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Hot money in bank credit flows to emerging markets during the banking globalization era

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Abstract

This paper investigates the relative importance of hot money in bank credit and portfolio flows from the US to 18 emerging markets over the period 1988-2012. We deploy state-space models à la Kalman filter to identify the unobserved hot money as the temporary component of each type of flow. The analysis reveals that the importance of hot money relative to the permanent component in bank credit flows has significantly increased during the 2000s relative to the 1990s. This finding is robust to controlling for the influence of push and pull factors in the two unobserved components. The evidence supports indirectly the view that global banks have played an important role in the transmission of the global financial crisis to emerging markets, and endorses the use of regulations to manage international capital flows.

Keywords: International capital flows; Hot money; Crisis transmission**;** Banking globalisation**;** Kalman filter.

JEL classification: E44; F20; F34; G1.

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"When one region of the world economy experiences a financial crisis, the world-wide availability of investment opportunities declines. As global investors search for new destinations for their capital, other regions will experience inflows of hot money. However, large capital inflows make the recipient countries more vulnerable to future adverse shocks, creating the risk of serial financial crises." (Korinek, 2011)

1. Introduction

International capital flows increased dramatically in the 1990s and it has been argued that they eventually led to the 1997 Asian Financial Crisis (Kaminsky and Reinhart 1998; Kaminsky, 1999; Chari and Kehoe, 2003). International capital flows resurged again until the late 2000s Global Financial Crisis (GFC). Global capital flows increased rapidly from less than 7% of world GDP in 1998 to over 20% in 2007, but suffer large reversals in late 2008, with bank credit flows being hit the hardest (Milesi-Ferretti and Tille, 2011; Tong and Wei, 2011; Forbes and Warnock, 2012). Is this reversal of global capital flows due to *hot money*?

The term *hot money* has been most commonly used for capital moving from one country to another in order to earn a short-term profit on interest rate differentials or anticipated exchange rate shifts. This speculative capital can lead to market instability (Martin and Morrison, 2008; Chari and Kehoe, 2003).[1] Recently, the equity premium has been suggested as a driver of hot money (Guo and Huang, 2010). Instead of ascertaining driving factors, some studies have sought to identify *hot money* via the unobserved-component models by focusing on its temporariness and reversibility aspects (see, e.g, Sarno and Taylor, 1999a, b).

A surge in hot money to emerging markets (EMs) may be destabilizing and trigger regulation, of which examples abound since 2009 such as Brazil, Taiwan, South Korea, Indonesia and Thailand among other countries. Thus, measuring hot money becomes crucial for appropriate policy design (IMF, 2011; Ostry et al., 2010; McCauley 2010; Korinek, 2011).

It is well known that distinct types of capital flows have distinct degrees of reversibility (Tong and Wei, 2011; Sarno and Taylor, 1999a).[2] In fact, a key feature of the post-1990s trend

[1] Huge movements of hot money have been historically not atypical in fixed exchange rate systems (e.g., during the final years of the Bretton Woods system). Recently, there is a growing interest on carry trade, seen as a type of hot money (McKinnon and Schnabl, 2009; McCauley, 2010; McKinnon, 2013; McKinnon and Liu, 2013).

[2] It is usually referred as the *composition* hypothesis. The rationale is that a more volatile form of capital will be more likely to fly out of the country in crisis. Tong and Wei (2011) do not find a connection between a country's

in capital flows to EMs up until the GFC is the dramatic resurgence of international bank credit flows relative to equity and bond flows (Bank for International Settlements, 2009; Goldberg 2009). Using Bank for International Settlements (BIS) statistics, Milesi-Ferretti and Tille (2011) show that the holdings of cross-border bank credit at year-end has increased notably, especially, during 2000-2007 and reached about 60% of world GDP. Thus, banking flows were hit the hardest compared to other types of capital flows during the GFC (Milesi-Ferretti and Tille, 2011). It is also recognized that the recent bank globalisation process has played a major role in the GFC transmission (Aiyar, 2012; Cetorelli and Goldberg, 2011, 2012a,b; De Haas and Van Horen, 2013; Giannetti and Laeven, 2012).

Such recent developments in international capital flows and especially in bank credit flows raise questions such as whether the banking sector played a key role in the transmission of the crisis to emerging markets as the literature on bank globalisation suggests. Related to that is the question how the relative amount of hot money in bank credit, and portfolio (equity and bond) flows has evolved in recent years, particularly, in the run-up to the late 2000s GFC?

This paper takes up the latter question by probing whether the relative importance of hot money in bank credit and portfolio flows to EMs has changed over the 1988-2012 period. We start by deploying unobserved component (or state-space) models à-la Kalman filter to gauge the temporariness of international capital flows from the US to 9 Asian countries and 9 Latin American countries which have attracted substantial capital flows over period the 1988 to 1997. We are able to confirm the earlier findings of Sarno and Taylor (1999a, b) over a similar time period and using a similar methodology. On average in the 1988-1997 period, portfolio flows (*i.e.*, equity and bond flows) were largely temporary but, in contrast, bank credit is found to be more permanent than temporary. This supports the widely held view that hot money in portfolio flows played a key role in the 1997 Asian Financial Crisis.

Reestimating the models over the full sample period from 1988 to 2012 our results reveal

exposure to capital flows and the extent of the liquidity crunch experienced by its manufacturing firms when they just include total volumes of capital inflows. However, they argue this masks an important compositional effect, as a different but consistent pattern emerges when they disaggregate capital flows into three types (FDI, foreign portfolio flows and foreign loans). This empirical evidence suggests that aggregating different capital flows may not be appropriate when one wishes to understand the connection between capital flows and a liquidity crunch in a crisis. See also Neumann et al. (2009) and Levchenko and Mauro (2007).

an important change: bank credit has gradually become more temporary in the recent decade, while the temporariness of portfolio flows has stayed roughly the same. Third, since the change of sample periods brings about completely different results for bank credit, we deploy the models over the recent sub-sample, 1998 to 2012, and the results confirm that bank credit has a marked temporary component. The dramatic resurgence of international bank credit in this recent decade broadly coincides with the period of banking sector globalization.

We provide additional evidence on the temporariness of the capital flows by estimating 'structural' state-space models which include global (push) and domestic (pull) macro factors as potential drivers of both latent components, permanent and transitory. This constitutes a methodological novelty and can be motivated as an attempt to incorporate fundamentals (i.e., adding some economic 'structure' to the state-space decomposition) in the unobserved components analysis of capital flows. To our knowledge, no previous study that assesses the importance of the temporary (vis-à-vis the permanent) part of international capital flows has deployed 'structural' state-space models that control for push/pull factors. Altogether the empirical analysis in the paper is intended to provide robust evidence on the relative importance of the temporary (hot money) and permanent components of capital flows.

Our finding of high temporariness in bank credit, equity and bond flows over the most recent decade suggests that all three types of capital flows have been dominated by hot money and hence, prone to large reversals. Thus, the paper provides indirect supporting evidence that hot money is a channel of crisis transmission and, most importantly, that global banks might have played an important role in the transmission of the recent financial crisis to emerging markets. Thus our analysis reinforces the main contention in Cetorelli and Goldberg (2011) on the role of bank lending in the GFC transmission.

The paper unfolds as follows. Section 2 provides some background literature. Sections 3 and 4 outline the data and empirical methodology, respectively. The empirical results are discussed in Section 5, while Section 6 concludes with a summary and policy implications.

2. Background Literature

Our paper relates to two strands of the literature. It directly draws upon studies that seek to identify 'hot money' in bank credit and/or portfolio flows. It is also linked, albeit more indirectly, with studies investigating the mechanisms of transmission of the late 2000s GFC.

One intriguing question about the GFC is how the US Subprime Crisis engulfed the entire world.[3] Initially, it was hoped that emerging markets (EMs) would stay unscathed as reforms were designed to insulate their economies from adverse foreign shocks (Kamin and DeMarco, 2012). These hopes evaporated by the fall of 2008 when many EMs without direct exposure to the 'toxic' assets, which were at the root of the financial crisis in advanced economies experienced sharp declines both in output and equity markets (Milesi-Ferretti and Tille, 2011).

The literature has identified various channels of cross-country transmission of financial turmoil: i) through tangible real and/or direct financial linkages (e.g., trade, portfolio investment and bank loans), ii) through reassessment of fundamentals (e.g., wake-up calls), iii) through market sentiment (e.g., self-fulfilling panic).[4] Hot money in portfolio flows has been shown to play a key role in the 1997 Asian Financial Crisis (Kaminsky and Reinhart, 1998; Kaminsky, 1999; Sarno and Taylor, 1999b; Chari and Kehoe, 2003).

More recent papers have attempted to shed light on the global incidence of the GFC. Milesi-Ferretti and Tille (2011) show that the turnaround for international capital flows has been much sharper than that for trade flows. Fratzscher (2009) analyzes the global transmission of the GFC via exchange rates. Acharya and Schnabl (2010) relate the incidence of the GFC to the issuance of asset-backed commercial paper. Ehrmann et al. (2009) assess stock market comovement in a sample of EMs and industrial economies, and find that macro risk dwarfed micro risk. Eichengreen et al. (2012) study the evolution of CDS spreads for 45 global banks and find that common factors became more important during of the crisis.

Theoretical models have been developed to show how crises in one area of the world

[3] Securities backed by subprime mortgages account only for about 3% of US financial assets (Eichengreen et al., 2012). Kamin and DeMarco (2012) examine whether industrial countries that held large amounts of US mortgage-backed securities experienced a greater degree of financial distress during the GFC but find no evidence of such direct spillovers.

[4] For reviews of the various channels of crisis transmission, see Kamin and DeMarco (2012) and Forbes (2012).

economy prompt hot money to flow into other areas (Korinek, 2011). However, there is no well-defined direct method for identifying the amount of hot money flowing into a country during a certain period. A widely-used tool is accounting labels. Hot money is traditionally defined as speculative or short-term international capital flows but it is difficult to track the (non)speculative nature of capital flows; the only measurable key characteristic of hot money has been its short-term aspect, especially before the 1990s. The balance-of-payment statistics of the IMF, World Bank and US Treasury sub-categorize various types of capital flows as short-term and long-term using one year as the typical threshold. Thus, any capital flowing into a country and staying there for more than a year is categorized as 'not hot money'.

Claessens et al. (1995) raises scepticism about the information value of accounting labels. Typically, the notion that short-term flows are more volatile than long-term flows is based on the fact that short-term-maturity inflows need to be repaid more quickly than long-term inflows. Although rapid repayment may lead to higher volatility of gross short-term flows, it need not make net flows more volatile. Short-term flows that are rolled over are equivalent to long-term assets, and a disruption of gross FDI inflows, for example, can cause its net flow to be equivalent to a repayment of a short-term flow. Their analysis suggests that the "short-term" and "long-term" accounting labels of capital flows do not provide a reliable indication of their degree of temporariness or reversibility. Levchenko and Mauro (2007) show that, under accounting labels, differences across types of flows are limited with respect to volatility, persistence, cross-country comovement, and correlation with growth at home and worldwide. However, consistent with conventional wisdom, FDI is the least volatile form of financial flow, particularly, during episodes of sudden stops; portfolio debt flows and, to a greater extent, bank flows and trade credits, mostly account for the latter.

Focusing instead on the time-series properties of observed capital flows, state-space models are utilized by Sarno and Taylor (1999a) to compare the size of their permanent and temporary components during the period 1988-1997. They find a significant temporary-to-permanent ratio in equity and bond flows, but not so in bank credit. Following this lead, Sarno and Taylor (1999b) find associations between stock market bubbles and sudden reversals of private portfolio flows, instead of bank credit and FDI, during the 1997 East Asian financial

crisis. They conclude that hot money in bank credit played a minor role in the latter. The rationale is that the terms of bank loans are usually fixed and the profitability of the corresponding bank will be seriously jeopardised if lending is suddenly withdrawn.

However, the recent literature about rollover risk (Acharya et al., 2011; He and Xiong, 2012) supports a different view. Precisely because the terms of bank loans are fixed and their prices do not adjust automatically, private banks prefer to sign very short-term contracts. Once there are signs of financial distress, banks adjust the quantity of lending, for instance, by not rolling-over existing contracts or even retrieving previous loans. This literature concludes that private banks are very sensitive to short-term uncertainty and risk, and bank loans become much more reversible and volatile in crisis periods than in normal periods.

Based on this idea and the unprecedented resurgence of cross-border bank credit in the era of banking sector globalisation, there is growing support for the view that bank lending played a major role in the transmission of the GFC. Cetorelli and Goldberg (2011) provide evidence in this regard using a cross-section of industrialized countries and a broad panel of EMs. Focusing on syndicated loans, Giannetti and Laeven (2012) show that banks exhibit a strong home bias during crises which materializes in a significant decrease in the proportion of foreign loans and a reduction in the extension of new loans.[5]

None of the above papers studies the temporariness (or 'hot money' component) of bank credit flows from the US to EMs in the new century. This is an important task given the background of the banking sector globalisation and the GFC. Our paper fills this gap.

3. Description of Variables and Preliminary Data Analysis

3.1 Capital Flows

We employ data on US capital flows to 9 Asian and 9 Latin American countries from January 1988 to December 2012.[6] The Asian countries are Mainland China, Taiwan China, India,

[5] Various microeconomic studies document a significant transmission of bank liquidity shocks to EMs; see, for instance, Khwaja and Mian (2008) for Pakistan, and Schnabl (2012) for Peru.

[6] Of more relevance for the purposes of this paper is the distinction between two definitions of hot money: *de jure* hot money, which is generally associated with accounting labels and based solely on data categories given in balance-of-payments statistics, and *de facto* hot money, which focuses on the temporary time-series properties of respective capital flows (Agosin and Huaita, 2011). This paper focuses on the latter definition.

Indonesia, South Korea, Malaysia, Pakistan, Philippines and Thailand. The Latin American countries are Argentina, Brazil, Chile, Colombia, Ecuador, Jamaica, Mexico, Uruguay and Venezuela.[7] According to World Bank (2011) statistics, as of 2010 these markets represent 23 per cent of the world GDP and over 70 per cent of the GDP of the 150 EMs listed by the IMF.

We use monthly data on US portfolio (*equity* and *bond*) flows in US$ millions to EMs collected from the US Treasury International Capital (TIC) database.[8] As previous studies, we use a net measure of equity flows and a gross measure of bond flows. The main motivation for using gross bond flows is to abstract from the effect of sterilization policy actions and other types of reserve operations by the monetary authorities (Chuhan et al., 1998; Taylor and Sarno, 1997; Sarno and Taylor, 1999a; Forbes and Warnock, 2012; Sarno et al., 2014). The TIC database reports "gross purchases by foreigners" which we classify as US sales and "gross sales by foreigners" which we classify as US purchases. We employ quarterly data on US *bank credit* flows to EMs which is obtained from the US Treasury Bulletin.[9]

Our analysis of capital flows is based on data over the 24-year period from 1988 to 2012. This allows us to replicate the analysis for the 1990s conducted by Sarno and Taylor (1999a), and to investigate further whether the role of 'hot money' in bank credit, equity and bond flows has experienced any significant change thereafter. Since the capital flows are expressed in US dollars, we scale them by the US consumer price index (CPI) from *Datastream* to control for any inflationary effects. We also conduct the analysis on the un-scaled capital flows, and the (unreported but available upon request) results are broadly similar in line with the fact that US inflationary pressures have been rather limited over the sample period.

Our data allows us to measure not only traditional banking linkages (direct cross-border

[7] These are the same countries considered in Sarno and Taylor (1999a) and Chuhan et al. (1998).

[8] The US international portfolio investment transactions are tracked by the Department of Treasury (DOT), the International Capital Form S reports and the International Capital Form B reports. Operationally, the 12 district Federal Reserve Banks, principally the Federal Reserve Bank of New York, maintain contact with the respondents, and ensure the accuracy and integrity of the information provided (Kester, 1995). The DOT compiles the data and publishes in its Quarterly Bulletin. This database has been widely used in the international finance literature (e.g. Tesar and Werner, 1994, 1995; Bekaert et al., 2002). Appendix A provides further details.

[9] The US Treasury Bulletin compiles data on foreign claims as reported by US banks and other depository institutions, brokers and dealers. Data on bank claims held for their own account are collected monthly. A comprehensive sample on bank credit flows (e.g., including domestic customer claims and foreign currency claims) is only available quarterly; see section on Capital Movements, Table CM-II-2 and Table CM-III-2.

lending) but also indirect ones through an affiliate in the borrower's country (internal capital market). Cross-border lending is a well-known channel of transmission. However, there is recent evidence that banks are setting up branches and subsidiaries in foreign locations to serve clients (Forbes, 2012; Cetorelli and Goldberg, 2012a, b). Applying basic corporate finance principles, it has been conjectured that global banks can respond to a funding shock by activating capital markets internal to the organization, reallocating funds across locations in response to their relative needs. Peek and Rosengren (1997), show how the drop in Japanese stock prices in 1990 could lead Japanese bank branches in the US to reduce credit. Cetorelli and Goldberg (2012a) provide evidence of actual cross border, intra-bank funding flows between global banks' head offices and their foreign operations in response to domestic shocks. Cetorelli and Goldberg (2012b) confirm the existence of an active cross-border, internal capital market and show high heterogeneity across branches in lending response.

Our data choices are geared towards capturing financial transactions that involve both a US resident and a foreign resident; a US resident includes any individual, corporation, or organization (including branches, subsidiaries, and affiliates of foreign entities) located in the US. In addition, any entity incorporated in the US system is considered a US resident even if it has no physical presence. Thus, a US branch of a Japanese bank is considered a US resident, and a London branch of a US bank is considered a foreign resident.[10]

The cross-border definition means that the data on foreign purchases of US securities include only those transactions that involve both a US seller and a foreign purchaser. These data exclude US-to-US transactions, e.g. transactions where the seller is a US securities broker and the purchaser is a US-based branch of a Japanese securities firm. They also exclude foreign-to-foreign transactions in securities, e.g. a purchase by a Japanese-resident broker of US Treasuries from a London-based broker. Appendix A provides further details.

3.2 Preliminary Data Analysis

We begin by plotting the time-series of net equity, net bond and net bank credit flows to Asian

[10] These data provide an unusual opportunity for a direct test of the existence of an internal capital market, since data on borrowing and lending within an organization is generally not available to researchers.

and Latin American countries from 1988 to 2012 in **Figure I.** The vertical axis represents US$ millions and the horizontal axis is quarters. Several interesting observations can be made. First, in the 21st century, bank credit surged and significantly dwarfed the equity and bond flows. Second, in both Asia and Latin America, the volatility of bond flows and bank credit flows increased significantly in the 21st century, especially in the run-up to and during the late 2000s GFC. Third, it is the bank credit flows, instead of portfolio flows, that suffered the sharpest reversal during the GFC. These patterns in capital flows in the 2000s seem quite different from the ones in the 1990s, and raise key questions concerning the temporariness (*i.e.*, hot money) in each category of capital flows in the recent decade.

Table I provides summary statistics for net bank credit flows, net equity flows and gross bond flows from the US to emerging markets over the period 1988-2012.[11] The ADF unit root test results broadly confirm that bank credit and bond flows have a unit root. However, the evidence for equity flows is less clearcut as the tests suggest non-stationarity over the early sample period of Sarno and Taylor (1999a) but stationarity over the full sample. Since there is no economic theory to suggest that equity flows have a drastically different data generating process from bank and credit flows, following the extant literature we conceptualize all three flows as realizations from first-difference stationary processes.[12] Hence, it makes sense to gauge the relative importance of their permanent and stationary components.

All three categories of capital flows to Asia surpass in size those to Latin America over the period under study. For most countries, the average net bank credit flows are negative, meaning that the US has been on the whole 'financed' by EMs in this category of capital. Average net equity flows are positive for all Asian countries but, in sharp contrast, mostly negative for Latin American countries (with the exception of Brazil, which shows a relatively

[11] As mentioned earlier we use a net measure of equity flows and a gross measure of bond flows to abstract from the effect of sterilization policy actions and other types of reserve operations by the monetary authorities (Chuhan et al., 1998; Taylor and Sarno, 1997; Sarno and Taylor, 1999a; Forbes and Warnock, 2012; Sarno et al., 2012). Appendix B provides summary statistics for net bond flows.

[12] Our methodology for the analysis of capital flows rests on the assumption that the dynamics of their unobserved persistent component can be approximated by a random walk model. However, as borne out by the mixed results of the unit root tests, other specifications could be plausible alternatives such as those in the autoregressive fractionally integrated moving average class known as ARFIMA models that can generate very persistent (non)stationary data. The random walk process is adopted because it is rather parsimonious (which helps in identification) and to ensure comparability with the prior literature (see e.g., Sarno and Taylor, 1999a).

large positive average net equity flow in contrast to all other Latin American countries, and Argentina to a lesser extent). Thus, over the sample period the US has financed all Asian EMs but only two Latin American countries (Brazil by a large amount, and Argentina) via net equity flows. However, the size of bank credit flows belittles the size of equity flows. Finally, capital flows to Asia appear more volatile than the flows to Latin America in all categories.

4. State-Space Models

Our analysis of the dynamics of capital flows is based on state-space (or unobserved components) models. One benefit of representing a dynamic system in state space form is that unobserved variables can be incorporated and estimated along with the observable variables. State space models have been widely used in economics to model latent variables such as (rational) expectations, permanent income and unobserved components such as trends and cycles. State-space models will allow us to decompose the observed bank, equity and bond flows into unobserved permanent and temporary components as it is explained next.

Let y_t denote the observed capital flow for a given country at time t. The unobserved components formulation of the capital flow is as follows

$$y_t = \mu_t + v_t + \varepsilon_t, \quad t=1, \ldots, T \tag{1}$$

where μ_t denotes the unobserved *permanent* (non-stationary) part of the flows, and $v_{it} + \varepsilon_{it}$ the unobserved *temporary* (stationary) part with a mean-reverting part v_{it} and an irregular (unpredictable) white noise part $\varepsilon_{it} \sim i.i.d.\, N(0, \sigma^2_{\varepsilon,i})$. The permanent (stochastic trend) component is commonly modelled as a random walk (RW) process

$$\mu_t = c + \mu_{t-1} + \eta_t \tag{2}$$

where c represents the drift, and $\eta_t \sim i.i.d.\, N(0, \sigma^2_\eta)$ is a white noise random error. The temporary component v_{it} is modelled as an order-two autoregressive (AR) process

$$v_t = \rho_1 v_{t-1} + \rho_2 v_{t-2} + \xi_t \tag{3}$$

with coefficients $(\rho_1 + \rho_2) < 1, (\rho_1 - \rho_2) < 1, |\rho_2| < 1$ and error $\xi_t \sim i.i.d.\, N(0, \sigma_\xi^2)$.

Estimation of the unobserved components model is usually handled through a state-space decomposition. This involves writing a *signal* equation linking the state vector of unobserved variables $(\mu_t, \nu_t, \varepsilon_t)'$ to the observed capital flow variable y_t as follows

$$y_t = \begin{pmatrix} 1 & 1 & 1 \end{pmatrix} \begin{pmatrix} \mu_t \\ \nu_t \\ \varepsilon_t \end{pmatrix}, \tag{4}$$

and a *transition* equation describing the dynamics of the state variables

$$\begin{pmatrix} \mu_t \\ \nu_t \\ \varepsilon_t \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \rho_\nu & 0 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} \mu_{t-1} \\ \nu_{t-1} \\ \varepsilon_{t-1} \end{pmatrix} + \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \eta_t \\ \xi_t \\ \varepsilon_t \end{pmatrix} \tag{5}$$

The above equations can be written more compactly to express the model as

$$y_t = \mathbf{H}\boldsymbol{\beta}_t, \tag{6}$$

$$\boldsymbol{\beta}_t = \mathbf{F}\boldsymbol{\beta}_{t-1} + \mathbf{R}\boldsymbol{\kappa}_t \tag{7}$$

$$\boldsymbol{\kappa}_t \sim IN\left(0, \sigma^2 \mathbf{Q}\right) \tag{8}$$

for t=1, . . . ,T, where $\mathbf{H}$ is a 1×3 unit vector, $\mathbf{F}$, $\mathbf{R}$ and $\mathbf{Q}$ are 3×3 matrices, and $\boldsymbol{\beta}_t$ is the unobservable 3×1 state vector. State-space models can be estimated by Maximum Likelihood (ML) using the recursive Kalman filter algorithm which is described in Appendix C.

In order to gauge the relative role of the temporary and permanent components of capital flows, we employ the *Q*-ratio, a standard scalar measure in the state-space modelling literature (bounded between 0 and 1) whose inputs are the elements of the disturbance covariance matrix **Q**. For instance, the *Q*-ratio of the permanent component is defined as

$$Q\text{-}ratio(\mu_t) = \frac{\sigma_\eta}{\max(\sigma_\eta, \sigma_\xi, \sigma_\varepsilon)}, \tag{9}$$

and the temporary component's role is subsumed in *Q-ratio*(ν_t) and *Q-ratio*(ε_t) which are defined similarly. If most of the dynamics in the corresponding capital flow is due to the permanent component then we expect *Q-ratio*(μ_t) =1 which implies that a large part of the capital flow remains in the country for an indeterminate period of time. Instead, if most of the variation in the capital flow is explained by the dynamics of the temporary component then *Q-ratio*(ν_t) =1 or *Q-ratio*(ε_t) =1 but this finding alone does not allow us to conclude that the capital flow is dominated by "hot money" because the temporary component could be highly persistent or slowly mean-reverting. Hence, we need to assess the degree of persistence of the temporary component of the capital flows for each of the countries concerned.

Many measures of persistence have been employed in the empirical finance literature and there is no consensus on which one is the most appropriate; see Dias and Marques (2005). The most popular measures are designed under the so-called univariate approach, namely, persistence is investigated by looking at the time-series representation of inflation. Following the latter, in our study a capital flow variable is judged as being dominated by "hot money" if two conditions are jointly met: i) the *Q*-ratio of the temporary component is 1, and ii) the half-life of the temporary component is below one and a half years. As it is standard in the empirical finance literature, the half-life of a dynamic process is approximated by $H = \ln(1/2)/\ln(\rho)$ where ρ is the sum of the coefficients of its AR representation.

Appendix D lists the candidate state-space model specifications. We identify the most appropriate one per country *i* and category of capital flow using: i) the coefficient of determination $R^2 = 1 - \frac{(T-d)\hat{\sigma}_\varepsilon^2}{\sum_{t=1}^{T}(y_{it}-\bar{y}_{it})^2}$ where *d* is the number of non-stationary elements in the state vector, and ii) the Akaike information criterion, *AIC*= log(*PEV*)+2(*m*/*T*), where *PEV* is the steady-state prediction error variance, *m* is the number of unknown parameters to estimate (the number of the variance parameters, together with damping factors for cycles and autoregressive coefficients) plus the number of non-stationary components in the state vector β_t, and *T* is the number of observations. For a detailed exposition, see Harvey (1989).

5. Empirical Results

We begin by analyzing the state-space model estimates and diagnostics for bank credit flows in order to gauge the importance of 'hot money'. Then we proceed similarly with the equity and bond flows. The analysis is conducted over the 1988-1997, 1997-2012 and full periods.

5.1 Reduced-form unobserved components model

Hot Money in Bank Credit

Has the amount of 'hot money' in bank credit flows become more relevant over the recent decade? To address this question, we discuss the state-space modelling results corresponding to the first subperiod (1988-1997), extended period (1988-2012) and most recent period (1998-2012) which are shown in **Table II**, Panels A, B and C, respectively.

Column 2 of the table notes the selected model specification among all the candidates considered (listed in Appendix A). The diagnostics shown in the last two columns suggest that the models provide a good fit: the coefficient of determination (R^2) is fairly large, and the Ljung–Box statistic (p-value) fails to reject the null hypothesis of no residual autocorrelation.

Columns 3-5 report the Q-ratios of the permanent (stochastic trend) component, and the temporary (AR and/or irregular) components. Column 6 reports the stochastic level in the final state vector and its root mean square error (RMSE); if the final stochastic level is significantly different from zero then we can conclude that, even if the Q-ratio of either of the temporary components is 1, there is a non-negligible permanent component. Column 7 shows the sum of the AR coefficients (or damping factor $\rho = \rho_1 + \rho_2$) whose proximity to 1 indicates the degree of persistence in the temporary component of the flows; equivalently, the (unreported) half-life of shocks to the temporary component is a nonlinear transformation of the damping factor, $H = \ln(1/2)/\ln(\rho)$, which is expressed in units of time.

The model estimates for bank credit over the period 1988-1997 suggest for all 18 EMs the permanent component explains most of the variation in the flows. Taking Mainland China as an example, the Q-ratio of the permanent component in Table II (Panel A) is equal to 1 and the

Q-ratio of the temporary component is 0.652. Hence, we conclude that bank credit flows to Asian and Latin American countries from 1988 to 1997 are largely permanent or persistent. These findings are well aligned with the empirical evidence in Sarno and Taylor (1999a).

However, Table II (Panel B) tells a different story. Over the full sample period from 1988 to 2012, the analysis of bank credit flows for both sets of countries suggests that the largest Q-ratios correspond now instead to the temporary part of the flows, captured by the vector $(\nu_t, \varepsilon_t)'$. Taking again Mainland China as an example in Table II (Panel B), the Q-ratio of the stochastic trend component μ_t is only 0.217. Therefore, it would seem appropriate to regard bank credit flows to Mainland China over the full sample period 1988-2012 as largely influenced by its temporary component which stands in sharp contrast with the evidence from similar state-space models estimated over the first subsample period 1988-1997. The contribution of the permanent (temporary) component to the total variation of capital flows is relatively small (large). The final level of the stochastic trend component μ_t is significant which, together with the Q-ratio, indicates that there is a non-negligible permanent component in bank credit flows, but it explains a small amount of the total time variation in bank credit relative to the temporary component. All countries considered, the dynamics of bank credit flows appear strikingly different over the pre-1990s and 1988-2012 periods.

Thus we conjecture that the temporariness of bank credit flows to Asian and Latin American countries may have increased substantially in the recent decade, coinciding with the process of banking sector globalisation. To test this conjecture, we re-estimate the models over the second subsample period 1998-2012. The results are reported in Table II (Panel C). Bank credit shows now, in contrast to the 1988-1997 period, a large degree of temporariness. Taking again Mainland China as an example, the two conditions stated in the previous section are met, namely, the Q-ratio of the AR component is 1 and the corresponding half-life of shocks at 3.3 quarters is low (below 6 quarters), implying that bank credit to Mainland China has become dominated by "hot money" over the most recent 15-year period. As clearly shown in Table II (Panel A), over the first subsample period 1988-1997 none of the countries meets the two conditions which allows us to conclude that banking flows are dominated by a permanent component pre-1990s in line with the prior literature. In sharp contrast, as Table II (Panel C)

shows, the same unobserved component models estimated post-1990s reveal that all countries except two (Argentina and Brazil with half-lives of 7 and 9 quarters, respectively) meet both conditions. This allows us to conclude that the relative role of "hot money" in bank credit has increased notably in the years leading to and during the GFC.

Hot Money in Portfolio Flows

Next we discuss the state-space model estimates and diagnostics for equity and bond flows which are reported in **Tables III** and **IV**, respectively. Again we deploy the models separately over the three sample periods: 1988-1997, 1988-2012, and 1998-2012. The coefficient of determination R^2 for equity (bond) flows ranges from 0.012 to 0.901 (0.150 to 0.930) in the 1988-1997 analysis and improves to between 0.05 and 0.929 (0.090 and 0.979) in the full sample analysis. The *p*-value from the Ljung–Box test uniformly for all 18 EMs and time periods rules out residual autocorrelation.

In contrast to our findings for bank credit, the largest variance of the disturbances for portfolio flows is always the temporary component (either irregular or AR component) consistently across all sample periods. The *Q*-ratios for the stochastic level components are low – ranging from negligible for equity flows to Mainland China to a maximum of 0.968 for bond flows to Argentina – suggesting that the contribution of the persistent component in explaining the dynamics of capital flows is low relative to the temporary component. As borne out by the estimated coefficient of the stochastic level in the final state vector and the corresponding RMSE (shown in column 4), the permanent component is significant but it explains a relatively small proportion of the dynamics in the observed flows. Actually, if we compare the results for bank credit, equity flows and bond flows over the latter sub-sample from 1998 to 2012, there are large similarities regarding the degree of temporariness. Hence, all three categories of capital flows have in recent years attained a high degree of reversibility. Thus, it appears likely that they may have been a channel for the transmission of the GFC.

Summing up, our findings thus far suggest that in the post-1997 era not only bond and equity flows but also bank credit flows to EMs are characterized by a 'hot money' component that is large relative to the permanent component; this means that all three types of capital flows

are plausible candidates as channels for the transmission of the GFC. Thus, bank credit surfaces as a new potential channel of crisis transmission given that it appears unlikely as channel of transmission of previous turmoils such as the 1997 Asian Financial Crisis. The finding of a high reversible component in bank credit flows to EMs is aligned with the recent literature about rollover risk, the banking sector globalisation and transmission of the GFC.

5.2. Unobserved components model with push/pull factors

A potential criticism of the reduced-form model on which the results thus far are based is that it lacks economic content. In order to shield our analysis from this criticism, we now reformulate the state-space models by incorporating one-period lagged macroeconomic factors as potential exogenous variables both in the permanent and temporary components of the flows. The aim is to impose some economic 'structure' to the state-space models with the purpose of adding robustness to our key finding that bank credit flows are newly characterized by a weighty temporary component (hot money) during the post-1997 era. *Q*-ratios thus computed from the covariance matrix **Q** of white noise residuals, account for the impact of the economic drivers. To our knowledge, no previous study that assesses the relative importance of the temporary (versus permanent) component of bank credit, equity and bond flows has deployed 'structural' state-space models that control for push/pull factors. Such models have been mainly used in the context of order flows and high-frequency trading (Menkveld et al., 2007; Brogaard et al., 2013; Hendershott and Menkveld, 2014).

We employ the following parsimonious state-space model with macro drivers

$$
\begin{aligned}
y_t &= \mu_t + v_t, \\
\mu_t &= \mu_{t-1} + \sum_{j=1}^{J} \kappa_j Z_{j,t-1} + \eta_t, \\
v_t &= \rho_1 v_{t-1} + \rho_2 v_{t-2} + \sum_{j=1}^{J} \lambda_j Z_{j,t-1} + \xi_t \ , \quad (\rho_1 + \rho_2) < 1, (\rho_2 - \rho_1) < 1, \ |\rho_2| < 1
\end{aligned}
\tag{10}
$$

where $Z_{j,t}$ denotes the *j*th macroeconomic factor, and $(\eta_t, \xi_t)'$ are white noise error terms. The total number of push/pull factors, *J*, which cannot be too large due to degrees of freedom constraints in estimation; to illustrate, the inclusion of say *J*=5 factors in the state-space model

implies ten additional parameters to estimate.[13]

This unobserved components model, equation (10), serves the purpose of addressing the potential criticism that the original model, equations (1) to (3), is a purely statistical decomposition of the flows into the latent temporary and permanent parts without any economic content. Instead, in this reformulation we extract the latent permanent and temporary components of the capital flows while controlling for various observed factors that have been shown in previous studies to be potential drivers.

Choosing an appropriate set of pull and push factors $\{Z_{1,t}, Z_{2,t},\ldots,Z_{J,t}\}$ is a non-trivial task because they ought to be relevant drivers for both the permanent and temporary components. Earlier studies have considered investor-fear risk, liquidity risk and interest rate risk as push (or global) factors, and depth of the financial system, real GDP growth, country indebtedness and capital controls as pull (or domestic) factors (see Forbes and Warnock, 2012; Fratzscher, 2012; Sarno, et al., 2013). However, a parallel literature has suggested other push/pull factors, that we describe below, as important drivers of hot money. We consider both sets in turn.

Inspired by McKinnon (2013), McKinnon and Liu (2013), McKinnon and Schnabl (2009), Korinek (2011), and Martin and Morrison (2008), we begin by considering as candidates for *push* factors the US interest rate and US equity index; and as *pull* factors, the EM interest rate, EM equity index, and the exchange rate defined as units of EM currency per US dollar. Strictly speaking, however, since the exchange rate has a US side and an EM side, it can be categorized as either push or a pull factor. Both interest rates and the exchange rate have been extensively used as drivers in the literature on carry trade, which has been categorised as hot money.[14] We include equity indices for two reasons. First, equity return differences in the US and EMs could trigger capital flows to globally re-allocate assets, either because of return-chasing or portfolio-rebalancing motives (Bekaert et al., 2002). Second, the equity market is commonly seen as a

[13] The above state-space model is an extension of the specification referred to as "Model 5" in Appendix D. It parsimoniously decomposes the flows into a permanent part and a temporary part without irregular components and drifts. After the inclusion of push or push and pull factors as explanatory variables, the irregular component and drifts decrease quickly, becoming insignificant. A similar model has been used in a different literature (Menkveld et al., 2007; Brogaard et al., 2013; Hendershott and Menkveld, 2014).

[14] The carry trade is a popular currency trading strategy that invests in high-interest currencies by borrowing in low-interest currencies. This strategy is at the core of active currency management and is designed to exploit deviations from uncovered interest parity.

confidence barometer, with a sharp decline often preceding an economic crisis, which makes hot money in bank credit responsive to the dynamics of the equity market (Kaminsky and Reinhart 1998, 1999; Kaminsky, 1999; Reinhart and Rogoff, 2009).

Regarding our priors, we expect the US interest rate to impact negatively on capital flows from the US to EMs, while the interest rate in EMs ought to have a positive impact on capital flowing from the US to EMs. Since a lower exchange rate means an appreciation of the EM currency versus the US$ which may arguably attract capital flows into EMs, it is expected that the exchange rate has a negative impact on capital flows from the US to EMs.

It is harder to form priors about the impact of the US and EMs stock markets on capital flows because the "return-chasing" and "portfolio-rebalance" hypotheses imply conflicting predictions (Bekaert et al., 2002). According to the return-chasing hypothesis, the performance of EMs (the US) stock markets influences positively (negatively) capital flows from the US to EMs because capital flows chase sizeable stock returns. In sharp contrast, according to the portfolio-rebalance hypothesis, the EMs (US) stock market performance affects negatively (positively) capital flows from the US to EMs because investors rebalance their investment portfolio to maintain their original (planned) asset allocation.

Table V shows the estimation results for the 'structural' state-space models of bank flows using the above factors as lagged (exogenous) drivers over the sample period 1998-2012. Due to data constraints, we perform the analysis on 8 EMs in our sample. The main result that the temporary component (hot money) in bank credit flows is responsible for most of the variation in the flows remains unchallenged. For all 8 EMs, the *Q*-ratios indicate that the temporary component weighs more heavily than the permanent component, confirming the role of hot money during that period. India has the largest *Q*-ratio for the permanent component (0.929) across all 8 EMs, followed by Thailand (0.813), Brazil (0.391) and Chile (0.340), while the *Q*-ratios of the permanent component for the other four EMs are close to 0.2. The R^2 is generally high and the Ljung-Box test suggests no residual autocorrelation.

Looking now at the coefficients of the push and pull factors, our results are consistent with the previous literature in that international capital flows are highly heterogeneous both over time and across countries (Milesi-Ferretti and Tile, 2011; Fratzscher, 2012; Warnock and

Forbes, 2012). For example, Fratzscher (2012) finds the effects of economic shocks on capital flows to be highly heterogeneous across countries, with a large proportion of the cross-country heterogeneity being ascribed to differences in the quality of domestic institutions, country risk and the strength of domestic macroeconomic fundamentals (pull factors). But he further shows that push factors were overall the main drivers of capital flows in the brunt of the GFC, while pull factors have become more dominant in the recent period 2009-2010, in particular, for EMs. Hence, there is evidence in the literature of both time and cross-country heterogeneity in the role of push/pull factors as drivers of capital flows.

Regarding statistical significance, we find push and pull factors to be equally important; only marginally, push factors play a more dominant role than pull factors in the permanent component.[15] The heterogeneity of the impact of push and pull factors across countries can be seen in the close examination of three of the BRIC countries in Sarno et al. (2014), where for China the importance of the pull factor is close to the world average, for India is much below the world average and for Brazil for bond flows is much higher than the world average.

The signs of the push/pull factor coefficients are rather mixed in line with the large heterogeneity (over time and across countries) on the drivers of capital flows documented in the literature. In our context, it may relate to the fact that the sample includes both crisis and non-crisis periods. On the one hand, the effects of shocks on capital flows have changed markedly since the GFC erupted about seven years ago (Fratzscher, 2012). On the other hand, as it is pointed out in Forbes and Warnock (2012), the same factor may have a different effect on capital flows when capital flows are in different stages (Surge/Stop/Flight/Retrenchment).

For completeness, we repeat the analysis for push and pull factors used in earlier work. The push factors are investor-fear risk, liquidity risk and interest rate risk. Investor fear is proxied by the VXO, a volatility index compiled by the Chicago Board Options Exchange using S&P 100 option prices, that represents a measure of the market's expectation of stock volatility over the next 30 day period.[16] Liquidity risk is proxied by year-on-year growth in US money supply

[15] We do not count the exchange rate since, as noted above, it can be seen both as a push or a pull factor.
[16] The factors we consider are similar to those in Forbes and Warnock (2012). Data on the VIX that tracks the S&P 500 index instead is only available from 2003. As it is shown in Forbes and Warnock (2012), VIX and VXO are very similar. Due also to data constraints, we use growth of money supply instead of TED spread.

(M2) and the yield on 20-year US government bonds is used for the interest rate factor. As pull factors, we consider the depth of the financial system (measured by each country's stock market capitalization divided by GDP), real GDP growth, country indebtedness (measured by public debt ratios) and capital controls (measured by Chinn-Ito indices). The data are obtained from *DataStream*. The estimation of these 'structural' state-space models is conducted over the full period due to the degrees-of-freedom constraint imposed by the large number of push/pull factors. The results (unreported for space constraints but available upon request) affirm that considering this distinct set of push/pull factors makes no meaningful difference to the findings. The temporary component in bank credit flows remains responsible for most of the variation in the bank credit flows; which is likely to reflect (as we saw earlier) the new dynamics in the post-1997 era.

6. Conclusions

Motivated by the dramatic increase in international capital flows in recent years, particularly in cross-border bank credit flows which reached 60% of global GDP during 2000-2007, this paper re-examines the role of hot money in bank credit and portfolio flows. We deploy state-space models à la Kalman filter to evaluate the relative size of the permanent component and temporary or 'hot money' component of the flows from the US to emerging markets (EMs) over the period 1988 to 2012. A key question we address is whether the degree of temporariness or potential reversibility of bank flows from the US to EMs has increased in recent years coinciding with the banking globalisation process.

A key result is that bank credit flows from the US to EMs have undergone a dramatic change from being predominantly permanent during the 1990s to being mainly temporary (or reversible) thereafter. This finding is robust to the inclusion of push and pull factors in the state-space decomposition, an estimation approach not used before in the literature on international capital flows. Our investigation confirms extant evidence that portfolio flows (but not bank credit flows) played a major role in the Asian Financial Crisis. The same state-space models applied to recent data suggest high temporariness of all three types of capital flows in the new century or equivalently, that all of them have been 'flooded' by hot money. Therefore it appears

that bank credit flows are as 'worrying' as equity flows for risk managers.

The findings represent tentative evidence that hot money in bank credit and portfolio flows may have been a potential channel via which the Subprime Crisis in the US evolved into a global financial crisis.[17] Thus our analysis indirectly supports the conjecture that bank lending played a key role in the late 2000s GFC transmission of which Cetorelli and Goldberg (2011) provide direct evidence from a different methodology. Moreover, the findings endorse the renewed interest by policymakers in using regulations, sometimes camouflaged as prudential banking regulations, to manage international capital flows, with the tacit approval of the IMF (Ostry et al., 2010; McCauley, 2010). An important question that this paper does not address is what type of bank credit is most responsible for the observed change from persistence to temporariness in the recent decade. Data limitations at the time of writing preclude us from pursuing it. We leave this work for further research.

[17] It is likely that various other direct channels (such as trade) and/or indirect channel (such as wake-up calls) may also have played an important role in turning the US housing slump into the GFC.

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Table I. Descriptive statistics

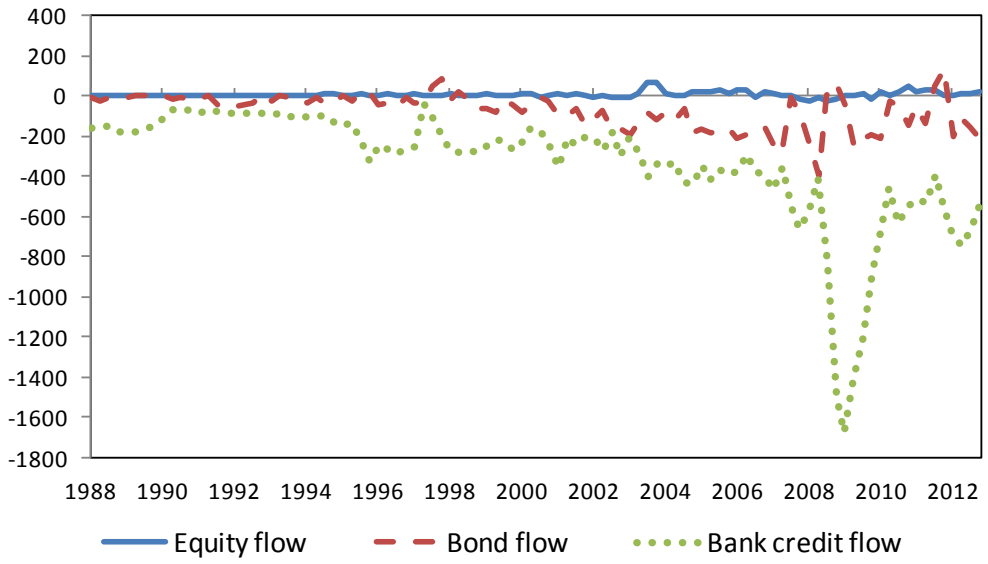
The table reports minimum, mean, maximum, and standard deviation (S.D.) of CPI-scaled capital flows in US$ millions. The last column reports the Augmented Dickey Fuller (ADF) test statistic for the null hypothesis of unit root (non-stationary) behaviour versus stationarity; the test regression includes a constant and linear time trend and the augmentation lag order is selected with the modified AIC (Ng and Perron, 2001). * and ** denote rejection at the 5% and 1% levels, respectively, using MacKinnon (1996) critical values. The sampling frequency is quarterly for bank flows and monthly for equity and bond flows over the period 1988 to 2012.

	Net bank credit flows					**Net Equity flows**					**Gross bond flows**				
	Min	Mean	Max	S.D.	ADF test	Min	Mean	Max	S.D.	ADF test	Min	Mean	Max	S.D.	ADF test
Panel A: Asia															
Mainland	-1164.10	-141.23	-3.63	198.83	-3.43	-13.84	0.09	21.16	2.47	-7.45 **	0.01	119.35	524.81	113.39	-4.11 **
Taiwan China	-185.87	-89.48	-43.18	33.44	-2.96	-15.87	0.90	37.40	4.42	-5.73 **	-0.45	25.95	105.09	17.32	-3.41
India	-158.05	-29.58	34.41	33.08	-1.75	-12.31	0.35	11.33	1.62	-4.21 **	0.00	5.35	57.11	8.15	-2.57
Indonesia	-143.43	-30.30	10.43	34.61	-2.57	-1.69	0.13	2.58	0.50	-1.96	-0.25	6.89	44.93	7.37	0.67
South Korea	-67.25	19.65	86.72	29.30	-3.94 *	-7.76	0.66	9.07	2.03	-4.71 **	0.01	41.02	136.85	36.70	-2.57
Malaysia	-22.43	-6.41	10.54	4.66	-2.34	-2.72	0.15	3.39	0.69	-4.09 **	-0.74	11.46	105.11	10.91	-3.82 *
Pakistan	-36.69	-6.92	4.42	8.34	-4.35 **	-0.37	0.02	0.79	0.11	-4.94 **	0.00	0.12	4.05	0.34	-8.17 **
Philippines	-49.78	-8.81	9.53	10.95	-0.76	-1.24	0.05	1.39	0.22	-5.35 **	0.02	6.43	32.27	6.46	-1.57
Thailand	-212.12	-42.79	1.34	47.21	0.00	-1.65	0.10	1.98	0.42	-2.39	0.02	9.63	41.69	7.35	-4.45 **
Average	*-226.64*	*-37.32*	*12.29*	*44.49*		*-6.38*	*0.27*	*9.90*	*1.39*		*-0.15*	*25.13*	*116.88*	*23.11*	
Total	*-2039.72*	*-335.87*	*110.59*	*400.43*		*-57.44*	*2.46*	*89.08*	*12.48*		*-1.38*	*226.20*	*1051.91*	*207.99*	
Panel B: Latin America															
Argentina	-74.63	-28.22	65.25	26.55	-3.13	-4.60	0.03	9.49	0.94	-4.02 **	-0.46	13.53	106.07	18.95	-2.41
Brazil	-136.03	40.97	257.07	82.54	-2.79	-9.85	1.56	41.56	4.03	-3.13	-0.26	61.23	383.67	58.74	-2.32
Chile	-48.46	-0.20	33.96	16.77	-2.51	-4.51	-0.02	4.37	0.83	-4.66 **	0.03	11.66	62.12	12.28	-3.42
Colombia	-74.12	-13.14	25.65	21.25	-2.88	-2.12	-0.02	2.24	0.35	-6.15 **	0.00	9.66	49.83	9.00	-1.34
Ecuador	-15.99	-6.39	10.24	6.74	-2.26	-1.72	-0.02	2.46	0.24	-4.90 **	-0.43	1.16	7.82	1.37	-3.18
Jamaica	-5.09	-1.72	1.45	1.22	-2.81	-0.74	-0.01	0.10	0.06	-5.86 **	0.00	1.29	9.47	1.70	-2.29
Mexico	-202.68	-74.74	115.92	75.64	-3.88 *	-7.17	-0.07	11.71	2.28	-7.03 **	0.02	38.90	171.50	29.13	-5.40 **
Uruguay	-43.08	-17.25	-4.49	10.44	-4.64 **	-1.21	-0.09	1.90	0.22	-13.90 **	0.02	5.58	31.63	4.94	-2.58
Venezuela	-138.37	-85.12	14.22	35.76	-1.21	-2.41	-0.04	4.06	0.48	-9.55 **	-0.23	4.88	30.20	3.94	-6.36 **
Average	*-82.05*	*-20.64*	*57.70*	*30.77*		*-3.81*	*0.14*	*8.66*	*1.05*		*-0.15*	*16.43*	*94.70*	*15.56*	
Total	*-738.45*	*-185.80*	*519.27*	*276.91*		*-34.32*	*1.30*	*77.90*	*9.42*		*-1.32*	*147.88*	*852.32*	*140.05*	

Figure I. Evolution of net capital flows

The graphs plot the time-series of CPI-scaled net equity flows, net bond flows and net bank credit flows from the US to Asian and Latin American countries on average. The vertical axis is US$ millions and the horizontal axis are quarters. The sample period is from 1988 to 2012 and the observations are quarterly.

Panel A: Net capital flows to Asia



Panel B: Net capital flows to Latin America

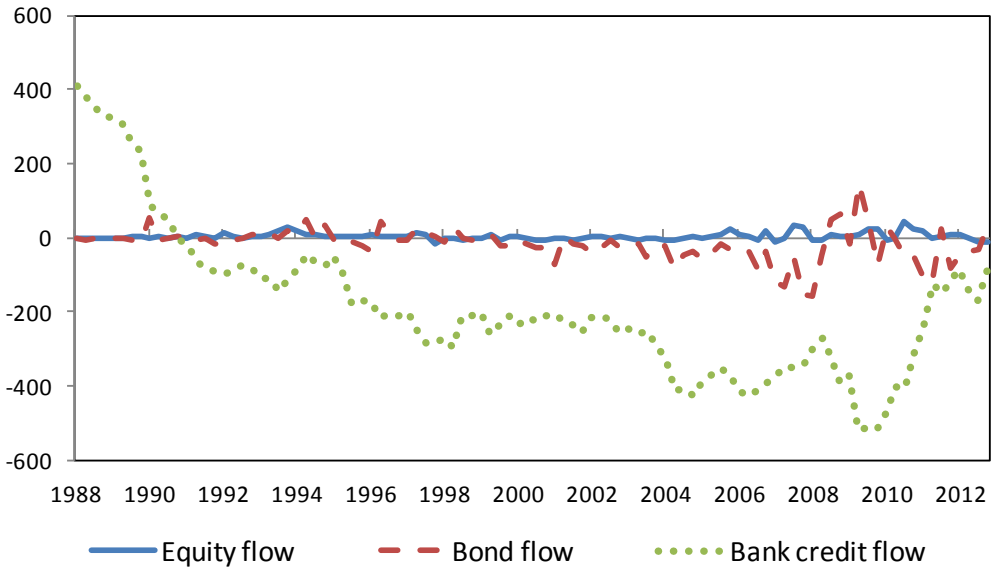


Table II. State-space model for bank credit flows.

For each country, quarterly bank credit flows scaled by CPI scaled are used to estimate the state-space models listed in Appendix D. The best specification is selected using the R^2 and AIC criteria. A dash indicates that the component at hand is absent from the model. $0 \leq Q$-ratio ≤ 1 is the standard deviation of the each component over the largest standard deviation across components, computed from the variance-covariance matrix of disturbances. Column five reports the final level of the stochastic trend and its root mean square error (RMSE); * and ** indicates statistical significance at the 5% and 1% level. The last column reports the *p*-value of the Ljung–Box test for the null hypothesis of no residual autocorrelation.

Country	Model	Q-ratios			Final level of stochastic trend component [RMSE]	AR persistence	R^2	Ljung-Box test
		Permanent (stochastic trend)	*Temporary* (irregular)	(AR)				
		μ_t	ε_t	v_t		$\rho_1+\rho_2$		
Panel A: First subperiod 1988Q1-1997Q4								
Mainland China	1	1.000	0.652	–	-110.151 [17.443]**	–	0.702	0.995
Taiwan China	1	1.000	0.374	–	-91.325 [18.134]**	–	0.926	0.466
India	1	1.000	0.449	–	-15.331 [1.109]**	–	0.696	0.945
Indonesia	1	1.000	0.000	–	-132.984 [18.646]**	–	0.957	0.808
South Korea	1	1.000	0.000	–	41.923 [41.923]**	–	0.875	0.098
Malaysia	6	1.000	0.001	–	-6.340 [0.0124]**	–	0.633	0.449
Pakistan	1	1.000	0.695	–	-3.969 [1.053]**	–	0.518	0.084
Philippines	1	1.000	0.744	–	-8.894 [1.647]**	–	0.852	0.213
Thailand	1	1.000	0.000	–	-29.453 [0.000]**	–	0.873	0.059
Argentina	1	1.000	0.426	–	-76.001 [4.696]**	–	0.897	0.181
Brazil	1	1.000	0.000	–	-56.080 [0.001]**	–	0.941	0.079
Chile	1	1.000	0.000	–	30.754 [0.000]**	–	0.884	0.080
Colombia	1	1.000	0.000	–	25.732 [0.000]**	–	0.926	0.737
Ecuador	2	1.000	0.377	0.000	-5.169 [0.401]**	0.064	0.893	0.863
Jamaica	1	1.000	0.505	–	-0.487 [0.185]**	–	0.787	0.155
Mexico	1	1.000	0.040	–	-100.012 [0.970]**	–	0.835	0.629
Uruguay	1	1.000	0.000	-	-12.818 [0.000]**	–	0.692	0.827
Venezuela	1	1.000	0.000	–	-140.947 [0.000]**	–	0.939	0.362
Panel B: Extended period 1988Q1-2012Q4								
Mainland China	2	0.217	0.756	1.000	-209.669 [83.536]*	0.734	0.927	0.272
Taiwan China	2	0.000	0.134	1.000	-132.426 [32.229]**	0.960	0.870	0.122
India	2	0.200	0.345	1.000	-27.084 [12.913]*	0.689	0.966	0.186
Indonesia	4	0.149	–	1.000	-58.136 [27.533]*	0.925	0.916	0.289
South Korea	2	0.000	0.118	1.000	24.789 [9.893]*	0.761	0.547	0.080
Malaysia	4	0.645	–	1.000	7.050 [3.015]*	0.463	0.539	0.171
Pakistan	2	0.877	0.819	1.000	-27.665 [2.793]**	0.560	0.870	0.066
Philippines	4	0.629	–	1.000	-16.548 [6.247]**	0.515	0.902	0.549
Thailand	2	0.208	0.214	1.000	-51.794 [16.458]**	0.820	0.976	0.123
Argentina	9	0.000	–	1.000	-524.585 [74.256]**	0.929	0.858	0.647
Brazil	9	0.000	–	1.000	-294.688 [77.563]**	0.902	0.719	0.102
Chile	9	0.281	–	1.000	-27.039 [13.628]*	0.936	0.917	0.216
Colombia	3	0.244	0.001	1.000	-30.110 [14.176]*	0.967	0.976	0.266
Ecuador	9	0.000	–	1.000	-23.441 [2.119]**	0.922	0.641	0.409
Jamaica	1	0.662	1.000	–	-3.017 [0.476]**	–	0.660	0.115
Mexico	4	0.630	–	1.000	-179.836 [23.720]**	0.632	0.914	0.937
Uruguay	4	0.757	–	1.000	-49.499 [2.273]**	0.236	0.939	0.607
Venezuela	4	0.518	–	1.000	-73.042 [15.614]**	0.771	0.950	0.142

(*Cont.*)

Country	Model	*Q*-ratios			Final level of stochastic trend component [RMSE]	AR persistence	R^2	Ljung-Box test
		Permanent (stochastic trend)	*Temporary* (irregular)	(AR)				
		μ_t	ε_t	v_t		$\rho_1+\rho_2$		
Panel C: Recent period 1998Q1-2012Q4								
Mainland China	5	0.081	–	1.000	-328.149 [147.798]*	0.815	0.765	0.463
Taiwan China	2	0.362	0.469	1.000	-163.056 [20.599]**	0.861	0.729	0.072
India	6	0.614	1.000	–	-103.219 [35.785]**	–	0.732	0.405
Indonesia	2	0.000	0.000	1.000	-46.832 [22.816]*	0.898	0.846	0.059
South Korea	1	0.767	1.000	–	48.021 [15.835]**	–	0.290	0.168
Malaysia	1	0.749	1.000	–	-11.699 [5.645]*	–	0.846	0.394
Pakistan	1	0.709	1.000	–	-12.363 [4.312]**	–	0.897	0.617
Philippines	1	0.951	1.000	–	-18.523 [7.382]**	–	0.900	0.770
Thailand	6	0.915	1.000	–	-129.524 [23.901]**	–	0.814	0.574
Argentina	4	0.000	–	1.000	-49.602 [8.715]**	0.907	0.840	0.823
Brazil	10	0.308	–	1.000	230.677 [98.202]*	0.934	0.140	0.295
Chile	4	0.336	–	1.000	-28.034 [14.530]*	0.889	0.866	0.570
Colombia	9	0.000	–	1.000	-78.464 [8.285]**	0.772	0.850	0.277
Ecuador	9	0.596	–	1.000	-21.646 [1.261]**	0.664	0.291	0.248
Jamaica	1	0.712	1.000	–	-3.034 [0.528]**	–	0.271	0.125
Mexico	2	0.313	0.000	1.000	-191.204 [20.043]**	0.488	0.598	0.672
Uruguay	4	0.716	–	1.000	-49.533 [2.797]**	0.217	0.905	0.478
Venezuela	2	0.000	0.248	1.000	-139.920 [4.797]**	0.719	0.429	0.071

Table III. State-space model for net equity flows.

For each country, monthly CPI-scaled equity flows are used to estimate the state-space model specifications listed in Appendix D. The best specification is selected using the R^2 and AIC criteria. A dash indicates that the component at hand is absent from the model. $0 \leq Q\text{-ratio} \leq 1$ is the standard deviation of the each component over the largest standard deviation across components, computed from the variance-covariance matrix of disturbances. Column five reports the final level of the stochastic trend and its root mean square error (RMSE); * and ** indicates statistical significance at the 5% and 1% level. The last column reports the *p*-value of the Ljung–Box test for the null hypothesis of no residual autocorrelation.

Country	Model	*Q*-ratios			Final level of stochastic trend component [RMSE]	AR persistence	R^2	Ljung-Box test
		Permanent (stochastic trend)	*Temporary* (irregular)	(AR)				
		μ_t	ε_t	v_t		$\rho_1+\rho_2$		
Panel A: First subperiod 1988M1-1997M12								
Mainland China	6	0.000	1.000	-	0.195 [0.059]**	-	0.510	0.091
Taiwan China	1	0.213	1.000	-	-0.292 [0.099]**	-	0.541	0.071
India	1	0.181	1.000	-	0.455 [0.048]**	-	0.772	0.076
Indonesia	1	0.064	1.000	-	0.250 [0.098]**	-	0.047	0.293
South Korea	2	0.179	0.000	1.000	0.846 [0.170]**	0.846	0.886	0.254
Malaysia	2	0.000	0.472	1.000	0.115 [0.061]*	0.461	0.143	0.202
Pakistan	6	0.732	1.000	-	-0.165 [0.047]**	-	0.116	0.139
Philippines	1	0.116	1.000	-	0.083 [0.049]*	-	0.415	0.138
Thailand	1	0.000	1.000	-	0.034 [0.014]*	-	0.501	0.499
Argentina	1	0.361	1.000	-	-0.435 [0.194]*	-	0.705	0.190
Brazil	1	0.082	1.000	-	0.975 [0.285]**	-	0.077	0.090
Chile	1	0.318	1.000	-	0.775 [0.162]**	-	0.653	0.840
Colombia	1	0.684	1.000	-	-0.473 [0.068]**	-	0.901	0.354
Ecuador	1	0.322	1.000	-	-0.018 [0.006]**	-	0.848	0.767
Jamaica	1	0.128	1.000	-	-0.080 [0.024]**	-	0.575	0.872
Mexico	1	0.186	1.000	-	2.646 [0.717]**	-	0.852	0.122
Uruguay	1	0.083	1.000	-	-0.165 [0.058]**	-	0.012	0.826
Venezuela	1	0.113	1.000	-	-0.137 [0.044]**	-	0.820	0.985
Panel B: Extended period 1988M1-2012M12								
Mainland China	6	0.217	1.000	-	1.702 [0.843]**	-	0.896	0.180
Taiwan China	7	0.027	0.440	1.000	4.857 [1.091]**	0.450	0.896	0.665
India	1	0.292	1.000	-	-2.653 [0.991]**	-	0.801	0.164
Indonesia	6	0.150	1.000	-	0.894 [0.096]**	-	0.851	0.206
South Korea	2	0.000	1.000	0.837	0.643 [0.319]*	0.888	0.193	0.251
Malaysia	2	0.000	0.000	1.000	0.139 [0.055]**	0.296	0.307	0.085
Pakistan	2	0.000	0.000	1.000	0.019 [0.008]*	0.346	0.278	0.111
Philippines	2	0.000	1.000	0.653	0.062 [0.026]**	-	0.306	0.285
Thailand	7	0.057	0.822	1.000	0.147 [0.134]**	0.358	0.708	0.368
Argentina	7	0.176	0.000	1.000	-0.926 [0.298]*	0.248	0.929	0.099
Brazil	2	0.079	1.000	0.924	2.690 [0.788]**	0.770	0.711	0.640
Chile	6	0.153	1.000	-	0.935 [0.258]**	-	0.727	0.119
Colombia	7	0.000	1.000	0.621	-0.113 [0.054]*	0.674	0.535	0.150
Ecuador	6	0.049	1.000	-	-0.051 [0.018]**	-	0.921	0.066
Jamaica	1	0.103	1.000	-	-0.047 [0.011]**	-	0.782	0.798
Mexico	7	0.000	0.849	1.000	-1.259 [0.398]**	0.564	0.351	0.140
Uruguay	1	0.031	1.000	-	-0.157 [0.037]**	-	0.032	0.559
Venezuela	1	0.076	1.000	-	-0.155 [0.045]**	-	0.888	0.617

(*Cont.*)

Country	Model	*Q*-ratios			Final level of stochastic trend component [RMSE]	AR persistence	R^2	Ljung-Box test
		Permanent (stochastic trend)	*Temporary* (irregular)	(AR)				
		μ_t	ε_t	v_t		$\rho_1+\rho_2$		
Panel C: Recent 1998M1-2012M12								
Mainland China	1	0.332	1.000	-	5.544 [1.298]**	-	0.790	0.398
Taiwan China	2	0.000	0.864	1.000	0.661 [0.298]**	0.689	0.886	0.522
India	7	0.347	1.000	0.752	5.392 [1.115]**	0.619	0.811	0.077
Indonesia	1	0.081	1.000	-	0.615 [0.112]**	-	0.470	0.133
South Korea	1	0.291	1.000	-	-4.466 [1.542]**	-	0.393	0.977
Malaysia	1	0.327	1.000	-	4.676 [0.678]**	-	0.434	0.051
Pakistan	2	0.188	0.000	1.000	0.275 [0.057]**	0.411	0.774	0.053
Philippines	1	0.346	1.000	-	-0.362 [0.138]**	-	0.483	0.271
Thailand	6	0.224	1.000	-	0.922 [0.151]**	-	0.642	0.225
Argentina	2	0.000	1.000	0.000	-1.705 [0.427]**	0.281	0.856	0.108
Brazil	2	0.090	1.000	0.900	3.005 [1.515]**	-	0.179	0.163
Chile	1	0.122	1.000	-	0.855 [0.304]**	-	0.438	0.159
Colombia	1	0.000	1.000	-	-0.063 [0.031]**	-	0.005	0.098
Ecuador	1	0.000	1.000	-	-0.025 [0.010]**	-	0.736	0.967
Jamaica	1	0.000	1.000	-	-0.020 [0.002]	-	0.784	0.400
Mexico	7	0.000	0.977	1.000	-1.231 [0.527]**	0.626	0.386	0.106
Uruguay	6	0.000	1.000	-	-0.171 [0.032]**	-	0.364	0.060
Venezuela	1	0.050	1.000	-	-0.152 [0.060]**	-	0.776	0.061

Table IV. State-space model for gross bond flows.

For each country, monthly CPI-scaled gross bond flows are used to estimate the state-space model specifications listed in Appendix D. The best specification is selected using the R^2 and AIC criteria. A dash indicates that the component at hand is absent from the model. $0 \leq Q$-ratio ≤ 1 is the standard deviation of the each component over the largest standard deviation across components, computed from the variance-covariance matrix of disturbances. Column five reports the final level of the stochastic trend and its root mean square error (RMSE); * and ** indicates statistical significance at the 5% and 1% level. The last column reports the *p*-value of the Ljung–Box test for the null hypothesis of no residual autocorrelation.

Country	Model	Q-ratios			Final level of stochastic trend component [RMSE]	AR persistence	R^2	Ljung-Box test
		Permanent (stochastic trend)	*Temporary* (irregular)	(AR)				
		μ_t	ε_t	ν_t		$\rho_1+\rho_2$		
Panel A: First subperiod 1988M1-1997M12								
Mainland China	2	0.125	0.000	1.000	56.353 [6.514]**	0.625	0.851	0.378
Taiwan China	6	0.000	1.000	-	32.706 [8.494]**	-	0.847	0.066
India	2	0.052	0.374	1.000	1.255 [0.477]**	0.875	0.592	0.409
Indonesia	2	0.149	0.350	1.000	8.311 [2.681]**	0.878	0.679	0.609
South Korea	1	0.470	1.000	-	18.027 [1.800]**	-	0.596	0.572
Malaysia	1	0.894	1.000	-	-32.311 [7.135]**	-	0.885	0.120
Pakistan	9	0.000	-	1.000	0.095 [0.032]**	0.170	0.432	0.996
Philippines	1	0.823	1.000	-	4.936 [0.672]**	-	0.666	0.108
Thailand	2	0.156	0.419	1.000	10.382 [2.525]**	0.755	0.610	0.421
Argentina	6	0.262	1.000	-	19.252 [6.335]**	-	0.767	0.183
Brazil	1	0.785	1.000	-	96.726 [7.976]**	-	0.868	0.678
Chile	1	0.457	1.000	-	5.934 [1.056]**	-	0.334	0.066
Colombia	1	0.164	1.000	-	7.193 [0.753]**	-	0.476	0.130
Ecuador	6	0.074	1.000	-	0.567 [0.212]**	-	0.930	0.361
Jamaica	1	0.146	1.000	-	0.392 [0.064]**	-	0.150	0.532
Mexico	1	0.722	1.000	-	25.710 [4.444]**	-	0.558	0.508
Uruguay	1	0.577	1.000	-	12.381 [0.975]**	-	0.675	0.317
Venezuela	1	0.434	1.000	-	11.501 [1.234]**	-	0.448	0.363
Panel B: Extended period 1988M1-2012M12								
Mainland China	2	0.241	1.000	0.825	277.109 [30.250]**	0.850	0.793	0.078
Taiwan China	7	0.000	0.821	1.000	41.921 [11.590]**	0.964	0.533	0.066
India	2	0.123	0.309	1.000	11.416 [3.091]**	0.443	0.862	0.058
Indonesia	1	0.520	1.000	-	32.085 [1.960]**	-	0.708	0.097
South Korea	2	0.335	0.845	1.000	103.788 [8.413]**	0.570	0.547	0.112
Malaysia	2	0.523	0.000	1.000	36.452 [5.844]**	0.356	0.764	0.729
Pakistan	2	0.046	0.491	1.000	0.155 [0.073]*	0.733	0.672	0.115
Philippines	6	0.437	1.000	-	24.261 [2.285]**	-	0.491	0.113
Thailand	1	0.361	1.000	-	6.277 [2.673]**	-	0.372	0.221
Argentina	1	0.968	1.000	-	18.128 [9.097]*	-	0.979	0.077
Brazil	1	0.346	1.000	-	155.919 [13.396]**	-	0.749	0.484
Chile	4	0.400	-	1.000	41.209 [2.902]*	0.123	0.782	0.063
Colombia	1	0.338	1.000	-	33.785 [1.768]*	-	0.812	0.113
Ecuador	1	0.444	1.000	-	1.729 [0.454]**	-	0.525	0.068
Jamaica	6	0.596	1.000	-	-2.963 [1.038]**	-	0.888	0.514
Mexico	1	0.139	1.000	-	74.416 [5.785]**	-	0.650	0.484
Uruguay	6	0.626	1.000	-	22.875 [1.709]**	-	0.678	0.689
Venezuela	1	0.208	1.000	-	5.061 [1.388]**	-	0.184	0.229

(*Cont.*)

Country	Model	*Q*-ratios			Final level of stochastic trend component [RMSE]	AR persistence	R^2	Ljung-Box test
		Permanent (stochastic trend)	*Temporary* (irregular)	(AR)				
		μ_t	ε_t	v_t		$\rho_1+\rho_2$		
Panel C: Recent period 1998M1-2012M12								
Mainland China	1	0.403	1.000	-	297.398 [31.369]**	-	0.530	0.189
Taiwan China	7	0.000	0.901	1.000	43.320 [8.575]**	0.909	0.766	0.139
India	1	0.815	1.000	-	28.346 [2.617]**	-	0.672	0.171
Indonesia	1	0.390	1.000	-	32.136 [2.121]**	-	0.691	0.125
South Korea	1	0.521	1.000	-	105.803 [9.696]**	-	0.602	0.054
Malaysia	1	0.556	1.000	-	10.476 [2.783]**	-	0.502	0.478
Pakistan	1	0.303	1.000	-	0.035 [0.173]	-	0.090	0.353
Philippines	1	0.951	1.000	-	-18.523 [7.382]**	-	0.900	0.770
Thailand	1	0.298	1.000	-	6.552 [2.945]**	-	0.155	0.651
Argentina	1	0.943	1.000	-	6.666 [2.688]**	-	0.842	0.058
Brazil	1	0.255	1.000	-	152.150 [14.760]**	-	0.616	0.765
Chile	1	0.447	1.000	-	42.006 [3.475]**	-	0.664	0.249
Colombia	1	0.359	1.000	-	33.898 [2.174]**	-	0.656	0.254
Ecuador	1	0.544	1.000	-	1.730 [0.387]**	-	0.517	0.622
Jamaica	1	0.412	1.000	-	0.699 [0.609]	-	0.498	0.555
Mexico	1	0.108	1.000	-	73.413 [6.300]**	-	0.374	0.717
Uruguay	1	0.362	1.000	-	16.366 [1.303]**	-	0.599	0.151
Venezuela	1	0.147	1.000	-	5.181 [1.391]**	-	0.014	0.155

Table V. State-space model with push and pull factors for bank credit flows from 1998Q1 to 2012Q4.

The table reports estimates for the state-space Model 5 in Appendix D with pull and push factors in both components of net bank credit flows. The pull (domestic) factors are the short-term interest rate and MSCI equity price index of each EM. The push (global) factors are US short-term interest rate and MSCI US equity price index. The foreign exchange rate is included as pull factor but could be classified as either. Seasonally unadjusted short-term interest rates and foreign exchange rates are obtained from *DataStream*. All push and pull factors are entered as one-period lagged drivers. Bank credit flows are scaled by US core CPI. "+/-" denotes the expected direction of the impact of the driver on the capital flows. $0 \leq Q$-ratio ≤ 1 is the standard deviation of each component over the largest standard deviation across components. The root mean square error (RMSE) is reported in brackets; * and ** indicates statistical significance at the 5% and 1% level. The last column reports the *p*-value of the Ljung–Box test statistic for the null hypothesis of no residual autocorrelation. The cross-section of countries is dictated by data availability.

	Q-ratios			Coefficients of push factors					Coefficients of pull factors							
	Perm.	*Temp.*	Final level of stochastic trend	*Permanent*		*Temporary*			*Permanent*			*Temporary*			R^2	Ljung-Box test
	μ_t	ν_t		US equity	US interest rate	US equity	US interest rate	EM interest rate	EM equity	FX rate	EM interest rate	EM equity	FX rate		
				(+)	(-)	(+)	(-)	(+)	(+)	(-)	(+)	(+)	(-)		
Panel A: Asia															
India	0.929	1.000	155.502 **	0.022 **	-3.100 **	0.002	3.450 **	0.003 **	2.062 **	-0.701 **	0.043 **	-1.555 **	-4.472 **	0.207	0.191
			[2.325]	[0.000]	[0.051]	[0.001]	[0.444]	[0.000]	[0.060]	[0.009]	[0.003]	[0.196]	[0.149]		
Malaysia	0.243	1.000	14.387 *	0.001	-0.176	-0.011	0.084	0.000	-0.199	-0.291	0.045	-0.893	-3.131	0.369	0.585
			[0.805]	[0.001	[0.218]	[0.011]	[1.004]	[0.003]	[0.667]	[0.291]	[0.026]	[0.614]	[9.489]		
Philippines	0.202	1.000	-57.847 **	-0.007	0.752	-0.002	0.331	0.011	0.023	0.057	-0.011	-0.186	0.422	0.767	0.673
			[0.951]	[0.013]	[1.081]	[0.014]	[1.723]	[0.021]	[0.577]	[0.185]	[0.038]	[1.739]	[0.890]		
Thailand	0.813	1.000	-223.076 **	-0.012 **	1.210 **	0.014 **	2.343 **	0.024 **	-0.544 **	0.179 **	-0.024 **	-1.470 **	1.230 **	0.889	0.236
			[1.522]	[0.000]	[0.044]	[0.001]	[0.146]	[0.000]	[0.073]	[0.002]	[0.005]	[0.110]	[0.075]		
Panel B: Latin America															
Argentina	0.202	1.000	-83.005 **	0.009	-1.034	0.005	0.002	0.001	-0.227	-2.666 **	-0.002	-0.047	7.319	0.182	0.328
			[1.574]	[0.005	[0.866]	[0.011]	[1.442]	[0.001]	[0.153]	[1.032]	[0.002]	[0.202]	[6.675]		
Brazil	0.391	1.000	-142.268 **	0.063 **	-11.078 **	-0.004	0.218	-0.007	0.788	-19.915	0.041 *	-0.827	10.725	0.889	0.762
			[10.058]	[0.015]	[4.361]	[0.082]	[9.477]	[0.005]	[2.182]	[10.418]	[0.018]	[2.285]	[13.373]		
Chile	0.340	1.000	172.306 **	-0.010	1.344	-0.012	-0.273	0.003	-0.096	0.373	-0.006	-0.630	-6.596	0.426	0.256
			[2.376]	[0.017]	[1.529]	[0.019]	[2.447]	[0.004]	[0.632]	[1.649]	[0.009]	[1.283]	[4.997]		
Mexico	0.202	1.000	-151.468 **	-0.027	-0.668	-0.083	9.512 *	0.003 **	1.245	0.689	0.012	-2.267	4.085	0.461	0.311
			[3.802]	[0.001]	[1.957]	[0.071]	[4.452]	[0.001]	[0.811]	[1.358]	[0.016]	[2.092]	[8.721]		

Appendix A. International capital form S and international capital form B.

This appendix summarizes key information from the US Department of Treasury's "Instructions for Preparation of Monthly Form S" and "Instructions for Preparation of Monthly Form B" available, at **http://www.treas.gov/tic/forms-s.shtml** and **http://www.treas.gov/tic/forms-b.shtml**, respectively.

All banks, brokers, dealers (and other financial institutions) and individuals are by law required to report the value of any long-term security transactions involving a foreign resident. American Depositary Receipts (ADR) transactions are included. Securities transactions are reported on a transactions basis. Securities transactions are recorded by the nationality of the person with whom the transaction is carried, not by the country that originally issued the security. A foreigner is any individual, branch, partnership, association, corporation or other organization located outside the United States. Additionally, securities are recorded according to the residency of the issuer and not their currency denomination.

The data collection system is specifically designed to capture US cross- border financial transactions for balance-of-payment purposes. That is, it is designed to capture only financial transactions that involve both a US resident and a foreign resident. Note that a US resident includes any individual, corporation, or organization located in the United States including branches, subsidiaries, and affiliates of foreign entities located in the United States. In addition, any corporation incorporated in the United States is considered a US resident even if it has no physical presence. Thus, a US branch of a Japanese bank is considered a US resident, and a London branch of a US bank is considered a foreign resident.

The cross-border definition means that the data on foreign purchases of US securities include only those transactions that involve both a US seller and a foreign purchaser. Thus, these data exclude any US-to-US transactions, including, for example, transactions where the seller is a US securities broker and the purchaser is a US-based branch of a Japanese securities firm. They also exclude foreign-to-foreign transactions in securities, for example if a Japanese-resident securities broker purchases US Treasuries from a London-based securities broker. Because many US securities, including US Treasury securities, trade in foreign financial markets, the data will not capture all foreign transactions in US securities.

These forms are the basis for the collection of data on purchases and sales of long-term securities, bank liabilities and bank claims by foreigners. The Treasury uses these data to provide timely and reliable information on international capital movements. This information is needed for preparation of the US capital accounts of the US balance-of-payment and the international investment position of the United States. These reports cover transaction by all banks, brokers, dealers, other financial institutions and individuals who carry transactions directly with foreigners.

Appendix B. Descriptive statistics for net bond flows.

The table reports minimum, mean, maximum, and standard deviation (S.D.) of CPI-scaled net bond flows in US$ millions from 1988M1 to 2012M12. The last column reports the Augmented Dickey Fuller (ADF) test for the null hypothesis of unit root (non-stationary) behaviour against the alternative hypothesis of stationarity; the test regression includes a constant and linear time trend and the augmentation lag order is selected with the modified AIC criterion (Ng and Perron, 2001). * and ** denote rejection at the 5% and 1% levels, respectively, using the critical values tabulated by MacKinnon (1996).

	Net bond flows				
	Min	Mean	Max	S.D.	ADF test
Panel A: Asia					
Mainland	-170.05	-17.00	164.59	33.39	-2.89
Taiwan China	-33.11	-3.76	31.99	8.70	-5.48 **
India	-16.56	-0.19	14.68	2.98	-7.00 **
Indonesia	-10.60	-0.07	11.40	2.67	-3.25
South Korea	-29.13	-2.19	59.26	8.74	-5.27 **
Malaysia	-19.74	-0.45	10.61	3.59	-3.96 **
Pakistan	-0.41	0.04	4.01	0.29	-9.04 **
Philippines	-11.19	-0.11	7.05	2.00	-3.88 *
Thailand	-29.64	-0.47	21.05	4.10	-4.80 **
Average	*-35.61*	*-2.69*	*36.07*	*7.38*	
Total	*-320.45*	*-24.20*	*324.64*	*66.46*	
Panel B: Latin America					
Argentina	-21.36	-0.24	14.93	2.79	-15.09 **
Brazil	-114.87	-2.97	92.67	16.46	-3.54 *
Chile	-15.00	-0.46	9.78	2.70	-4.33 **
Colombia	-13.18	-0.23	15.59	2.62	-4.54 **
Ecuador	-2.48	-0.09	4.07	0.52	-3.39
Jamaica	-1.04	-0.04	2.13	0.32	-3.97 *
Mexico	-74.65	-1.33	51.69	10.58	-3.02
Uruguay	-3.88	-0.23	5.46	1.07	-15.17 **
Venezuela	-8.30	-0.09	25.17	2.61	-16.80 **
Average	*-28.31*	*-0.63*	*24.61*	*4.41*	
Total	*-254.75*	*-5.67*	*221.49*	*39.67*	

Appendix C. The Kalman-filter algorithm for state-space model estimation.

With reference to model equations (7) and (8), the goal is to estimate the unobserved state vector $\boldsymbol{\beta}_t$. Let $\boldsymbol{\beta}_{t|t-1}$.denote the best linear mean-squared estimate of $\boldsymbol{\beta}_t$ using all data up to time t-1. We can obtain $\boldsymbol{\beta}_{t|t}$ and its covariance matrix recursively via the Kalman-filter algorithm described by the equations

$$\boldsymbol{\beta}_{t|t-1} = \mathbf{F}\boldsymbol{\beta}_{t-1|t-1}, \tag{A.1}$$

$$\mathrm{P}_{t|t-1} = \mathbf{F}\mathrm{P}_{t-1|t-1}\mathbf{F}' + \sigma^2\mathbf{Q}, \tag{A.2}$$

$$u_{t|t-1} = y_{\mathrm{t}} - \mathbf{H}\boldsymbol{\beta}_{t|t-1} \tag{A.3}$$

$$\mathbf{f}_{t|t-1} = \mathbf{H}\mathbf{P}_{t|t-1}\mathbf{H}' + \sigma^2 \tag{A.4}$$

$$\boldsymbol{\beta}_{t|t} = \boldsymbol{\beta}_{t|t-1} + \mathbf{P}_{t|t-1}\mathbf{H}'\left[\mathbf{f}_{t|t-1}\right]^{-1} u_{t|t-1}, \tag{A.5}$$

$$\mathbf{P}_{t|t} = [\mathbf{I} - \mathbf{P}_{t|t-1}\mathbf{H}'\left[\mathbf{f}_{t|t-1}\right]^{-1}\mathbf{H}]\mathbf{P}_{t|t-1} \tag{A.6}$$

where

$$\mathbf{P}_{t|t-1} = E\left[\left(\boldsymbol{\beta}_t - \boldsymbol{\beta}_{t|t-1}\right)\left(\boldsymbol{\beta}_t - \boldsymbol{\beta}_{t|t-1}\right)'\right], \text{ and } \mathbf{P}_{t|t} = E\left[\left(\boldsymbol{\beta}_t - \boldsymbol{\beta}_{t|t}\right)\left(\boldsymbol{\beta}_t - \boldsymbol{\beta}_{t|t}\right)'\right]$$

are the error covariance matrices for $1 \le t \le T$. The one-step-ahead prediction error, $u_{t|t-1}$, is used to perform the Ljung-Box test for no residual autocorrelation. More efficient estimates of the state vector and its error covariance matrix are obtained by using all information up to time T via the smoother

$$\boldsymbol{\beta}_{t-1|T} = \boldsymbol{\beta}_{t-1|t-1} + \mathbf{J}_{t-1}\left[\boldsymbol{\beta}_{t|T} - \mathbf{F}\boldsymbol{\beta}_{t|t-1}\right] \tag{A.7}$$

$$\mathbf{P}_{t-1|T} = \mathbf{P}_{t-1|t-1} + \mathbf{J}_{t-1}\left(\mathbf{P}_{t|T} - \mathbf{P}_{t|t-1}\right)\mathbf{J}'_{t-1} \tag{A.8}$$

$$\mathbf{J}_{t-1} = \mathbf{P}_{t-1|t-1}\mathbf{F}'\mathbf{P}^{-1}_{t|t-1} \tag{A.9}$$

which is computed by a backwards recursion for $t = T$-1, T-2 ,…, 1.

The Kalman filter treats the model parameters as known. In practice, the parameters (entries of matrices **H**, **F**, **R** and **Q)** are unknown and need to be estimated. Gathered in $\boldsymbol{\alpha}$, the parameters can be estimated by maximizing the log-likelihood function

$$L(\boldsymbol{\alpha} \mid \mathbf{z}, \mathbf{g}) \;=\; \text{const} - \frac{1}{2}\sum_{t=1}^{T}\left(\ln\left[\det\left(\mathbf{f}_{t|t-1}\right)\right] + u'_{t|t-1}\left[\mathbf{f}_{t|t-1}\right]^{-1} u_{t|t-1}\right), \tag{A.10}$$

where $u_{t|t-1}$ and $\boldsymbol{f}_{t|t-1}$ are both implicit functions of the unknown parameter vector $\boldsymbol{\alpha}$ and are evaluated using the Kalman filter. Once the ML estimate of $\boldsymbol{\alpha}$ has been obtained, one can compute the smoothed estimates of the state vector and its error covariance matrix via the Kalman filter and the full-sample smoother formalized above. The log-likelihood function can be maximized using numerical optimisation procedures (Cuthbertson et al., 1992, Ch. 2). We employ the Broyden-Fletcher-Goldfarb-Shanno quasi-Newton algorithm (Harvey, 1989).

Appendix D. Candidate state-space model specifications for capital flows.

Model 1: Random walk + irregular	Model 6: Random walk with drift + irregular
$y_t = \mu_t + \varepsilon_t$	$y_t = \mu_t + \varepsilon_t$
$\mu_t = \mu_{t-1} + \eta_t$	$\mu_t = \mu_{t-1} + c + \eta_t$
Model 2: Random walk + AR(1) + irregular	Model 7: Random walk with drift + AR(1) + irregular
$y_t = \mu_t + v_t + \varepsilon_t$	$y_t = \mu_t + v_t + \varepsilon_t$
$\mu_t = \mu_{t-1} + \eta_t$	$\mu_t = \mu_{t-1} + c + \eta_t$
$v_t = \rho_1 v_{t-1} + \xi_t \quad \lvert\rho_1\rvert < 1$	$v_t = \rho_1 v_{t-1} + \xi_t \quad \lvert\rho_1\rvert < 1$
Model 3: Random walk + AR(2) + irregular	Model 8: Random walk with drift + AR(2) + irregular
$y_t = \mu_t + v_t + \varepsilon_t$	$y_t = \mu_t + v_t + \varepsilon_t$
$\mu_t = \mu_{t-1} + \eta_t$	$\mu_t = \mu_{t-1} + c + \eta_t$
$v_t = \rho_1 v_{t-1} + \rho_2 v_{t-2} + \xi_t \quad (\rho_1 + \rho_2) < 1, (\rho_2 - \rho_1) < 1, \lvert\rho_2\rvert < 1$	$v_t = \rho_1 v_{t-1} + \rho_2 v_{t-2} + \xi_t \quad (\rho_1 + \rho_2) < 1, (\rho_2 - \rho_1) < 1, \lvert\rho_2\rvert < 1$
Model 4: Random walk + AR(1)	Model 9: Random walk with drift + AR(1)
$y_t = \mu_t + v_t$	$y_t = \mu_t + v_t$
$\mu_t = \mu_{t-1} + \eta_t$	$\mu_t = \mu_{t-1} + c + \eta_t$
$v_t = \rho_1 v_{t-1} + \xi_t \quad \lvert\rho_1\rvert < 1$	$v_t = \rho_1 v_{t-1} + \xi_t \quad \lvert\rho_1\rvert < 1$
Model 5: Random walk + AR(2)	Model 10: Random walk with drift + AR(2)
$y_t = \mu_t + v_t$	$y_t = \mu_t + v_t$
$\mu_t = \mu_{t-1} + \eta_t$	$\mu_t = \mu_{t-1} + c + \eta_t$
$v_t = \rho_1 v_{t-1} + \rho_2 v_{t-2} + \xi_t \quad (\rho_1 + \rho_2) < 1, (\rho_2 - \rho_1) < 1, \lvert\rho_2\rvert < 1$	$v_t = \rho_1 v_{t-1} + \rho_2 v_{t-2} + \xi_t \quad (\rho_1 + \rho_2) < 1, (\rho_2 - \rho_1) < 1,$