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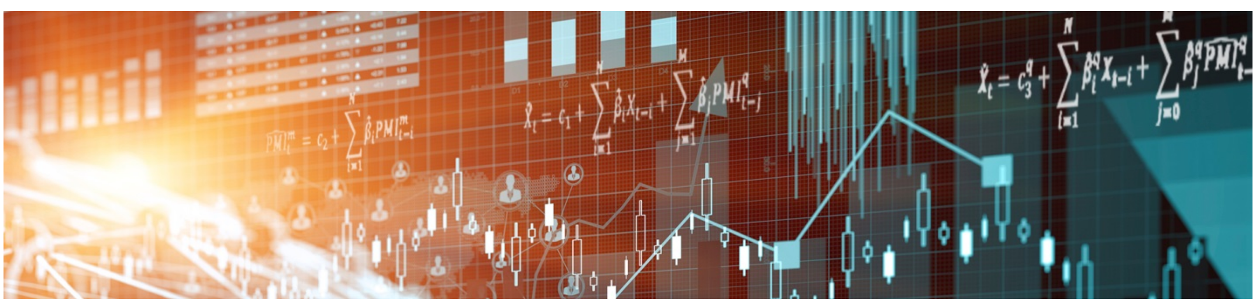
The Dynamics of Capital Flow Episodes



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Abstract

This paper proposes a novel methodology for identifying episodes of strong capital flows based on a regime-switching model. In comparison with the existing literature, a key advantage of our methodology is to estimate capital flow regimes without the need for context- and sample-specific assumptions. We implement this approach using weekly fund flows data for a large set of advanced and emerging economies. As an application of our methodology to the global financial cycle literature, we 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.

JEL classification: F21, F32, G11
Bank classification: International topics; International financial markets; Econometric and statistical methods; Uncertainty and monetary policy

Résumé

Nous proposons une méthodologie nouvelle pour repérer les épisodes de flux importants de capitaux. Cette méthode repose sur un modèle de Markov à changement de régime. Le grand avantage de ce type de modèles sur les approches retenues dans la littérature est qu'il permet de classifier les mouvements de capitaux en différents régimes sans qu'il soit nécessaire de formuler des hypothèses spécifiques au contexte ou à l'échantillon choisi. Nous appliquons cette méthode en exploitant des données hebdomadaires qui retracent les flux de capitaux au sein d'un ensemble imposant composé d'économies avancées et émergentes. Conformément à l'approche suivie dans le cadre des études sur le cycle financier mondial, nous évaluons l'incidence que les variations de la volatilité du marché boursier américain (VIX) et les chocs de la politique monétaire des États-Unis ont sur les mesures agrégées des sorties et des entrées de capitaux liés à des fonds d'actions. Nous employons pour ce faire un modèle VAR structurel à paramètres variables dans le temps. Nous concluons que tant les variations de la volatilité que les chocs de la politique monétaire américaine ont eu des effets très fluctuants sur les épisodes de flux importants de capitaux pendant la période étudiée.

Classification JEL : F21, F32, G11
Classification de la Banque : Questions internationales; Marchés financiers internationaux; Méthodes économétriques et statistiques; Incertitude et politique monétaire

Non-Technical Summary

The triad of events comprising the global financial crisis, record-low interest rates and the use of unconventional monetary policies in many advanced economies has rekindled an interest in evaluating the dynamics of global capital flows. In particular, both policy-makers and academics have focused their attention on the consequences of sharp fluctuations in capital flows. To disentangle extended periods of strong capital flows from regular variations, the literature relies on methods to classify capital flows into different episodes.

In this paper, we build on the seminal works of Forbes and Warnock (2012) and Ghosh et al. (2014), who classify episodes of strong capital flows based on exogenously defined thresholds (e.g., deviations in standard deviation units of capital flow series from their historical means). We contribute to this research agenda along two key dimensions.

First, we propose a novel approach for identifying episodes of strong capital flows based on estimates from a regime-switching model. Compared with the existing literature, a key advantage of our methodology is that it allows us to estimate capital flow regimes without the need for context- and sample-specific assumptions. We implement this approach using data on weekly fund flows for a large set of advanced and emerging economies. Moreover, estimates from our regime-switching model suggest that differences in within-regime growth rates of capital flows are strongly correlated with the quality of a country's institutions, the level of financial development and the share of foreign currency liabilities. We also document the cross-country variations in equity and bond flow episodes (e.g., in terms of frequency of occurrence and average length).

Second, as an application of our methodology to the global financial cycle literature, we use a time-varying structural vector-autoregressive (VAR) model to assess the impact of U.S. stock market volatility (VIX) and U.S. monetary policy shocks on global measures of equity outflow and equity inflow episodes. Our results indicate that both the VIX and the monetary policy shocks had time-varying effects on episodes of strong capital flows over the past 15 years. In particular, the impact of a VIX shock has been considerably stronger in times of elevated uncertainty, although VIX shocks have almost consistently led to more equity outflow episodes and fewer equity inflow episodes over our entire sample period. In contrast, the sign of the effects of a U.S. monetary policy shock on global equity outflow and global equity inflow episodes has changed over time. For example, in the wake of the global financial crisis, U.S. monetary policy shocks have led to more equity outflow episodes and fewer equity inflow episodes compared with the pre-crisis period.

1 Introduction

Following the triad of events comprising the global financial crisis, record-low interest rates and the use of unconventional monetary policies 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, the global financial crisis has renewed the interest in investigating and understanding the determinants and consequences of international capital flows over the recent past.

Building on the seminal work of Forbes and Warnock (2012) and Ghosh et al. (2014), who classify episodes of strong capital flows using approaches based on exogenously defined thresholds (such as standard deviations or distribution percentiles derived from historical experiences), we add to this research agenda as follows. First, we make a methodological contribution. Using high-frequency data, we employ a novel methodology for identifying episodes of strong capital flows 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 the context- and sample-specific assumptions that are required by threshold approaches. Second, as an application of our methodology to the global financial cycle literature, we then use a structural vector-autoregressive (VAR) model with time-varying parameters to study the dynamic interactions between an aggregated measure of global equity flow episodes; U.S. stock market volatility, measured by the CBOE (Chicago Board Options Exchange) Volatility Index (VIX); U.S. monetary policy; and the U.S. business cycle over time.

Determinants of international capital flows have been investigated at least since Calvo et al. (1993), who introduced the differentiation between international "push" and domestic "pull" factors. A rich body of literature followed, culminating in a wealth of studies analyzing capital flow dynamics in the recent past.[1] The analysis of the consequences of international capital flows, on the other hand, 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 (e.g., Caballero (2014), Magud et al. (2014) and Benigno et al. (2015)). In the context of international capital flows, an episode classification is particularly

[1]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 (2015), 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); and, in normal and in crises times, Broner et al. (2013)).

helpful for two reasons. First, capital flows are volatile (e.g., see Bluedorn et al. (2013)) and exhibit a lot of noise – especially at high frequencies. Hence, the aggregation of individual capital flow observations over certain time periods into "episodes" provides 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 (e.g., see Abiad et al. (2009)). Thus, some of the macroeconomic effects of capital flows can only be observed when the level of capital 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 balance of payments (BoP) at quarterly frequencies in a sample of 58 emerging and developed economies between 1980 and 2009. Ghosh et al. (2014) instead focus on surges of net capital flows. The authors define net flow surges as the difference between gross flow surges and gross flow retrenchments, both understood in the sense of Forbes and Warnock (2012). 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.

Using international data at weekly frequencies on equity and bond fund flows into up to 80 different countries[2] over the period 2000 to 2014, we can 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).[3] Following the application of our methodology, we show that the differences in estimated in- and outflow regimes within a country correlate strongly with the quality of its institutions, the level of financial development and 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 average length, across countries. Our findings further appear to be highly consistent with the results of Forbes and Warnock (2012) but allow for the additional identification of strong, but rather short-lived, episodes because of the higher-frequency data that we are using.

The subsequent application of our methodology to the global financial cycle literature builds on earlier work conducted by Rey (2013), who argues that asset prices and capital

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

[3]Section 2.1.2 will discuss the similarities and differences between our work and the other two studies in detail.

flows closely follow the dynamics of U.S. monetary policy and U.S. stock market volatility. Rey's findings suggest that the traditional trilemma – the impossibility of having independent monetary policy, an open capital account and a fixed exchange rate at the same time – reduces to a dilemma by leaving policy-makers the choice between independent monetary policy and an open capital account even in the presence of flexible exchange rates. Hence, the effects that U.S. macroeconomic and financial shocks have on the global financial system are of high interest to policy-makers and academics.

Our findings from the structural VAR analysis indicate that both the VIX and the 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 high uncertainty 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 can affect the economic and financial cycles of other countries. On the other hand, our results demonstrate that the impact of these shocks on the rest of the world can differ 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 a novel methodology for identifying episodes of strong capital flows based on regime-switching models. In particular, it contains a description of the empirical methodology, as well as a presentation and discussion of our episode-classification results. Section 3 then shows 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. Finally, Section 4 concludes.

2 Classification of Capital Flow Episodes

This section proposes an alternative and novel methodology for identifying episodes of strong capital flows, henceforth simply referred to as "episodes."[4] We first highlight the motivation for the introduction of a new methodology, characterize the nature of our data and describe our econometric model. We then present the outcome of the estimation process, discuss the results of our empirical analysis and, finally, end this section by placing our results

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

in the perspective of the previous literature.

2.1 A New Episode-Identification Methodology

2.1.1 Motivation

While episode classifications based on threshold approaches that are currently used in the literature have served well in the past and fit anecdotal evidence of periods with strong capital flows fairly well, there is still room for improvements. Our approach adds to the current literature along the following three dimensions.

First, the existing literature on the identification of capital flow episodes differs on the way to define such thresholds. For example, the two most prominent papers in the literature, Forbes and Warnock (2012) and Ghosh et al. (2014), 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, focus on the 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).

Second, even if there was a common modelling approach, the value of these thresholds would likely have to be changed depending on the available data, such as country type (i.e., advanced economies vs. emerging markets); time period (i.e., inclusion of the 1980s, the global financial crisis, etc.); data frequency (i.e., annual vs. higher-frequency); and capital flow definition (i.e., foreign direct investment vs. portfolio flows, gross vs. net flows). Given the absence of good benchmarks for such changes, the outcomes will reflect a certain degree of discretion. Moreover, in light of the increased interest of policy institutions in monitoring capital flow dynamics, the use of high-frequency data is becoming increasingly common to track capital flows. Therefore, threshold values derived from annual data may not be appropriate for high-frequency monitoring exercises, which rely on weekly or monthly series that exhibit substantial volatility. As such, a more systematic approach to the estimation of capital flow episodes is needed.

Third, current definitions of capital flow episodes based on the threshold approach lead to a binary indicator that provides limited information on how distant the actual data are from the threshold. In contrast, a probabilistic approach better reflects 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.

2.1.2 Data

In order to estimate the regime-switching models at the country level, we require high-frequency data that are comparable across countries. As a result, we use weekly data on capital flows from the Emerging Portfolio Fund Research (EPFR) database. The data we use from the EPFR database are aggregated to the destination country level and are characterized by the "country flows" concept, which is derived 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).[5] 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).[6]

Some of the components of our EPFR data have featured prominently in the literature. The fund flows dimension, for example, which underlies the country-allocation dimension that we are employing, has been used by Jotikasthira et al. (2012) and by Fratzscher (2012), for example. 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."* 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.[7] Figure 1 indicates

[5]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.

[6]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.

[7]For the EPFR data, which record equity inflows as the percentage change in outstanding investments at

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 record the same underlying capital flow dynamics.

The EPFR data for equity and bond flows are treated separately and come with varying country coverage and sample start dates. The final sample for equity capital 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).[8] The final dataset of bond capital flows contains 66 countries and the start dates extends from the first week of January 2004 to the first week of January 2006. The end dates 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.

Given that we propose an alternative methodology for the identification of capital flow episodes, it is important to set our results in perspective of the current literature. 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. On the one hand, Forbes and Warnock (2012) classify strong capital flows into episodes of “surges” (inflows of capital from foreigners), “stops” (outflows of capital from foreigners), “retrenchments” (inflows of capital from residents) and “capital flights” (outflows of capital flows from residents). Ghosh et al. (2014), on the other hand, focus on “net flow surges” that are defined as a combination of liability-side capital inflows (i.e., non-resident investments into the country) – and thus (gross flow) surges under the definition by Forbes and Warnock (2012) – and asset-side capital inflows (i.e., the repatriation of foreign assets by domestic residents) – and thus (gross flow) retrenchments under the definition by Forbes and Warnock (2012).

Using data from the EPFR database, which reports cross-border capital flows to and from investment funds, we only observe capital movements originating abroad (i.e., by foreigners/non-residents). This leaves us with the two episode classifications “inflow episodes”

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 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.

[8] 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.

– corresponding to the surges definition from Forbes and Warnock (2012) – and "outflow episodes" – corresponding to their definition of stops.[9] While there could be a positive relationship 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 comparable to those of Forbes and Warnock (2012), since the definition of net flow surges in Ghosh et al. (2014) contains retrenchments of capital 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, e.g., 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.

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 the EPFR database is the availability of data at a weekly frequency, which is helpful for inference on regimes, since we need long samples for computational reasons. Moreover, using data at a weekly frequency allows us to better track fluctuations in capital flows, given the volatility observed in capital flows.[10] In detail, the baseline univariate model we estimate is

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

[9] Investments (disinvestments) in investment funds by residents of a large country can take on traces of capital flights (retrenchments), when the associated fund is heavily exposed to 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.

[10] Note that EPFR data are also available at a daily frequency. However, we refrain from using such data because of the excessive volatility observed in the daily series. Hence, it is likely that the additional information contained in daily data would be clouded by the noise they contain. Moreover, it is doubtful that portfolio managers would make their investment decisions at a daily frequency, so that we do not lose much by using weekly data for identifying capital flow regimes.

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.[11] We estimate all regime-switching models with quasi-maximum likelihood, using the expectation-maximization algorithm (see Hamilton (1990)).[12]

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 our 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 regional aggregates). 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 $\mu_3 > \mu_2$). The second regime is instead a "normal" regime characterized by neither strong inflows nor strong outflows (i.e., $\mu_1 < \mu_2 < \mu_3$). Further, the differences in the intercepts' estimates (i.e., $\mu_3 - \mu_1$) 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 replicates this finding and provides correlation evidence between the differences in equity flow regimes within countries (left axes) 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.[13] In the first five cases, we observe a negative correlation, suggesting that a higher per capita income, more GDP growth, a higher quality of institutions and more financial development are associated with a lower difference in the regimes for a country. In addition, a higher share of foreign currency liabilities is associated with a larger difference in regimes. Hence, in line with the previous literature on boom and bust cycles in emerging markets, these correlations suggest that especially in emerging markets, which,

[11] 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 in the other two regimes.

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

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

at times, 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.

Turning next to the transition probabilities, we find that for both advanced and emerging-market economies, the first regime is the least persistent compared with the other two regimes (i.e., the transition probability of staying in the first regime p_{11} is lower than p_{22} and p_{33}). When focusing on the unconditional probability of being in a regime, the second regime turns out to be the most prevalent one, since the unconditional probability of being in the second regime ($P(S_t = 2)$) is the highest compared with the unconditional probabilities of being in the other regimes.

Finally, the individual estimation results for the United States and Brazil confirm the evidence obtained from the aggregated comparison. In particular, we find for both equity and bond flows that the differences in regimes are less strong for the United States than for Brazil (since the absolute values of the intercepts are lower in the United States), that the regimes are more persistent in the United States than in Brazil (since the transition probabilities are systematically higher in the United States) and that the United States and Brazil will remain for most of the time in the second regime (since the unconditional probability is highest for the second regime).

2.2.2 Episode Classification and Discussion of Findings

This section presents and discusses the classification of episodes for different aggregates and for individual countries. We obtain a separate set of episodes for equity outflows, equity inflows, bond outflows and bond inflows. Table 2 presents the aggregated results across all sample countries, the sample of advanced countries and the emerging-market sample (Tables 3 to 6 show the results for individual countries). The column "Avg. Probability" presents the average probability of a country being in a different regime than the normal regime. To obtain a discrete outcome variable that indicates the presence of a distinct capital flow pattern, we define two additional conditions that, when fulfilled, characterize an "episode."[14] 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 per cent. The second condition is that this is the case for at least four consecutive weeks. The column "Avg. Share in Episode" shows the corresponding average

[14]Both assumptions are relatively weak and are required only 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, it might even be possible to work with the probabilities directly. In such a case, there would be no need for any additional assumptions.

time of the sample period that each country spends in an episode. Finally, the column labelled "Frequency" indicates the number of episodes the country experiences over the sample period and the column "Avg. Length" contains the average length of an episode in the respective country.[15]

Turning next to the content of the tables, we observe the following three facts based on the episode classification exercise (see especially Table 2). First, the average country spends around 25 percent of the time in an episode ("Avg. Share in Episode").[16] Second, while the average probability ("Avg. Probability") directly inferred from the regime-switching model indicates a longer duration for strong capital flow regimes, both series are still fairly similar and suggest that the periods of strong capital flows generally extend beyond four weeks. Third, returning to the "Avg. Share in Episode" column, the average share of time that advanced and emerging markets spend in bond flow episodes is very similar (i.e., 0.27 and 0.29 for bond inflows into advanced countries and emerging markets, repectively; 0.23 and 0.24 for bond outflows from both country groups, respectively). However, the average share of time that advanced countries spend in equity flow episodes is significantly larger than the share that emerging markets spend in such episodes (i.e., 0.31 and 0.22 for equity inflows into advanced countries and emerging markets; 0.35 and 0.28 for equity outflows from both regions, respectively).

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

When we turn to the average length of the identified episodes, we see that for the average country, the length of inflow episodes (i.e., 20.0 weeks for equity inflow episodes and 19.0 weeks for bond inflow episodes) is higher than the length of outflow episodes (i.e., 17.4 weeks for equity outflow episodes and 16.8 weeks for bond outflow 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 significantly longer episodes than emerging markets (between 10.4 weeks for equity outflow episodes and 17 weeks for bond inflow episodes).

[15] The product of frequency and average length, divided by the total number of observations in each country corresponds to the value in the "Avg. Share in Episode" column.

[16] The share of time the average country spends in equity outflow episodes is somewhat higher and the share of time that is spent in bond outflow episodes is somewhat lower.

Finally, we look at the contemporaneous correlation between different types of episodes. The bottom part of Table 2 shows the average correlations across the entire sample of countries, as well as across advanced countries and emerging markets (Table 7 presents the results for individual countries).[17] Starting with the correlation between equity inflows and bond inflows, a strong positive correlation between both capital classes indicates that inflows occur at the same time, and investors do not differentiate much among different 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, indicates that investors differentiate among asset classes within countries and thus points to lower country-specific risks or a better availability of information. The correlation between equity inflows and bond inflows for the average country in the sample is about 0.17. While the average emerging market experiences a correlation of 0.26, the average advanced country has a (slightly) negative correlation of 0.05. Focusing on the country level (Table 7), we see that seven countries obtain a negative correlation, with the correlation in Finland being around -0.23 and the correlation in the United Kingdom being close to zero. Assessing next the correlation between equity outflows and bond outflows, a higher correlation coefficient indicates that outflows across different capital classes appear at the same time, while a negative correlation coefficient shows that overall capital flows to the country are more balanced. Again, the correlation between both capital classes is stronger for the average emerging market (0.42) than for the average advanced country (0.27), indicating that investors substitute among asset classes more often in advanced countries than in emerging markets.

2.2.3 Comparison with the Literature

This section relates our episode-classification results to the episodes identified in Forbes and Warnock (2012).[18] To make our results comparable to those of Forbes and Warnock (2012), we modify our episode data in the following way. First, since Forbes and Warnock (2012) use aggregated data on portfolio flows to classify their episodes (i.e., they do not distinguish between equity and bond-based episodes), we create an additional variable that captures aggregated episodes and takes on the value of one as long as either an equity episode or a bond episode exists. Second, since the sample coverage of this paper (starting in 2000 at the earliest and ranging until the end of 2014) differs from the one in Forbes and Warnock

[17] In the United States, only a single equity inflow episode has been identified and it takes place at a time when the bond flow sample has not yet started. Hence, it is not possible to compute a correlation coefficient for equity inflows into the United States.

[18] As pointed out in Section 2.1.2, a comparison with the episodes identified in Ghosh et al. (2014) is difficult since their definition of net flow surges contains the retrenchment of capital from abroad by residents for which we do not have data. Further, Ghosh et al. (2014) use annual data, which might identify inflow and outflow episodes at much lower frequencies.

(2012) (starting in 1980 and ending in 2009), we focus our comparison only on the overlapping periods (i.e., 2000 to 2009).[19]

Based on the results of Forbes and Warnock (2012) and those of our paper, we then compute aggregated measures of outflow episodes that capture the share of sample countries in a (sudden) stop episode in Forbes and Warnock (2012) and in a joint (i.e., in an equity and/or a bond) outflow episode in our paper. Figure 3 reports the corresponding measures for our paper (red line) and for Forbes and Warnock (2012) (blue line). The two lines have a correlation coefficient of 0.37 and move closely together for most of the sample.[20] Most outflow episodes identified by both papers are located after the bursting of the dotcom bubble in the early 2000s and, more recently, during the global financial crisis. With a higher data frequency, our paper additionally identifies a set of strong but rather short-lived episodes during the sample period that might be missed in lower-frequency data.[21]

We also compute aggregated measures of inflow episodes for both papers. Figure 4 shows the corresponding results. Again, the correlation coefficient between our share measure (red line) and the one based on Forbes and Warnock (2012) (blue line) is high, amounting even to 0.63 this time.[22] Most inflow episodes took place in the years before the global financial crisis, as evidenced by several sharp inflow spikes during this period.

To sum up, our methodology for identifying episodes of extreme capital flows based on a regime-switching model has produced a set of outflow and inflow episodes that is comparable to previous episodes classifications in the literature. At the same time, our methodology requires fewer assumptions on the nature of the threshold that is appropriate for a given dataset and thus can easily be applied to high-frequency data. As Figures 3 and 4 also show, the use of high-frequency data has the advantage of allowing us to identify strong, but rather short-lived, episodes and also allows us to obtain information on capital flow dynamics almost in real time – well ahead of traditional BoP data releases.

[19]Since Forbes and Warnock (2012) have not identified any inflow episodes in 2009 and this is the last year of their sample, we truncate the inflow episode comparison in 2008.

[20]The correlation coefficient of the blue line with a corresponding measure of equity outflows amounts to 0.25 and with a measure of bond outflows to 0.45.

[21]The episode classification in Forbes and Warnock (2012) changes only at a quarterly frequency because of the nature of their underlying BoP data.

[22]The correlation coefficient of the blue line with a corresponding measure of equity inflows amounts to 0.58 and with a measure of bond inflows to 0.23.

3 Equity Flow Episodes in the Global Financial Cycle

As an application for our previously defined episodes of strong capital flows, we study the dynamic interactions between the share of countries in an equity flow episode, the U.S. monetary policy stance and U.S. stock market volatility, measured by the VIX, using a vector-autoregression (VAR) model. This exercise follows 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 time-varying parameter VAR that allows us to model the changing impact of the two shock variables on our measure of capital flow episodes over time.

3.1 Empirical Methodology

3.1.1 Data

Our VAR models include the following variables: the share of countries in an equity flow episode; the U.S. real federal funds rate to assess the stance of U.S. monetary policy; the VIX, as a measure of U.S. stock market volatility; and industrial production to proxy the U.S. business cycle.

Capital Flow Episodes: We use the share of countries in an equity outflow episode (or an equity inflow episode) to capture the dynamics of capital flow episodes across countries.[23] In doing so, we consider different country groupings, such as emerging markets and advanced economies separately, as well as an aggregate measure that covers all countries in our sample. We concentrate our analysis on equity flow data, since bond flow data are available only over a shorter sample period. Figures 5 and 6 present the corresponding sets of share measures for outflow and inflow episodes.

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 first 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

[23] 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.

extending from January 2009 to December 2014.[24] Note that we use the real federal funds rate; that is, we subtract the annual change in the CPI from the nominal short-term rate. Figure 7 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. 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 macroeconomic uncertainty to the extent that it is related to financial markets fluctuations.

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

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 volatility index, and a capital flow measure.

In doing so, we assume a recursive structure in the system, ordering the variables from slow- to fast-moving variables. As a result, the measure of global capital flows is placed last

[24]In detail, Wu and Xia (2015) derive a shadow interest rate from a shadow rate 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.

in the VAR, which assumes that the global 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. In contrast, 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. Finally, the monetary policy measure is placed second in the VAR, which implies that it reacts only contemporaneously to the business cycle variable.

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 outflows 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. Finally, the linear VAR cannot take into account changes in domestic fundamentals in the countries of our sample (with the exception of the United States). As a result, we also estimate a time-varying parameter VAR model (TVP-VAR) that 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. The TVP-VAR model (with stochastic volatility) 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 8 reports the impulse-response functions for the share of countries in an equity outflow episode following a VIX shock (i.e., a 10-point increase in the VIX) and a U.S. monetary policy shock (i.e., a 100-basis-point increase in the interest rate).[25]

First, we assess the impact of the VIX shock, which is displayed in the first panel of the top row in Figure 8. When considering an unexpected increase in the VIX by 10 points, we

[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 real interest rate is slightly positive, but largely insignificant, and the effect of the VIX on industrial production is negative. The response of the VIX to the monetary policy shock is negative but largely insignificant, the response of the real interest rate documents the persistence of the shock, and the response of industrial production to the monetary policy shock is negative (and again largely insignificant).

observe a sharp increase in the share of countries in an outflow episode upon impact (about 15 percent). Since the associated bootstrapped 90 percent confidence bands are above zero at impact, the increase in the share measure is significant. This is in line with economic theory: an increase in the VIX indicates a higher level of stock market volatility and is a good proxy for uncertainty in financial markets. In such an environment, investors are more likely to instantly redeem their equity fund shares and to invest in safer asset classes, such as government bonds instead. Hence, equity funds will withdraw their investments more often, leading to a more frequent occurrence of outflow episodes, and thus also to an increase in the share measure. As pointed out before, the confidence bands show that the reaction of the share measure to a VIX shock is relatively short-lived, with the response not being statistically different from zero after two months. However, this is not surprising since the underlying capital flow data are derived from 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), which is shown in the first panel of the bottom row of Figure 8. For the linear VAR, it turns out that the U.S. monetary policy shock has 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 indicates higher returns for investors,[26] and thus we would observe a reduction in capital outflows (represented by a lower share of countries in equity outflow episodes in our case) as a consequence.[27] On the other hand, a higher real interest rate can indicate tighter financial conditions and thus lead to more difficulties for investors to maintain or increase their leverage. This, in turn, could lead to an increase in equity outflows. Since it is likely that different interpretations have played a role at different points in time, we investigate this finding further in Section 3.2.2, using 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. Our initial result, an insignificant response of the share of countries in an outflow episode, also lines up relatively well with the findings 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

[26]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.

[27]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.

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, although it can be associated with significant financial turmoil in these economies, as exemplified by the events of the summer of 2013.

Next, we conduct the same exercise for equity inflow episodes. Figure 9 reports the responses of the share of countries in an equity inflow episode to a VIX shock (first panel, top row) and a U.S. monetary policy shock (first panel, bottom row).[28] 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 and fades out very quickly. Note also that, in absolute value, the reaction on impact is somewhat smaller compared with Figure 8, suggesting some evidence for non-linear effects. In other words, U.S. stock market volatility shocks seem, on average, to affect outflow episodes relatively stronger 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 in the real interest rate leads to a significant increase in the share of countries in an inflow episode. As pointed out above, this finding appears to suggest that the interpretation of the interest rate as a return measure (or the additionally mentioned crisis-normalization interpretation) outweighs the leverage interpretation.

So far, we have conducted our analysis for all countries in the sample. However, given that the previous literature has found substantial differences in capital flow dynamics between advanced and emerging markets, we also compare the impulse-response functions of both groups. In doing so, we estimate the VAR model represented by Equation (2) using the share of countries in an outflow or an inflow episode calculated only from advanced economies, and only from emerging markets. Figure 10 reports the difference between the impulse responses obtained from emerging markets and advanced economies to a U.S. stock market volatility shock and a U.S. monetary policy shock.[29]

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

[28] 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 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 monetary policy shock is negative, the response of the 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.

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

and significant impact in the difference impulse-response function shown in the top left panel of Figure 10. This finding is suggested by economic theory and previous findings in the literature (e.g., Gourio et al. (2014)). Since investments in emerging markets are riskier in general, 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. Hence, the previously observed finding that the monetary policy shock has an unambiguous effect on the share of countries in an outflow episode seems to apply to both country groups. However, the difference impulse-response function suggests that the reduction in the share of countries in an outflow episode pertains more to emerging markets than to advanced countries after a period of 10 months. Hence, it appears that over the medium term, emerging markets are more negatively affected by a tightening in U.S. monetary policy than advanced countries.

We also assess the differential impact on inflow episodes across country groups. 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 10 suggests that the impact of the VIX shock on inflow episodes is more positive/less negative for emerging markets than for advanced countries. At the first instance, this finding is somewhat surprising. However, the fact that higher uncertainty increases the share of both inflow and outflow episodes in emerging markets more than in advanced countries, could also point to a portfolio rebalancing effect within the emerging-market sample. While more caution about emerging-market investments on the investor side could explain the first observation, the proceeds could be reinvested in less-risky emerging markets and explain the second observation.

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, we observe that there is no significant difference between the two country groups.

3.2.2 Results from the Time-Varying Parameter VAR

Following the insignificant response of the share of countries in an equity outflow episode to the U.S. monetary policy shock in the linear VAR model, we now provide evidence from the time-varying parameter VAR. Figure 11 shows the time-varying impulse responses to a VIX shock and to a 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 measure 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 non-linearity in that the effect of a VIX shock seems greater in times of heightened uncertainty. 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.[30]

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 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. (Note that 68 percent posterior credible sets exclude a zero response of the share of countries in an equity outflow episode after 2011.) Potential explanations for this change have already been presented above. A negative relationship between the two variables (i.e., an unexpected increase in the U.S. real interest rate leads to fewer countries being in an outflow episode) represents a return-based interpretation of the interest rate; that is, investors invest in countries where the returns, here represented by the real interest rate, are higher. In contrast, the recently observed positive relationship (i.e., a surprise increase in the U.S. real interest rate leads to more countries being in an outflow episode) favours an interpretation based on leverage. With the deleveraging process at play in the aftermath of the financial crisis, investors might find it less attractive to invest in funds that are active in other countries following a tightening of U.S. monetary policy.[31]

To assess whether there are differences between the full sample and different country groups, we re-estimate the time-varying parameter VAR for emerging countries only. Panels (a) and (b) of Figure 12 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 only. The responses are similar to Figure 11, except that the

[30]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.

[31]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 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.

responses to monetary policy shocks and VIX shocks 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.

Finally, in Figure 13, we assess the time-varying impact of the two shocks on the share of countries in equity inflow episodes. Panel (a) shows that the impact of the VIX shock on equity inflow episodes is negative for most of the sample period (with an even stronger negative impact 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 6, 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 13 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 11. 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 global financial crisis has reversed the sign of this relationship as well. As a result, the 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 in the recent past. On the one hand, this supports the earlier findings by Rey (2013) that U.S. macroeconomic and financial shocks can affect the economic and financial cycles of other countries. On the other hand, this demonstrates that the impact of these shocks on the rest of the world can differ substantially over time – making it potentially even more difficult for policy-makers elsewhere 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. Both research questions are beyond the scope of this paper and are left for future research.

4 Conclusion

This paper has contributed to the literature along two dimensions. First, we proposed a novel methodology for identifying episodes of strong capital flows based on a regime-switching model. A key advantage of this approach is to endogenously determine capital flow regimes without the need for context- and sample-specific assumptions. We then applied our methodology to international fund flows into up to 80 different countries over the period 2000 to 2014 at weekly frequencies. Based on this analysis, we have shown that differences in estimated inflow and outflow regimes within a country correlate strongly with the quality of institutions, the level of financial development and the country's share of foreign currency liabilities. We have also documented the main features of equity and bond flow episodes, such as their frequency of appearance and average length, across countries. Our findings appear to be highly consistent with the results of Forbes and Warnock (2012) but allow for the additional identification of intensive but short-lived episodes because of the higher-frequency data that we are using. However, the exercise does not have to stop here. Instead of converting the obtained probabilities into zero-one measures of episodes, one could also make use of the resulting information in continuous terms. This procedure could deliver a better understanding of the stability and expected persistence of an episode at each point in time and thus facilitate the use of episode classifications for monitoring the needs of policy institutions.

Second, as an application of our methodology to the global financial cycle literature, we have used a time-varying structural VAR 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 the VIX and the 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 high uncertainty 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. This result is of particular interest in terms of the current debate on the spillover effects of U.S. monetary policy in that our analysis suggests a substantial degree of time variation in the effects of U.S. monetary policy, as well as U.S. stock market volatility, on the dynamics of global capital flows since the turn of the millennium.

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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 the Regional Aggregates

The samples for equity and bond flows are not identical since, in some countries, data are only available for a single asset class ($^{\mathrm{E}}$ = equity sample only; $^{\mathrm{B}}$ = 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$^{\mathrm{E}}$, Norway, Portugal$^{\mathrm{E}}$, Spain, Sweden, Switzerland, United Kingdom, and the United States.

The *emerging-market sample* includes[32] Argentina, Bosnia and Herzegovina$^{\mathrm{B}}$, Brazil, Bulgaria$^{\mathrm{E}}$, Chile, China, Colombia, Costa Rica$^{\mathrm{B}}$, Croatia, Cyprus$^{\mathrm{E}}$, Czech Republic, Dominican Republic$^{\mathrm{B}}$, Ecuador$^{\mathrm{B}}$, Egypt, El Salvador$^{\mathrm{B}}$, Estonia$^{\mathrm{E}}$, Ghana$^{\mathrm{B}}$, Guatemala$^{\mathrm{B}}$, Hong Kong, Hungary, India, Indonesia, Iraq$^{\mathrm{B}}$, Ivory Coast$^{\mathrm{B}}$, Kazakhstan, Lebanon$^{\mathrm{B}}$, Lithuania$^{\mathrm{E}}$,

[32]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."

Malaysia, Mauritius[E], Mexico, Morocco[E], Nigeria, Oman[E], Pakistan, Panama, Peru, Philippines, Poland, Qatar[B], Romania, Russia, Serbia[B], Singapore, Slovenia[E], South Africa, Sri Lanka[E], Taiwan[E], Thailand, Trinidad and Tobago[B], Tunisia, Turkey, Ukraine, Uruguay[B], Venezuela[B], Vietnam, Zambia[E], and Zimbabwe[E].

C Details on 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 $\frac{3.5}{9} \times 10^{-4}$.[33]

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.

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

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

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

[33] 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 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

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

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

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

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

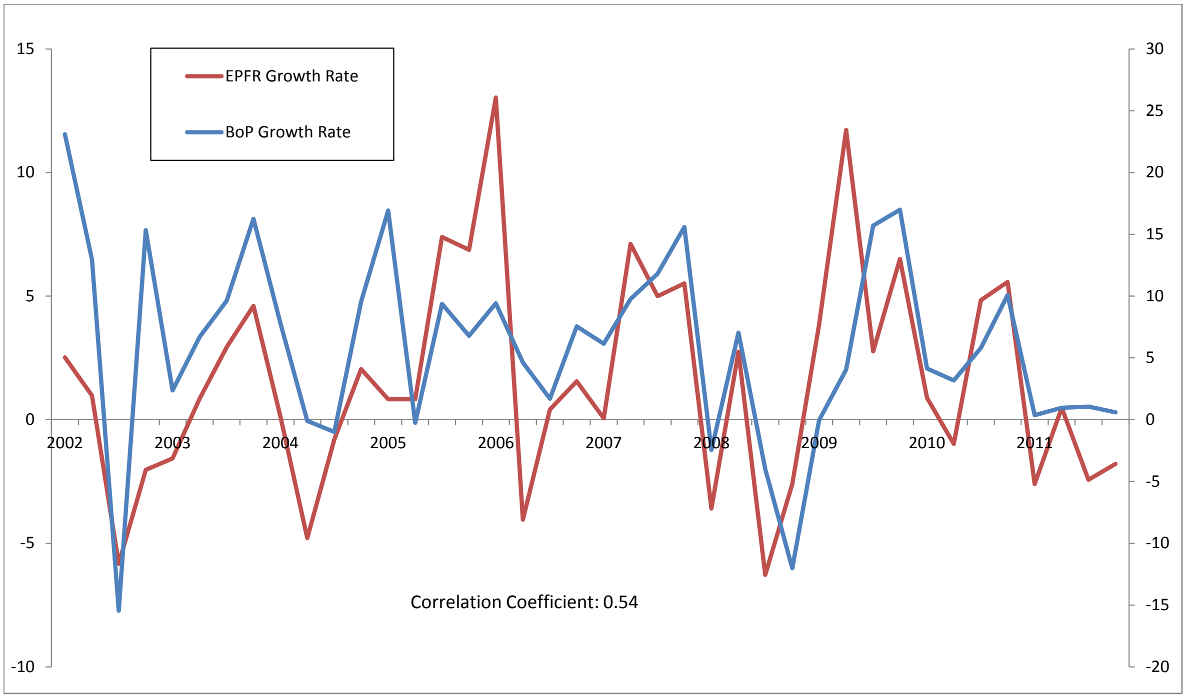
Step 4: Using the draw for the $b_{ij,t}$s, we calculate the residuals l_{it}s and draw the three blocks of D (that is, the innovations in the law of motion for the "structural" parameters $b_{ij,t}$s) from an inverted Wishart distribution.

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.

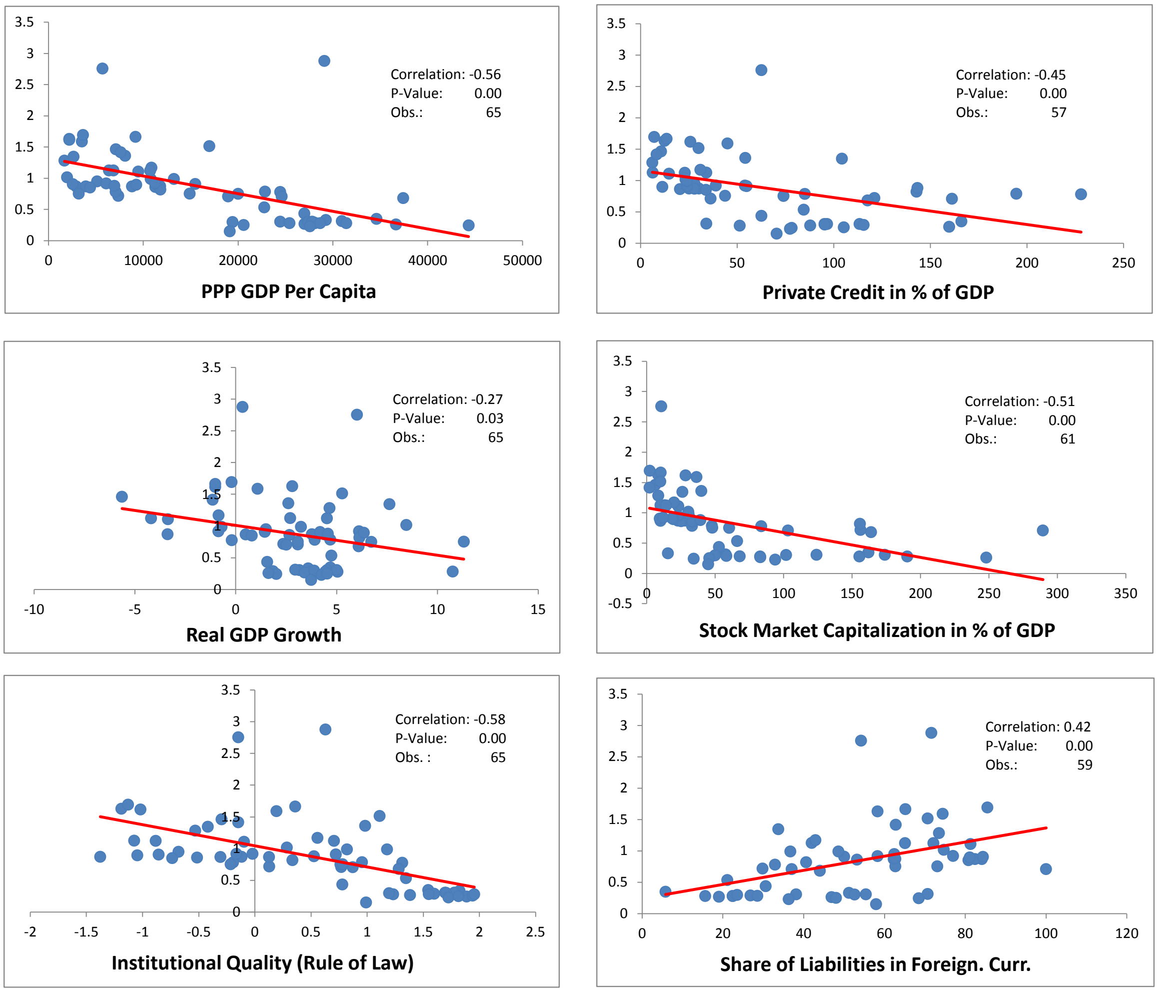
Step 7: The MCMC algorithm simulates the posterior distribution of the states and hyperparameters, iterating over Steps 1 to 6. We use a burn-in period of 50,000 iterations to converge to the ergodic distribution and run a further 30,000 iterations sampling every third draw to reduce the autocorrelation 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



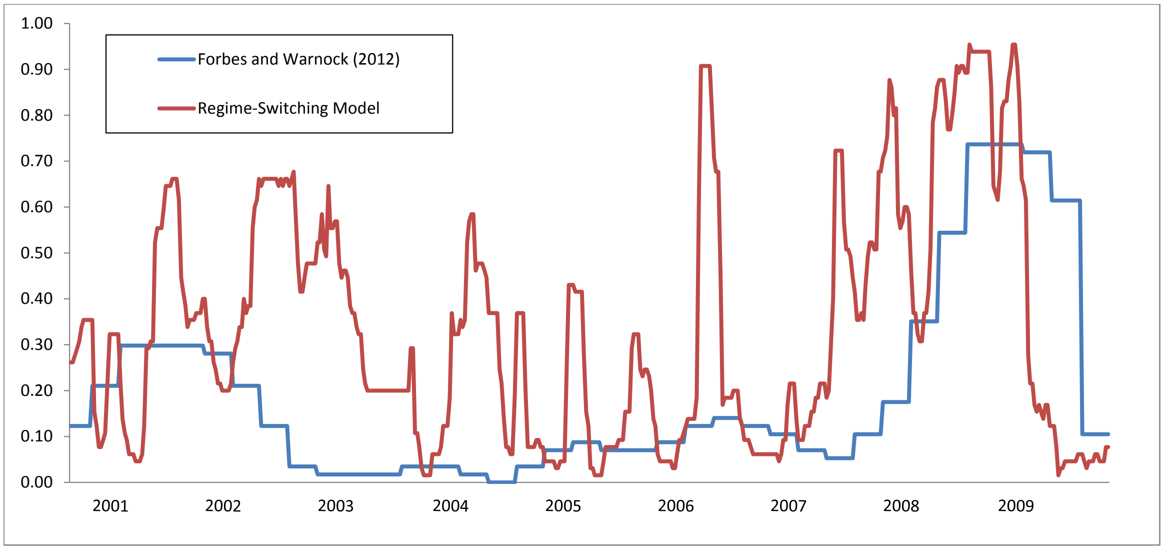
Note: *EPFR Growth Rates (Left Axis):* The original EPFR data consist of equity inflows into Brazil as the percentage change in outstanding investments at the start of the week. The red line represents the corresponding quarter-on-quarter growth rate of this measure. *BoP Growth Rates (Right Axis):*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

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



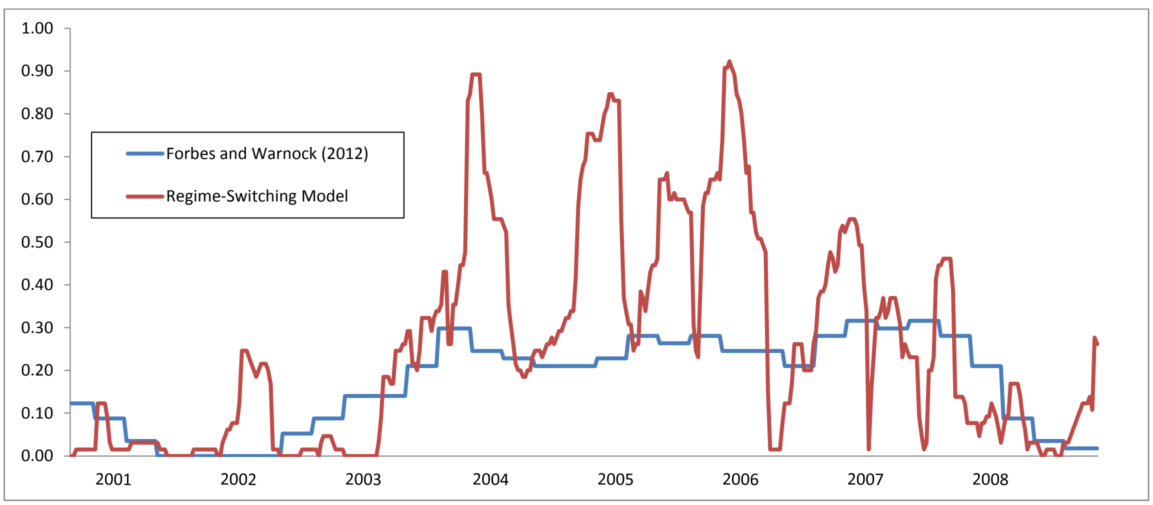
Left-hand-side variable: Difference between the intercepts of the third and first regime for each country. *Right-hand-side variables*: PPP GDP Per Captia and Real GDP Growth have been obtained from the IMF's WEO Database October 2015. Institutional Quality (Rule of Law) has been obtained from the World 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: Comparison of Outflow Episodes with Forbes and Warnock (2012)



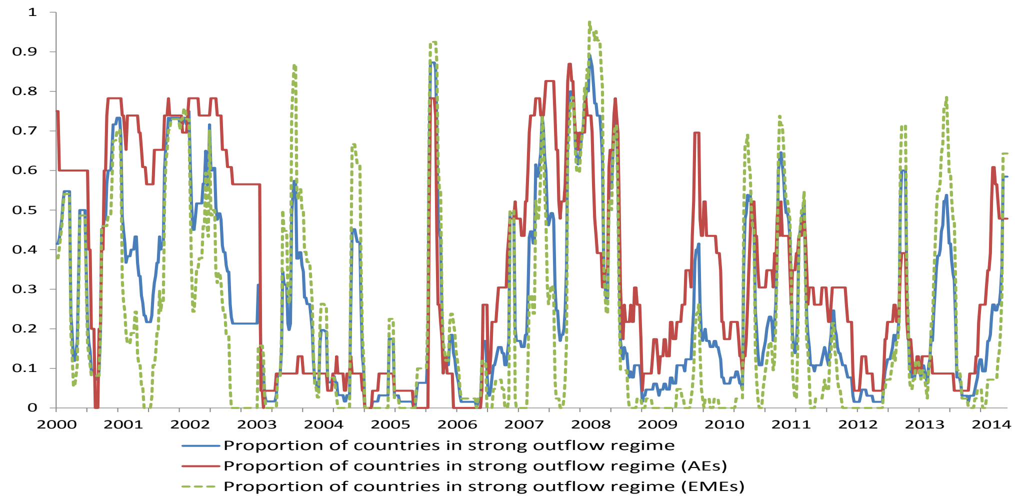
Note: The comparison of outflow episodes from this paper ("Regime-Switching Model") is identified using a regime-switching model on EPFR data, with those in Forbes and Warnock (2012). Outflow episodes from both sources are expressed as a share of sample countries that are currently in an episode of strong capital outflows. To better match the data in Forbes and Warnock (2012), for this specific comparison, the share of outflow episodes from this paper is based on "joint outflow episodes." Measures of joint outflow episodes take on the value of one when at least one equity outflow episode or a bond outflow episode is present.

Figure 4: Comparison of Inflow Episodes with Forbes and Warnock (2012)



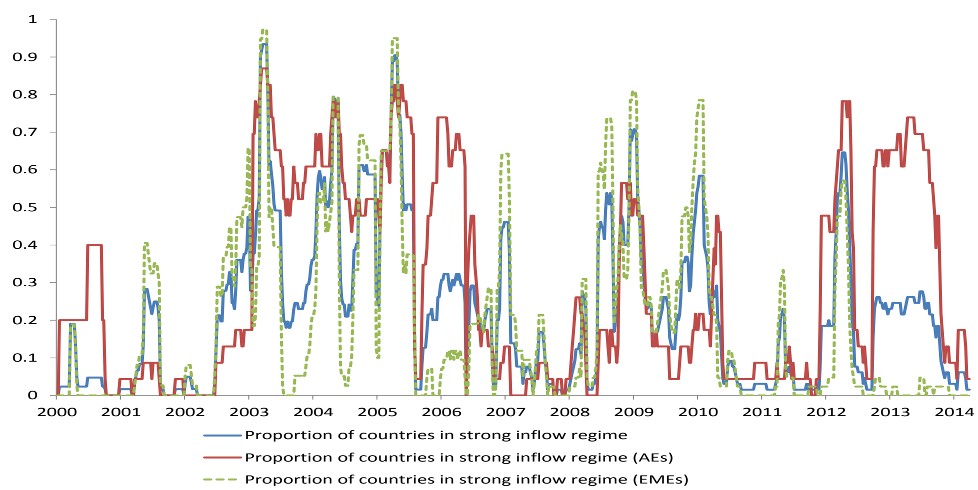
Note: The comparison of inflow episodes from this paper ("Regime-Switching Model") is identified using a regime-switching model on EPFR data, with those in Forbes and Warnock (2012). Inflow episodes from both sources are expressed as a share of sample countries that are currently in an episode of strong capital inflows. To better match the data in Forbes and Warnock (2012), for this specific comparison, the share of inflow episodes from this paper is based on "joint inflow episodes." Measures of joint inflow episodes take on the value of one when at least one equity inflow episode or a bond inflow episode is present.

Figure 5: Share of Countries in an Equity Outflow Episode



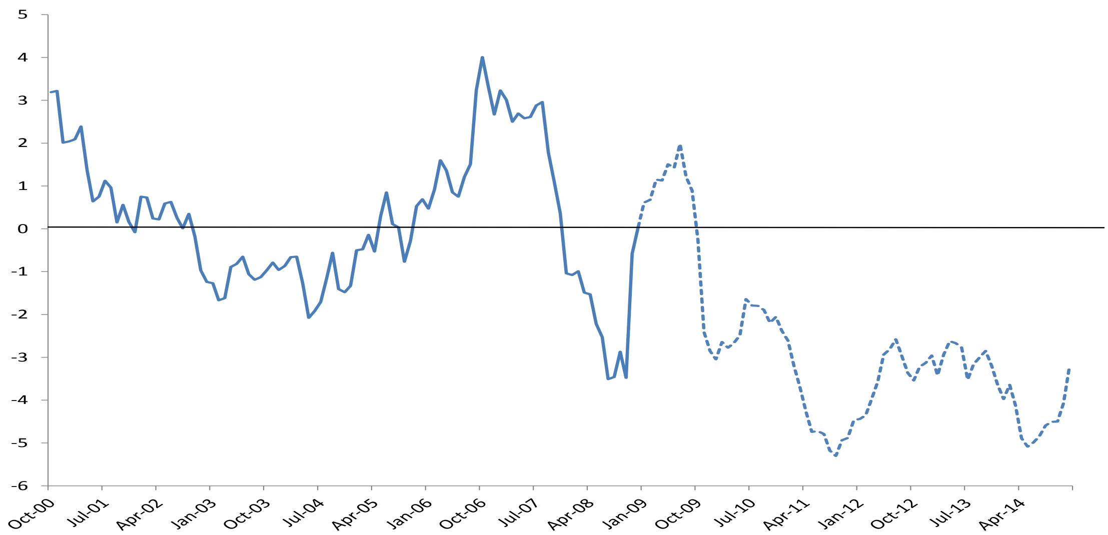
Note: This figure reports the share of countries in an equity outflow episode for the entire dataset, for advanced economies (AEs) and for emerging-market economies (EMEs). The sample size extends from the last week of October 2000 to the last week of December 2014.

Figure 6: Share of Countries in an Equity Inflow Episode



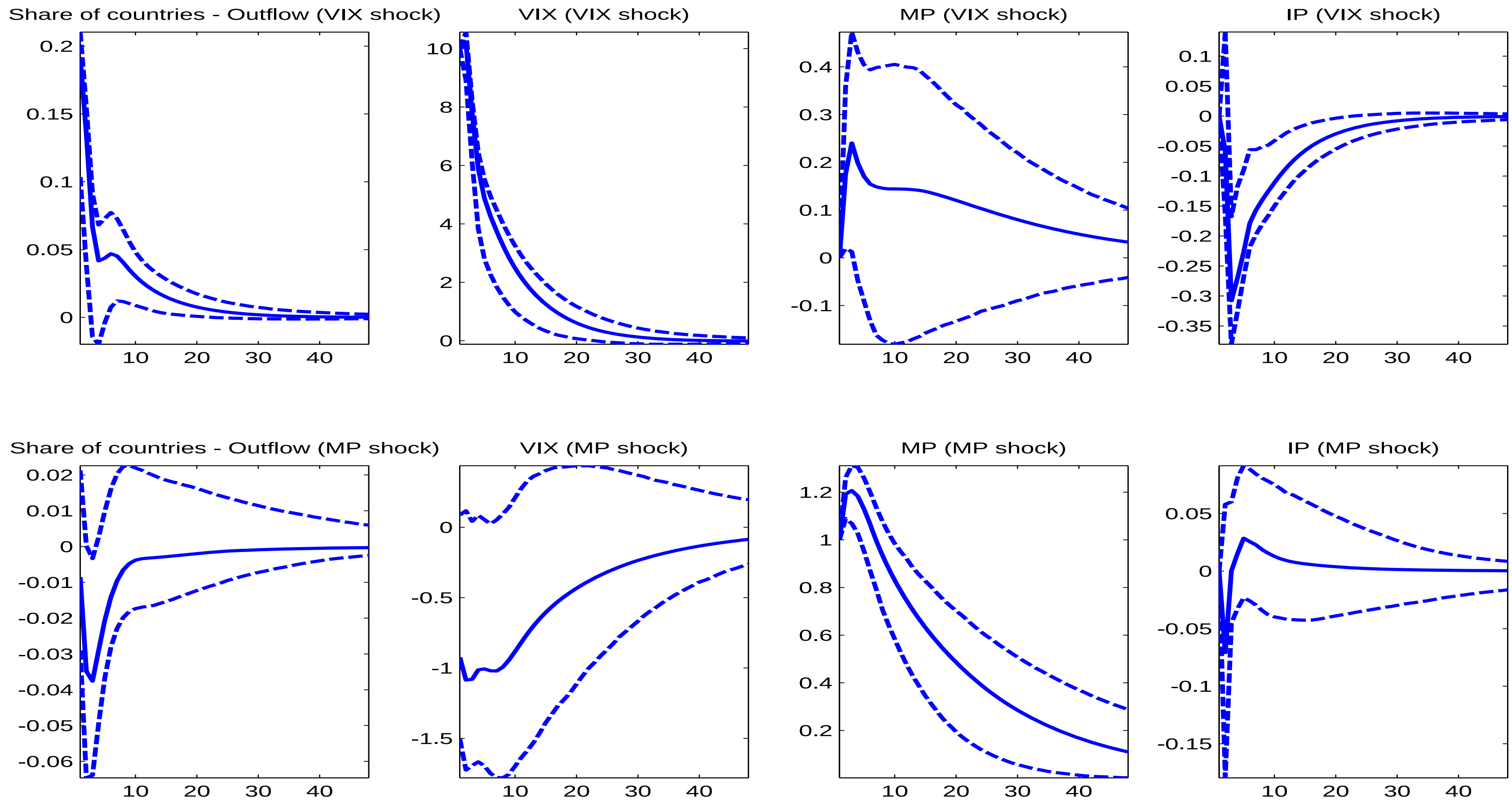
Note: This figure reports the share of countries in an equity inflow episode for the entire dataset, for advanced economies (AEs) and for emerging-market economies (EMEs). The sample size extends from the last week of October 2000 to the last week of December 2014.

Figure 7: Real Interest Rate – October 2000 to December 2014



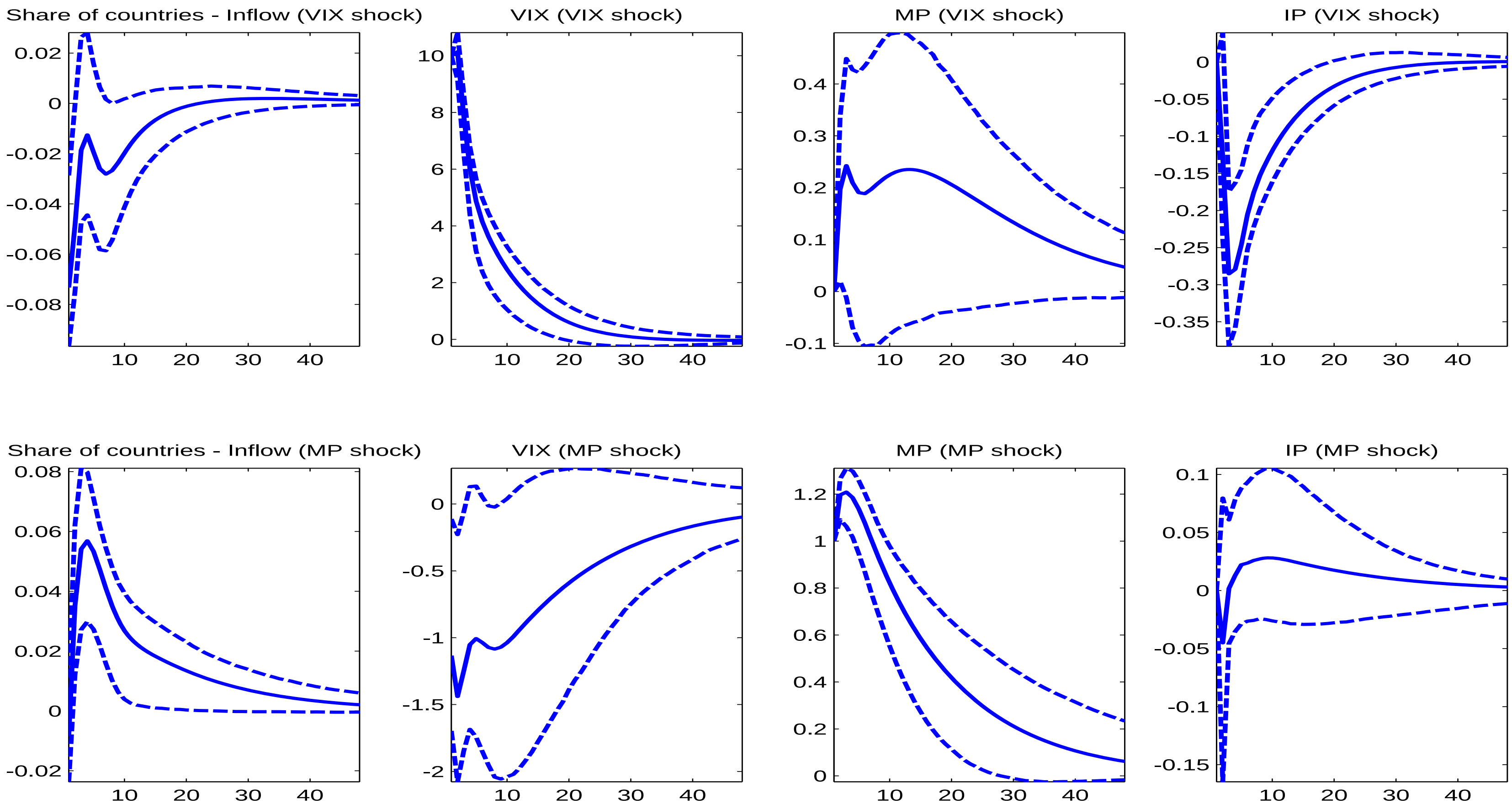
Note: The real interest rate is calculated as the difference between the nominal federal funds rate and the annual inflation rate (annual change in the CPI). From January 2009 onwards, we use the shadow interest rate from Wu and Xia (2015) instead of the nominal federal funds rate.

Figure 8: Impulse-Response Functions – Equity Outflow Episodes



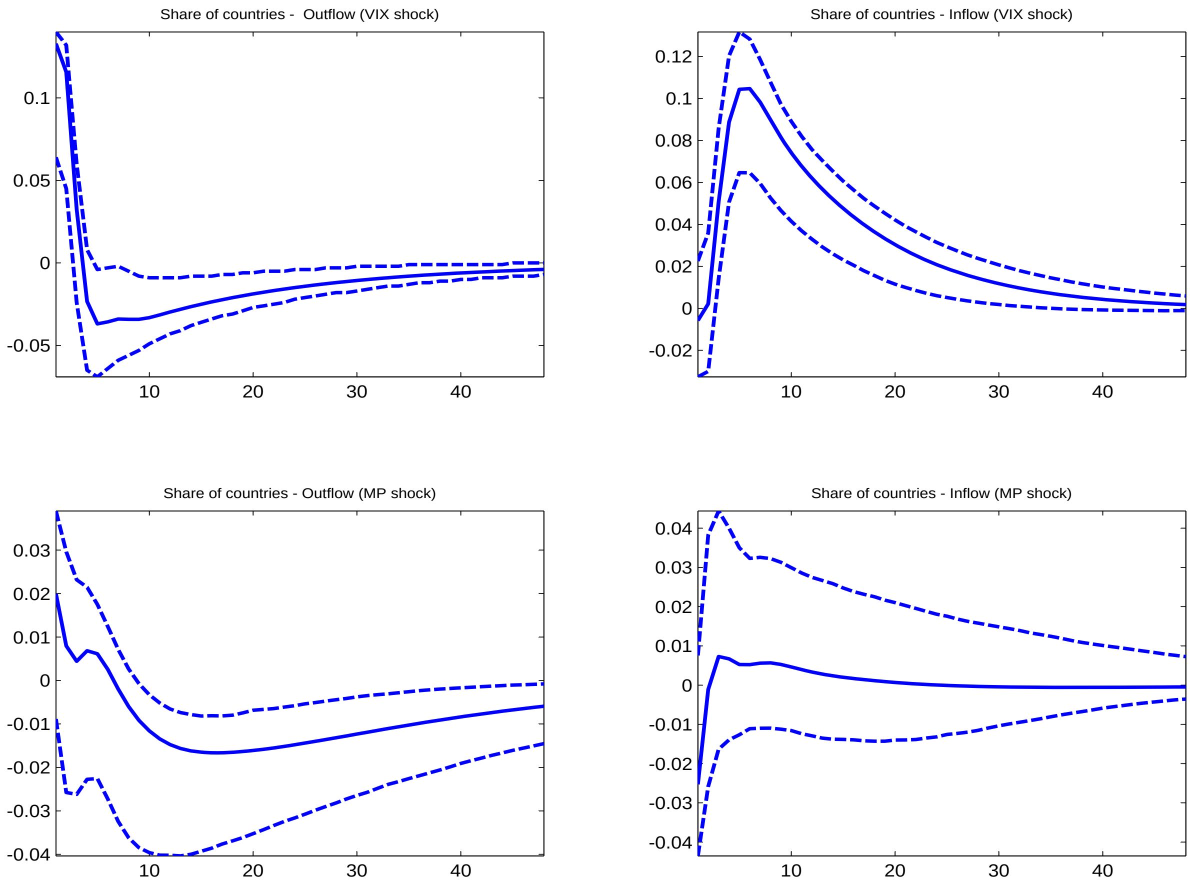
Note: Estimated structural impulse-response functions (solid lines), and 90 percent bootstrapped confidence intervals (dotted lines) for the 4-variable VAR consisting of the share of countries in an equity outflow episode, the VIX, the U.S. real interest rate, and U.S. industrial production. The model 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 9: 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

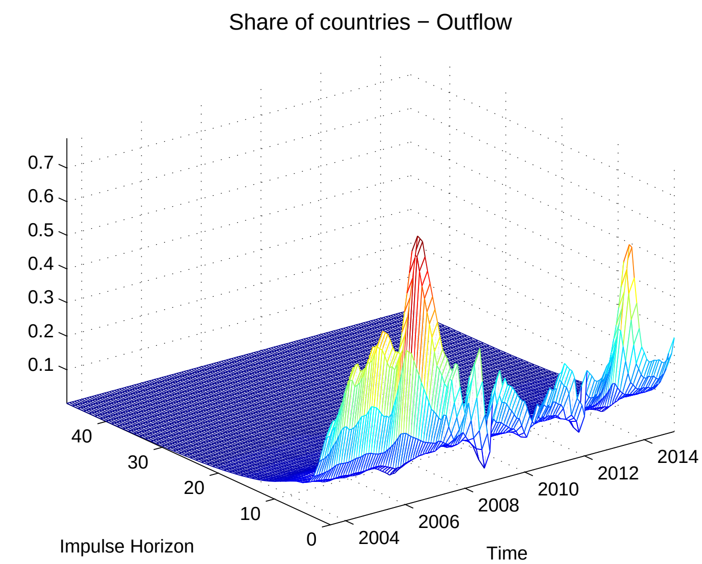
Figure 10: Impulse-Response Functions – Difference between Emerging Markets and Advanced Economies



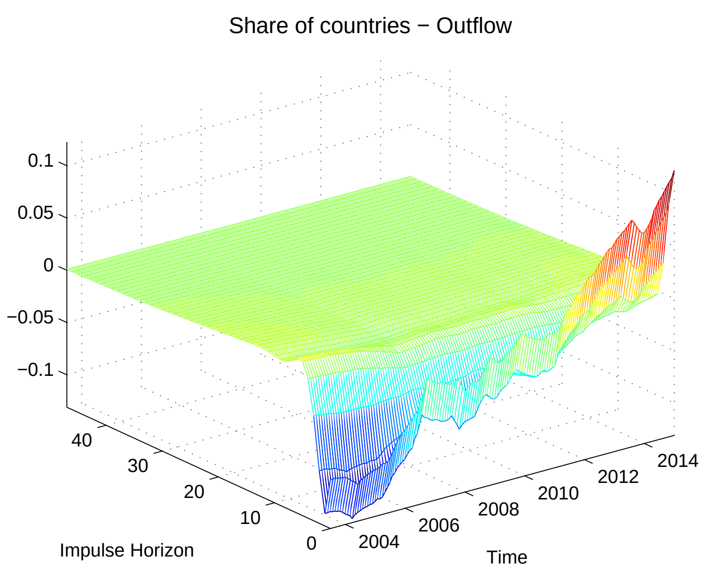
Note: Estimated structural impulse-response functions (solid lines), and 90 percent bootstrapped confidence intervals (dotted lines) for the 4-variable VAR consisting of the share of countries in an equity outflow episode, the VIX, the U.S. real interest rate, and U.S. industrial production. The model is identified with a recursive identification scheme. The first row 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 11: Time-Varying Responses of Equity Outflow Episodes – All Countries

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



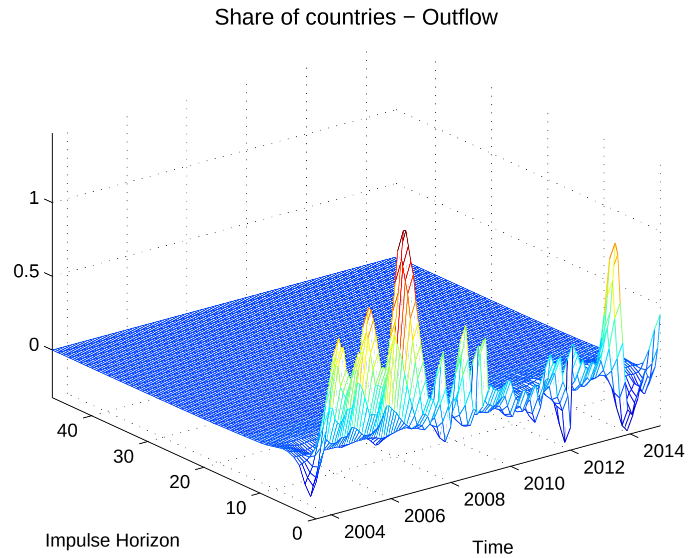
(b) Response of Equity Outflow Episodes to a U.S. Monetary Policy Shock



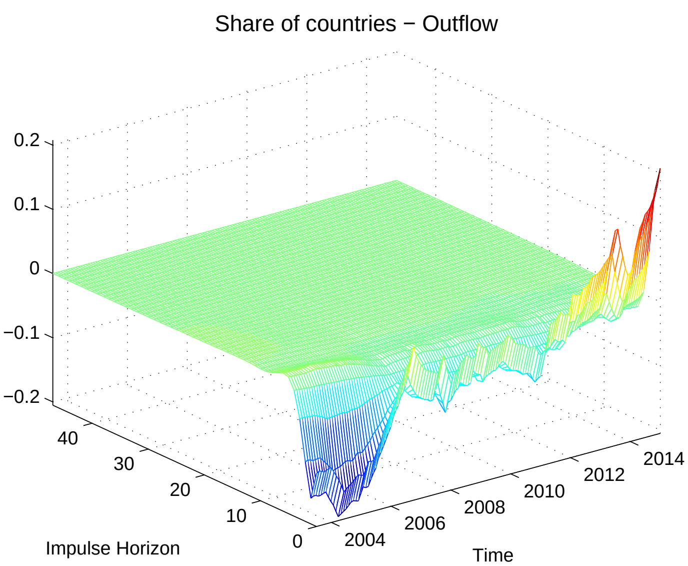
Note: This figure reports the median time-varying (structural) impulse responses for the 4-variable VAR consisting of the share of countries in an equity outflow episode, the VIX, the U.S. real interest rate, and U.S. industrial production. The share of countries in an equity outflow episode is calculated 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 12: Time-Varying Responses of Equity Outflow Episodes – Emerging Markets

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



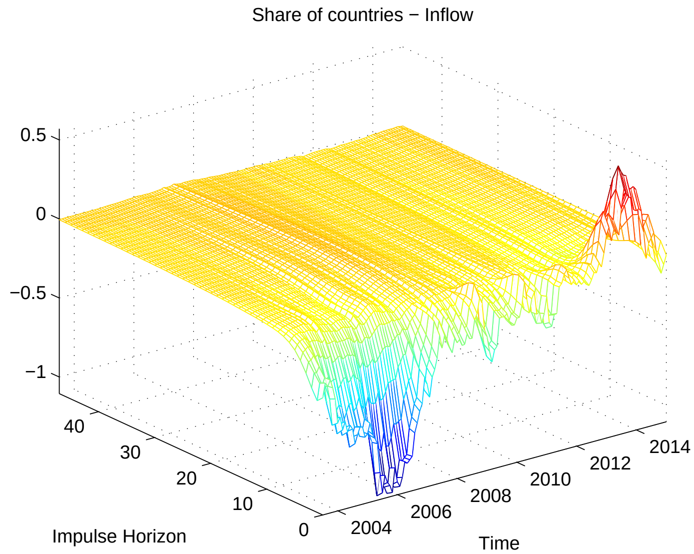
(b) Response of Equity Outflow Episodes to a U.S. Monetary Policy Shock



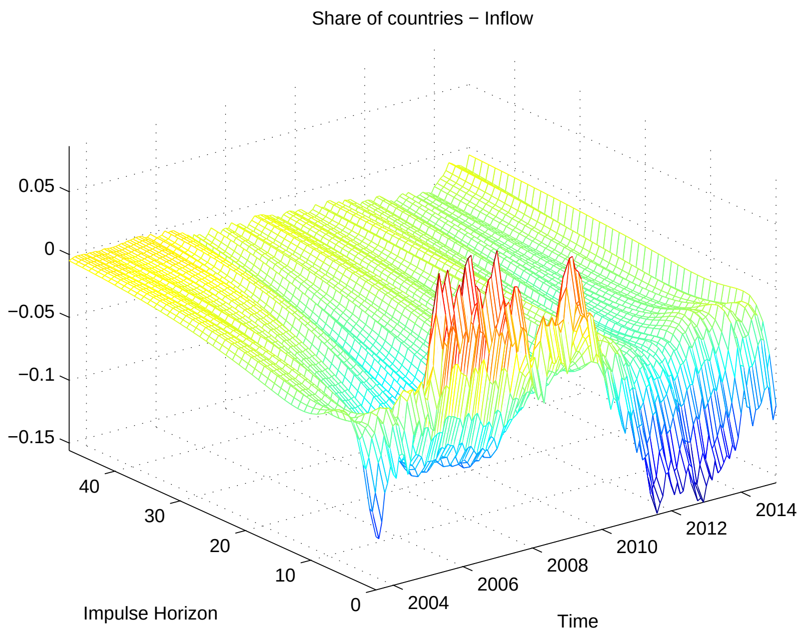
Note: This figure reports the median time-varying (structural) impulse responses for the 4-variable VAR consisting of the share of countries in an equity outflow episode, the VIX, the U.S. real interest rate, and U.S. industrial production. The share of countries in an equity outflow episode is calculated 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 13: 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				
	U.S.	Brazil	Average	Advanced	Emerging	U.S.	Brazil	Average	Advanced	Emerging
μ_1	-0.072**	-0.339**	-0.350	-0.110	-0.481	-0.248**	-0.660**	-0.588	-0.508	-0.626
	[0.029]	[0.036]				[0.033]	[0.083]			
μ_2	0.016	0.135**	0.030	0.008	0.041	0.055**	0.057	0.162	0.098	0.192
	[0.010]	[0.030]				[0.016]	[0.038]			
μ_3	0.275*	0.529**	0.513	0.250	0.658	0.323**	0.649**	0.736	0.563	0.817
	[0.143]	[0.076]				[0.013]	[0.037]			
p_{11}	0.982	0.896	0.857	0.941	0.812	0.940	0.884	0.871	0.860	0.877
p_{22}	0.987	0.889	0.905	0.916	0.899	0.942	0.884	0.905	0.906	0.904
p_{33}	0.966	0.890	0.886	0.910	0.873	0.957	0.936	0.919	0.934	0.911
$P(S_t = 1)$	0.320	0.366	0.306	0.348	0.283	0.291	0.209	0.245	0.242	0.246
$P(S_t = 3)$	0.109	0.251	0.248	0.301	0.218	0.233	0.429	0.280	0.269	0.286

Note: This table shows the estimation results for the regime-switching model (i.e., Equation (1)) using data for the United States and Brazil for both equity and bond portfolio flows, as well as averaged results over the entire dataset and for advanced and emerging markets. p_{11} is the transition probability of staying in the first regime (i.e., the strong outflow regime), 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. Standard errors for the intercepts are reported in brackets and are calculated from the inverse of the outer product estimate of the Hessian. **,* indicate statistical significance for the country-specific results 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 number of inflow or outflow episodes, and "Avg. Length" is the average length of time spent in an inflow or outflow episode. Panel B reports the correlation between equity outflow (inflow) and bond outflow (inflow) episodes.

Table 3: Country Results: Equity Outflows

Country	Avg. Probability	Avg. Share in Episode	Frequency	Avg. Length	Country	Avg. Probability	Avg. Share in Episode	Frequency	Avg. Length
Argentina	0.31	0.27	17	11.8	Mexico	0.34	0.28	22	9.5
Australia	0.30	0.29	6	33.8	Morocco	0.17	0.09	9	7.8
Austria	0.40	0.38	21	12.6	Netherlands	0.32	0.29	10	20.7
Belgium	0.30	0.25	9	19.2	New Zealand	0.14	0.11	8	9.4
Brazil	0.36	0.33	19	12.7	Nigeria	0.15	0.13	6	9.3
Bulgaria	0.18	0.11	11	7.4	Norway	0.28	0.27	10	19.3
Canada	0.53	0.53	5	74.8	Oman	0.15	0.08	7	8.7
Chile	0.32	0.26	20	9.7	Pakistan	0.37	0.33	20	12.3
China	0.20	0.16	16	7.5	Panama	0.22	0.15	10	9.5
Colombia	0.26	0.22	15	10.9	Peru	0.36	0.33	21	11.7
Croatia	0.26	0.20	16	9.3	Philippines	0.47	0.43	18	17.6
Cyprus	0.40	0.35	19	8.9	Poland	0.27	0.22	18	9.1
Czech Rep.	0.29	0.23	17	9.8	Portugal	0.31	0.31	10	22.7
Denmark	0.28	0.26	8	22.6	Romania	0.20	0.13	9	10.9
Egypt	0.22	0.13	11	8.6	Russia	0.28	0.22	17	9.7
Estonia	0.26	0.21	16	9.9	Singapore	0.32	0.29	14	15.1
Finland	0.35	0.34	15	15.7	Slovenia	0.16	0.10	7	10.4
France	0.31	0.31	6	36.3	South Africa	0.37	0.29	20	10.7
Germany	0.42	0.42	16	18.6	Spain	0.50	0.49	6	57.0
Greece	0.41	0.40	9	32.8	Sri Lanka	0.43	0.39	22	13.0
Hong Kong	0.37	0.35	17	15.2	Sweden	0.38	0.34	12	19.8
Hungary	0.26	0.19	16	8.6	Switzerland	0.36	0.32	11	20.7
India	0.26	0.21	18	8.6	Taiwan	0.37	0.32	22	10.8
Indonesia	0.46	0.43	19	16.7	Thailand	0.35	0.29	20	10.9
Ireland	0.30	0.28	7	27.9	Tunisia	0.27	0.22	9	12.9
Israel	0.39	0.37	8	34.6	Turkey	0.19	0.06	8	5.8
Italy	0.36	0.35	6	41.5	Ukraine	0.15	0.09	10	6.6
Japan	0.32	0.30	9	23.8	United Kingdom	0.27	0.26	3	60.3
Kazakhstan	0.18	0.07	9	6.0	United States	0.33	0.30	5	44.8
Korea	0.48	0.47	13	26.6	Vietnam	0.36	0.33	13	19.1
Lithuania	0.23	0.18	11	12.0	Zambia	0.16	0.11	6	8.0
Malaysia	0.38	0.35	21	12.2	Zimbabwe	0.20	0.08	10	5.7
Mauritius	0.21	0.09	12	5.8					

Note: "Avg. Probability" is the average probability of being in an outflow or inflow 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 outflow or inflow episode, where an episode is identified as the probability of strong outflows (or strong inflows) being higher than 0.5 for at least four consecutive weeks. "Frequency" is the number of outflow or inflow episodes over the sample period, and "Avg. Length" is the average time spent in an outflow or inflow episode (in weeks).

Table 4: Country Results: Equity Inflows

Country	Avg. Probability	Avg. Share in Episode	Frequency	Avg. Length	Country	Avg. Probability	Avg. Share in Episode	Frequency	Avg. Length
Argentina	0.17	0.15	10	11.4	Mexico	0.34	0.30	20	11.2
Australia	0.27	0.24	20	8.4	Morocco	0.22	0.21	6	26.2
Austria	0.31	0.21	14	10.4	Netherlands	0.39	0.38	6	44.7
Belgium	0.29	0.28	11	18.0	New Zealand	0.50	0.52	19	19.1
Brazil	0.25	0.21	12	13.1	Nigeria	0.27	0.27	3	40.3
Bulgaria	0.19	0.18	9	14.4	Norway	0.43	0.44	11	28.1
Canada	0.12	0.06	7	6.0	Oman	0.16	0.14	7	15.3
Chile	0.28	0.26	14	13.9	Pakistan	0.15	0.11	10	7.8
China	0.20	0.18	10	13.5	Panama	0.34	0.31	15	12.9
Colombia	0.28	0.27	15	13.1	Peru	0.31	0.30	15	14.7
Croatia	0.27	0.25	13	14.1	Philippines	0.13	0.10	10	7.5
Cyprus	0.14	0.12	5	11.4	Poland	0.22	0.20	13	11.4
Czech Rep.	0.20	0.19	8	17.4	Portugal	0.38	0.37	5	55.4
Denmark	0.41	0.42	8	36.8	Romania	0.21	0.19	10	14.0
Egypt	0.24	0.22	11	14.8	Russia	0.35	0.33	11	22.4
Estonia	0.21	0.19	7	20.6	Singapore	0.30	0.29	12	18.1
Finland	0.35	0.35	4	60.8	Slovenia	0.25	0.24	5	36.0
France	0.40	0.41	6	48.0	South Africa	0.14	0.12	8	10.9
Germany	0.46	0.47	10	32.8	Spain	0.17	0.15	8	13.4
Greece	0.15	0.11	8	10.4	Sri Lanka	0.14	0.09	9	7.6
Hong Kong	0.24	0.19	16	8.6	Sweden	0.39	0.39	10	27.4
Hungary	0.25	0.21	13	12.2	Switzerland	0.25	0.24	10	17.1
India	0.24	0.22	12	13.3	Taiwan	0.26	0.22	18	9.2
Indonesia	0.14	0.10	11	6.5	Thailand	0.16	0.10	9	8.6
Ireland	0.40	0.41	7	40.9	Tunisia	0.24	0.23	7	17.4
Israel	0.42	0.43	12	26.5	Turkey	0.23	0.18	13	10.0
Italy	0.30	0.29	8	25.8	Ukraine	0.18	0.17	10	12.6
Japan	0.21	0.19	7	19.0	United Kingdom	0.26	0.26	10	18.6
Kazakhstan	0.11	0.09	7	10.0	United States	0.05	0.05	1	35.0
Korea	0.13	0.08	8	7.8	Vietnam	0.23	0.15	13	8.6
Lithuania	0.18	0.17	9	13.8	Zambia	0.27	0.27	6	19.5
Malaysia	0.27	0.21	18	8.7	Zimbabwe	0.11	0.11	1	82.0
Mauritius	0.14	0.15	3	36.3					

Note: "Avg. Probability" is the average probability of being in an outflow or inflow 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 outflow or inflow episode, where an episode is identified as the probability of strong outflows (or strong inflows) being higher than 0.5 for at least four consecutive weeks. "Frequency" is the number of outflow or inflow episodes over the sample period, and "Avg. Length" is the average time spent in an outflow or inflow episode (in weeks).

Table 5: Country Results: Bond Outflows

Country	Avg. Probability	Avg. Share in Episode	Frequency	Avg. Length	Country	Avg. Probability	Avg. Share in Episode	Frequency	Avg. Length
Argentina	0.19	0.17	9	11.0	Japan	0.27	0.23	7	15.9
Australia	0.35	0.34	8	20.4	Kazakhstan	0.30	0.28	12	13.5
Austria	0.21	0.18	2	46.5	Korea	0.34	0.33	11	17.4
Belgium	0.23	0.18	2	44.5	Lebanon	0.22	0.20	7	14.1
Bosnia and Herz.	0.19	0.16	8	11.6	Malaysia	0.27	0.26	9	16.4
Brazil	0.21	0.20	9	12.7	Mexico	0.34	0.32	12	15.5
Canada	0.25	0.19	4	22.8	Netherlands	0.27	0.23	5	22.4
Chile	0.26	0.23	9	14.8	Nigeria	0.27	0.24	11	12.5
China	0.29	0.26	11	13.5	Norway	0.25	0.23	7	15.7
Colombia	0.27	0.22	10	12.9	Pakistan	0.21	0.19	7	15.1
Costa Rica	0.37	0.36	14	14.9	Panama	0.23	0.21	9	13.6
Croatia	0.14	0.08	5	9.0	Peru	0.27	0.24	10	13.8
Czech Rep.	0.54	0.52	8	37.1	Philippines	0.21	0.18	7	14.7
Denmark	0.23	0.20	9	10.9	Poland	0.36	0.35	8	25.0
Dominican Rep.	0.24	0.21	9	13.6	Qatar	0.08	0.06	3	12.3
Ecuador	0.32	0.28	12	13.6	Romania	0.12	0.08	5	9.0
Egypt	0.11	0.07	4	10.3	Russia	0.24	0.22	10	12.7
El Salvador	0.08	0.04	2	11.5	Serbia	0.26	0.24	7	16.3
Finland	0.25	0.23	4	27.3	Singapore	0.27	0.26	7	21.7
France	0.23	0.19	2	46.0	South Africa	0.34	0.32	11	16.6
Germany	0.15	0.10	7	7.0	Spain	0.23	0.20	6	16.0
Ghana	0.30	0.27	8	15.8	Sweden	0.18	0.13	4	15.8
Greece	0.22	0.19	7	13.4	Switzerland	0.08	0.03	2	7.5
Guatemala	0.35	0.35	9	21.1	Thailand	0.27	0.24	9	15.6
Hong Kong	0.36	0.36	9	22.8	Trin. and Tob.	0.11	0.10	5	9.2
Hungary	0.44	0.43	8	30.6	Tunisia	0.26	0.23	10	13.2
India	0.28	0.24	8	17.0	Turkey	0.10	0.07	4	10.0
Indonesia	0.26	0.24	10	13.9	Ukraine	0.10	0.08	5	9.0
Iraq	0.18	0.15	6	12.3	United Kingdom	0.16	0.09	7	6.7
Ireland	0.23	0.18	2	43.0	Uruguay	0.10	0.08	5	8.8
Israel	0.16	0.13	7	9.9	United States	0.27	0.25	7	20.4
Italy	0.31	0.27	8	16.3	Venezuela	0.24	0.21	9	13.6
Ivory Coast	0.08	0.06	4	8.5	Vietnam	0.28	0.25	10	14.6

Note: "Avg. Probability" is the average probability of being in an outflow or inflow 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 outflow or inflow episode, where an episode is identified as the probability of strong outflows (or strong inflows) being higher than 0.5 for at least four consecutive weeks. "Frequency" is the number of outflow or inflow episodes over the sample period, and "Avg. Length" is the average time spent in an outflow or inflow episode (in weeks).

Table 6: Country Results: Bond Inflows

Country	Avg. Probability	Avg. Share in Episode	Frequency	Avg. Length	Country	Avg. Probability	Avg. Share in Episode	Frequency	Avg. Length
Argentina	0.45	0.44	14	17.9	Japan	0.28	0.29	7	19.7
Australia	0.26	0.25	7	17.4	Kazakhstan	0.22	0.21	8	15.3
Austria	0.24	0.23	5	23.4	Korea	0.17	0.17	4	24.0
Belgium	0.24	0.23	4	28.0	Lebanon	0.23	0.22	6	18.0
Bosnia and Herz.	0.42	0.41	13	17.9	Malaysia	0.13	0.12	5	13.8
Brazil	0.43	0.42	11	21.8	Mexico	0.21	0.21	8	15.1
Canada	0.19	0.19	5	18.0	Netherlands	0.21	0.20	4	24.8
Chile	0.20	0.18	8	13.1	Nigeria	0.20	0.19	9	12.1
China	0.24	0.22	7	18.3	Norway	0.32	0.31	7	21.4
Colombia	0.22	0.20	9	12.9	Pakistan	0.24	0.23	6	22.0
Costa Rica	0.39	0.38	13	16.7	Panama	0.22	0.20	9	12.8
Croatia	0.22	0.19	9	12.1	Peru	0.21	0.20	9	12.7
Czech Rep.	0.15	0.12	5	14.2	Philippines	0.25	0.23	8	16.8
Denmark	0.33	0.32	10	15.7	Poland	0.32	0.32	8	22.9
Dominican Rep.	0.21	0.19	9	12.1	Qatar	0.50	0.49	11	25.8
Ecuador	0.22	0.20	9	12.7	Romania	0.16	0.14	6	13.8
Egypt	0.48	0.46	15	17.7	Russia	0.25	0.25	9	16.0
El Salvador	0.48	0.47	13	20.9	Serbia	0.23	0.22	5	21.2
Finland	0.21	0.20	4	24.0	Singapore	0.19	0.15	6	14.7
France	0.21	0.20	4	24.5	South Africa	0.21	0.20	7	16.6
Germany	0.38	0.34	8	20.8	Spain	0.33	0.30	6	24.5
Ghana	0.21	0.21	5	19.6	Sweden	0.32	0.33	6	26.3
Greece	0.36	0.34	7	23.3	Switzerland	0.25	0.24	7	16.3
Guatemala	0.41	0.40	19	11.6	Thailand	0.21	0.16	6	15.3
Hong Kong	0.15	0.08	5	9.6	Trin. and Tob.	0.47	0.48	8	27.8
Hungary	0.19	0.19	5	22.2	Tunisia	0.23	0.21	10	12.0
India	0.21	0.19	5	20.8	Turkey	0.48	0.47	15	17.9
Indonesia	0.16	0.15	4	21.3	Ukraine	0.44	0.42	14	17.4
Iraq	0.45	0.45	9	24.1	United Kingdom	0.29	0.29	4	38.0
Ireland	0.26	0.25	5	24.0	Uruguay	0.45	0.44	15	16.9
Israel	0.36	0.34	11	15.7	United States	0.25	0.25	4	35.3
Italy	0.26	0.24	5	23.4	Venezuela	0.22	0.20	9	12.8
Ivory Coast	0.48	0.48	11	24.8	Vietnam	0.21	0.20	8	14.4

Note: "Avg. Probability" is the average probability of being in an outflow or inflow 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 outflow or inflow episode, where an episode is identified as the probability of strong outflows (or strong inflows) being higher than 0.5 for at least four consecutive weeks. "Frequency" is the number of outflow or inflow episodes over the sample period, and "Avg. Length" is the average time spent in an outflow or inflow episode (in weeks).

Table 7: Country Results: Correlation Statistics

Country	Eq Out vs. Bd Out	Eq In vs. Bd In	Country	Eq Out vs. Bd Out	Eq In vs. Bd In
Argentina	0.41	0.12	Korea	0.45	0.18
Australia	0.20	0.09	Malaysia	0.53	0.29
Austria	0.07	0.09	Mexico	0.53	0.22
Belgium	0.44	-0.03	Netherlands	0.39	-0.06
Brazil	0.49	0.14	Nigeria	0.34	0.51
Canada	0.12	0.10	Norway	-0.05	-0.06
Chile	0.51	0.36	Pakistan	0.50	0.31
China	0.26	0.02	Panama	0.41	0.36
Colombia	0.32	0.22	Peru	0.41	0.38
Croatia	0.40	0.36	Philippines	0.54	0.21
Czech Rep.	0.44	0.50	Poland	0.34	-0.08
Denmark	0.41	0.00	Romania	0.43	0.36
Egypt	0.58	0.31	Russia	0.53	0.43
Finland	0.20	-0.23	Singapore	0.29	0.24
France	-0.25	0.01	South Africa	0.53	0.33
Germany	0.17	-0.01	Spain	0.43	0.17
Greece	0.39	0.19	Sweden	0.38	0.00
Hong Kong	0.13	0.13	Switzerland	0.31	0.03
Hungary	0.43	0.28	Thailand	0.35	0.18
India	0.29	0.07	Tunisia	0.20	0.25
Indonesia	0.46	0.25	Turkey	0.50	0.35
Ireland	0.59	0.04	Ukraine	0.69	0.23
Israel	0.38	0.40	United Kingdom	0.34	-0.02
Italy	0.56	0.08	United States	-0.15	n.a.
Japan	0.38	0.00	Vietnam	0.33	0.21
Kazakhstan	0.34	0.22			

Note: This table reports various combinations of correlations between equity (Eq) and bond (Bd) flows and inflow (In) and outflow (Out) episodes for the countries in our sample.