The Dynamics of Capital Flow Episodes*

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Abstract

In this paper, we first propose a novel methodology for identifying episodes of equity and bond flows that employs estimates from a regime-switching model, which has the advantage of keeping context- and sample-specific assumptions to a minimum. We then use a time-varying structural vector-autoregressive (VAR) model to assess the impact of U.S. stock market volatility (VIX) shocks and U.S. monetary policy shocks on aggregated measures of equity outflow and equity inflow episodes. Our results indicate that both VIX and U.S. monetary policy shocks had substantially time-varying effects on episodes of strong capital flows over our sample period.

Keywords: capital flow episodes; Markov-switching models, global financial cycle

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1 Introduction

Following the triad of events comprising the global financial crisis, unconventional monetary policies and negative interest rates in many advanced economies, the assessment of global capital flow dynamics has forcefully re-entered the research agendas of policy-makers and academics. In particular, these recent experiences have renewed the interest in investigating and understanding the determinants and consequences of international capital flows.

Building on the seminal work of Forbes and Warnock (2012) and Ghosh et al. (2014), who classify episodes of strong capital flows in quarterly and annual data, respectively, we contribute to this research agenda in two ways.[1] First, using equity and bond fund flow data at a weekly frequency, we employ a novel methodology for identifying episodes of strong capital flows in high-frequency data that is based on estimates from a regime-switching model. A key advantage of regime-switching models is that they allow us to determine the underlying regimes endogenously, without the need for context- and sample-specific assumptions. Moreover, using high-frequency data is important, since it allows us to obtain a timely and precise classification of sharp movements in capital flows, which would be difficult to obtain with Balance of Payments (BoP) data due to their lower release frequencies and publication lags. Second, we then use a structural vector-autoregressive (VAR) model with time-varying parameters to study the dynamic interactions between aggregated measures of equity flow episodes and global drivers of capital flows, such as U.S. stock market volatility shocks and U.S. monetary policy shocks, over time.

Our first contribution relates to a growing literature that examines consequences and implications of international capital flows. In particular, it concentrates on the impact of capital flows on destination countries, mostly emerging markets. Examples of such impacts are credit booms and currency mismatches on the financial side and appreciating currencies and inflationary developments from a macroeconomic perspective. To investigate these issues, the literature makes increasing use of episode classifications to separate extended periods of strong capital flows from regular fluctuations.[2]

In the context of international capital flows, an episode classification is particularly helpful for two reasons. First, since capital flows are volatile (e.g., see Bluedorn et al. (2013)), the aggregation of individual capital flow observations into episodes can provide a clearer pattern of the direction and the magnitude of flows. Second, the literature has shown that the macroeconomic effects of capital flows can differ according to the level of capital flows

[1] Earlier studies that have empirically identified episodes of strong capital flows are Calvo et al. (2004) for "sudden stop" episodes as well as Reinhart and Reinhart (2009) and Cardarelli et al. (2010) for "surges."

[2] Examples of studies that have recently worked with episode classifications are Caballero (2014), Magud et al. (2014), Benigno et al. (2015), and Eichengreen and Gupta (2016).

(e.g., see Abiad et al. (2009)). Thus, some of the macroeconomic or financial effects of capital flows can only be observed when the level of flows reaches a certain magnitude.

The corresponding classification of capital flow episodes has mainly been popularized by Forbes and Warnock (2012) and Ghosh et al. (2014). Forbes and Warnock (2012) divide episodes of strong capital flows into "surges" (inflows of capital from foreigners), "stops" (outflows of capital from foreigners), "retrenchments" (inflows of capital from residents) and "capital flights" (outflows of capital from residents). Based on a threshold approach that identifies deviations from a long-term average as periods of strong capital flows, the authors apply these categorizations to gross capital flows from the BoP in a sample of 58 emerging and developed economies at quarterly frequencies between 1980 and 2009. Ghosh et al. (2014) instead focus on surges of net capital flows. The authors use a related, but differently defined, identification methodology than in Forbes and Warnock (2012) and apply their episode definitions to annual BoP data in a sample of 56 emerging-market economies between 1980 and 2011.

Complementing quarterly and annual classifications of capital flow episodes with a classification for high-frequency data is desirable for at least two reasons. First, from an academic view point, it is important to better understand the transmission of shocks across the global financial system, such as the impact of U.S. monetary policy shocks and U.S. stock market volatility shocks on other countries. Amplified by high levels of financial integration and the widespread use of the U.S. dollar, these shocks can be transmitted rapidly into domestic financial systems with potentially adverse implications for financial stability. Second, from a more practical view point, it is often of first order importance for central banks and various other policy institutions to monitor international capital flow dynamics in a timely manner. Since BoP data are released at low frequencies and with substantial time lags, the use of weekly capital flow data provides timely information for monitoring emerging patterns more thoroughly and gives policy-makers additional time to respond.

Based on data that record equity and bond fund flows into up to 80 different countries[3] at weekly frequency over the period 2000 to 2014, we identify episode types that are most closely related to the definition of surges and stops by Forbes and Warnock (2012) and partially to the definition of net surges by Ghosh et al. (2014). Following the application of our methodology, we show that the differences in estimated in- and outflow regimes within a country correlate negatively with the quality of its institutions and the level of financial development as well as positively with the country's share of foreign currency liabilities. We also document the main features of equity and bond flow episodes, such as their frequency of appearance and their average length for both advanced and emerging-market economies.

[3]There are 65 countries in our equity sample and 66 countries in our bond sample. The notion of 80 different countries emerges since several countries appear in only one of the two samples.

Our second contribution, the subsequent analysis of aggregated capital flow dynamics, relates to a stream of literature that assesses the determinants of international capital flows. Dating back at least to Calvo et al. (1993), who introduced the distinction between international "push" and domestic "pull" factors, a rich body of literature developed and culminated in a wealth of studies analyzing capital flow dynamics during and after the global financial crisis.[4] Our analysis relates in particular to recent work by Rey (2013), who argues that asset prices and capital flows closely follow the dynamics of U.S. monetary policy and U.S. stock market volatility. Rey suggests that this so called "global financial cycle" reduces the traditional trilemma – the impossibility of having independent monetary policy, an open capital account and a fixed exchange rate at the same time – to a dilemma by leaving policy-makers only the choice between independent monetary policy and an open capital account, even in the presence of a freely floating exchange rate. Hence, the effects that U.S. macroeconomic and financial shocks have on international capital flows are of high interest to policy-makers and academics.

The results of our structural VAR analysis indicate that both U.S. stock market volatility, measured by the VIX,[5] and U.S. monetary policy had substantially time-varying effects on episodes of strong capital flows over our sample period. The impact of a VIX shock has been stronger in times of crises but has almost consistently led to more equity outflow episodes and fewer equity inflow episodes in each period. The impact of a U.S. monetary policy shock, however, has changed sign over our sample period in that, in the wake of the financial crisis, such a shock has led to more equity outflow episodes and fewer equity inflow episodes compared with the pre-crisis period. On the one hand, our results support the earlier findings by Rey (2013) that U.S. macroeconomic and financial shocks affect the economic and financial cycles of other countries substantially. On the other hand, our results show that the impact of these shocks on the rest of the world differs substantially over time – making it potentially even more difficult for policy-makers elsewhere to design an appropriate policy response.

Our paper is organized into four sections and proceeds as follows. After this introduction, Section 2 presents our methodology for identifying episodes of strong capital flows, henceforth simply referred to as "episodes,"[6] in high-frequency data. In particular, this section contains a description of the empirical methodology and a discussion of our episode-classification re-

[4]The most prevalent methods in the literature are factor models (e.g., Forster et al. (2014), Puy (2016), and, with a focus on the global financial crisis, Fratzscher (2012)); and panel data models (e.g., Ahmed and Zlate (2014); Bruno and Shin (2015a), and, with a focus on the global financial crisis, Milesi-Ferretti and Tille (2011)). Also, the cyclical properties of capital flows have been analyzed frequently (e.g., Contessi et al. (2013), Broner et al. (2013), and Bussière et al. (2016)).

[5]VIX refers to the CBOE index of implied volatility on S&P500 options.

[6]Periods with strong capital inflows are referred to as "inflow episodes" and periods with strong capital outflows are referred to as "outflow episodes."

sults. Section 3 then presents the results of a structural VAR analysis that assesses the impact of VIX shocks and U.S. monetary policy shocks on aggregated measures of equity inflow and outflow episodes across our sample countries. Finally, Section 4 concludes.

2 Classification of Capital Flow Episodes

This section proposes a methodology that is well suited for identifying capital flow episodes in high-frequency data and novel in the context of capital flows. We first highlight the motivation for adapting a new methodology in the context of high-frequency data, characterize the nature of our data and describe our econometric approach. We then present the outcome of the estimation process and discuss the results of our empirical analysis.

2.1 Episode Classification Methodology

2.1.1 Motivation

While the most common methodology to identify capital flow episodes in the existing literature is based on a threshold approach, which assigns periods with above-threshold values the label of an "episode," there is no agreement on how to design the underlying threshold. Forbes and Warnock (2012) and Ghosh et al. (2014), for example, use two largely different threshold definitions to identify episodes of "surges" in BoP data.

Forbes and Warnock (2012), on the one hand, compute rolling means and standard deviations of year-on-year changes in quarterly gross capital flows over the last five years. The authors then define a surge episode as fulfilling two conditions: (i) capital flow dynamics are eligible for an episode classification as long as the year-on-year changes in capital flows are greater than one standard deviation above the rolling mean; and (ii) to be eventually counted as an episode, there must be an increase of year-on-year changes in capital flows of more than two standard deviations above the rolling mean during at least one quarter of the episode. Ghosh et al. (2014), on the other hand, work with data at annual frequency and define a surge episode based on the following two conditions: (i) an observation is eligible to be classified as a surge episode if it lies in the top 30$^{\text{th}}$ percentile of the country's own distribution of net capital flows (as a percentage of GDP); and (ii) to be eventually counted as an episode, the observation also has to be in the top 30$^{\text{th}}$ percentile of the entire (cross-country) sample's distribution of net capital flows (as a percentage of GDP).

However, even if there was a common approach in the literature, threshold values could require additional adjustments depending on the characteristics of the dataset, such as data frequency (e.g., annual vs. higher-frequency), country type (e.g., advanced economies vs.

emerging markets), time period (e.g., inclusion of the 1980s, the global financial crisis, etc.) asset class (e.g., foreign direct investment vs. portfolio flows) and capital flow definition (e.g., gross vs. net flows). While episode classifications based on threshold approaches for low-frequency data have served well in the past and have been generally in line with anecdotal evidence, it is challenging to convincingly select the appropriate threshold for high-frequency data in the absence of a "true" benchmark for capital flow episodes. In particular, exogenously imposed thresholds based on moments of the capital flow distribution for annual or quarterly data may not be appropriate for high-frequency data, which is characterized by a higher degree of volatility.

We therefore propose a novel methodology for identifying capital flow episodes in high-frequency data based on estimates from a set of country-specific regime-switching models that allow us to determine the underlying regimes endogenously, without the need to make explicitly context- and sample-specific assumptions. This approach is also particularly suitable to monitor capital flow movements in real-time, which is of prime importance for policy-makers.[7]

2.1.2 Data

We use weekly data from the Emerging Portfolio Fund Research (EPFR) database, which records international equity and bond fund flows at high frequencies. The EPFR data have featured prominently in the literature, such as in Jotikasthira et al. (2012) and in Fratzscher (2012), who recently used major components of the data that we are employing. In addition, Fratzscher states that the EPFR's fund flow data *"[...] is the most comprehensive one of international capital flows, in particular at higher frequencies and in terms of its geographic coverage at the fund level."*

There are two main differences between equity and bond fund flows from the EPFR database and conventional BoP data. The first difference refers to the coverage of asset classes. BoP data, on the one hand, records all foreign direct investment flows, portfolio equity and debt investment flows as well as other investment flows (which are mostly bank flows) of a country. The EPFR data, on the other hand, cover only portfolio equity and debt investments and thus do not represent the universe of capital flows.[8] The second difference relates to the coverage of financial system participants. While the BoP records cross-border capital flows by all participants of the financial system, regardless of their location, the EPFR

[7] In addition, most of the definitions of capital flow episodes in the literature lead to a binary indicator that provides limited information on how distant the actual data are from the threshold. In contrast, a probabilistic approach, such as the one introduced below, could better reflect the uncertainty surrounding the estimation of capital flow episodes, and how likely a country is to enter or exit such episodes, which constitutes important information for policy-makers and financial market participants.

[8] One important implication of this fact is that capital inflows and outflows across all sample countries do not necessarily sum to zero in our analysis.

data are limited to international investments that are intermediated by equity and bond funds and thus comprise only a subset of financial system participants as well as only those capital movements that originate abroad (i.e., from non-residents). However, since the segment of equity and bond fund flows is an important part of total flows and financial transactions by non-residents have traditionally been highly relevant, in particular for emerging markets, the more timely available EPFR database has become a key data source for policy institutions.

Further, Pant and Miao (2012) show for emerging-market economies that there is a strong correspondence between the U.S.-dollar values of EPFR and BoP data. Since our measure of capital flows is defined as the percentage change in outstanding investments, we present additional evidence in this paper that the alternative measurement of capital flows does not affect the comparability of data across the two sources. In particular, we compare the quarter-on-quarter growth rates of weekly EPFR data and quarterly BoP data for equity inflows into Brazil.[9] Figure 1 indicates that the two growth rates follow each other closely and shows that their correlation coefficient amounts to 0.54. Hence, these observations suggest that the weekly EPFR data and the quarterly BoP data experience largely similar capital flow dynamics.

The EPFR data that we use are aggregated to the destination country level and are characterized by the "country flows" concept, which is defined as the product of capital inflows into investment funds (i.e., the "fund flows" dimension) and the respective country allocation of these investment funds (i.e., the "country allocation" dimension).[10] We therefore obtain a country-time-specific value of net capital inflows for each country. The data are expressed as a percentage change in outstanding investments (i.e., the total estimated allocation of money in absolute dollar terms) at the start of the period (i.e., the previous week).[11]

[9] For the EPFR data, which record equity inflows as the percentage change in outstanding equity investments at the start of a week, we conduct the following modifications. First, we apply all weekly percentage changes in equity inflows into Brazil to an index that takes on the value of 100 at the beginning of our sample. Second, we use this cumulated series of week-on-week growth rates to derive the corresponding quarter-on-quarter growth rates. For the BoP data, we start from a measure that captures the quarterly change in Brazil's net foreign equity liabilities in U.S. dollars. First, to normalize this series by the equivalent of the outstanding investments, we take the ratio of the U.S.-dollar figure to quarterly GDP. Second, we cumulate the series and derive the corresponding quarter-on-quarter growth rate. While the overlapping period between both data sources is 2001 to 2011, we start the comparison in 2002 to reduce the impact of the initial growth rates.

[10] Consider the following example: To calculate the country flows to Country X, the fund weightings for Country X are multiplied by each fund group's net fund flows for the period. The resulting country flow is then an estimate of how much new investor money will be put to work in Country X.

[11] In the EPFR database, this definition is denoted as "Country Flow/$US\$\%$". We also do not restrict investment funds to be from a specific source country and thus use investment funds from "all domiciles" in our sample.

We treat the data for equity and bond flows separately as they come with varying country coverage and sample start dates. The final sample for equity flows contains data from 65 advanced and emerging-market countries, and the start date ranges from the last week of October 2000 to the last week of July 2006, depending on data availability (precise details on the criteria we used to select the underlying series are presented in Appendix A).[12] The final dataset of bond flows contains 66 countries and the start date extends from the first week of January 2004 to the first week of January 2006. The end date of both the estimation samples is the last week of December 2014. Finally, to reduce the impact of outliers in the empirical analysis, we winsorize the capital flow data of each country at the top 1 per cent and the bottom 1 per cent of the capital flow distribution.

Our data choice determines also the types of episodes that we can identify. As pointed out in the introduction, Forbes and Warnock (2012) and Ghosh et al. (2014) are the two most closely related studies that identify capital flow episodes. Using data from the EPFR database with the above discussed characteristics, we can identify two types of episodes: "inflow episodes" – corresponding to the surges definition from Forbes and Warnock (2012) – and "outflow episodes" – corresponding to their definition of stops.[13] While there is a certain correspondence between our measure of inflow episodes and the measure of net flow surges from Ghosh et al. (2014), the results of our analysis will be more closely related to those of Forbes and Warnock (2012), since the definition of net flow surges in Ghosh et al. (2014) contains capital movements by residents, for which we do not have data.

2.1.3 The Regime-Switching Model

Regime-switching models have been used in economics and finance since the seminal work of Hamilton (1989). In particular, they have been widely applied in the context of business cycle analysis (see, for example, Chauvet (1998)) and empirical macroeconomics to study, for example, the effects of monetary policy across different regimes (see Sims and Zha (2006)). Likewise, there is a vast body of literature on regime changes in finance (see, e.g., the literature review in Ang and Timmermann (2012)). The underlying idea of Markov-switching models is to estimate discrete changes from a continuous variable. Hence, when studying capital flows, regime-switching models allow us to estimate discrete shifts in the data from the (continuous) capital flows series.

[12] The emerging-market sample contains a few countries that are generally considered to be low-income countries rather than emerging markets. However, in order to keep the analysis tractable, we refer to the group of emerging-market and low-income countries as "emerging markets" in the remainder of the paper.

[13] Investments (disinvestments) in investment funds by residents of a large country can take on traces of capital flights (retrenchments), when the associated fund is predominantly funded from the home country. However, given that we do not restrict the selection of investment funds along the geographical dimension, the investments carried out by residents of a single country should be sufficiently small.

Following Baele et al. (2014), who estimate a three-regime Markov-switching model using equity and bond returns to estimate flight-to-safety episodes, we fit a three-regime Markov-switching model to the EPFR equity and bond flow series. The first regime with a negative intercept (i.e., $\mu_1 < 0$) is associated with strong outflows, the third regime with a positive intercept (i.e., $\mu_3 > 0$) is associated with strong inflows, and the second regime is a "normal" regime, where capital flows exhibit neither strong increases nor strong decreases (i.e., $\mu_1 < \mu_2 < \mu_3$). A key advantage of using data at a weekly frequency is that it allows us to better track fluctuations in capital flows.[14] In detail, the baseline univariate model we estimate is

$$y_{i,t} = \mu_i(S_t) + \epsilon_{i,t}(S_t), \tag{1}$$

where $\epsilon_{i,t}|S_t \sim \mathrm{N}(0,\sigma_i^2)$, and $y_{i,t}$ is the portfolio data associated with either equity or bond flows for country i at time t.[15] We estimate all regime-switching models with quasi-maximum likelihood, using the expectation-maximization algorithm (see Hamilton (1990)).[16]

2.2 Episode Classification Results

2.2.1 Estimation Results from the Regime-Switching Model

Table 1 presents the results of the country-specific regime-switching models that were estimated separately for equity and bond flows. The table shows the average parameter estimates of all sample countries as well as the average of the parameter estimates calculated from advanced and emerging markets only (see Appendix B for a definition of these country groupings). For illustrative purposes, we also report individual estimation results for the United States and Brazil – an advanced country and an emerging market from our dataset.

The results indicate that the first regime is systematically associated with (large) negative outflows (i.e., $\mu_1 < 0$), and the third regime with large positive inflows (i.e., $\mu_3 > 0$ and $\mu_3 > \mu_2$). Finally, the second or "normal" regime is characterized by neither strong inflows nor strong outflows (i.e., $\mu_1 < \mu_2 < \mu_3$).[17] Moreover, the differences in the intercepts'

[14]Note that EPFR data are also available at a daily frequency. However, following Fratzscher (2012), we refrain from using such data because it is unlikely that fund managers make portfolio decisions at such high frequency.

[15]Note that we also model changes in the variance of the innovation, since we obtained a better fit with such a specification. The innovation variance in the second regime is systematically lower than the innovation variance in the other two regimes.

[16]The regime-switching models are estimated with the GAUSS 9.0 software without imposing constraints on the model parameters, except for the transition probabilities to ensure irreducibility of the Markov chain.

[17]We also implemented the Carrasco et al. (2014) test for regime-switching parameters in the mean and variance of equation (1). In all cases, we found overwhelming evidence in favor of regime-switching parameters. Detailed results are available on request.

estimates, defined as $\mu_3 - \mu_1$, in both equity and bond flows are lower for the group of advanced economies than for the group of emerging markets in our sample.

Figure 2 explores this finding further and provides correlation evidence between the differences in intercepts across regimes (left axes), i.e., $\mu_3 - \mu_1$, and potential explanatory variables (bottom axes). The six variables are the gross domestic product (GDP) per capita in purchasing-power-parity (PPP) units (to represent the income difference between both country groups), the real GDP growth rate in percent, a measure of institutional quality, private credit as a percentage of GDP, stock market capitalization as a percentage of GDP and the share of liabilities in foreign currency.[18] In the first five cases, we observe a negative correlation, suggesting that a higher per capita income, more real GDP growth, a higher quality of institutions and more financial development are associated with a lower difference in the intercepts of the two extreme regimes for a country. In addition, a higher share of foreign currency liabilities is associated with a larger difference in regime intercepts. Hence, in line with the previous literature on boom and bust cycles in emerging markets, these correlations suggest that countries, which are characterized by poor macroeconomic/growth performance, weak institutions (e.g., Klein (2005)), a low level of financial development (e.g., Caballero and Krishnamurthy (2001)) and a high share of foreign currency liabilities (e.g., Eichengreen et al. (2003)), will experience more distinct inflow and outflow regimes; that is, more abrupt changes in capital flows.

Turning next to the transition probabilities, we find that regimes in advanced economies are more persistent than in emerging-market economies. This is the case because the transition probabilities of staying in each regime (p_{11}, p_{22}, and p_{33}), are systematically higher in the first compared to the second country group. When focusing on the unconditional probabilities of being in a certain regime, it turns out that overall the second regime is the most prevalent one, since the unconditional probability of being in the second regime, $(P(S_t = 2))$, is the highest compared with those of being in any of the other regimes in almost all cases.

Finally, the individual estimation results for the United States and Brazil confirm the evidence obtained from the aggregated results. In particular, we find for both equity and bond flows that the differences in regime intercepts are smaller for the United States than for Brazil, that regimes are more persistent in the United States than in Brazil and that both countries will spend most of the time in the second regime. However, relative to the United States, Brazil is more likely to spend time in the two extreme regimes (because the unconditional probabilities of the first and the third regime are higher for Brazil).

[18] To reduce the impact of capital flows on these variables, we rely on the 1999 values of all six variables.

2.2.2 Episode Classification and Discussion of Findings

Based on Table 2, this section presents and discusses the classification of different types of episodes and their appearance across different country groupings. We obtain a separate set of episodes for equity outflows, equity inflows, bond outflows and bond inflows and present these results aggregated across all sample countries, across all advanced countries and across all emerging markets of our sample.[19] The column "Avg. Probability" in Panel A presents the average probability of being in a different regime than the normal regime. To move from here to a discrete outcome variable that indicates the presence of a distinct pattern of capital flows, we define two additional conditions that, when fulfilled, characterize an "episode."[20] Both conditions are based on information contained in the smoothed regime probabilities. The first condition is that the probability of being in a regime other than the normal one is greater than 50 percent. The second condition is that this is the case for at least four consecutive weeks. The column "Avg. Share in Episode" presents the result of the corresponding episode classification by indicating the average time of the sample period that the three country groupings spend in each type of episode. Moreover, the column labelled "Frequency" indicates the frequency with which each type of episode appears over the sample period and the column "Avg. Length" contains information on its associated average length. Based on Panel A of Table 2, we derive five facts from the episode classification exercise.

First, even though the average probability obtained from the regime-switching model is by definition higher than the average share of inflow and outflow episodes, the similarity of both series suggests that periods of strong capital flows generally extend beyond four weeks.

Second, the average country in the sample spends between 21.1 and 26.8 percent of the time in each type of episode. While, the average time that advanced and emerging markets spend in each type of bond flow episode is very similar (i.e., 19.5 and 21.8 for bond outflows from advanced countries and emerging markets, respectively; 26.2 and 27.1 for bond inflows into both country groupings, respectively), the average time that advanced countries spend in both types of equity flow episodes is significantly larger than the time that emerging markets spend in such episodes (i.e., 33.2 and 22.1 for equity outflows from advanced countries and emerging markets; 29.4 and 19.5 for equity inflows into both regions, respectively).

Third, we observe that the average country in the sample faces equity flow episodes more frequently than bond flow episodes (i.e., 12.8 equity outflow and 9.9 equity inflow episodes compared with 7.3 bond outflow and 8.0 bond inflow episodes). While the distribution of frequencies between advanced and emerging-market economies is fairly similar in three out

[19]The disaggregated country-specific results are available on request.

[20]These assumptions are only required to convert the probabilities of being in a given regime into discrete measures of episodes as they are commonly used in the literature. Depending on the application, one could work with these probabilities directly and there would be no need for any additional assumptions.

of the four cases, equity outflow episodes have a significantly higher frequency in emerging markets (14.7 cases for the average emerging country) than in advanced countries (9.3 cases for the average advanced country).

Fourth, we see that for the average country in the sample, the length of outflow episodes (i.e., 17.4 weeks for equity outflow episodes and 16.8 weeks for bond outflow episodes) is shorter than the length of inflow episodes (i.e., 20.0 weeks for equity inflow episodes and 19.0 weeks for bond inflow episodes). We also observe that advanced countries (between 21.2 weeks in the case of bond outflow episodes and 30.3 weeks in the case of equity outflow episodes) experience a significantly higher persistence of episodes than emerging markets (between 10.4 weeks for equity outflow episodes and 17.0 weeks for bond inflow episodes).

Finally, in Panel B of Table 2, we examine the contemporaneous correlation coefficient of episodes across asset classes for the entire sample as well as for advanced countries and for emerging markets separately.[21] A strong positive correlation between both capital classes could be an indication that investors do not substantially differentiate between asset classes within countries (e.g., because of the presence of country-specific risks or a lack of information about a country). A negative number, on the other hand, could point to a higher differentiation because of fewer country-specific risks or a better availability of information. Starting with the correlation between equity outflows and bond outflows, the number for the overall sample amounts to 0.36 and indicates that both asset classes behave in a fairly synchronized way. Splitting up the number into a separate one for the two country groupings shows that investors differentiate more often between asset classes in advanced countries (where the correlation amounts to 0.27) than in emerging markets (where the correlation amounts to 0.42). The correlation between equity inflows and bond inflows for the average country in the overall sample is somewhat lower and amounts to 0.17, with, again, a higher correlation coefficient for the average emerging market (0.26) than for the average advanced country (0.05).

3 Equity Flow Episodes and the Global Financial Cycle

In this section, we study the dynamic interactions between the share of countries in equity flow episodes and a set of global factors, such as U.S. stock market volatility and the U.S. monetary policy stance, using vector-autoregression (VAR) models along the lines of Bruno and Shin (2015b). Thematically, our analysis relates closely to the literature on the global financial cycle, proposed by Rey (2013), who argues that the VIX is the main driver of international capital flows and asset prices and that U.S. monetary policy shocks in turn are strong drivers of the VIX. We conduct our analysis using first a linear VAR, followed by a

[21]The disaggregated country-specific results are available on request.

time-varying parameter VAR that allows us to model the changing impact of the two shocks on our measures of capital flow episodes over time.

3.1 Empirical Methodology

3.1.1 Data

Our VAR models build on the empirical methodology in Bruno and Shin (2015b). We adapt their VAR specification for the international dimension to our research question by replacing their measure of international bank flows with our measure of countries in capital flow episodes. As in Bruno and Shin (2015b), we further include the U.S. real federal funds rate, to measure the U.S. monetary policy stance, and the VIX, to capture U.S. stock market volatility. We deviate slightly from their specification (i) by replacing their measure of banking sector leverage with a measure of the U.S. business cycle since our research question deals with market-based instead of bank-based financial intermediation and (ii) by abstracting from the computation and inclusion of a real effective exchange rate as its value-added in a cross-country sample is very limited. Next, we describe the variables included in our VAR models in detail:

Capital Flow Episodes: We use the share of countries in an equity outflow episode and the share of countries in an equity inflow episode as two separate measures of capital flow episodes across countries.[22] In doing so, we rely on a measure that comprises all countries in our sample as well as on two other measures that focus on the country groupings of emerging markets and advanced economies, respectively. We concentrate our analysis on equity flow data, since bond flow data are available only over a shorter sample period. Figures 3 and 4 present the share of countries in an equity outflow and an equity inflow episode (for the entire sample and for both country groupings separately). The peaks of the outflow share measures are located in the aftermath of the dot-com bubble and during the global financial crisis. The peaks of the inflow share measures are clustered in the four years prior to the global financial crisis and appear sporadically during the post-crisis period as well.

U.S. Stock Market Volatility: We use the CBOE index of implied volatility on S&P500 options (VIX) in the VAR system, since it is a commonly used measure of global financial market volatility (see, e.g., Rey (2013)). The VIX is an attractive measure to proxy the global financial cycle in that it directly captures not only financial market volatility, but also uncertainty to the extent that it is related to financial markets fluctuations.

[22]Note that we use the share of countries in a given regime directly in the VAR model for consistency in the analysis throughout the paper, but impulse responses based on a log scale for the share of countries in a given regime yield qualitatively similar results.

U.S. Monetary Policy Stance: A standard choice for evaluating the effects of monetary policy is to use the effective federal funds rate (see, e.g., Christiano et al. (1999) or Bernanke et al. (2005)). However, as the federal funds rate reached the zero lower bound in December 2008 and the Federal Reserve started large-scale asset purchases, the short-term interest rate no longer conveyed comprehensive information about the stance of U.S. monetary policy. As a result, our measure of monetary policy is the effective federal funds rate until December 2008, complemented by the Wu and Xia (2015) shadow federal funds rate for the period extending from January 2009 to December 2014.[23] As in Bruno and Shin (2015b), we use the real federal funds rate; that is, we subtract the annual change in the CPI from the nominal short-term rate. Figure 5 represents this measure of monetary policy, i.e., the real federal funds rate until December 2008, and the estimated real shadow interest rate from January 2009.

U.S. Business Cycle Fluctuations: Finally, we use U.S. industrial production as a measure of business cycle fluctuations (taken as 100 times the change in the log index), since it is a widely used measure of U.S. monthly economic activity.

While Bruno and Shin (2015b) do not include pull factors, such as the state of the business cycle and the monetary policy stance in countries other than the U.S., in their specification, it should be noted that the relevance of pull factors as determinants of international capital flows has been demonstrated in the past. We therefore check the correlation between our measure of the U.S. business cycle and the (real) U.S. monetary policy stance with their respective counterparts calculated from all other countries in our sample. Since we obtain highly positive correlations of 0.79 in case of the median (0.79 in case of the mean) for the business cycle and of 0.78 (0.58) for the real policy interest rate, we follow Bruno and Shin (2015b) again and abstract from pull factors in our analysis as well.[24]

[23]In detail, Wu and Xia (2015) derive a shadow interest rate from a term-structure model. Based on this shadow interest rate, they find that monetary policy affects the U.S. macroeconomic environment in a similar fashion in the post- and pre-Great Recession periods, suggesting that using the Wu and Xia (2015) shadow federal funds rate from January 2009 onwards is appropriate to study the effects of monetary policy in a sample that includes zero lower bound episodes.

[24]It should further be noted that the identification of episodes has been conducted separately for each country so that the intercepts of the Markov-switching models are country-specific. This implicitly controls for all country-specific factors that are time-invariant.

3.1.2 VAR Methodology

Linear VAR Model

We first conduct our analysis with a linear VAR model. The reduced-form version of the model is a K-dimensional VAR(p) model

$$Y_t = \nu + A_1 Y_{t-1} + ... + A_p Y_{t-p} + U_t, \tag{2}$$

where Y_t is a $(K \times 1)$ vector of observable time series, ν is a constant term, the A_js $(j = 1, ..., p)$ are $(K \times K)$ coefficient matrices and U_t is a zero-mean error term. The structural shocks ϵ_t we are interested in are obtained from the reduced-form residuals by a linear transformation, $\epsilon_t = B^{-1} U_t$, where B is such that ϵ_t has an identity covariance matrix; that is, $\epsilon_t \sim (0, I_K)$ and the reduced-form residual covariance matrix is decomposed as $E(U_t U_t') = \Sigma_U = BB'$. The model is identified using a recursive structure, i.e., choosing the B matrix by a Choleski decomposition so as to achieve identification. Our baseline specification includes the four following variables in this order: industrial production, the real interest rate, the VIX, and a measure of capital flow episodes.

In doing so, we assume a recursive structure in the system, ordering the variables from slow- to fast-moving. As a result, the measure of capital flow episodes is placed last in the VAR, which assumes that the capital flow variable reacts contemporaneously to all other variables in the system (i.e., business cycle measure, monetary policy measure, and the VIX). The VIX is placed third in the system so that it reacts contemporaneously to the business cycle and monetary policy variables. The monetary policy measure is placed second in the VAR, which implies that it reacts only contemporaneously to the business cycle variable. Finally, our measure of business cycle activity is placed first in the VAR system, which assumes that the business cycle variable is predetermined in that it is affected only with a lag by the other variables in the system.

The model is estimated with standard least squares, and the lag length of the VAR is selected according to the Akaike information criterion. The sample size extends from April 2001 to December 2014. Note also that the analysis is done at a monthly, and not weekly, frequency for two main reasons. First, some of the variables in the system are not available at a weekly frequency (e.g., U.S. industrial production or the Wu and Xia (2015) shadow interest rate). Second, conducting the analysis at a monthly frequency permits a more straightforward comparison with the existing literature, since this type of structural VAR analysis is typically done at a monthly or quarterly frequency.

Time-Varying Parameter VAR Model

We then extend our analysis of equity flow episodes to a time-varying parameter (TVP) VAR. One caveat of the linear VAR model represented in Equation (2) is that impulse responses derived from this model are constant over time. However, there are a number of reasons to think that this assumption may potentially be too restrictive. For example, following the unconventional monetary policy measures employed in a number of advanced economies, it could well be that capital flows react differently to monetary policy shocks after the global financial crisis than during the pre-crisis period. Likewise, in the wake of the global financial crisis, the changing landscape of the financial sector could affect global risk aversion and, hence, change the reaction of capital flows to volatility shocks. As a result, we also estimate a TVP-VAR model, which can be seen as a general approximation to the linear model described in Equation (2). This permits us to evaluate the degree of time variation in the impulse responses. Following Primiceri (2005), we estimate a TVP-VAR model with stochastic volatility using Bayesian methods. This model can be written as follows

$$Y_t = \nu_t + A_{1,t}Y_{t-1} + ... + A_{p,t}Y_{t-p} + V_t, \tag{3}$$

where $V_t \sim N(0, \Sigma_t)$ are the reduced-form shocks with a $(K \times K)$ heteroskedastic VAR covariance matrix, Σ_t. We estimate a model with two autoregressive lags, but the results are robust to the inclusion of additional autoregressive lags. We define $\alpha_t = [\nu_t, A_{1,t}, ..., A_{p,t}]'$ as the vector of parameters in the model (stacked by rows), which evolve according to a driftless random walk process

$$\alpha_t = \alpha_{t-1} + e_t, \qquad e_t \sim iidN(0, Q). \tag{4}$$

The variance-covariance matrix Q is assumed to be diagonal, and the innovations e_t are assumed to be uncorrelated with the VAR innovations V_t. The innovations V_t are normally distributed, and their variances are time-varying

$$V_t \sim N(0, \Sigma_t), \qquad \Sigma_t = B_t^{-1} H_t (B_t^{-1})'. \tag{5}$$

The matrix B_t (that summarizes the contemporaneous relationships between the K variables in the system) is a lower triangular matrix with ones on its diagonal; that is, we assume the same identification scheme as in the linear case. The dynamics of the non-zero and non-one elements of B_t are governed by the following dynamics

$$B_t = B_{t-1} + l_t, \qquad var(l_t) = D. \tag{6}$$

The matrix H_t is a diagonal matrix with elements $h_{i,t}$, following a geometric random walk

$$ln(h_{i,t}) = ln(h_{i,t-1}) + \eta_{i,t}, \qquad \eta_{i,t} \sim iidN(0, \sigma_i^2), \tag{7}$$

for $i = \{1, 2, 3, 4\}$. Additional details on the model and the estimation method are reported in Appendix C.

3.2 Global Financial Cycle Results

3.2.1 Results from the Linear VAR

We start by presenting the results from the linear VAR. Figure 6 reports the impulse-response functions for the share of countries in an equity outflow episode following a VIX shock and a U.S. monetary policy shock.[25]

First, we assess the impact of the VIX shock (i.e., a 10-point increase in the VIX[26]) on the outflow share measure, which is displayed in the first panel of the top row in Figure 6. When considering an unexpected increase in the VIX, we observe a sharp increase in the share of countries in an outflow episode upon impact (about 15 percent). This increase in the share measure is statistically significant on impact, since the associated bootstrapped 90 percent confidence bands are above zero. This is in line with economic theory: an increase in the VIX indicates a higher level of stock market volatility and proxies for uncertainty in financial markets. In such an environment, investors are more likely to withdraw their equity fund investments and move to safer asset classes, such as government bonds, instead. Hence, equity outflow episodes appear more often across countries and thus the outflow share measure increases. Further, the confidence bands show that the reaction of the outflow share measure to a VIX shock is relatively short-lived, with an insignificant response after two months. However, short-lived reactions are not unusual in the context of high-frequency financial data, where the inflow and outflow cycles are considerably shorter than in lower-frequency data.

Second, we assess the impact of a U.S. monetary policy shock (i.e., a 100-basis-point increase in the real federal funds rate) on the outflow share measure, which is shown in the first panel of the bottom row of Figure 6. For the linear VAR, it turns out that the U.S. monetary policy shock has essentially no significant impact on the share of countries in an outflow episode. However, the expected sign of the effect is not clear a priori. On the one hand, a higher real interest rate could proxy for higher investment returns,[27] and thus, following a increase in the interest rate, we would observe a reduction in the share of

[25]For completeness, we also report the impulse responses of the other variables in the system to these two shocks. The results are as follows. The response of the VIX to its own shock documents the persistence of the shock, the response of the U.S. real interest rate is slightly positive, but largely insignificant, and the effect of the VIX on U.S. industrial production is negative. The response of the VIX to the U.S. monetary policy shock is negative but largely insignificant, the response of the U.S. real interest rate documents the persistence of the shock, and the response of U.S. industrial production to the U.S. monetary policy shock is negative (and again largely insignificant).

[26]This is of similar magnitude as a one-standard-deviation change of the VIX in our sample, which amounts to 8.6 points.

[27]In fact, in such a case, the presence of a spread over the U.S. interest rate would most likely increase interest rates in all other countries more than proportionally.

countries in an outflow episode.[28] On the other hand, a higher real interest rate can be a sign of tighter financial conditions and thus an indication of increased risks. This, in turn, could lead to an increase in the share of countries in an outflow episode. Since it is possible that, in light of our above discussed finding, different interpretations have played a role at different points in time, we return to this observation in Section 3.2.2.[29] This finding is, however, consistent with the linear VAR results in Bruno and Shin (2015b), who do not find a statistically significant initial response of the international bank flow measure to a shock in the real fed funds rate either. It also lines up with the results of Dahlhaus and Vasishtha (2014), who identify a "monetary policy normalization shock" in a linear VAR system that includes a factor extracted from capital flows going to emerging-market economies. In detail, they identify a monetary policy normalization shock as a shock that increases both the yield spread of U.S. long-term bonds and monetary policy expectations, while leaving the policy rate unchanged. Their results suggest that a monetary policy normalization shock in the United States has a relatively small economic impact on emerging-market portfolio flows.

Next, we conduct the same exercises for equity inflow episodes. Figure 7 reports the responses of the share of countries in an equity inflow episode to a VIX shock (first panel, top row) and to a U.S. monetary policy shock (first panel, bottom row).[30] First, as expected, a surprise increase in the VIX leads to a decline in the share of countries in an inflow episode. Hence, an increase in uncertainty leads to a sharp reduction of equity fund flows that materializes in our analysis in the form of a lower share of countries experiencing such episodes. However, the largest effect appears on impact again and fades out very quickly. Note also that, in absolute value, the reaction on impact is somewhat smaller compared with Figure 6, suggesting some evidence for non-linear effects. In other words, U.S. stock market volatility shocks seem, on average, to affect outflow episodes relatively more than inflow episodes. Second, the bottom row reports the responses of the same set of variables to a U.S. monetary policy shock. The main result is that, in the linear VAR, an increase

[28] Relatedly, and in particular during the period when the U.S. short-term interest rate was at the zero lower bound, an increase in the (nominal) interest rate can be seen as an improvement in the Fed's view of the U.S. economy and thus a sign of economic recovery and higher growth. Such an interpretation would also support the evidence of a decrease in the share of countries in an outflow regime following an increase in interest rates.

[29] In Section 3.2.2, we will use a time-varying parameter VAR to assess whether the effects of U.S. monetary policy on capital flow dynamics may have changed over recent years.

[30] We again report the impulse-response functions of the other variables for completeness. The response of the VIX to its own shock shows the persistence of the shock; that the response of the U.S. real interest rate to the VIX shock is positive, but largely insignificant; and that U.S. industrial production responds negatively. The response of the VIX to the U.S. monetary policy shock is negative, the response of the U.S. real interest rate to its own shock indicates the shock persistence again, and the impact on U.S. industrial production is slightly negative but insignificant again.

in the real interest rate leads to a significant increase in the share of countries in an inflow episode. Following the explanation above, this finding appears to assign more weight to an interpretation of the real interest rate as a measure of returns than as a measure of risks.

So far, we have conducted our analysis for share measures that comprise all countries in the sample. However, since the previous literature has found substantial differences in capital flow dynamics between advanced economies and emerging markets, we also compare the impulse-response functions for both country groupings separately. In doing so, we estimate the VAR model represented by Equation (2) using the share of countries in an outflow and an inflow episode, respectively, calculated only from advanced economies, and only from emerging markets. Figure 8 reports the difference between the impulse responses obtained from emerging markets and advanced economies to a VIX shock and a U.S. monetary policy shock.[31]

A VIX shock, that had an overall increasing effect on the share of countries in an outflow episode, has an even stronger impact on emerging markets, which is shown by the positive and significant impact in the difference-impulse-response function in the top left panel of Figure 8. This finding is suggested by economic theory and previous analyses in the literature (e.g., Gourio et al. (2014)). Since investments in emerging markets are generally riskier, an increase in uncertainty will affect emerging-market investments more than proportionally. Moving then to the U.S. monetary policy shock, which in the full sample had no significant impact on the share of countries in outflow episodes, the difference-impulse-response function in the bottom left panel does not show a difference between emerging markets and advanced countries on impact either.

We also assess the differential impact on inflow episodes across country groupings. Starting with the response to a VIX shock, which in the full sample had a reducing effect on the share of countries in an inflow episode but faded out very quickly, we observe a strong difference between both groups. The positive response of the difference-impulse-response function in the top right panel of Figure 8 suggests that the impact of the VIX shock on inflow episodes is more positive/less negative for emerging markets than for advanced countries. Finally, we examine the impact of a monetary policy shock that, overall, increased the share of countries in an inflow regime. Based on the insignificant difference-impulse-response function in the bottom right panel, however, we observe that there is no significant difference between the two country groupings.

[31] We compute the difference of the two impulse-response functions (IRF) as follows: IRF (Difference) = IRF (Emerging Markets) – IRF (Advanced Countries).

3.2.2 Results from the Time-Varying Parameter VAR

We now provide results from the time-varying parameter VAR to investigate the degree of time variation in the impulse responses. Figure 9 shows the time-varying impulse responses to a VIX shock and to a U.S. monetary policy shock using the share of countries in an outflow episode as a measure of capital flow dynamics.

Starting with the response to a VIX shock in Panel (a), we observe that the impact of a surprise increase in the VIX on the share of countries in an outflow episode is positive throughout the sample period but varies significantly over time. A shock in the VIX has a stronger impact during the period of the financial crisis and at the very recent end of the sample. This suggests evidence in favour of a non-linearity, such as the effect of a VIX shock seems greater in turbulent times. However, with an increase in the VIX resulting in an increase in the share of outflows, throughout the sample, the results from the linear VAR are generally confirmed.[32]

Next, Panel (b) depicts the response to the U.S. monetary policy shock. Interestingly, we observe a highly time-varying pattern in the case of our share measure for equity outflows that explains the, on average, insignificant response of this variable to a U.S. monetary policy shock in the linear VAR. While the impact of a U.S. monetary policy shock on the share measure was negative from the beginning of our sample until around 2011, the share of countries in an equity outflow episode increases in response to a U.S. monetary policy shock after this date.[33] Potential explanations for this finding have already been presented above. A negative relationship between the unexpected increase in the U.S. real interest rate and the share of countries in an outflow episode in the early part of the sample, possibly represents a return-based interpretation of the real interest rate; that is, investors invest in countries where returns, here proxied by the real interest rate, are higher. In contrast, the more recently observed positive relationship between an unexpected increase in the U.S. real interest rate and the share of countries in an outflow episode, favours an interpretation based on risks. That is, following a tightening of U.S. monetary policy in the aftermath of the financial crisis,[34] investors might have found it less attractive to invest in risky investments abroad.[35] A possible explanation for the observed change in the response of the outflow

[32]To conserve space, we do not report the time-varying responses of the other variables in the system. The responses are as follows. The U.S. real interest rate responds to the VIX shock in a similar way throughout the sample with an unexpected increase in the VIX having a positive effect on this variable. The impact of the VIX on U.S. industrial production is negative throughout.

[33]Note that 68 percent posterior credible sets exclude a zero response of the share of countries in an equity outflow episode after 2011.

[34]It should be noted that the tightening of U.S. monetary policy refers to an increase in the shadow interest rate.

[35]The other variables react to a U.S. monetary policy shock as follows. An increase in the U.S. real interest rate leads to a reduction in the VIX. However, the impulse-response function from the time-varying parameter

episode share measure to the U.S. monetary policy shock over our sample period might be associated with a re-pricing of risks that occurred in the aftermath of the global financial crisis.

To assess whether there are differences between the full sample and the two subsamples, we re-estimate the time-varying parameter VAR for emerging countries only. Panels (a) and (b) of Figure 10 report the corresponding time-varying impulse responses to a VIX shock and a U.S. monetary policy shock using the share of countries in an outflow episode calculated for emerging markets. The responses are similar to Figure 9, except that the responses to a VIX shock and a U.S. monetary policy shock are magnified. As such, this is not too surprising, since we found earlier that emerging-market capital flow regimes are more prone to abrupt changes. Further, our finding that an unexpected tightening in U.S. monetary policy leads to a significant increase in the share of countries in an outflow episode in 2013 and 2014 (with this effect being larger among emerging markets) lines up well with the conclusions from Dedola et al. (2015), who find that emerging-market economies are relatively more affected than advanced economies by U.S. monetary policy shocks.

Next, in Figure 11, we assess the time-varying impact of the two shocks on the share of countries in an equity inflow episode. Panel (a) shows that the impact of the VIX shock on the share of countries in an equity inflow episode is negative for most of the sample period and becomes even more negative in the pre-crisis period. From around mid-2012 onwards, however, the impact of the VIX shock reverses its sign and associates an increase in the VIX with an increase in equity inflow episodes until mid-2014. This somewhat surprising finding is most likely driven by strong capital flows from emerging markets into advanced countries following the Fed's tapering announcement. Support for this interpretation also comes from Figure 4, where the share of countries in an equity inflow episode is separately reported by country group. While the share of advanced countries in an equity inflow episode reaches between 70 to 80 percent in 2013, the share of emerging markets in an equity inflow episode, amounting to a value between 20 and 30 percent at the same time, is much lower. The substantial difference between both share measures therefore indicates that most of this period's inflows have occurred in advanced countries.

Finally, Panel (b) in Figure 11 depicts the response to the U.S. monetary policy shock. Consistent with the strongly time-varying response of equity outflow episodes to this shock, we observe a similar time-varying response of equity inflow episodes that presents the mirror image of Panel (b) in Figure 9. While the U.S. monetary policy shock led mostly to an increase in the share of countries in an equity inflow episode in the early part of the sample, the sign of this relationship reverses with the global financial crisis as well. As a result, the

VAR suggests that this impact decreases continuously over time. The impact of the U.S. monetary policy shock on U.S. industrial production is consistently negative over a medium-term horizon.

U.S. monetary policy shock is associated with a reduction of equity inflow episodes across countries, particularly since the beginning of the post-crisis period in 2010.

Overall, our empirical analysis suggests that unexpected changes in both the VIX and in U.S. monetary policy have had time-varying effects on the dynamics of equity flow episodes over our sample period. On the one hand, these findings support the earlier observations that U.S. macroeconomic and financial shocks substantially affect the economic and financial cycles of other countries as suggested by Rey (2013). On the other hand, these findings demonstrate that the impact of both shocks on the rest of the world differs substantially over time – making it potentially even more difficult for policy-makers abroad to design an appropriate policy response. However, it should be mentioned that our VAR approach does not explicitly disentangle the roles of push and pull factors as drivers of capital flows (e.g., such as in Fratzscher (2012)) nor does it directly address the economic and financial effects of unconventional monetary policies (e.g., such as in Forbes et al. (2016)). Both research questions are beyond the scope of this paper and are left for future research.

4 Conclusion

This paper has identified episodes of strong capital flows in weekly fund flow data and assessed their dynamics for a large set of advanced and emerging economies. It has contributed to the literature along two dimensions.

First, we have proposed a novel methodology for identifying episodes of strong capital flows that is suitable for high-frequency data. In particular, we have estimated regime-switching models on data of equity and bond fund flows into up to 80 different countries at weekly frequency over the period 2000 to 2014. A key advantage of this approach is to endogenously determine capital flow regimes without the need for context- and sample-specific assumptions that might be hard to derive in a convincing way when data are sampled at a high frequency. Operating at high-frequency is important since it allows us to obtain a precise and timely characterization of capital flow episodes. Based on this analysis, we have shown that differences in estimated inflow and outflow regimes within countries correlate positively with the quality of institutions and the level of financial development as well as negatively with a country's share of foreign currency liabilities. We have also documented the main features of equity and bond flow episodes, such as the time a typical country spends in different episodes types as well as their frequency of appearance and their average length.

Second, we then have used linear and time-varying structural VARs to assess the impact of U.S. stock market volatility shocks and U.S. monetary policy shocks on aggregated measures of equity outflow and equity inflow episodes. Our results indicate that both the VIX and the U.S. monetary policy shock had substantially time-varying effects on episodes of strong capital flows over our sample period. The impact of a VIX shock has been stronger in times of crises but has almost consistently led to more equity outflow episodes and fewer equity inflow episodes in each period. The impact of a U.S. monetary policy shock, however, has changed sign over our sample period in that, in the wake of the financial crisis, such shocks have led to more equity outflow episodes and fewer equity inflow episodes compared with the pre-crisis period. Overall, finding evidence in favor of a time-varying response of capital flows to shocks originating in the U.S. is an important input into the current debate on international spillover effects of U.S. monetary policy decisions and highlights additional challenges that policy-makers abroad might face when designing their intended policy responses.

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Appendices

A Dataset Construction

This appendix provides a summary of the steps required to construct our sample of equity and bond capital flows based on the EPFR database. In general, data availability is determined by the EPFR data and differs between equity and bond flows.

A.1 Equity Flows

- We download weekly data on capital flows, aggregated to the destination country level, from equity funds, based in all domiciles, between the last week of October 2000 and the last week of December 2014:
  - For 108 countries/regional aggregates, there is at least one observation in the data.
  - For 47 countries/regional aggregates, the data are entirely complete over the period (i.e., 741 observations).
  - For 61 countries/regional aggregates, there is at least one observation missing (the number of missing observations ranges between 2 and 739).
- In order to have a continuous time series of data (which is required by our empirical approach), we drop all countries that have a missing value between the first week of January 2007 and the last week of December 2014 (8 years):
  - This leaves 71 countries/regional aggregates in the sample.
- From this set of countries/regional aggregates, we eliminate (i) all regional aggregates, (ii) all observations before the first missing observation in each country, and (iii) Saudi Arabia (where equity flow dynamics during our sample period contain strong outliers).
  - Hence, the final sample of equity flows contains 65 countries with start dates ranging from the last week of October 2000 to the last week of July 2006.

A.2 Bond Flows

- We download weekly data on capital flows, aggregated to the destination country level, from bond funds, based in all domiciles, between the first week of January 2004 and the last week of December 2014:

  - For 122 countries/regional aggregates, there is at least one observation in the data.
  - For 43 countries/regional aggregates, the data are entirely complete over the period (i.e., 574 observations).
  - For 79 countries/regional aggregates, there is at least one observation missing (the number of missing observations ranges between 9 and 570).

- In order to have a continuous time series of data (which is required by our empirical approach), we drop all countries/regional aggregates that have a missing value between the first week of January 2007 and the last week of December 2014 (8 years):
  - This leaves 71 countries/regional aggregates in the sample.
- From this set of countries/regional aggregates, we eliminate (i) all regional aggregates, and (ii) all observations before the first missing observation in each country.
  - Hence, the final sample of bond flows contains 66 countries with start dates ranging from the first week of January 2004 to the first week of January 2006.

B Definition of Country Groupings

The samples for equity and bond flows are not identical since, in some countries, data are only available for a single asset class ([E] = equity sample only; [B] = bond sample only).

The *full sample* includes all countries that are available from the following two lists.

The *advanced-country sample* contains Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, Korea, Netherlands, New Zealand[E], Norway, Portugal[E], Spain, Sweden, Switzerland, United Kingdom, and the United States.

The *emerging-market sample* includes[36] Argentina, Bosnia and Herzegovina[B], Brazil, Bulgaria[E], Chile, China, Colombia, Costa Rica[B], Croatia, Cyprus[E], Czech Republic, Dominican Republic[B], Ecuador[B], Egypt, El Salvador[B], Estonia[E], Ghana[B], Guatemala[B], Hong

[36] As pointed out in the main text, the emerging-market sample contains a few countries that are generally considered to be low-income countries rather than emerging markets. However, in order to keep the analysis tractable, we refer to the group of emerging markets and low-income countries as "emerging markets."

Kong, Hungary, India, Indonesia, Iraq$^{\mathrm{B}}$, Ivory Coast$^{\mathrm{B}}$, Kazakhstan, Lebanon$^{\mathrm{B}}$, Lithuania$^{\mathrm{E}}$, Malaysia, Mauritius$^{\mathrm{E}}$, Mexico, Morocco$^{\mathrm{E}}$, Nigeria, Oman$^{\mathrm{E}}$, Pakistan, Panama, Peru, Philippines, Poland, Qatar$^{\mathrm{B}}$, Romania, Russia, Serbia$^{\mathrm{B}}$, Singapore, Slovenia$^{\mathrm{E}}$, South Africa, Sri Lanka$^{\mathrm{E}}$, Taiwan$^{\mathrm{E}}$, Thailand, Trinidad and Tobago$^{\mathrm{B}}$, Tunisia, Turkey, Ukraine, Uruguay$^{\mathrm{B}}$, Venezuela$^{\mathrm{B}}$, Vietnam, Zambia$^{\mathrm{E}}$, and Zimbabwe$^{\mathrm{E}}$.

C The Markov-Chain Monte Carlo Procedure

This appendix provides details on the Markov-chain Monte Carlo (MCMC) procedure. We follow Benati (2014) for the presentation of the prior distributions and the simulation of the posterior distribution.

C.1 Prior Distributions

The model has two sets of time-varying coefficients, the α_ts and the $b_{ij,t}$s, as well as a stochastic volatility model for the diagonal elements of H_t (i.e., the $h_{i,t}$s).

To calibrate the priors on α_0, b_0, and h_0, we use the estimates of a linear VAR model estimated over the period extending from April 2001 to March 2005. (The actual estimation sample runs from April 2003 to December 2014; that is, we discard only half of the observations in the initial estimation sample so as not to eliminate too many observations.) The prior for α_0 is set as follows

$$\alpha_0 \sim N[\hat{\alpha}_{OLS}, 4\hat{V}(\hat{\alpha}_{OLS}]. \tag{C-1}$$

We define the matrix C as the matrix resulting from the Cholesky factorization of the variance-covariance matrix of the residuals from the linear VAR (i.e., $CC' = \hat{\Sigma}_{OLS}$), and set the prior for h_0 as

$$ln(h_0) \sim N(ln(\mu_0), 10 \times I_n), \tag{C-2}$$

where μ_0 is a vector collecting the logarithms of the squared elements on the diagonal of C, n is the number of variables in the system and I_n is the identity matrix with dimension n. Each column of C is then divided by the corresponding element on the diagonal of C, so that we obtain a matrix denoted as $\tilde{C}$ and the prior for b_0 is set as

$$b_0 \sim N(b_0, V(b_0)), \tag{C-3}$$

where b_0 is a vector collecting all the non-zero and non-one elements from $\tilde{C}^{-1}$ (e.g., for the four-variable VAR, $b_0 = [b_{0,21}, b_{0,31}, b_{0,32}, b_{0,41}, b_{0,42}, b_{0,43}]'$), and its covariance matrix,

$V(b_0)$ is assumed to be diagonal with elements equal to ten times the absolute value of the corresponding elements in b_0.

Following the literature, we assume that all innovations in the model are distributed as multivariate normal distribution with zero mean and the following diagonal structure

$$V = var\begin{pmatrix}\epsilon_t \\ e_t \\ l_t \\ \eta_t\end{pmatrix} = \begin{pmatrix}I_n & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & D & 0 \\ 0 & 0 & 0 & W\end{pmatrix}, \tag{C-4}$$

where $\eta_{i,t} \sim N(0, W)$.

The matrix Q – which governs the amount of time variation in the VAR parameters α_t – is assumed to follow an inverted Wishart distribution

$$Q \sim IW(Q_0^{-1}, T_0), \tag{C-5}$$

with prior degrees of freedom T_0 and scale matrix $T_0\bar{Q}$. T_0 is set to the length of β plus one. $\bar{Q}$ is calibrated as $\bar{Q} = \gamma \times \hat{\Sigma}_{OLS}$, setting γ to $\frac{3.5}{9} \times 10^{-4}$.[37]

The three blocks of D are assumed to follow inverted Wishart distribution; that is,

$$D_i \sim IW(T, L_{it}^{'}L_{it} + D_{i,0}), \tag{C-6}$$

where T represents the degrees of freedom and the scale parameter is $L_{it}^{'}L_{it} + D_{i,0}$. The prior scale matrix for $D_{1,0}$ is set to 10^{-3}, the prior scale matrix for $D_{2,0}$ is set to $10^{-3} \times I_2$ and the prior scale matrix for $D_{3,0}$ is set to $10^{-3} \times I_3$.

For the variances of the stochastic volatility innovations, we assume that the σ_is follow an inverse gamma distribution for the elements of W; that is,

$$\sigma_i^2 \sim IG(\frac{(0.01/3)^2}{2}, \frac{1}{2}). \tag{C-7}$$

C.2 Posterior Distribution Simulations

The Carter and Kohn algorithm is combined with the Metropolis-Hastings (MH) algorithm to sample sequentially the different sets of parameters conditional on the other blocks of parameters since sampling directly from the joint posterior distribution is not straightforward.

[37] Based on quarterly data, Cogley and Sargent (2005) set $\gamma = 3.5 \times 10^{-4}$, which is modified as $\gamma = (\frac{3.5}{9}) \times 10^{-4} = (\frac{3.5^{\frac{1}{2}} \times 10^{-2}}{3})^2$, since we deal with monthly data.

Step 1: We first draw the coefficients α_t using the Carter and Kohn algorithm.

Step 2: The unrestricted posterior for Q is $Q \sim \; IW(Q_1^{-1}, T_1)$, where $T_1 = T + T_0$, and

$$Q_1 = \Big[Q_0 + \sum_{t=1}^{T} e_t e_t'\Big]^{-1}, \tag{C-8}$$

where the e_t terms are the residuals from the transition equation (i.e., $e_t = \alpha_t - \alpha_{t-1}$).

Step 3: We then draw the elements of B_t (i.e., the $b_{ij,t}$) using the Carter and Kohn algorithm (see Primiceri (2005), assuming that D has a diagonal structure), by applying the independence MH algorithm (conditional on σ_i) to the following set of equations

$$l_{1,t} = \epsilon_{1,t}, \tag{C-9}$$

$$l_{2,t} = \epsilon_{2,t} - b_{12,t} l_{1,t}, \tag{C-10}$$

$$l_{3,t} = \epsilon_{3,t} - b_{13,t} l_{1,t} - b_{23,t} l_{2,t}, \tag{C-11}$$

$$l_{4,t} = \epsilon_{4,t} - b_{14,t} l_{1,t} - b_{24,t} l_{2,t} - b_{34,t} l_{3,t}. \tag{C-12}$$

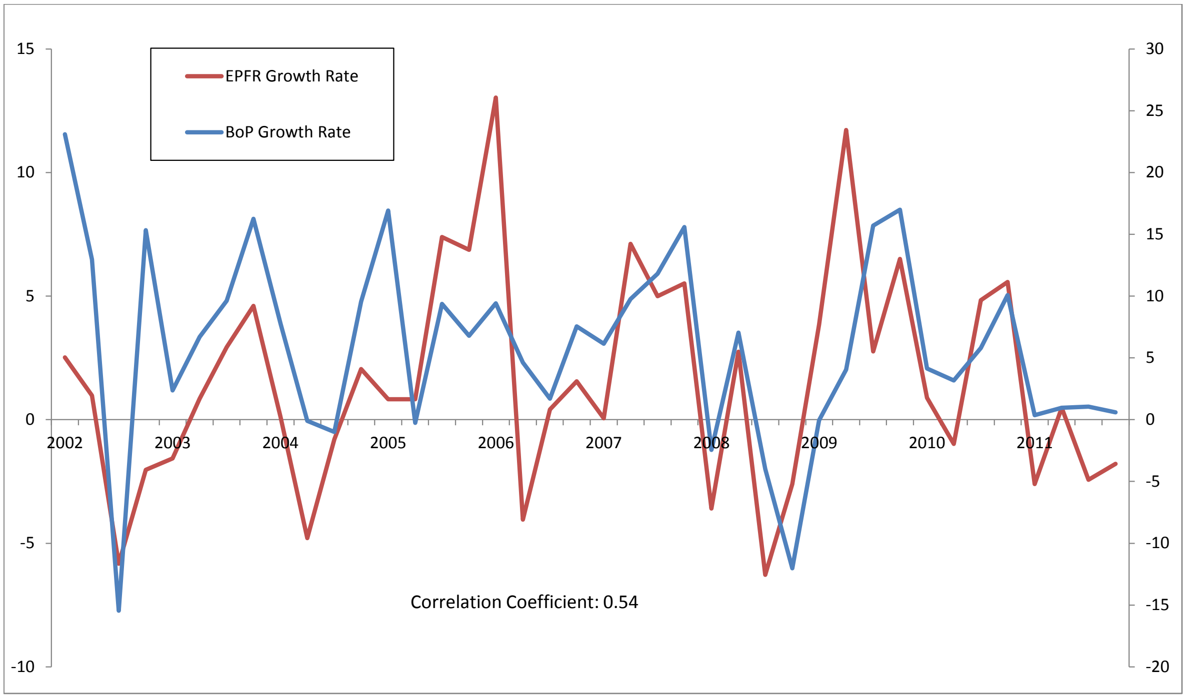
Step 4: Using the draw for the $b_{ij,t}$s, we calculate the residuals l_{it}s and draw the three blocks of D (that is, the innovations in the law of motion for the "structural" parameters $b_{ij,t}$s) from an inverted Wishart distribution.

Step 5: Using the draw from B_t, we calculate $\epsilon_t = B_t l_t$, where $\epsilon_t = (\epsilon_{1,t}, \epsilon_{2,t}, \epsilon_{3,t}, \epsilon_{4,t})'$. Note that the ϵ_ts are contemporaneously uncorrelated so that we can draw the elements of H_t (i.e., the volatility states $h_{i,t}$) one at a time.

Step 6: Using the draw for the volatility states $h_{i,t}$, we can draw the innovations of the stochastic volatility equation σ_i^2 from an inverse gamma distribution.

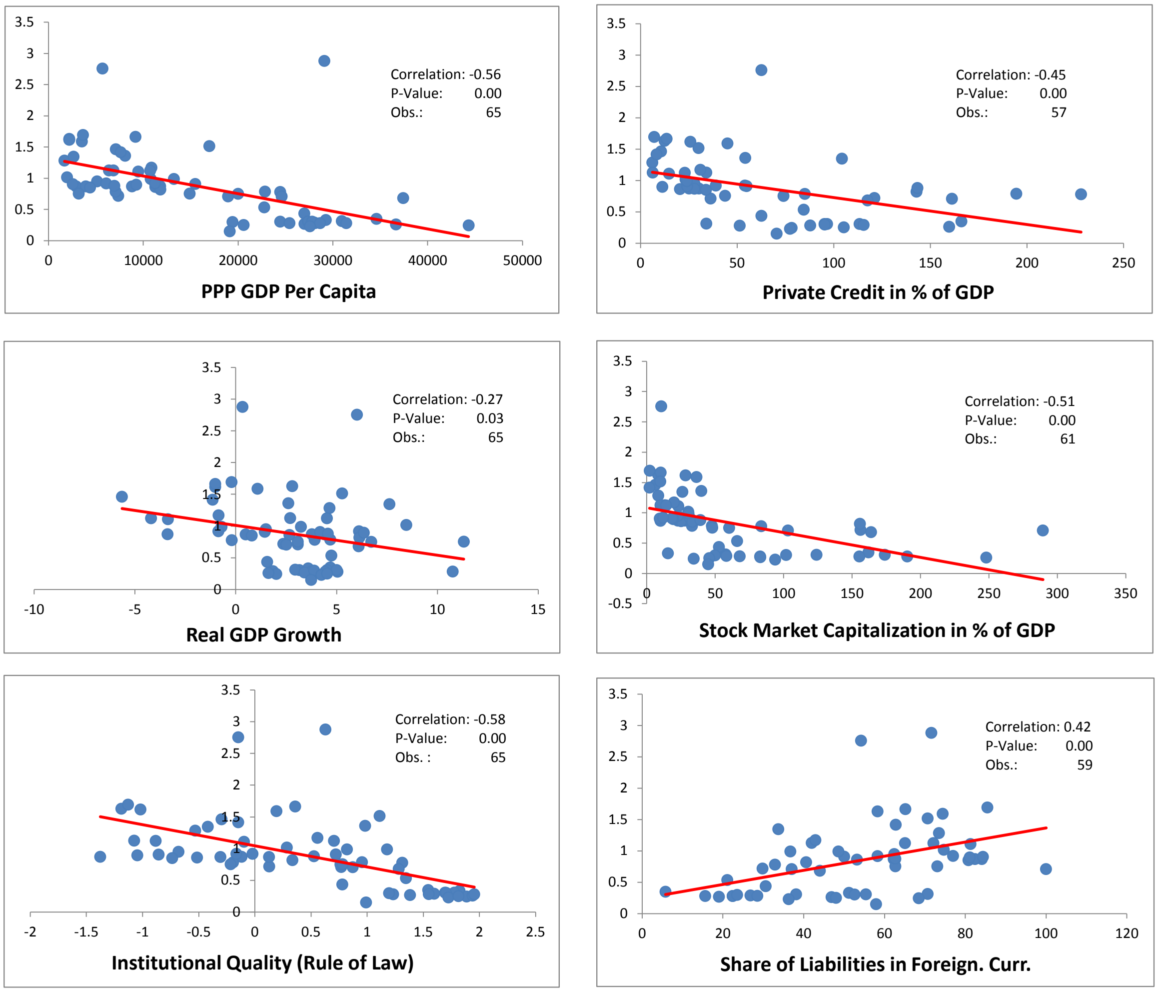
Step 7: The MCMC algorithm simulates the posterior distribution of the states and hyperparameters, iterating over Steps 1 to 6. We use a burn-in period of 50,000 iterations to converge to the ergodic distribution and run a further 30,000 iterations sampling every third draw to reduce the autocorrelation across draws. To assess convergence, we plot the recursive means of the retained draws. Recursive means vary little, suggesting evidence in favour of convergence.

Figure 1: Data Comparison of Equity Inflows into Brazil between EPFR and BoP



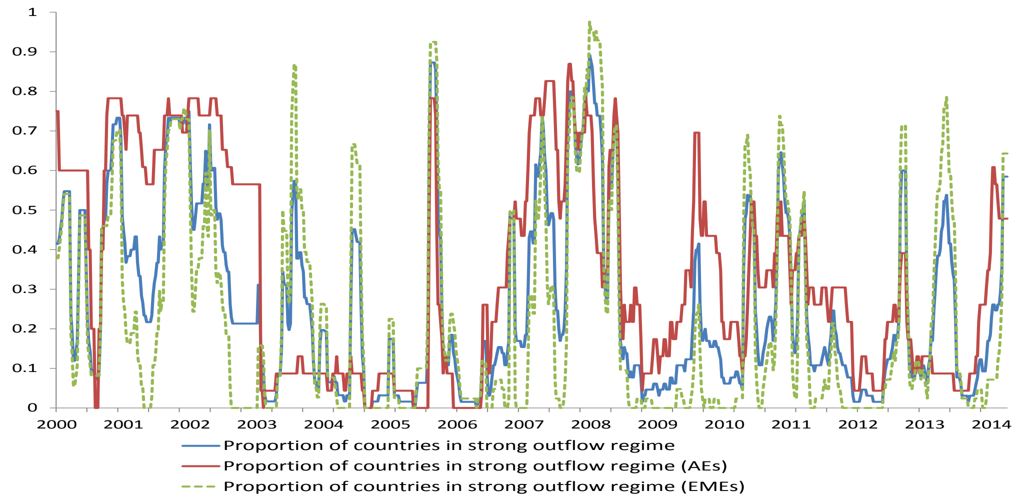
Note: *EPFR Growth Rates (Left Axis):* The original EPFR data consist of equity inflows into Brazil as the percentage change in outstanding equity investments at the start of the week. The red line represents the corresponding quarter-on-quarter growth rate of this measure. *BoP Growth Rates (Right Axis):* The original BoP data consist of the quarterly change in net foreign equity liabilities in U.S. dollars. The blue line represents the quarter-on-quarter growth rate of net foreign equity liabilities as the percentage change of cumulated net foreign equity liabilities in percent of quarterly GDP.

Figure 2: Explaining Differences in Regimes (left axis) across Countries



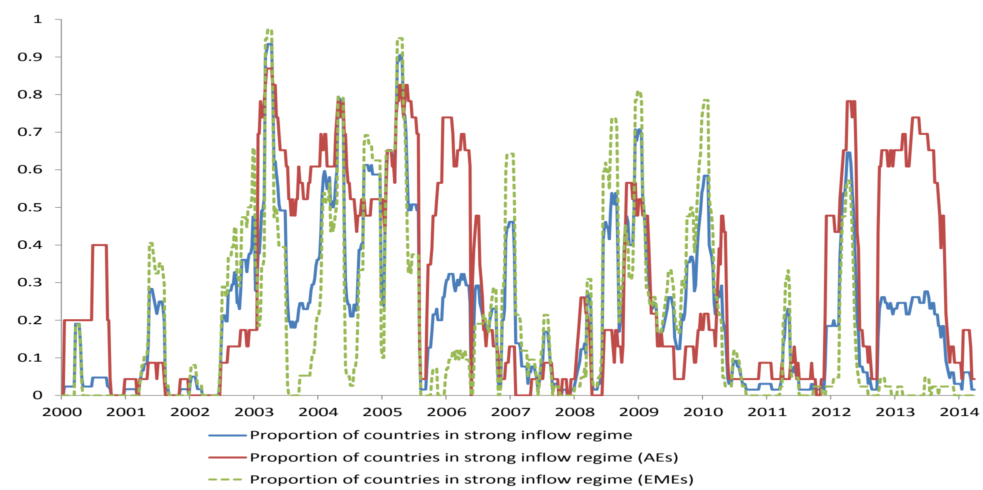
Left-hand-side variable: Difference between the intercepts of the third and first regime, i.e., $\mu_3 - \mu_1$, for each country. *Right-hand-side variables*: PPP GDP Per Captia and Real GDP Growth have been obtained from the IMF's WEO Database October 2015. Institutional Quality (Rule of Law) has been obtained from the World Bank's Worldwide Governance Indicators (WGI) 2015. Private Credit as a percentage of GDP and Stock Market Capitalization as a percentage of GDP have been obtained from the World Bank's Financial Development and Structure Dataset 2013. The Share of Liabilities in Foreign Currency has been obtained from the Lane and Shambaugh (2010) dataset. The values of all right-hand-side variables are from 1999.

Figure 3: Share of Countries in an Equity Outflow Episode



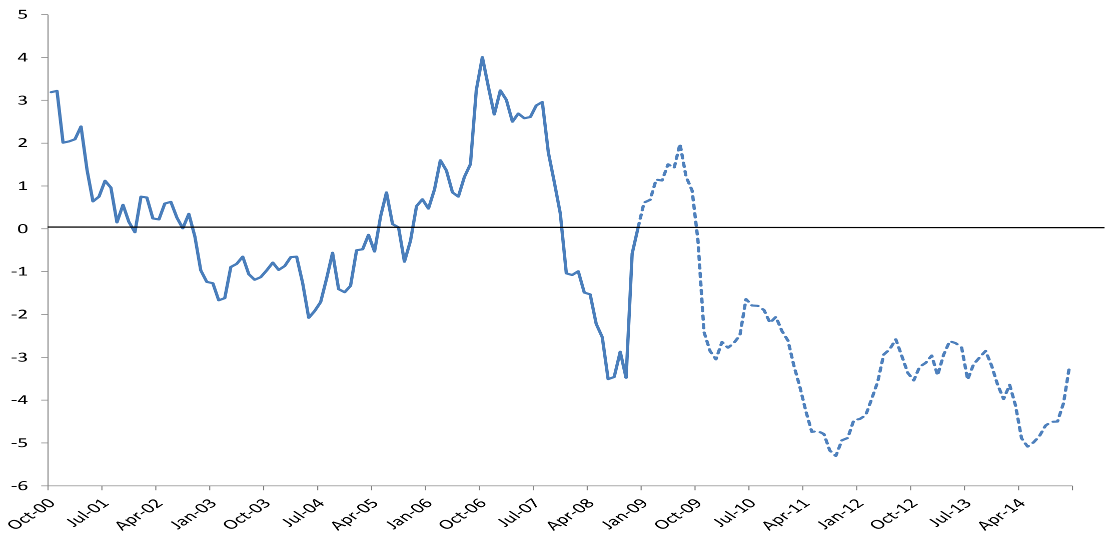
Note: This figure reports the share of countries in an equity outflow episode for the entire dataset, for advanced economies (AEs) and for emerging-market economies (EMEs). The sample size extends from the last week of October 2000 to the last week of December 2014.

Figure 4: Share of Countries in an Equity Inflow Episode



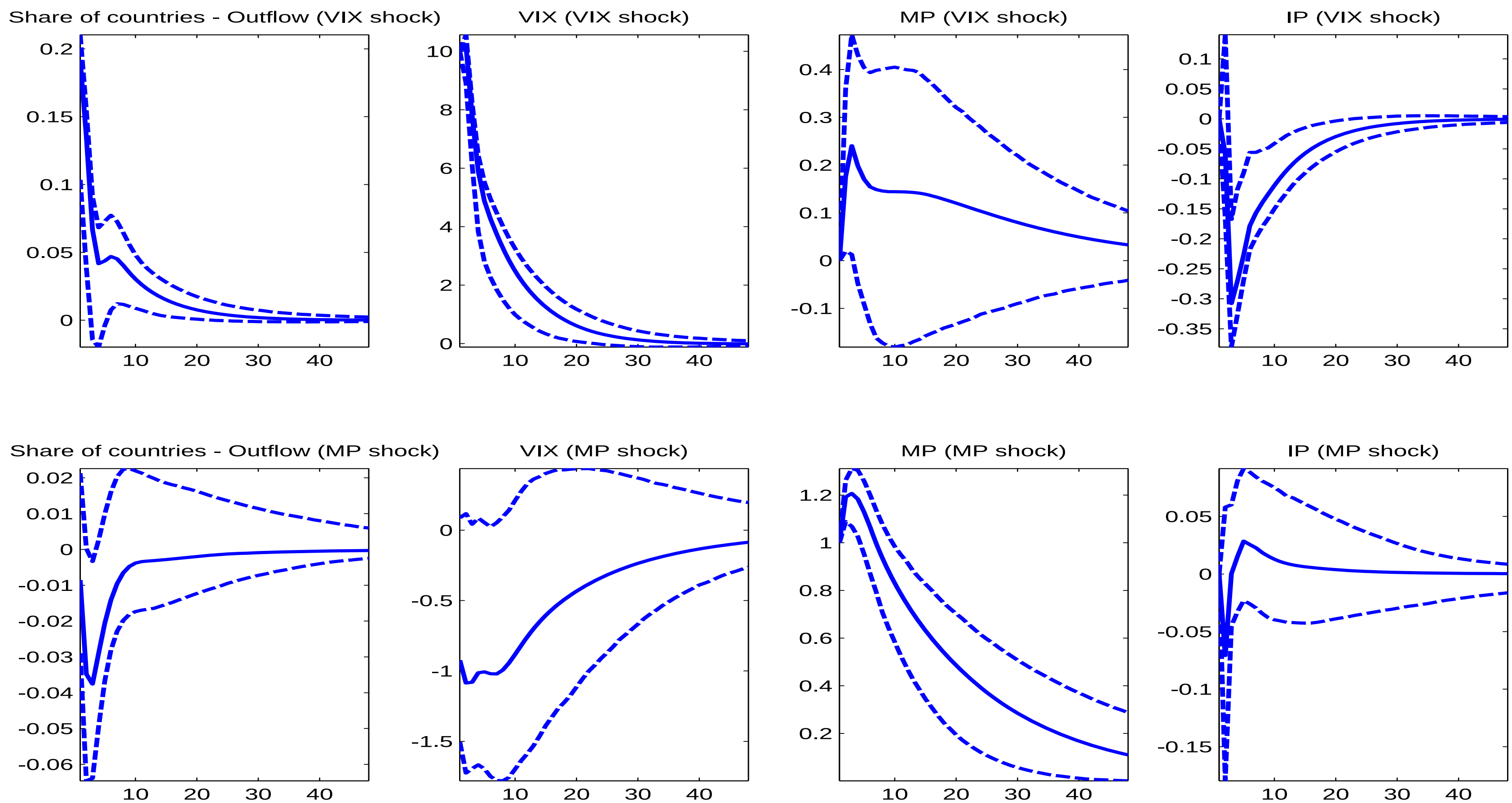
Note: This figure reports the share of countries in an equity inflow episode for the entire dataset, for advanced economies (AEs) and for emerging-market economies (EMEs). The sample size extends from the last week of October 2000 to the last week of December 2014.

Figure 5: Real Interest Rate – October 2000 to December 2014



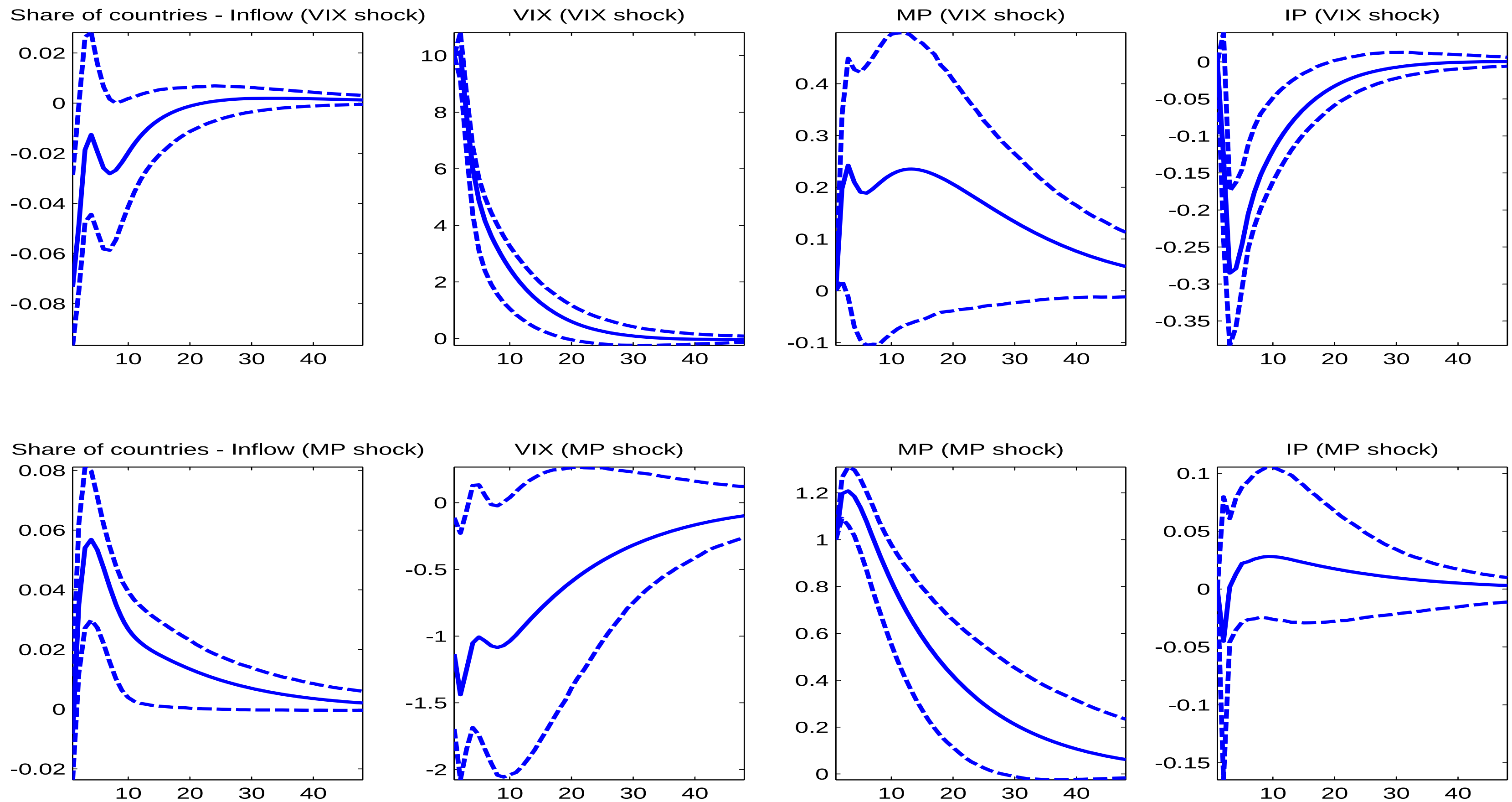
Note: The real interest rate is calculated as the difference between the nominal federal funds rate and the annual inflation rate (annual change in the CPI). From January 2009 onwards, we use the shadow interest rate from Wu and Xia (2015) instead of the nominal federal funds rate.

Figure 6: Impulse-Response Functions – Equity Outflow Episodes



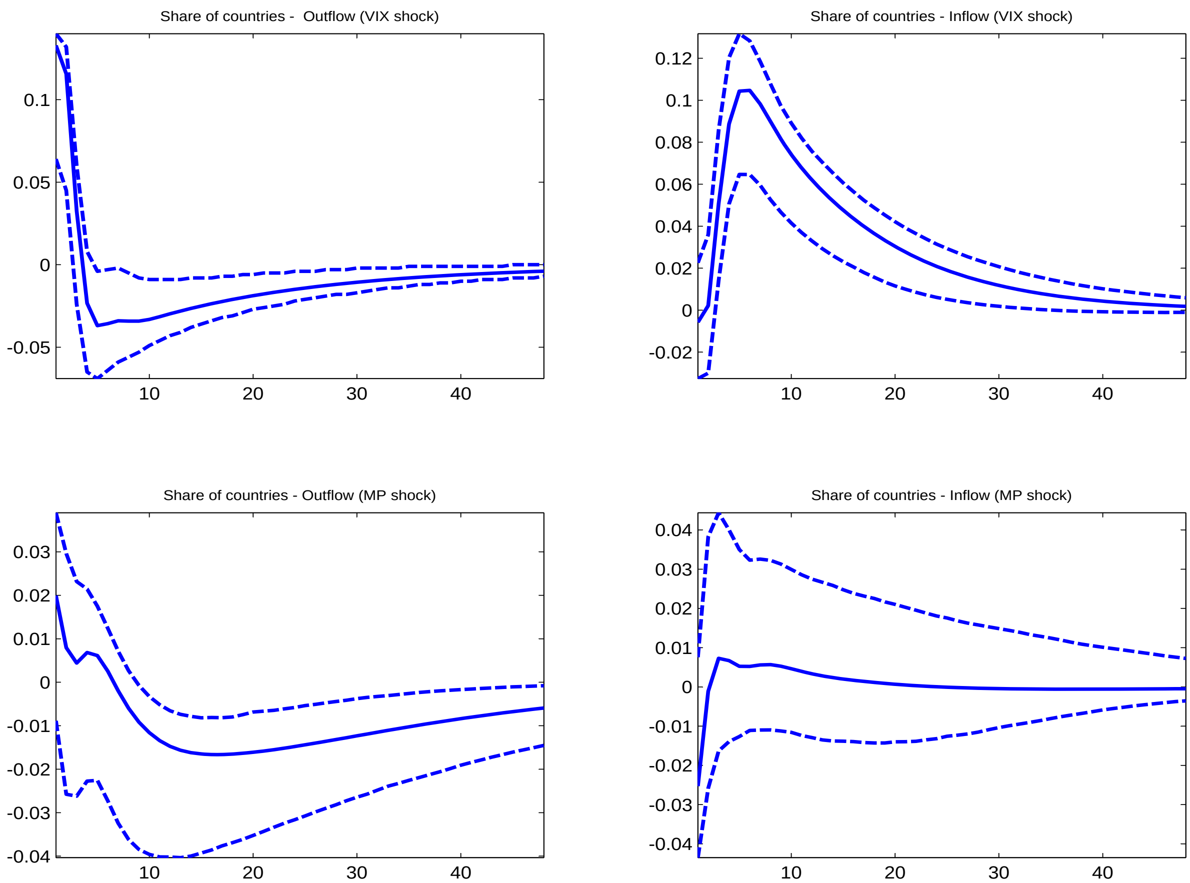
Note: Estimated structural impulse-response functions (solid lines), and 90 percent bootstrapped confidence intervals (dotted lines) for the 4-variable VAR consisting of the share of countries in an equity outflow episode, the VIX, the U.S. real interest rate, and U.S. industrial production. The model is identified with a recursive identification scheme. The first row represents the responses to a 10-point increase in the VIX, and the second row shows the responses to a monetary policy shock (i.e., a 100-basis-point increase in the real interest rate). The estimation sample extends from April 2001 to December 2014.

Figure 7: Impulse-Response Functions – Equity Inflow Episodes



Note: Estimated structural impulse-response functions (solid lines), and 90 percent bootstrapped confidence intervals (dotted lines) for the 4-variable VAR consisting of the share of countries in an equity inflow episode, the VIX, the U.S. real interest rate, and U.S. industrial production. The model is identified with a recursive identification scheme. The first row represents the responses to a 10-point increase in the VIX, and the second row shows the responses to a monetary policy shock (i.e., a 100-basis-point increase in the real interest rate). The estimation sample extends from April 2001 to December 2014.

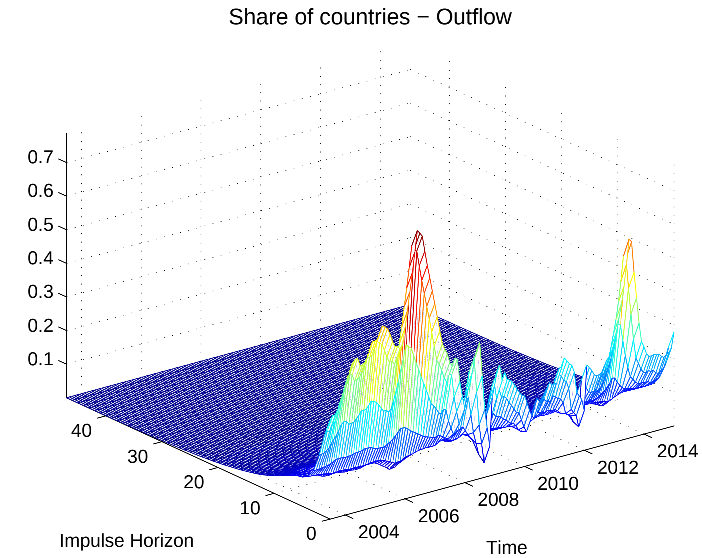
Figure 8: Impulse-Response Functions – Difference between Emerging Markets and Advanced Economies



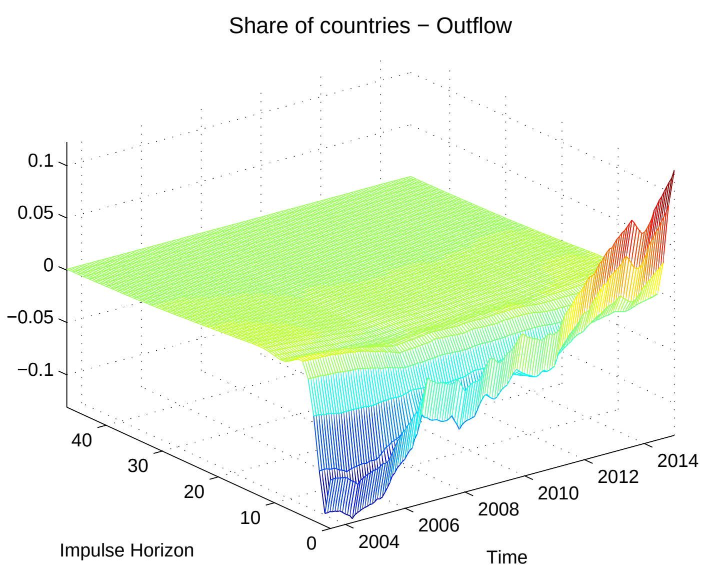
Note: Estimated structural difference-impulse-response functions (solid lines), and 90 percent bootstrapped confidence intervals (dotted lines) for the 4-variable VAR consisting of the share of countries in an equity outflow or inflow episode, the VIX, the U.S. real interest rate, and U.S. industrial production. We compute the difference-impulse-response function as the difference of the two impulse-response functions (IRF): IRF (Difference) = IRF (Emerging Markets) – IRF (Advanced Countries). The model is identified with a recursive identification scheme. The first row shows the responses to a 10-point increase in the VIX, and the second row reports the responses to a monetary policy shock (i.e., a 100-basis-point increase in the real interest rate). The estimation sample extends from April 2001 to December 2014.

Figure 9: Time-Varying Responses of Equity Outflow Episodes – All Countries

(a) Response of Equity Outflow Episodes to a VIX Shock



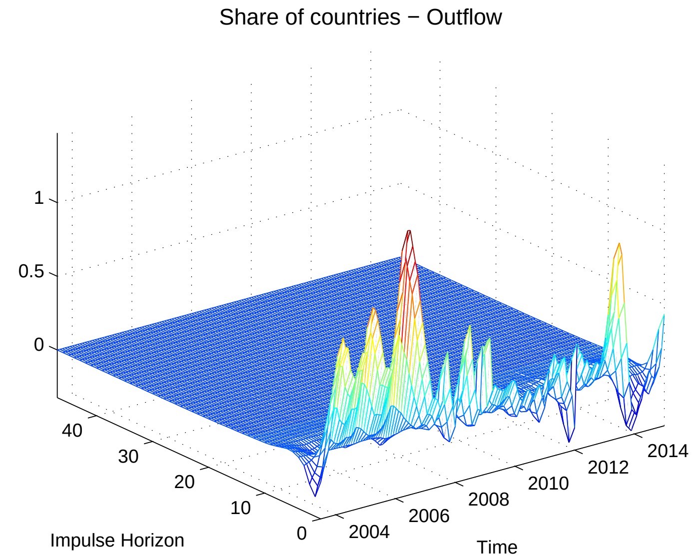
(b) Response of Equity Outflow Episodes to a U.S. Monetary Policy Shock



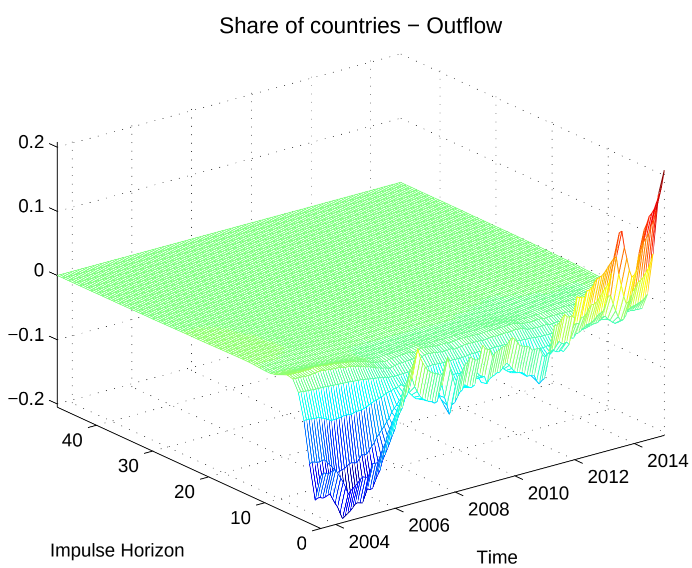
Note: This figure reports the median time-varying (structural) impulse responses for the 4-variable VAR consisting of the share of countries in an equity outflow episode, the VIX, the U.S. real interest rate, and U.S. industrial production. The share of countries in an equity outflow episode is calculated based on all countries in the sample. The model is identified with a recursive identification scheme. Panel (a) shows responses to a 10-point increase in the VIX and Panel (b) shows responses to a 100-basis-point increase in the real interest rate. The estimation sample extends from June 2003 to December 2014.

Figure 10: Time-Varying Responses of Equity Outflow Episodes – Emerging Markets

(a) Response of Equity Outflow Episodes to a VIX Shock



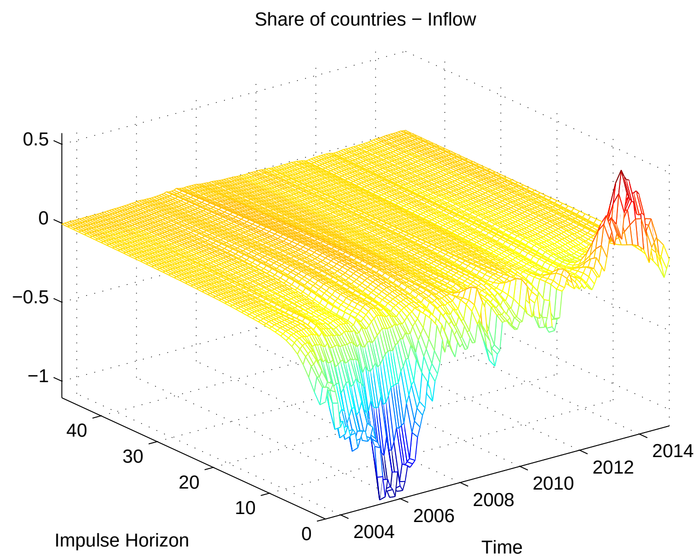
(b) Response of Equity Outflow Episodes to a U.S. Monetary Policy Shock



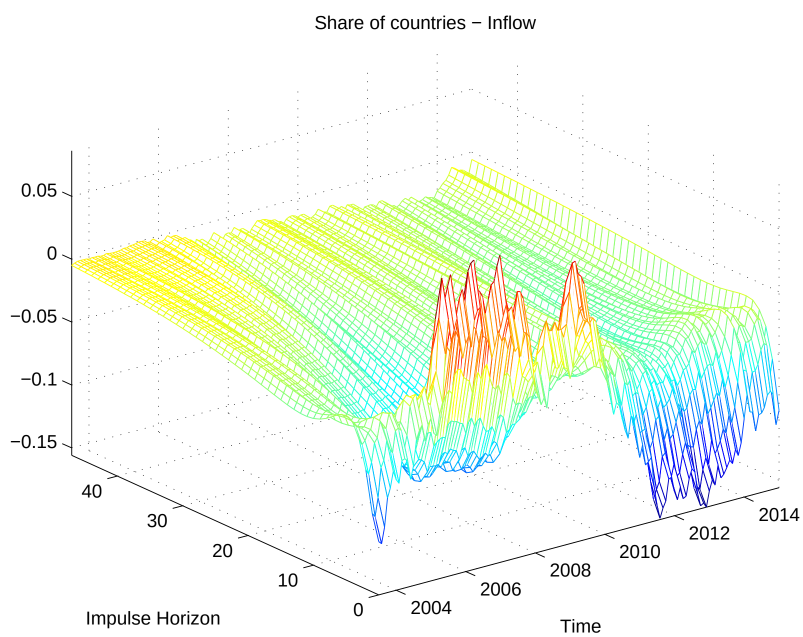
Note: This figure reports the median time-varying (structural) impulse responses for the 4-variable VAR consisting of the share of countries in an equity outflow episode, the VIX, the U.S. real interest rate, and U.S. industrial production. The share of countries in an equity outflow episode is calculated based on all emerging markets in the sample. The model is identified with a recursive identification scheme. Panel (a) shows responses to a 10-point increase in the VIX and Panel (b) shows responses to a 100-basis-point increase in the real interest rate. The estimation sample extends from June 2003 to December 2014.

Figure 11: Time-Varying Responses of Equity Inflow Episodes – All Countries

(a) Response of Equity Inflow Episodes to a VIX Shock



(b) Response of Equity Inflow Episodes to a U.S. Monetary Policy Shock



Note: This figure reports the median time-varying (structural) impulse responses for the 4-variable VAR consisting of the share of countries in an equity inflow episode, the VIX, the U.S. real interest rate, and U.S. industrial production. The share of countries in an equity inflow episode is calculated based on all countries in the sample. The model is identified with a recursive identification scheme. Panel (a) shows responses to a 10-point increase in the VIX and Panel (b) shows responses to a 100-basis-point increase in the real interest rate. The estimation sample extends from June 2003 to December 2014.

Table 1: Results of the Regime-Switching Model

	Equity					Bond				
	Average	Advanced	Emerging	U.S.	Brazil	Average	Advanced	Emerging	U.S.	Brazil
μ_1	-0.350	-0.110	-0.481	-0.072**	-0.339**	-0.588	-0.508	-0.626	-0.248**	-0.660**
				[0.029]	[0.036]				[0.033]	[0.083]
μ_2	0.030	0.008	0.041	0.016	0.135**	0.162	0.098	0.192	0.055**	0.057
				[0.010]	[0.030]				[0.016]	[0.038]
μ_3	0.513	0.250	0.658	0.275*	0.529**	0.736	0.563	0.817	0.323**	0.649**
				[0.143]	[0.076]				[0.013]	[0.037]
p_{11}	0.857	0.941	0.812	0.982	0.896	0.871	0.860	0.877	0.940	0.884
p_{22}	0.905	0.916	0.899	0.987	0.889	0.905	0.906	0.904	0.942	0.884
p_{33}	0.886	0.910	0.873	0.966	0.890	0.919	0.934	0.911	0.957	0.936
$P(S_t = 1)$	0.306	0.348	0.283	0.320	0.366	0.245	0.242	0.246	0.291	0.209
$P(S_t = 3)$	0.248	0.301	0.218	0.109	0.251	0.280	0.269	0.286	0.233	0.429

Note: This table presents the estimation results (i.e., based on Equation (1)) of the country-specific regime-switching models for equity and bond fund flows separately. The results shown in the table consist of the average results based on the entire sample, the advanced country sample and the emerging market sample, as well as the country-specific results for the United States and for Brazil. μ_1, μ_2 and μ_3 are the intercepts for the three regimes. p_{11} is the transition probability of staying in the first regime (i.e., the strong outflow regime), p_{22} is the transition probability of staying in the second regime (i.e., the "normal" regime) and p_{33} is the transition probability of staying in the third regime (i.e., the strong inflow regime). $P(S_t = 1)$ is the unconditional probability of being in the first regime and $P(S_t = 3)$ is the unconditional probability of being in the third regime. For the six country-specific intercepts, we also provide standard errors in brackets. The standard errors are calculated from the inverse of the outer product estimate of the Hessian. **,* indicate statistical significance at the 5 percent and 10 percent level, respectively.

Table 2: Summary Results: Characterizing Capital Flow Regimes

Panel A: Descriptive Statistics				
Equity Outflows	Avg. Probability	Avg. Share in Episode	Frequency	Avg. Length
All Countries	0.304	0.261	12.785	17.421
Advanced	0.349	0.332	9.261	30.248
Emerging	0.279	0.221	14.714	10.397
Equity Inflows	Avg. Probability	Avg. Share in Episode	Frequency	Avg. Length
All Countries	0.250	0.230	9.908	20.020
Advanced	0.306	0.294	9.130	26.522
Emerging	0.220	0.195	10.333	16.459
Bond Outflows	Avg. Probability	Avg. Share in Episode	Frequency	Avg. Length
All Countries	0.239	0.211	7.303	16.831
Advanced	0.233	0.195	5.619	21.216
Emerging	0.242	0.218	8.089	14.784
Bond Inflows	Avg. Probability	Avg. Share in Episode	Frequency	Avg. Length
All Countries	0.281	0.268	7.985	19.010
Advanced	0.272	0.262	5.905	23.260
Emerging	0.285	0.271	8.956	17.026

Panel B: Selected Correlations		
	Equity Outflows vs. Bond Outflows	**Equity Inflows vs. Bond Inflows**
All countries	0.358	0.175
Advanced	0.274	0.049
Emerging	0.417	0.259

Note: "Avg. Probability" is the average probability of being in a strong inflow or strong outflow regime, which is obtained from the regime-switching model (see Equation (1)). "Avg. Share in Episode" is the average percent of time a country spends in an inflow or an outflow episode, where an episode is identified if the probability of being in a strong inflow or strong outflow regime is higher than 0.5 for at least four consecutive weeks. "Frequency" is the frequency with which inflow or outflow episodes appear, and "Avg. Length" is the average number of weeks spent in an inflow or outflow episode. Panel B reports the correlation coefficient between equity outflow (inflow) and bond outflow (inflow) episodes.