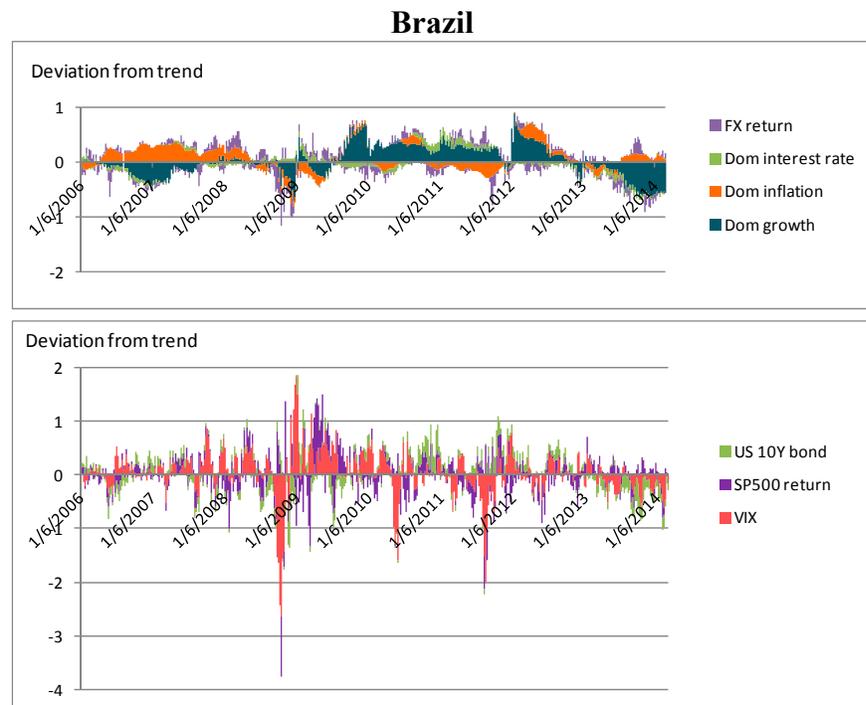
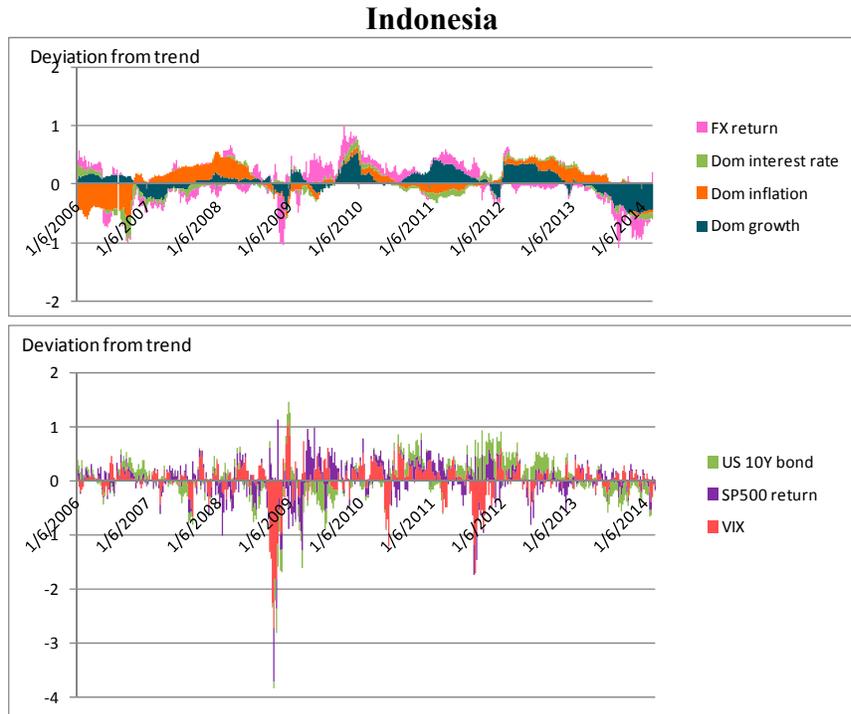
Figure 4. Variance Decomposition of Weekly Fund Flows
(In percent of total variance)



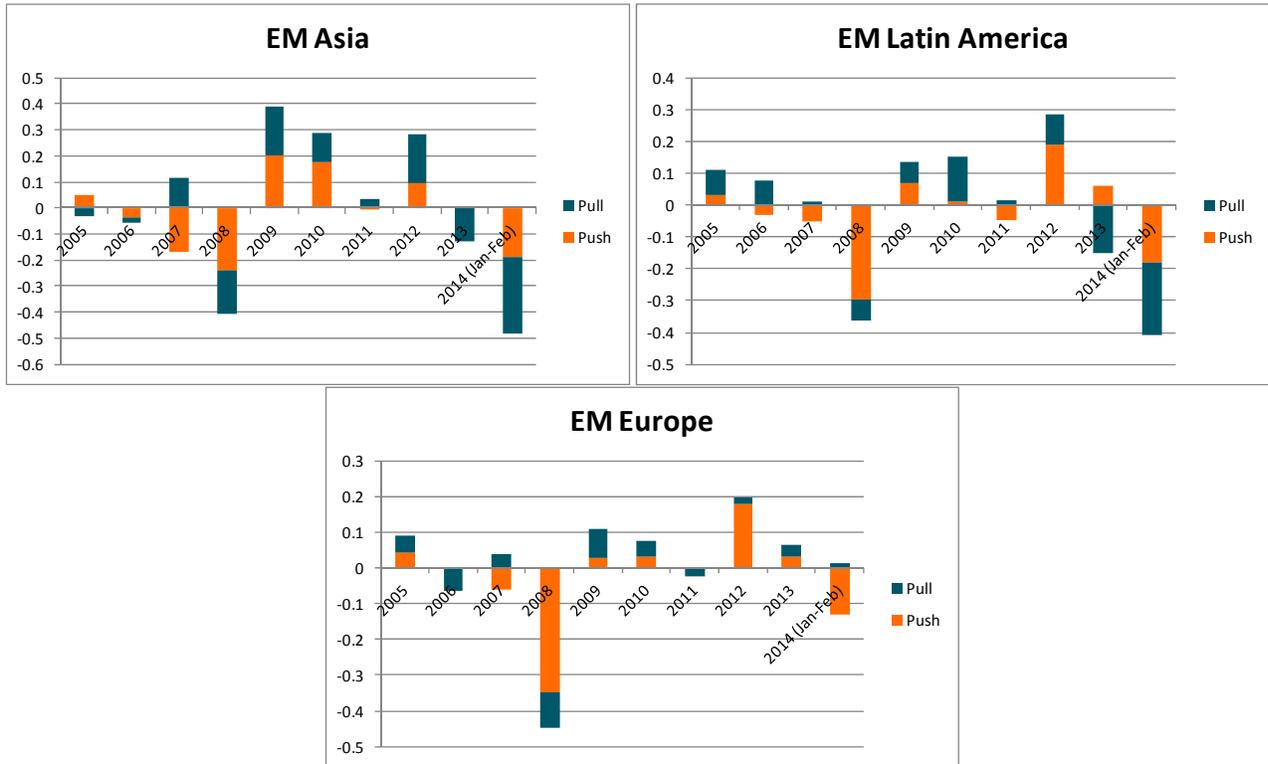
More detailed historical decompositions reveal that **the contributions from domestic pull factors to the historical deviation of portfolio flows from their trend are by and large more persistent than global factors.** Figure 5 illustrates this stylized finding for the cases of Indonesia and Brazil as an example. The same pattern—*persistent* contributions from domestic factors versus *volatile* contributions from global factors—holds true for all other countries. This is intuitive given the more volatile nature of global financial variables in comparison with more stable domestic macroeconomic fundamentals. And precisely because of the more fickle nature of global financial variables, it is possible that when the relationships between capital flows and other variables are analyzed using data at quarterly or annual frequency, the contribution of global financial factors on capital flows becomes smaller as its weekly fluctuations cancel out. This makes the domestic pull factors appear more important in analyses over longer horizons. In Figure 6 simple averages (over a year) of historical contributions of global and local factors illustrates this point: the contribution of push and pull factors to portfolio flows now turning out to be more comparable. This historical decomposition also shows that relative importance of the push and pull factors varies over time, with the push factors being dominant drivers of flows to EMs during the crisis period, in line with Fratzscher (2012).²⁰

²⁰ As a caveat, a key omitted variable in this analysis could be policy responses by each country during the crisis time. Several countries in the sample imposed capital controls and macroprudential measures to deal with the macroeconomic and financial instability challenges posed by the post-crisis surge in capital inflows, which may have had an effect on the level of inflows (as well as on asset prices in the main analysis of the paper).

Figure 5. Historical Decomposition of Weekly EFPR Flows in Selected Countries
 (Contribution of each factor to total deviation of weekly flows from trend, in z-score unit)



**Figure 6. Historical Decomposition of Total Fund Flows Deviation
Pull vs. Push Drivers (annual average of weekly effects)**



III. METHODOLOGY

To quantify the impact of portfolio flows and global risk aversion on asset prices, we estimate a country-specific Multivariate GARCH (MGARCH) model on stock returns, bond yields, and exchange rates. The advantage of using a MGARCH framework is two-fold: first, it is well-known that asset returns exhibit significant volatility clustering, that is, higher volatility tends to be followed by high volatility, making it important to allow for time-dependent volatility for the model to capture the dynamics of asset prices; second, the MGARCH model allows for relationships between the volatility processes of the three assets, capturing important cross-market spillover effects. In particular, the Dynamic Conditional Correlations (DCC) MGARCH allows these spillover effects to change over time, which is often the case with financial variables.²¹

To look at the high-frequency impact of portfolio flows, we use weekly data from 2004 to early 2014. The portfolio flow data are based on net equity and bond inflows to EMs for registered funds from EPFR. As a proxy for global risk aversion, we use the VIX index. The analysis covers 17 major

²¹ DCC-MGARCH model was first proposed by Engle (2002) and since then has been widely used and extended to study dynamic covariances and correlations across financial asset prices. For example, Cappiello et al. (2006) extended the model to allow for asymmetries in correlation dynamics in studying the behavior of international equities and bonds. Kasch and Caporin (2013) applied a threshold structure to the model and found evidence of contagion as indicated by an increase in cross-market comovement between international stock markets in turbulent periods.

emerging economies,²² including 6 Asian countries (China, India, Indonesia, Thailand, Malaysia, the Philippines), 5 Latin American economies (Brazil, Argentina, Mexico, Colombia, Chile), as well as 6 CEE/CIS countries (Bulgaria, Romania, Hungary, Poland, Russia, Turkey).

The general GARCH model is composed of the mean equation and the volatility equation.

$$\begin{aligned} y_t &= Cx_t + \varepsilon_t \\ \varepsilon_t &= H_t^{1/2} v_t \end{aligned}$$

where y_t is an $m \times 1$ vector of dependent variables; C is an $m \times k$ matrix of parameters, x_t is a $k \times 1$ vector of independent variables; $H_t^{1/2}$ is the Cholesky factor of the time-varying conditional covariance matrix H_t and v_t is an $m \times 1$ vector of zero-mean, unit-variance, and independent and identically distributed innovations. In conditional correlation models, H_t is decomposed into a matrix of conditional correlations R_t and a diagonal matrix of conditional variances D_t

$$H_t = D_t^{1/2} R_t D_t^{1/2}$$

In our model, the **mean equation** captures the effect of capital flows and global risk aversion on the *level* of asset returns, specified as follows:²³

$$\begin{pmatrix} S_t \\ B_t \\ E_t \end{pmatrix} = \begin{pmatrix} C_s \\ C_b \\ C_e \end{pmatrix} + \begin{pmatrix} \beta_s & \alpha_s \\ \beta_b & \alpha_b \\ \beta_e & \alpha_e \end{pmatrix} * \begin{pmatrix} EPFR_t \\ VIX_t \end{pmatrix} + \begin{pmatrix} \varepsilon_{s,t} \\ \varepsilon_{b,t} \\ \varepsilon_{e,t} \end{pmatrix}$$

where S_t stands for stock market returns, B_t represents changes in 10-year government bond yields, and E_t is the change in the log exchange rate (a positive change implies an appreciation). Among the regressors, C is the constant, $EPFR_t$ refers to the corresponding flow variables. Here $EPFR$ flow variables are calculated as z-scores of equity flows (for the stock market return equation), bond flows (for the bond yields equation), and total portfolio flows (for the exchange rate equation).

In the **volatility equation**, the conditional variance matrix D_t includes the conditional variance of each asset returns,

$$D_t = \begin{pmatrix} \sigma_{s,t}^2 & 0 & 0 \\ 0 & \sigma_{b,t}^2 & 0 \\ 0 & 0 & \sigma_{e,t}^2 \end{pmatrix}$$

²² The choice of EM economies from each region is based mainly on the availability of EPFR portfolio flows and asset price data since the pre-crisis period. For comparative purposes, we also include two financial centers in Asia (Hong Kong SAR and Singapore) in our study.

²³ The complexity of the model and the high-frequency nature of the data limit the choice of determinants included in the mean and volatility equations. An issue of potential omitted variables bias is discussed when interpreting the results.

where each $\sigma_{i,t}^2$ (i stands for s, b, or e) is assumed to follow a GARCH (1, 1) process, with the VIX as an additional regressor.²⁴

$$\sigma_{i,t}^2 = c_{\sigma,i} + \gamma_i \sigma_{i,t-1}^2 + \delta_i \epsilon_{i,t-1}^2 + \theta_i * VIX_t$$

In the correlation matrix R the conditional correlations $\rho_{i,j}$ among the three asset prices are allowed to be time-varying.

$$R_t = \begin{pmatrix} 1 & \rho_{sb,t} & \rho_{se,t} \\ \rho_{sb,t} & 1 & \rho_{be,t} \\ \rho_{se,t} & \rho_{be,t} & 1 \end{pmatrix}$$

$$R_t = \text{diag}(Q_t)^{-1/2} Q_t \text{diag}(Q_t)^{-1/2}$$

$$Q_t = (1 - \lambda_1 - \lambda_2)R + \lambda_1 \tilde{\epsilon}_{t-1} \tilde{\epsilon}'_{t-1} + \lambda_2 Q_{t-1}$$

where $\tilde{\epsilon}_t = D_t^{-1/2} \epsilon_t$ is a $m \times 1$ vector of standardized residuals, λ_1 and λ_2 are the parameters that govern the dynamics of conditional correlations; they are both non-negative and satisfy $\lambda_1 + \lambda_2 < 1$. The R matrix is a weighted average of the unconditional covariance matrix of the standardized residuals $\tilde{\epsilon}_t$.

To compare the crisis and non-crisis periods, a crisis dummy and an interaction term between the crisis dummy (August 2008 to June 2009) and capital flows is added to the mean equations to examine the potential differential effect of capital flows during the global financial crisis (GFC) period, while the volatility equation remains the same as in the baseline.

$$\begin{pmatrix} S_t \\ B_t \\ E_t \end{pmatrix} = \begin{pmatrix} C_s \\ C_b \\ C_e \end{pmatrix} + \begin{pmatrix} C_{s1} \\ C_{b1} \\ C_{e1} \end{pmatrix} * Dummy_t + \begin{pmatrix} \beta_s & \alpha_s & \beta_{s1} \\ \beta_b & \alpha_b & \beta_{b1} \\ \beta_e & \alpha_e & \beta_{e1} \end{pmatrix} \begin{pmatrix} EPFR_t \\ VIX_t \\ EPFR_t * Dummy_t \end{pmatrix} + \begin{pmatrix} \epsilon_{s,t} \\ \epsilon_{b,t} \\ \epsilon_{e,t} \end{pmatrix}$$

The model is estimated for each country separately by maximum likelihood. The log-likelihood function based on the multivariate normal distribution for observation t is

$$l_t = -0.5m \log(2\pi) - 0.5 \log\{\det(R)\} - \log\{\det(D_t^{1/2})\} - 0.5 \epsilon_t R^{-1} \epsilon_t'$$

Where $\epsilon_t = D_t^{-1/2} \tilde{\epsilon}_t$ is a $m \times 1$ vector of standardized residuals. The log-likelihood function is $\sum_{t=1}^T l_t$.

²⁴ In the order flow literature, the volume of flows is often considered as a determinant of asset volatility. Our main results discussed in the next section are robust to an inclusion of the absolute value of portfolio flows as an additional regressor in the volatility equations.

IV. EMPIRICAL RESULTS

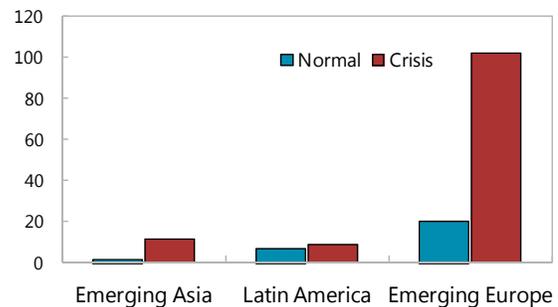
Overall, the dynamics of asset price returns and their cross-correlations appear to be well-captured by the DCC-MGARCH(1,1) model, with the ARCH and the GARCH effects as well as the adjustment parameters statistically significant in most cases across all three assets and their dynamic correlations. Details on the interpretation of results are as follows.

A. Impact of Capital Flows on the Level of Asset Returns

The estimation results show that portfolio inflows have an economically significant impact on asset returns, especially during the global financial crisis.^{25, 26}

- In the case of the *stock market***, the impact of foreign equity flows in EMs seems to be small in emerging Asia, where a 0.1 percent GDP increase in equity inflows²⁷ leads on average to a 1.6 percentage point increase in stock market returns, while the impact is larger in Latin America (7 percentage points) and significantly larger for emerging Europe (20 percentage points). In addition, for both emerging Asia and emerging Europe, the impact of EPFR flows increase sharply during the crisis, when the same amount of outflows led to 11 and 100 percentage point declines in stock returns, respectively.²⁸ Admittedly, this finding might reflect omitted factors, such as domestic investors selling off at the same time as foreign investors during the crisis, or shrinking market liquidity leading

Figure 7: Impact of Equity Flows on Stock Returns
(Percentage change in equity return per 0.1 percent GDP increase in equity flows)



²⁵ In this sub-section, regional averages of the impact of portfolio flows on asset returns are reported in terms of change in the asset return per an increase in portfolio flows of the size equivalent to 0.1 percent of GDP. This interpretation of results is to indirectly take into account the cross-country differences in market size (proxied by GDP) that may affect the sensitivity of asset returns to capital flows. Appendix III reports the raw estimation results whereby the coefficient on EPFR flows in the mean equation can be interpreted as a change in asset return per one standard deviation of flows.

²⁶ As a caveat, the weekly flows measure as the z-score of EPFR flows used in this study may be subject to upward bias due to a well-known problem with EPFR data, i.e. the increased coverage of funds in the database overtime. One potential solution to this problem is to normalize the weekly flows by the reporting funds' total asset under management (AUM) in each recipient economy. However, this alternative measure is also subject to excessive volatility at early years when the coverage as a denominator remains small. We compare EPFR flows in their z-score and in percentage of AUM over time for each country and find that their behaviors tend to converge starting in 2006. Thus, as a robustness check, the same baseline DCC-MGARCH specification is performed for a shorter period covering 2007 to early 2014. Overall, results do not change much in most cases except that, with a smaller sample, the model has difficulty converging for some countries. Details can be provided upon request.

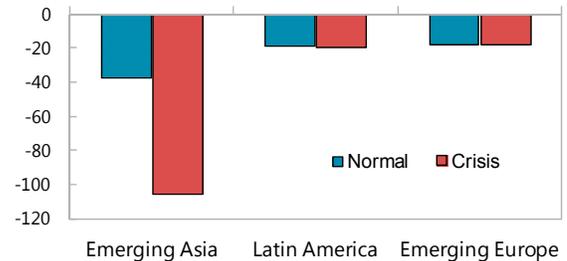
²⁷ Note that a 0.1 percent GDP increase in flows is a fairly large shock for most economies. A one standard deviation of EPFR portfolio flows is in the range of 0.001 to 0.07 percent of GDP, with the median of 0.02 percent of GDP.

²⁸ Some of these results may seem implausibly large especially in the case of EM Europe. This is because the size of one standard deviation of weekly equity flows to EM Europe is relatively small: on average about half of that of Latin America and three times smaller than that of EM Asia. Thus, 0.1 percent of GDP will be equivalent to many more standard deviations of weekly flows for EM Europe than in the case of EM Asia and Latin America (See also footnotes 25 and 27).

to a larger price impact of a given capital outflow, though effects of these omitted factors should partially be captured by the crisis dummy included in the equation.

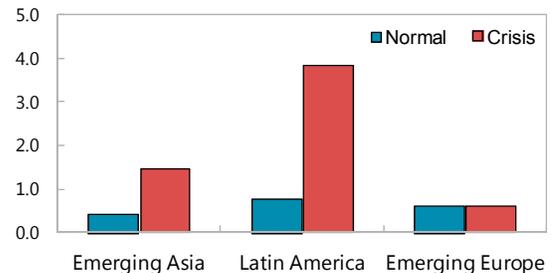
- In the bond market**, the average effect of foreign bond inflows on yields is also small in normal times, and it is relatively larger in emerging Asia (where a 0.1 percent GDP increase of inflows drives down yields by around 40 basis points) compared to Latin America and emerging Europe (20 basis points). Similar to the stock market, the effect increases sharply during the crisis for emerging Asia, where a 0.1 percent GDP increase of outflows coincided with an increase in yields by 100 basis points.²⁹

Figure 8: Impact of Bond Flows on Bond Yields
(Basis point change in bond yields per 0.1 percent GDP increase in bond flows)



- For exchange rates**, the average effect of flows on returns is similar across all regions during normal times, where a 0.1 percent GDP increase of flows leads to 0.4-0.8 percent exchange rate appreciation. The effect becomes three times larger during the crisis for emerging Asia (driven by India and Indonesia) and five times larger for Latin America (driven by Argentina, Brazil and Mexico). For emerging Europe, portfolio flows do not seem to have a stronger impact on exchange rates during the crisis. This could reflect the fact that several currencies in emerging Europe are pegged to euro, implying that their exchange rate vis-à-vis the U.S. dollar therefore does not vary with country-specific flows.

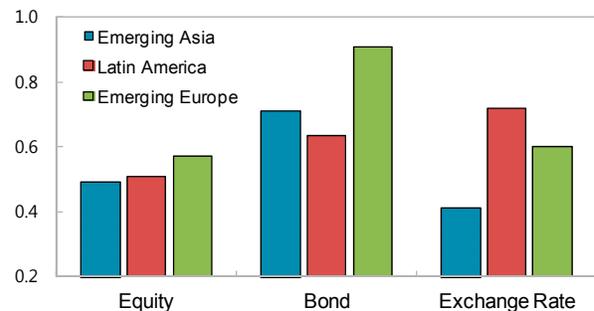
Figure 9: Impact of Portfolio Flows on Exchange Rate
(Percentage point appreciation per per 0.1 percent GDP increase in portfolio flows)



B. Impact of Global Risk Aversion on the Volatility of Asset Returns

The analysis shows that changes in global risk aversion have significant effects on asset price volatilities across regions. An increase in the VIX—a rise in global risk aversion—increases the volatility of all three asset prices, with the impact more pronounced for bonds. On average, a 10 unit increase in the VIX increases stock return variance by around 0.5,³⁰ without significant regional difference; the impact on bond market variance ranges from 0.6 to 1.0, with Latin American economies featuring the

Figure 10: Impact of VIX on Asset Volatility cross Regions
(Increase in volatility per 10 unit increase in the VIX)

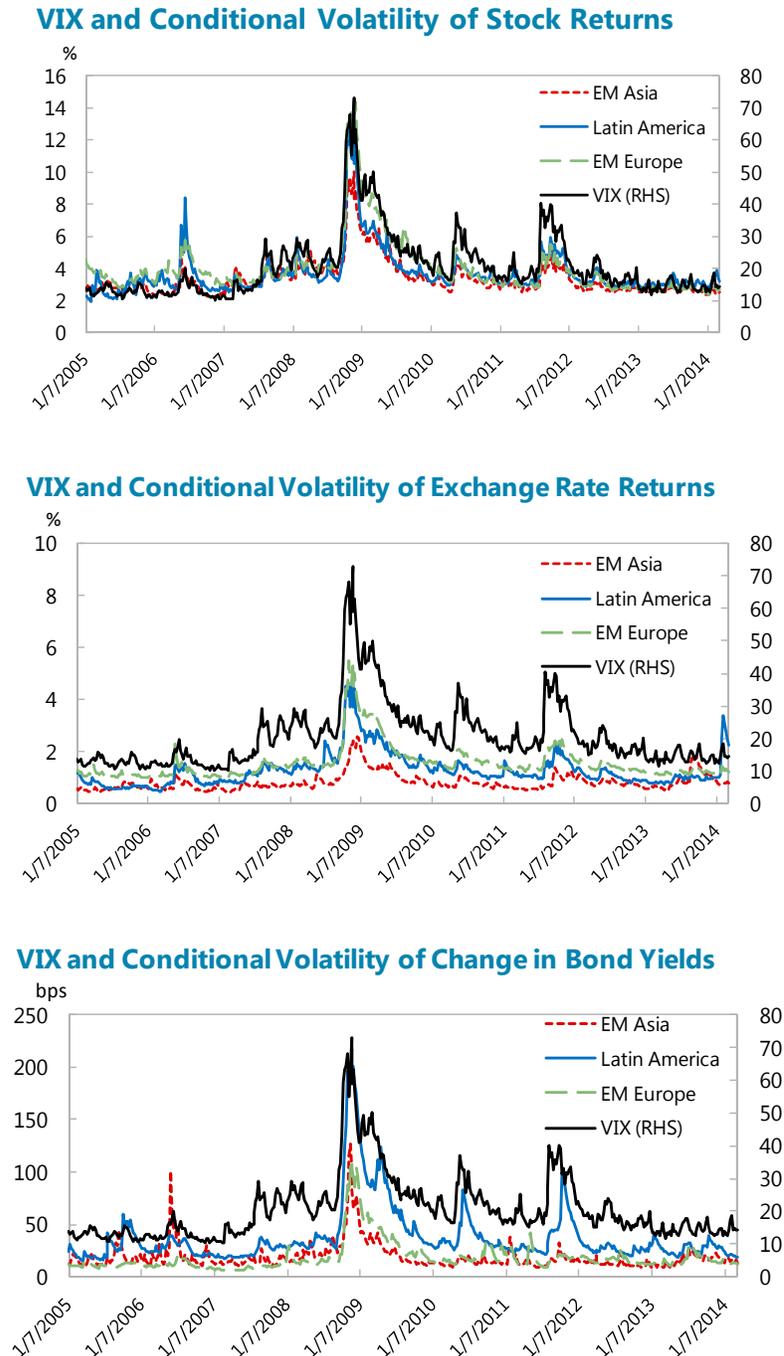


²⁹ The dramatic crisis effect in emerging Asia is mostly driven by Indonesia.

³⁰ Average volatilities of stock returns in EM Asia, Latin America, and EM Europe are 3.0, 3.3 and 3.7, respectively; for change in bond yields: 16.9, 21.8, and 17.4; and for exchange rate changes: 0.7, 1.3, and 1.5.

largest impact; for the exchange rate, a 10 unit increase in the VIX increases the variance of currency returns by around 0.7 in emerging Europe and Latin America, while the impact is much smaller in emerging Asia, partly reflecting the more managed exchange rate regimes. Figure 11 shows the model's implied conditional volatility of asset prices for each region. For all the asset markets, the conditional volatility skyrocketed as VIX spiked, especially during the Lehman event and the peak of the euro crisis around end-2011.

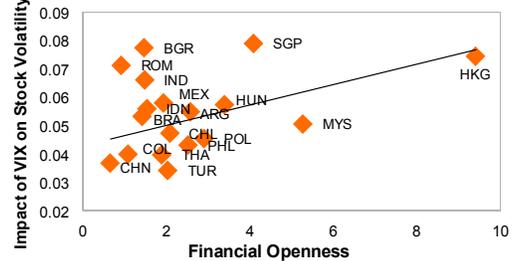
Figure 11. VIX and Conditional Volatility of Asset Returns in Emerging Markets



The average regional effect masks important cross-country variation. While the average impact of the VIX does not differ significantly on average across regions, there is still wide cross-country variation, which appears to correlate with country characteristics.³¹

- ***The impact of the VIX on stock market volatility is larger in economies with very high degrees of financial openness.***³² There are various measures of financial openness in the literature; here we use the ratio of portfolio liabilities to GDP, which relates a priori more closely to the financial transmission mechanism for VIX shocks. For financial centers such as Hong Kong SAR and Singapore, the effect of the VIX on stock volatility is more than twice as large as in financially more closed economies like China and Colombia.

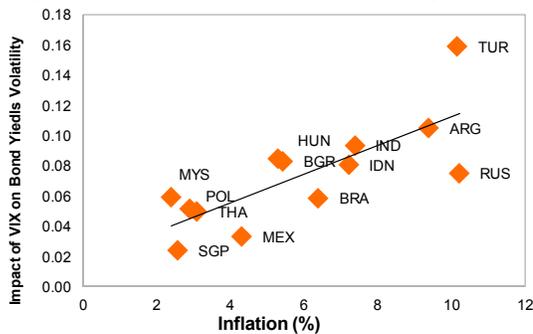
Figure 12: Impact of VIX on Stock Volatility vs. Financial Openness



Source: IMF staff estimates.
Note: Financial openness measured as absolute size of portfolio liabilities in percentage of GDP, 2003-12 average.

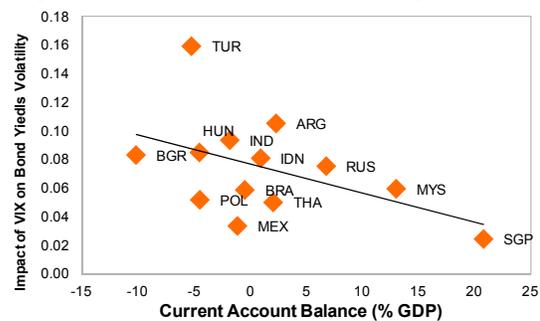
- ***The impact of the VIX on bond market volatility correlates with indicators of macroeconomic stability of the host country, such as inflation and the current account balance.*** In economies where inflation has been persistently high, bond yield volatility reacts more strongly to changes in global risk sentiment. For example, in Turkey and Argentina, the impact of the VIX on 10-year bond yield volatility is more than twice as large as in Malaysia and Thailand. Similarly, bond yield volatility in current account surplus countries tends to exhibit less sensitivity to global risk aversion shocks.

Figure 13: Impact of VIX on Bond Yields Volatility vs. Inflation



Source: IMF staff estimates.
Note: 10-year bond yields used in the analysis. Inflation is 2003-12 average.

Figure 14: Impact of VIX on Bond Yields Volatility vs. CA Balance



Source: IMF staff estimates.
Note: 10-year bond yields are used in the analysis. Current account balance is 2003-12 average.

³¹ Scatter plots in this sub-section plot the country-specific coefficients of the VIX index from the DCC-MGARCH volatility equation for each asset type against macroeconomic variables (averaged over 2003–12) in the country considered.

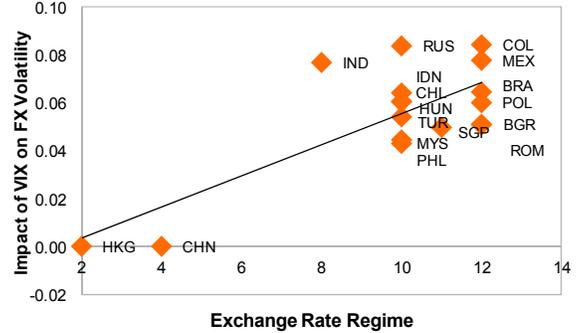
³² This result, as well as the following relationships with macroeconomic fundamentals, holds when we compare the impact of VIX across emerging Asia and advanced Asia. In fact, the correlations become much stronger once advanced economies are added to the scatter plots as they introduce greater variation in the fundamental variables than comparing among emerging economies alone. See IMF (2014) for details.

- **The impact of VIX on bond yield volatility also declines for shorter maturities.** For most emerging economies in the study, the VIX has a significant effect on 10-year bond yields. By contrast, for shorter maturities, including five-year and one-year bonds, the effect is only significant for a few countries. Furthermore, the figure below shows that for these countries, the effect of the VIX typically becomes smaller as maturity shortens. This could reflect that short-term bond yields are more closely related to monetary policy, while long-term bond yields are more sensitive to external risk factors.

- **The impact of the VIX on exchange rate volatility depends on the rigidity of the exchange rate regime.** In economies where the currency is pegged against U.S. dollar or heavily managed (China), the VIX does not have any significant impact on the exchange rate. But in countries with more flexible exchange rate regimes, such as Colombia and Mexico, the impact of the VIX on exchange rate volatility can be quite large, with a 10 units rise in the VIX increasing volatility by 0.1.

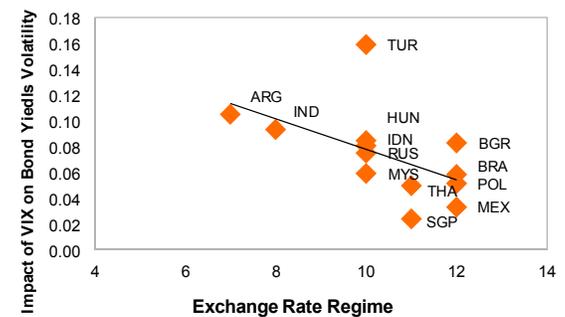
Interestingly, while the VIX has limited impact on exchange rate volatility when the currency is heavily managed, its impact on bond prices seems to be amplified in these economies, potentially due to the inability of the exchange rate to serve as a shock absorber.³³

Figure 15: Impact of VIX on Exchange Rate Volatility vs. Exchange Rate Regime



Source: IMF staff estimates.
 Note: The exchange rate regime index is based on Ilzetzki, Reinhart and Rogoff (2008), where a larger number indicates a more flexible exchange rate regime. The index for Bulgaria is reclassified from 2 to 12, as the currency is pegged against Euro, which is free floating against US dollar.

Figure 16: Impact of VIX on Bond Yields Volatility vs. Exchange Rate Regime



Source: IMF staff estimates.
 Note: 10-year bond yields are used in the analysis. The exchange rate regime index is based on Ilzetzki, Reinhart and Rogoff (2008), where a larger number indicates a more flexible exchange rate regime. The index for Bulgaria is reclassified from 2 to 12, as the currency is pegged against Euro, which is free floating against US dollar.

³³ A previous study also shows that the impact of capital flows on housing prices is more pronounced in economies with rigid exchange rate regimes. See Cho and Rhee (2013).

C. Spillovers across Asset Markets

Asset prices tend to exhibit strong co-movements across different markets.³⁴ The estimated correlations show that exchange rate changes are generally more closely related to stock market returns than they are to changes in bond yields, especially in emerging Asia.³⁵ This might reflect that equity flows convey more private information on growth prospect of the economy than bond flows.³⁶ Thus, equity flows might have a greater price impact on the domestic currency, leading to a closer linkage between stock prices and the exchange rate than between bond yields and the exchange rate.

Figure 17: Correlation between Equity Returns and Exchange Rate Returns (full-sample average)

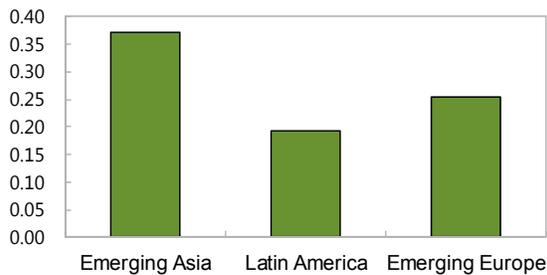
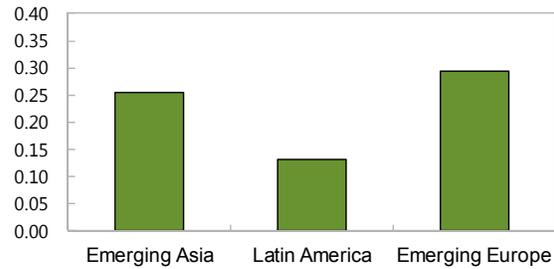


Figure 18: Correlation between Change in Bond Yields and Exchange Rate Returns (full-sample average)



Note: The correlations between change in bond yields and exchange rate returns here are shown in absolute values.

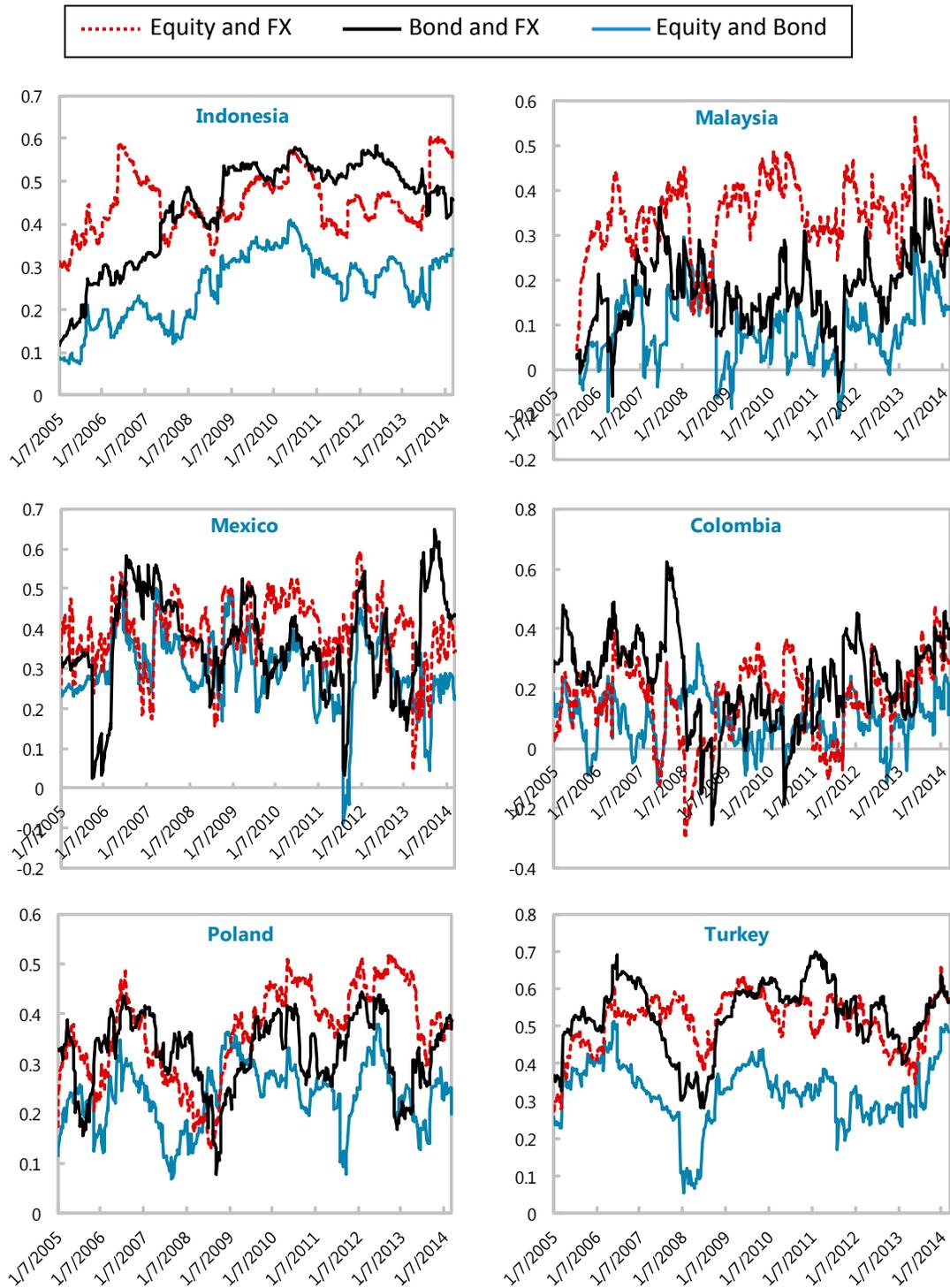
A natural question to ask in the literature on cross-market spillovers is whether asset market co-movements become stronger during crisis compared to non-crisis times. Figure 19 shows the dynamic correlation for selected countries. The time-varying correlations between each pair among the three asset types are volatile and do not appear to exhibit similar patterns across different emerging economies. This heterogeneity could be attributable to differences in the size, liquidity, and degree of openness of each type of financial market in a particular economy. Nonetheless, for most cases, the cross-asset co-movements are generally above their sample averages during the global financial crisis and also the “tapering tantrum” episodes. This could reflect confidence contagion across markets (herding behavior) or liquidity constraints faced by portfolio investors. The observed increase in cross-market spillovers during these “risk-off” episodes calls for a better understanding of cross-market linkages, as they may have important implications for preventive policy measures to avoid joint crashes of asset markets especially in emerging markets.

³⁴ The correlation shown here is the average correlation over time.

³⁵ This is also supported by empirical analysis where the impacts of equity and bond inflows on the exchange rate are studied separately.

³⁶ Gyntelberg, et al. (2012) finds that capital flows related to stock market transactions have a greater and more lasting impact on the exchange rate than capital flows related to bond market transactions. In line with the *order flow* literature, they relate this finding to the superior amount of private information conveyed by equity market investors compared to bond market investors.

Figure 19. Time-Varying Conditional Correlations of Asset Markets (Selected Countries)



Note: Time-varying correlations are estimated based on the Dynamic Conditional Correlation model of MGARCH. The figure shows correlations between equity returns, change in bond yields, and exchange rate appreciation. The correlations between change in bond yields and the other asset returns are shown in absolute terms (i.e., with the negative signs omitted), so that positive figures indicate co-movements of the bond market and the other asset markets.

V. CONCLUSIONS

In recent years, capital flows to emerging markets have become increasingly large and volatile. At the same time, asset prices in EMs have also experienced large swings, in many instances coinciding with episodes of capital flow surges and reversals. This begs the question of whether, and if so to what extent, these cross-border flows drive asset price volatility in EMs. Using weekly EPFR portfolio flows and a Dynamic Conditional Correlation Multivariate GARCH framework, this paper analyzes the effect of capital flows and global risk aversion on the *level* and *volatility* of three financial asset prices (stock market returns, bond yields and exchange rate variations) in 17 emerging economies.

The analysis suggests that EPFR flows have a significant effect on asset prices, which was magnified during the global financial crisis. The impact of foreign equity and bond flows on the three asset prices is relatively small during normal times across regions, while it was typically amplified by 5–10 times during the crisis—although this may have also reflected other concomitant factors such as shrinking market liquidity and/or sell-off by domestic investors. We also find that portfolio flows as captured in EPFR are largely driven by global push factors at high frequency. Domestic pull factors appear to be a smaller but more persistent contributor to portfolio flow variation. This finding implies that global financial factors may be relatively more important in driving short-run portfolio flow fluctuations, while the buildup of foreign portfolio investment positions over time may be more related to domestic macroeconomic fundamentals of the recipient economy.

The analysis also shows that global risk aversion has a significant impact on the volatility of EM asset prices, with the magnitude of this effect varying with country characteristics. In particular, the impact of the VIX on stock market volatility is correlated with the financial openness of the country, as measured by total financial liabilities as a percent of GDP. The more exposed a country is to external fund flows, the greater is the volatility spillover stemming from higher global risk aversion to the domestic equity market. However, no similar pattern is observed in the bond market. In contrast, it appears that the sensitivity of bond yield volatility to the VIX correlates more closely with domestic fundamentals such as those related to macroeconomic stability, especially inflation and the current account balance. The impact is also most pronounced at the longer end of the yield curve. Regarding exchange rate volatility, the spillover effect of the VIX unsurprisingly depends on the exchange rate regime, with more managed currencies showing much less sensitivity to global risk aversion. Interestingly, the impact of the VIX on bond yield volatility seems to be amplified in these (managed currency) economies, possibly due to the inability of the exchange rate to serve as a shock absorber.

Overall, we find that as a country's degree of financial integration rises, domestic asset prices are likely to become more susceptible to global risk aversion shocks. More rigid exchange regimes could help dampen the impact on exchange rate, but potentially at the cost of introducing more volatility in other asset markets. In any event, solid macroeconomic fundamentals appear to provide important buffers to international contagion. In particular, sustaining low inflation and avoiding unsustainably large current account deficits may significantly reduce the sensitivity of bond prices to global shocks.

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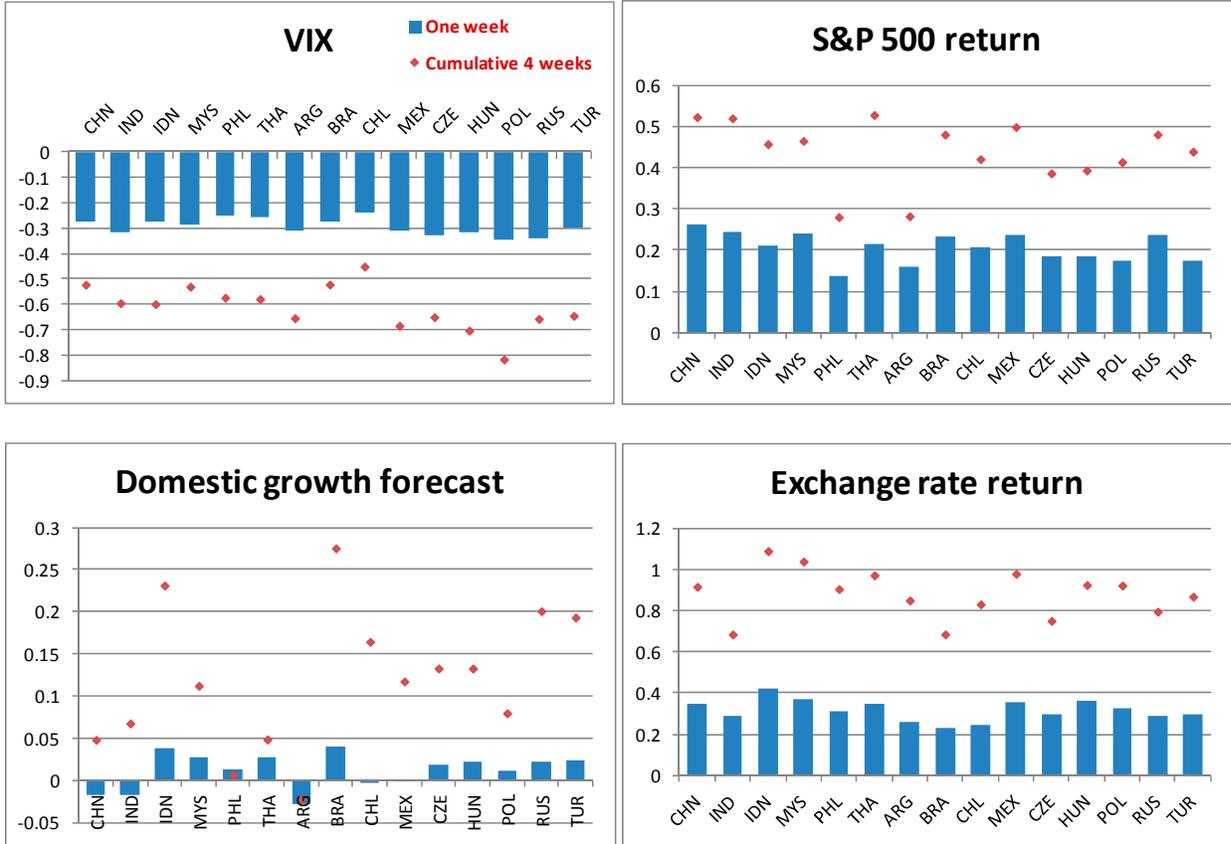
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Appendix I. Summary Statistics of EPFR Flows

Weekly EPFR flows (in millions USD)												
	Equity Flows						Bond flows					
	Obs	Mean	S.D.	Min	Max	Mean (abs.) % AUM	Obs	Mean	S.D.	Min	Max	Mean (abs.) % AUM
EM Asia												
China	583	77	546	-3,242	2,169	0.49	531	5	36	-290	367	0.61
India	583	21	197	-1,352	544	0.41	522	1	11	-98	38	0.60
Indonesia	583	9	50	-282	231	0.36	531	13	49	-319	164	0.54
Malaysia	583	4	45	-198	156	0.39	531	7	29	-201	115	0.52
Philippines	583	3	17	-99	130	0.35	531	6	22	-143	76	0.56
Thailand	583	7	56	-276	248	0.37	531	2	15	-105	60	0.61
EM Latin America												
Argentina	584	1	6	-34	22	0.35	532	5	20	-107	56	0.56
Brazil	584	40	334	-1,479	1,607	0.42	532	11	105	-790	317	0.55
Chile	584	2	21	-92	125	0.46	532	2	12	-123	44	0.53
Colombia	584	2	10	-36	69	0.49	532	7	39	-295	377	0.59
Mexico	584	11	117	-595	524	0.45	532	18	78	-589	319	0.49
EM Europe												
Bulgaria	584	0	0	-4	1	0.53	510	0	2	-8	6	0.54
Hungary	584	1	20	-157	82	0.41	532	3	23	-143	66	0.68
Poland	584	-1	33	-220	112	0.46	532	8	37	-281	140	0.59
Romania	584	0	1	-12	5	0.50	532	0	6	-68	23	0.60
Russia	584	15	219	-1,164	873	0.44	532	14	73	-644	327	0.53
Turkey	584	6	59	-299	329	0.42	532	7	46	-373	191	0.57
Financial Centers												
Hong Kong												
SAR	583	18	140	-840	592	0.31	531	4	14	-89	78	0.65
Singapore	583	4	55	-331	246	0.31	531	3	13	-70	53	0.59

Appendix II. Impulse Responses of Total Fund Flows to Global and Domestic Factors (One week and cumulative 4-week impact)



Appendix III. Country-Specific DCC-MGARCH Estimates

EQUATION	VARIABLES	Baseline: Emerging Asia						Financial Centers	
		China	India	Indonesia	Malaysia	Philippines	Thailand	Hong Kong SAR	Singapore
Stock Returns									
Mean eq.	Equity flows	0.386** (2.351)	0.282** (2.472)	0.0883 (0.855)	0.0206 (0.338)	0.183* (1.750)	0.207* (1.884)	0.217* (1.911)	0.109 (1.188)
	VIX	-0.0225 (-0.954)	-0.0490*** (-2.613)	-0.0476** (-2.437)	-0.0143 (-1.358)	-0.0332* (-1.764)	-0.00527 (-0.286)	-0.0512** (-2.326)	-0.0510*** (-2.844)
	Constant	0.579 (1.305)	1.328*** (4.116)	1.348*** (3.865)	0.428** (2.231)	0.995*** (3.024)	0.330 (0.986)	1.083*** (2.945)	1.030*** (3.506)
Variance eq.	L.arch	0.0923*** (3.351)	0.437*** (3.084)	0.212*** (3.488)	0.240*** (4.256)	0.0583** (2.085)	-0.0155 (-0.814)	0.0121 (0.302)	0.109** (1.987)
	L.garch	0.837*** (15.69)	0.600*** (5.071)	0.364*** (2.682)	0.624*** (8.004)	-0.513 (-1.162)	-0.529** (-2.033)	0.281 (1.209)	0.256 (0.889)
	VIX	0.0369*** (2.846)	0.0661*** (5.438)	0.0560*** (7.888)	0.0506*** (4.929)	0.0432*** (6.779)	0.0398*** (6.990)	0.0744*** (9.804)	0.0789*** (9.978)
	Constant	-0.658 (-1.265)	-0.117 (-0.220)	0.295 (0.943)	-1.839*** (-4.763)	1.564*** (3.988)	1.666*** (6.714)	0.0966 (0.267)	-0.588 (-1.271)
Bond Yield (change)									
Mean eq.	Bond flows	0.127 (0.581)	-0.760* (-1.829)	-0.637 (-0.684)	-0.515** (-2.554)	-0.689 (-1.306)	-0.0758 (-0.172)	-0.552 (-1.345)	-0.701* (-1.917)
	VIX	-0.0469 (-1.399)	0.0104 (0.168)	0.111 (0.703)	-0.0617 (-1.635)	-0.144** (-2.352)	-0.108 (-1.482)	-0.240*** (-4.095)	-0.121** (-2.572)
	Constant	0.718 (0.970)	0.225 (0.203)	-4.768 (-1.618)	0.899 (1.220)	1.493 (1.018)	1.445 (1.049)	4.175*** (3.551)	1.794* (1.908)
Variance eq.	L.arch	0.308*** (4.653)	0.339*** (3.570)	0.408*** (5.108)	0.333*** (5.700)	1.052*** (6.174)	0.136*** (3.628)	0.103*** (3.052)	0.0571*** (2.801)
	L.garch	0.693*** (15.96)	0.804*** (18.46)	0.530*** (8.509)	0.657*** (16.21)	0.284*** (4.449)	0.754*** (12.32)	0.876*** (22.10)	0.885*** (29.81)
	VIX	-0.00229 (-0.147)	0.0933*** (4.326)	0.0807*** (7.320)	0.0593*** (3.937)	-0.0457* (-1.718)	0.0498*** (4.632)	-0.0105 (-0.196)	0.0242* (1.903)
	Constant	1.683*** (4.364)	-0.109 (-0.127)	2.946*** (7.794)	-0.0445 (-0.107)	4.838*** (10.11)	1.710*** (3.728)	1.194 (1.407)	1.059** (2.395)
Exchange Rate Returns									
Mean eq.	Total flows	-0.00134 (-0.218)	0.115*** (4.581)	0.0117 (0.417)	0.123*** (4.129)	0.0805*** (3.151)	0.134*** (5.363)	0.00228 (1.167)	0.0203 (0.857)
	VIX	-0.00206*** (-4.438)	-0.0142*** (-3.172)	-0.00549 (-1.024)	-0.00679* (-1.777)	-0.00651* (-1.742)	-0.00466** (-2.140)	-6.86e-05 (-0.478)	-0.00543 (-1.353)
	Constant	0.0686*** (6.404)	0.266*** (3.400)	0.0891 (0.881)	0.178** (2.430)	0.148** (2.146)	0.132** (2.505)	0.00153 (0.480)	0.162** (2.232)
Variance eq.	L.arch	0.349*** (5.153)	0.329*** (2.914)	0.238*** (5.035)	0.139*** (2.736)	0.128*** (3.464)	0.460*** (4.797)	0.445*** (5.642)	0.111** (2.482)
	L.garch	0.676*** (15.17)	0.800*** (13.07)	0.746*** (18.08)	0.803*** (12.19)	0.791*** (13.21)	0.200** (2.264)	0.651*** (16.47)	0.607*** (4.437)
	VIX	-0.0342 (-1.589)	0.0767*** (4.615)	0.0640*** (4.811)	0.0429*** (3.591)	0.0444*** (4.132)	-0.0229* (-1.828)	-0.0689 (-1.349)	0.0496*** (5.844)
	Constant	-5.855*** (-14.21)	-4.665*** (-6.739)	-4.008*** (-8.617)	-4.340*** (-6.826)	-4.178*** (-7.897)	-1.532*** (-5.367)	-8.585*** (-9.752)	-3.439*** (-7.344)
Corr(stock, bond)		0.102** (2.034)	-0.178*** (-3.480)	-0.601*** (-3.998)	-0.121* (-1.762)	-0.160 (-1.333)	-0.0117 (-0.0996)	0.0671 (1.133)	0.0659 (0.195)
Corr(stock, FX)		0.0434 (0.870)	0.347*** (7.544)	0.747*** (6.153)	0.376*** (6.516)	0.463*** (4.931)	0.424*** (4.835)	0.292*** (5.465)	0.358 (1.389)
Corr(bond, FX)		0.0735 (1.525)	-0.0532 (-1.028)	-0.726*** (-7.113)	-0.236*** (-3.711)	-0.246** (-2.365)	-0.278** (-1.986)	-0.0118 (-0.198)	-0.198 (-0.565)
Observations		531	522	531	450	531	531	531	531

z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

EQUATION	VARIABLES	Baseline: Latin America				
		Argentina	Brazil	Chile	Colombia	Mexico
Stock Returns						
Mean eq.	Equity flows	0.251*	0.0850	0.255***	0.00494	0.0759
		(1.754)	(0.624)	(2.715)	(0.0597)	(0.745)
	VIX	-0.0687***	-0.00702	0.0165	-0.0238	-0.0372*
		(-2.614)	(-0.264)	(1.098)	(-1.396)	(-1.958)
	Constant	1.432***	0.297	-0.177	0.797**	0.969***
		(2.899)	(0.584)	(-0.576)	(2.275)	(2.905)
Variance eq.	L.arch	0.150*	-0.0112	0.515***	0.308***	0.0144
		(1.885)	(-0.244)	(2.890)	(4.723)	(0.414)
	L.garch	0.669***	-0.0738	0.244	0.504***	-0.0244
		(4.151)	(-0.333)	(1.426)	(5.829)	(-0.106)
	VIX	0.0549***	0.0533***	0.0474***	0.0400***	0.0580***
		(5.175)	(8.893)	(4.012)	(4.251)	(9.793)
	Constant	0.765	1.218***	0.605	-0.0792	0.755***
		(1.127)	(4.828)	(1.412)	(-0.193)	(2.866)
Bond Yield (change)						
Mean eq.	Bond flows	-2.320	-2.089**	0.238	-2.209**	-1.671***
		(-1.488)	(-2.541)	(0.851)	(-2.551)	(-2.609)
	VIX	0.445	0.0282	-0.216***	-0.160	-0.0113
		(1.474)	(0.162)	(-3.618)	(-1.485)	(-0.115)
	Constant	-5.063	-0.0601	3.666***	3.436	-0.158
		(-1.033)	(-0.0171)	(3.159)	(1.488)	(-0.0839)
Variance eq.	L.arch	0.196**	0.0665	0.644***	0.416***	0.104**
		(2.261)	(1.453)	(2.684)	(5.222)	(2.014)
	L.garch	0.737***	0.513***	0.486***	0.723***	0.0497
		(8.494)	(3.437)	(3.955)	(19.77)	(0.286)
	VIX	0.105***	0.0585***	0.0515***	-0.0599	0.0333***
	(9.525)	(8.871)	(3.242)	(-0.725)	(5.971)	
	Constant	3.872***	3.965***	2.167***	3.559**	4.642***
		(7.551)	(8.954)	(4.259)	(2.389)	(20.14)
Exchange Rate Returns						
Mean eq.	Total flows	0.0359**	0.289***	0.184***	0.00932	0.125***
		(2.323)	(5.139)	(3.980)	(0.261)	(3.224)
	VIX	0.00162	0.00416	-0.00558	-0.0121*	-0.0215***
		(0.616)	(0.297)	(-0.671)	(-1.781)	(-2.766)
	Constant	-0.198***	0.00637	0.122	0.215**	0.368***
		(-3.023)	(0.0237)	(0.763)	(2.003)	(2.790)
Variance eq.	L.arch	0.383***	0.0568**	0.224***	0.298***	0.100***
		(3.659)	(2.037)	(2.737)	(5.386)	(2.612)
	L.garch	0.790***	-0.521***	0.776***	0.744***	0.629***
		(15.24)	(-3.411)	(10.51)	(18.22)	(4.501)
	VIX	-0.143	0.0644***	0.0605***	0.0841***	0.0776***
	(-0.815)	(8.181)	(3.998)	(4.824)	(9.864)	
	Constant	-2.503	-0.442	-2.568***	-5.065***	-2.874***
		(-0.996)	(-1.495)	(-4.000)	(-7.011)	(-5.193)
Corr(stock, bond)		0.177	-0.194*	0.0245	-0.164*	-0.189***
		(0.148)	(-1.884)	(0.398)	(-1.841)	(-2.767)
Corr(stock, FX)		-0.543	0.432***	0.195***	0.284***	0.311***
		(-0.257)	(5.279)	(3.237)	(3.341)	(4.455)
Corr(bond, FX)		0.395	-0.273***	0.0906	-0.396***	-0.263***
		(0.198)	(-2.987)	(1.468)	(-5.004)	(-3.875)
Observations		441	393	375	532	532

z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

		Baseline: Emerging Europe					
EQUATION	VARIABLES	Bulgaria	Hungary	Poland	Romania	Russia	Turkey
Stock Returns							
Mean eq.	Equity flows	0.175* (1.746)	0.291** (2.351)	0.163 (1.521)	0.535** (2.047)	0.0210 (0.174)	-0.0252 (-0.175)
	VIX	-0.101*** (-5.552)	-0.0542** (-2.450)	-0.0501*** (-2.856)	-0.0786* (-1.959)	-0.0375 (-1.589)	-0.0119 (-0.593)
	Constant	1.946*** (5.354)	1.126*** (2.904)	1.221*** (3.840)	1.615** (2.419)	1.102** (2.565)	0.583 (1.508)
Variance eq.	L.arch	0.361** (2.184)	0.193*** (3.052)	0.0473 (1.146)	0.0830 (0.946)	0.283*** (4.082)	0.0110 (0.671)
	L.garch	0.689*** (4.338)	0.123 (0.436)	-0.287 (-1.335)	-0.231 (-0.566)	0.842*** (24.28)	-0.843*** (-12.67)
	VIX	0.0774*** (4.197)	0.0574*** (8.352)	0.0455*** (7.287)	0.0712*** (3.721)	-0.0257 (-0.243)	0.0343*** (5.497)
	Constant	-1.369 (-1.268)	0.813* (1.771)	1.218*** (5.124)	0.314 (0.561)	-0.0305 (-0.0183)	2.543*** (18.80)
Bond Yield (change)							
Mean eq.	Bond flows	-0.441 (-0.709)	-2.397*** (-3.393)	-1.459*** (-3.543)	-1.432*** (-3.218)	-1.463*** (-4.093)	-0.951* (-1.772)
	VIX	-0.0724 (-0.946)	0.297** (2.306)	0.0738 (1.323)	0.132** (2.441)	0.103* (1.825)	-0.0445 (-0.674)
	Constant	1.630 (1.120)	-5.928*** (-2.665)	-1.756 (-1.571)	-4.381*** (-2.710)	-1.719* (-1.793)	0.396 (0.382)
Variance eq.	L.arch	0.617*** (3.594)	0.0958*** (3.707)	0.147*** (4.419)	0.0416 (0.626)	1.057*** (4.835)	0.331*** (5.844)
	L.garch	0.563*** (6.804)	0.823*** (24.93)	0.789*** (17.36)	0.514** (2.401)	0.000210 (0.340)	0.718*** (21.98)
	VIX	0.0829*** (3.583)	0.0847*** (9.180)	0.0516*** (3.059)	-0.160*** (-7.076)	0.0751*** (6.248)	0.159*** (8.752)
	Constant	1.764*** (2.666)	1.595*** (3.778)	0.816 (1.154)	6.259*** (13.15)	2.899*** (10.75)	-2.141*** (-2.846)
Exchange Rate Returns							
Mean eq.	Total flows	0.0279 (0.430)	0.0353 (0.576)	0.115* (1.786)	0.00875 (0.188)	0.124*** (4.655)	0.0487 (1.055)
	VIX	-0.0228*** (-2.809)	-0.0352*** (-2.969)	-0.0253* (-1.915)	-0.0449** (-2.569)	-0.00535 (-0.985)	-0.0178** (-2.250)
	Constant	0.511*** (3.179)	0.648*** (3.142)	0.570** (2.557)	0.735** (2.407)	0.138 (1.587)	0.282** (1.992)
Variance eq.	L.arch	0.106 (1.205)	0.0314 (0.872)	0.0368 (0.783)	-0.00359 (-0.0815)	0.241*** (3.056)	0.275*** (4.484)
	L.garch	0.772*** (5.490)	0.696*** (3.422)	-0.0423 (-0.101)	0.785*** (4.731)	0.846*** (21.14)	0.406*** (3.330)
	VIX	0.0509*** (4.205)	0.0603*** (9.248)	0.0599*** (8.862)	0.0507*** (2.676)	0.0836*** (4.532)	0.0540*** (6.771)
	Constant	-2.005** (-2.296)	-1.534* (-1.922)	-0.283 (-0.635)	-2.340** (-2.270)	-5.096*** (-7.693)	-1.525*** (-4.553)
Corr(stock, bond)		-0.0144 (-0.181)	-0.322*** (-5.647)	-0.237** (-2.166)	0.412 (0.218)	-0.187*** (-3.637)	-0.350*** (-3.346)
Corr(stock, FX)		0.0280 (0.358)	0.359*** (6.471)	0.426*** (3.964)	-1.793 (-0.299)	0.226*** (4.504)	0.557*** (6.736)
Corr(bond, FX)		-0.0586 (-0.747)	-0.522*** (-11.19)	-0.347*** (-3.509)	-0.630 (-0.427)	-0.209*** (-4.073)	-0.540*** (-6.625)
Observations		348	532	532	144	529	532

z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Country-Specific DCC-MGARCH Estimates with Crisis Dummy

EQUATION	VARIABLES	Interaction w/ Crisis Dummy: Emerging Asia						Financial Center	
		China	India	Indonesia	Malaysia	Philippines	Thailand	Hong Kong SAR	Singapore
Stock Returns									
Mean eq.	Equity flows	0.318** (1.990)	0.221* (1.959)	0.0820 (0.790)	-0.0105 (-0.162)	0.180* (1.768)	0.200* (1.837)	-0.0487 (-0.335)	0.201* (1.743)
	Equity flows*Crisis	0.804 (0.877)	2.637*** (3.495)	1.860 (1.133)	2.205*** (3.851)	3.130** (1.979)	2.759** (2.391)	1.142 (1.253)	1.541* (1.816)
	Crisis dummy	2.128** (1.973)	2.003** (2.322)	1.467* (1.676)	0.0844 (0.173)	1.296 (1.591)	0.591 (0.742)	2.925** (2.030)	-0.136 (-0.130)
	VIX	-0.0887*** (-3.246)	-0.0662*** (-3.192)	-0.0659*** (-2.958)	-0.0164 (-1.203)	-0.0566** (-2.284)	-0.0193 (-0.885)	-0.0348 (-1.275)	-0.0537*** (-2.272)
	Constant	2.059*** (4.072)	1.525*** (4.268)	1.636*** (4.238)	0.491* (1.918)	1.374*** (2.957)	0.599 (1.558)	0.929* (1.923)	1.119*** (2.863)
Variance eq.	L.arch	0.127 (1.564)	0.208*** (3.692)	0.219*** (3.502)	0.271*** (3.939)	0.0851 (1.599)	-0.00233 (-0.0802)	0.00966 (0.566)	0.0176 (0.415)
	L.garch	0.866*** (8.248)	0.643*** (8.758)	0.340** (2.245)	0.602*** (7.054)	-0.236 (-0.595)	-0.392 (-1.169)	-0.833*** (-11.34)	0.285 (1.185)
	VIX	0.0314* (1.897)	0.0638*** (6.192)	0.0548*** (7.666)	0.0397*** (3.484)	0.0479*** (6.684)	0.0403*** (7.231)	0.0331*** (5.774)	0.0728*** (9.505)
	Constant	0.0455 (0.0449)	-0.986** (-2.333)	0.348 (1.050)	-1.528*** (-3.498)	1.128*** (2.662)	1.498*** (4.831)	2.560*** (19.38)	0.117 (0.312)
	Bond Yield (change)								
Mean eq.	Bond flows	0.0360 (0.245)	-0.646 (-1.133)	-0.391 (-0.416)	-0.554*** (-2.704)	-1.620* (-1.854)	-0.0514 (-0.116)	-0.765 (-1.595)	-0.238 (-0.556)
	Bond flows*Crisis	6.285 (0.631)	15.600 (1.641)	-23.44** (-2.252)	8.120* (1.930)	7.590*** (3.246)	3.136 (0.447)	-10.20*** (-2.691)	-4.810 (-0.891)
	Crisis dummy	1.295 (0.641)	5.040 (1.043)	-11.49 (-1.319)	3.260 (1.140)	6.780*** (3.035)	3.812 (0.839)	-19.15 (-0.840)	-7.152 (-0.976)
	VIX	-0.0439 (-1.373)	-0.0503 (-0.704)	0.117 (0.705)	-0.0790* (-1.790)	-0.232*** (-2.609)	-0.123 (-1.343)	-0.0619 (-0.878)	-0.402*** (-5.708)
	Constant	0.931 (1.470)	1.590 (1.279)	-4.997 (-1.639)	1.340 (1.480)	4.260** (2.180)	1.537 (0.917)	0.656 (0.604)	6.737*** (5.098)
Variance eq.	L.arch	1.124*** (2.976)	0.163*** (3.628)	0.422*** (5.153)	0.343*** (5.230)	0.927*** (4.836)	0.137*** (3.576)	0.349*** (5.475)	0.142*** (3.058)
	L.garch	0.181 (1.196)	0.799*** (19.63)	0.512*** (8.069)	0.636*** (13.86)	0.256*** (2.962)	0.744*** (11.23)	0.709*** (20.07)	0.813*** (12.97)
	VIX	0.0270* (1.708)	0.0699*** (4.413)	0.0778*** (7.414)	0.0727*** (5.135)	-0.0536* (-1.745)	0.0476*** (4.488)	0.162*** (9.122)	0.0108 (0.452)
	Constant	2.284*** (5.105)	-8.901*** (-17.05)	3.026*** (8.169)	-9.571*** (-21.55)	-4.251*** (-7.321)	1.836*** (3.990)	-2.356*** (-3.290)	1.496** (2.210)
	Exchange Rate Returns								
Mean eq.	Total flows	-0.00318 (-0.955)	0.110*** (3.364)	0.00633 (0.223)	0.111*** (3.597)	0.0967*** (3.361)	0.131*** (5.170)	0.0469 (1.013)	0.00270 (1.278)
	Total flows*Crisis	-0.0102 (-0.790)	0.525** (2.265)	0.642* (1.854)	0.151 (0.679)	-0.213 (-1.104)	-0.0124 (-0.0848)	0.279 (0.840)	-0.00238 (-0.420)
	Crisis dummy	0.0173 (1.267)	0.360 (1.376)	0.331 (1.093)	-0.0405 (-0.199)	-0.0251 (-0.118)	0.182* (1.660)	-0.254*** (-3.298)	-0.369 (-0.802)
	VIX	0.00151*** (-3.823)	-0.0174*** (-2.848)	-0.00636 (-1.115)	-0.00203 (-0.331)	-0.00800 (-1.348)	0.00903*** (-2.682)	-0.0197** (-2.019)	-9.66e-05 (-0.529)
	Constant	0.0394*** (4.194)	0.298*** (2.953)	0.106 (1.002)	0.0745 (0.591)	0.176 (1.567)	0.214*** (3.060)	0.310* (1.873)	0.00190 (0.522)
Variance eq.	L.arch	0.795*** (4.138)	0.235*** (4.371)	0.237*** (5.016)	0.197*** (2.707)	0.123** (2.360)	0.470*** (4.729)	0.279*** (4.492)	0.449*** (5.476)
	L.garch	0.670*** (13.06)	0.714*** (13.27)	0.747*** (18.19)	-0.330 (-1.549)	0.631*** (4.042)	0.196** (2.122)	0.399*** (3.286)	0.647*** (15.30)
	VIX	-0.151 (-0.674)	0.0731*** (6.064)	0.0627*** (4.784)	0.0178** (2.166)	0.0365*** (3.979)	-0.0240* (-1.937)	0.0539*** (6.824)	-0.0620 (-1.075)
	Constant	-6.235 (-1.576)	-4.484*** (-9.208)	-3.999*** (-8.666)	-0.873*** (-2.752)	-2.862*** (-4.749)	-1.513*** (-5.147)	-1.514*** (-4.585)	-8.681*** (-8.894)
	Corr(stock, bond)								
		0.144* (1.935)	-0.132** (-2.108)	-0.579*** (-3.913)	-0.143* (-1.811)	-0.178* (-1.775)	-0.00840 (-0.0783)	-0.341*** (-3.256)	0.0632 (1.021)
Corr(stock, FX)									
		0.0467 (0.617)	0.391*** (7.341)	0.732*** (6.182)	0.409*** (6.740)	0.466*** (6.022)	0.418*** (5.237)	0.556*** (6.725)	0.307*** (5.522)
Corr(bond, FX)									
		0.0189 (0.242)	0.0375 (0.628)	-0.710*** (-7.101)	-0.238*** (-3.551)	-0.253*** (-2.646)	-0.274** (-2.458)	-0.532*** (-6.524)	-0.0207 (-0.332)
Observations		452	484	531	387	388	484	531	531

z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

EQUATION	VARIABLES	Interaction w/ Crisis Dummy: Emerging Latin America				
		Argentina	Brazil	Chile	Colombia	Mexico
Stock Returns						
Mean eq.	Equity flows	0.192 (1.325)	0.0500 (0.359)	0.244** (2.553)	-0.00778 (-0.0935)	0.0536 (0.525)
	Equity flows*Crisis	1.779 (1.622)	1.188* (1.799)	0.182 (0.216)	0.808 (0.344)	1.259 (1.228)
	Crisis dummy	2.255** (2.030)	-0.136 (-0.130)	0.341 (0.404)	1.565** (2.096)	0.674 (0.809)
	VIX	-0.104*** (-3.524)	-0.0177 (-0.599)	0.00899 (0.435)	-0.0479** (-2.368)	-0.0478** (-2.153)
	Constant	2.012*** (3.760)	0.487 (0.893)	-0.0443 (-0.112)	1.203*** (3.039)	1.142*** (3.023)
	Variance eq.	L.arch	0.148* (1.698)	-0.0203 (-0.465)	0.521*** (2.879)	0.318*** (4.652)
	L.garch	0.617*** (2.982)	-0.0367 (-0.170)	0.229 (1.320)	0.499*** (5.736)	-0.0160 (-0.0699)
	VIX	0.0555*** (5.503)	0.0526*** (8.672)	0.0470*** (3.959)	0.0362*** (3.531)	0.0577*** (9.711)
	Constant	0.937 (1.290)	1.202*** (4.787)	0.636 (1.474)	-0.0124 (-0.0306)	0.743*** (2.829)
Bond Yield (change)						
Mean eq.	Bond flows	-2.421 (-1.548)	-1.858** (-2.224)	0.227 (0.806)	-2.243*** (-2.683)	-1.666*** (-2.604)
	Bond flows*Crisis	-24.56** (-2.192)	-8.676 (-1.559)	24.39** (2.306)	-11.83 (-0.564)	3.071 (0.536)
	Crisis dummy	-19.15 (-0.840)	-7.152 (-0.976)	1.411 (0.351)	-11.02 (-1.625)	1.705 (0.354)
	VIX	0.486 (1.574)	0.0804 (0.400)	-0.143** (-1.993)	-0.100 (-0.876)	-0.0132 (-0.109)
	Constant	-5.248 (-1.054)	-0.997 (-0.258)	2.412* (1.783)	2.503 (1.040)	-0.173 (-0.0792)
	Variance eq.	L.arch	0.171** (1.998)	0.0675 (1.497)	0.620*** (2.591)	0.445*** (5.334)
	L.garch	0.758*** (8.183)	0.518*** (3.554)	0.469*** (3.712)	0.705*** (18.28)	0.0555 (0.310)
	VIX	0.104*** (9.493)	0.0573*** (8.588)	0.0535*** (3.651)	-0.0615 (-0.821)	0.0328*** (5.312)
	Constant	3.806*** (6.860)	3.969*** (9.122)	2.205*** (4.344)	3.745*** (2.763)	4.644*** (19.66)
Exchange Rate Returns						
Mean eq.	Total flows	0.0345** (2.244)	0.253*** (4.537)	0.184*** (3.971)	0.00356 (0.0987)	0.116*** (2.958)
	Total flows*Crisis	0.190*** (2.850)	1.198*** (3.794)	-0.294 (-0.615)	1.942 (1.631)	1.132** (2.083)
	Crisis dummy	-0.254*** (-3.298)	-0.369 (-0.802)	0.490 (1.221)	0.686 (0.811)	0.122 (0.272)
	VIX	0.00440* (1.655)	0.000953 (0.0737)	-0.0132 (-1.266)	-0.00947 (-1.235)	-0.0203** (-2.424)
	Constant	-0.251*** (-3.783)	0.0661 (0.280)	0.252 (1.323)	0.179 (1.514)	0.350** (2.510)
	Variance eq.	L.arch	0.493*** (3.524)	0.0433 (1.164)	0.221*** (2.745)	0.297*** (5.413)
	L.garch	0.724*** (10.02)	-0.414*** (-2.777)	0.775*** (10.63)	0.746*** (18.48)	0.738*** (5.453)
	VIX	-0.0938 (-0.862)	0.0648*** (9.085)	0.0618*** (4.163)	0.0822*** (4.525)	0.0766*** (9.061)
	Constant	-2.903* (-1.772)	-0.562** (-2.359)	-2.608*** (-4.108)	-5.064*** (-6.967)	-3.302*** (-4.390)
Corr(stock, bond)		0.119 (0.153)	-0.189* (-1.899)	0.0191 (0.313)	-0.148 (-1.555)	-0.195*** (-2.781)
Corr(stock, FX)		-0.431 (-0.306)	0.420*** (5.271)	0.186*** (3.070)	0.277*** (3.097)	0.310*** (4.317)
Corr(bond, FX)		0.422 (0.242)	-0.257*** (-2.845)	0.0924 (1.495)	-0.392*** (-4.701)	-0.272*** (-3.867)
Observations		440	392	374	531	531

z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

		Interaction w/ Crisis Dummy: Emerging Europe					
EQUATION	VARIABLES	Bulgaria	Hungary	Poland	Russia	Turkey	
Stock Returns							
Mean eq.	Equity flows	0.161 (1.591)	0.249** (2.060)	0.132 (1.222)	-0.0517 (-0.424)	-0.0487 (-0.335)	
	Equity flows*Crisis	4.292*** (2.693)	2.531* (1.912)	0.783 (1.122)	4.246 (1.436)	1.142 (1.253)	
	Crisis dummy	0.841 (0.662)	2.139** (2.065)	1.162 (1.416)	-0.295 (-0.167)	1.213 (1.191)	
	VIX	-0.104*** (-5.133)	-0.0736*** (-2.894)	-0.0646*** (-3.034)	-0.0292 (-0.997)	-0.0348 (-1.275)	
	Constant	1.981*** (5.010)	1.435*** (3.319)	1.455*** (3.957)	0.887* (1.797)	0.929* (1.923)	
	Variance eq.	L.arch	0.330* (1.826)	0.192*** (2.917)	0.0380 (0.986)	0.223*** (3.674)	0.00966 (0.566)
L.garch		0.720*** (3.959)	-0.0423 (-0.179)	-0.279 (-1.236)	0.862*** (22.50)	-0.833*** (-11.34)	
VIX		0.0804*** (4.256)	0.0556*** (8.542)	0.0453*** (7.327)	0.0475 (0.238)	0.0331*** (5.774)	
Constant		-1.608 (-1.232)	1.047*** (3.179)	1.210*** (4.981)	-1.389 (-0.443)	2.560*** (19.38)	
Bond Yield (change)							
Mean eq.		Bond flows	-0.412 (-0.661)	-2.462*** (-3.424)	-1.508*** (-3.646)	-1.153*** (-4.098)	-0.765 (-1.595)
	Bond flows*Crisis	-2.214 (-0.570)	-3.317 (-0.442)	3.676 (1.079)	2.512 (0.446)	-10.20*** (-2.691)	
	Crisis dummy	2.474 (0.421)	-8.606 (-0.883)	1.275 (0.472)	8.076 (1.247)	-3.556 (-0.672)	
	VIX	-0.0881 (-1.128)	0.356** (2.533)	0.0844 (1.311)	0.123*** (2.907)	-0.0619 (-0.878)	
	Constant	1.891 (1.282)	-6.774*** (-2.852)	-1.931 (-1.565)	-2.207*** (-3.130)	0.656 (0.604)	
	Variance eq.	L.arch	0.610*** (3.576)	0.0963*** (3.689)	0.151*** (4.370)	0.345*** (3.722)	0.349*** (5.475)
L.garch		0.575*** (6.992)	0.823*** (24.87)	0.784*** (16.26)	0.783*** (18.11)	0.709*** (20.07)	
VIX		0.0782*** (3.040)	0.0843*** (8.956)	0.0506*** (2.906)	0.106*** (4.739)	0.162*** (9.122)	
Constant		1.798*** (2.622)	1.593*** (3.791)	0.866 (1.187)	-1.146 (-1.590)	-2.356*** (-3.290)	
Exchange Rate Returns							
Mean eq.		Total flows	0.0185 (0.281)	0.0312 (0.507)	0.114* (1.743)	0.113*** (4.302)	0.0469 (1.013)
	Total flows*Crisis	0.448 (1.434)	0.488 (0.865)	-0.121 (-0.207)	0.341 (0.493)	0.279 (0.840)	
	Crisis dummy	0.691* (1.778)	0.862 (1.344)	-0.0232 (-0.0405)	-0.0885 (-0.225)	0.189 (0.446)	
	VIX	-0.0256*** (-2.607)	-0.0412*** (-3.014)	-0.0257* (-1.711)	-0.00321 (-0.519)	-0.0197** (-2.019)	
	Constant	0.550*** (2.953)	0.735*** (3.192)	0.575** (2.327)	0.101 (1.042)	0.310* (1.873)	
	Variance eq.	L.arch	0.123 (1.394)	0.0359 (0.999)	0.0357 (0.758)	0.200*** (3.329)	0.279*** (4.492)
L.garch		0.765*** (5.513)	0.702*** (3.795)	-0.0549 (-0.126)	0.882*** (32.61)	0.399*** (3.286)	
VIX		0.0502*** (4.001)	0.0595*** (9.051)	0.0598*** (8.838)	0.0968*** (4.612)	0.0539*** (6.824)	
Constant		-2.001** (-2.342)	-1.554** (-2.063)	-0.266 (-0.582)	-5.996*** (-7.246)	-1.514*** (-4.585)	
Corr(stock, bond)							
			-0.0150 (-0.182)	-0.319*** (-5.574)	-0.241** (-2.253)	-0.186** (-2.223)	-0.341*** (-3.256)
Corr(stock, FX)							
		0.0109 (0.134)	0.360*** (6.481)	0.430*** (4.005)	0.259*** (3.068)	0.556*** (6.725)	
Corr(bond, FX)							
		-0.0532 (-0.656)	-0.522*** (-11.24)	-0.343*** (-3.556)	-0.253*** (-3.222)	-0.532*** (-6.524)	
Observations		348	531	531	530	531	

z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1