

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 estimate hot money as the temporary component in each type of flow. The analysis reveals that hot money in bank credit flows has increased during the 2000s relative to the 1990s. This finding is robust to controlling for the influence of push and pull factors in the unobserved components. The evidence indirectly supports 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

¹ Huge movements of hot money have been historically observed under fixed exchange rate systems (*e.g.*, in the final years of the Bretton Woods system). Recently, researchers have developed 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).

(Tong and Wei, 2011; Sarno and Taylor, 1999a).² In fact, a key feature of the post-1990s trend 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 when they 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 how the 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. Has the banking sector played a key role in the transmission of the crisis to emerging markets as the literature on bank globalisation suggests?

This paper provides answers to the above questions by probing whether the relative importance of hot money in bank credit and portfolio flows to EMs has changed over the period 1988-2012. We deploy 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 1988 to 1997. We are able to confirm the earlier findings of Sarno and Taylor (1999a, b) over a similar time period and from 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

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 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).

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 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.

Finally, we provide evidence on the robustness of our results by estimating ‘structural’ state-space models which include global (push) and domestic (pull) macro factors as drivers of the expected part of the unobserved components, permanent and transitory, of capital flows. This approach of including these drivers of capital flows can be interpreted as an attempt to incorporate fundamentals (i.e., adding ‘structure’ to the state-space decomposition) in order to model the expected part of capital flows. The latter will allow us more robustly to extract the unexpected component from which appropriate measures of the relative importance of the temporary (hot money) and permanent components, the so-called Q ratios, are obtained. This constitutes a methodological novelty. 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.

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 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 draws from two related strands of the literature, namely, studies that seek to identify the amount of hot money in bank credit and/or portfolio flows, and studies that investigate 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 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 but reports mixed results. 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 (firm-level) risk. Eichengreen et al. (2012) study the evolution of CDS spreads for 45 global banks and find that common factors became

³ Securities backed by subprime mortgages account only for about 3 percent 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 overviews of various channels of crisis transmission and different ways to categorize them see, for instance, Kamin and DeMarco (2012) and Forbes (2012).

more important with the advent of the crisis.

At the same time, theoretical models have been developed to show how crises in one area of the world 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. In fact, possibly the earliest academic paper about hot money, Gray (1964), refers to short-term capital/funds. The balance-of-payment statistics of governmental bodies such as 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’.

However, an influential paper by 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. After empirical examination, they conclude 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 originally utilized by Sarno and Taylor (1999a) to estimate 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 against the background of the banking sector globalisation and the GFC. This is the focus of our paper.

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.

3. Data Description and Preliminary Analysis

3.1 Description of Capital Flow Variables

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, 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 the World Bank (World Development Indicators, July 2011), 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., 2013). 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 25-year period from 1988 to 2012. This allows us to replicate the analysis for the 1990s conducted by Sarno and Taylor (1999a),

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.

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.

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 flow observations are expressed in US dollars, we scale the data by the US consumer price index (CPI) to control for any inflationary effects. The CPI series is obtained from *Datastream*. We also conduct the analysis on the original capital flows, and the results are qualitatively similar (unreported for space constraints but available from the authors upon request) in line with the fact that inflationary pressures in the US have been limited over the period.

It is noteworthy that our data allows us to measure not only direct cross-border lending (traditional banking linkages) but also indirect ones through an affiliate in the borrower’s country (internal capital market). The traditional channel of transmission through cross-border lending is well-documented. 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. We should stress that a US resident includes any individual, corporation, or organization (including branches, subsidiaries, and affiliates of foreign entities) located in the United States. In addition, any entity incorporated in the United States 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

¹⁰ These data provide an unusual opportunity for a direct test of the existence of an internal capital market, since

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 and Latin American countries from 1988 to 2012 in **Figure I**. The vertical axis is 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 summarizes the main three variables in our analysis (net bank credit flow, net equity flow and gross bond flows) over the period 1988-2012. The word ‘net’ refers to the amount that home country (US) residents are lending to foreigners (EMs) minus the amount that foreigners are lending to the home country.¹¹ All flows are scaled by the US consumer price index sourced from *Datastream* to shield the analysis from potential inflation effects.

All three categories of capital flows to Asia surpass in magnitude those to Latin America on average over the period under study. For most of the sample countries, the average net

data on borrowing and lending within an organization (*i.e.*, between an organization’s different components) is generally not available to researchers.

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.

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 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. With regard to the standard deviation, capital flows to Asia are more volatile than the flows to Latin America in all categories.

4. State-Space Models

The main tool for our empirical analysis is a state-space model of the dynamics of capital flows. One benefit of representing a dynamic system in state space form is that this allows unobserved (state) variables to be incorporated and estimated along with the observable model. 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. Here the main appeal of state-space models is that they allow us to decompose the observed capital flows into their unobserved permanent and temporary components.

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

$$y_t = \mu_t + v_t + \varepsilon_t, \quad t=1, \dots, T \quad (1)$$

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

$$\mu_t = c + \mu_{t-1} + \eta_t \quad (2)$$

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

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

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 $(\mu_t, v_t, \varepsilon_t)$ to the observed flows

$$y_t = (1 \ 1 \ 1) \begin{pmatrix} \mu_t \\ v_t \\ \varepsilon_t \end{pmatrix}, \quad (4)$$

and a transition equation describing the dynamics of the state variables

$$\begin{pmatrix} \mu_t \\ v_t \\ \varepsilon_t \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \rho_v & 0 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} \mu_{t-1} \\ v_{t-1} \\ \varepsilon_{t-1} \end{pmatrix} + \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \eta_t \\ \xi_t \\ \varepsilon_t \end{pmatrix} \quad (5)$$

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

$$y_t = \mathbf{H} \boldsymbol{\beta}_t, \quad (6)$$

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

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

for $t=1, \dots, T$, where \mathbf{H} is a known unit vector of dimension 1×3 as expressed in (4); \mathbf{F} , \mathbf{R} and \mathbf{Q} are fixed matrices of dimension 3×3 , 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 importance of the temporary and permanent components, we employ the standard measure in the state-space modelling literature known as the Q -ratio

which is based on the disturbance covariance matrix \mathbf{Q} . For instance, the Q -ratio measure

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

provides a gauge of the relative contribution of the permanent component. Thus, the Q -ratios are scaled measures of the importance of the unobserved permanent and temporary components of the flows. If most of the dynamics in the flows is due to the permanent component, then we expect the Q -ratio for the stochastic level to be one; this means that a large part of the capital flows will remain in the country concerned for an indeterminate period of time. Instead, if most of the variation in capital flows is explained by the dynamics of the temporary component then the Q -ratio of the AR component or the irregular component is equal to 1. This means that the capital flows under consideration are dominated by hot money and hence, prone to reversals.

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

Next we deploy the state-space modelling approach described above to bank credit, equity and bond flows, separately, to identify their ‘hot money’ components.

5.1 Reduced-form unobserved components model

Hot Money in Bank Credit

We now discuss importance of hot money in bank credit flows by examining the estimates

and diagnostics of the state-space models. The results corresponding to the first subperiod (1988-1997), extended period (1988-2012) and most recent period (1998-2012) are shown in **Table II**, Panels A, B and C, respectively.

Column 2 of the table indicates the selected model specification with reference to the candidates 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 we report the Q -ratios for the permanent (stochastic trend) component, and the two temporary (AR and irregular) component. Column 6 reports the estimated stochastic level in the final state vector and associated root mean square error (RMSE). If the estimated 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 estimated AR coefficient (damping factor) whose proximity to the unit root circle indicates the degree of persistence in the temporary component of the flows.

The model estimates for bank credit flows over the period 1988-1997 suggest for all 18 EMs the permanent component explains most of the variation in the data. Taking Mainland China as an example, the Q -ratio of the permanent component in Table II(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 those in Sarno and Taylor (1999a).

However, Table II(B) tells a different story. Over the full sample period from 1988 to 2012, the analysis of bank credit for both sets of countries suggests that the largest Q -ratios now instead corresponds to the temporary part of bank credit 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 now only 0.217, while that of the AR component ν_t is equal to 1. Therefore, it would seem appropriate to regard bank credit flows to Mainland China over the full sample period 1988-2012 as more temporary than permanent, which is in sharp contrast with the findings (from similar state-space models) over the first subsample period

1988-1997. Put differently, the contribution of the permanent (temporary) component to the total variance of capital flows is relatively small (large). The estimated level of the stochastic trend component μ_t in the final state vector is significant which, together with the Q -ratios, 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. Bank credit flows are on the whole largely temporary for both Asian and Latin American countries over the full period 1988- 2012.

We thus conjecture that the temporariness of bank credit has 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(C). Bank credit shows now, in contrast to the first subsample period 1988-1997, a large degree of temporariness. Taking again Mainland China as an example, the Q -ratio of the AR component is 1 whereas the Q -ratio of the stochastic trend component is 0.081, implying that bank credit to Mainland China has become predominantly temporary over the most recent 15-year period. Thus, we conclude that the degree 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 statistically significant but small permanent component relative to their ‘hot money’ component; hence, all three types of capital flows are plausible candidates as channels for the transmission of the GFC. Bank credit surfaces as a new channel of crisis transmission given that is not seen 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 consistent with the recent literature about rollover risk, banking sector globalisation and the transmission of the GFC.

5.2. Unobserved components model with push/pull factors

We now reformulate the state-space models by incorporating various 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 \mathbf{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.¹²

Choosing a set of pull and push factors $\{Z_{1,t}, Z_{2,t}, \dots, Z_{J,t}\}$ is a challenging task because it ought to include relevant drivers for both components, permanent and temporary. Earlier studies have considered as push (or global) factors investor-fear risk, liquidity risk and interest rate risk factors; and as pull (or domestic) factors the depth of the financial system, real GDP growth, country indebtedness and capital controls (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 more relevant as 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 the 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. We should note, however, that since changes in the exchange rate can come from the US side or the EM side, it can be strictly-speaking categorized as either a push or a pull factor. The rationale of including interest rates and the exchange rate is obvious: both of them have been

¹² 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).

extensively used as drivers in the literature on carry trade, which has been categorised as hot money recently.¹³ We include the equity indices of the US and of EMs 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 stress/ stress/confidence barometer, with a sharp decline often preceding an economic crisis, which makes hot money in bank credit responsive to equity price movements (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

¹³ 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.

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 Tille, 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.¹⁴ 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. (2013), 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 coefficients of the push/pull factors are rather mixed. As noted above, large heterogeneity on the drivers of capital flows, both in time and across countries, has been documented in the literature. In the present context, it may relate to the fact that our time span 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

¹⁴ We do not count the exchange rate since, as noted above, it can be seen both as push or pull factor.

(Surge/Stop/Flight/Retrenchment).

For completeness, we repeat the analysis with a different set of push and pull factors used in earlier work. Accordingly, the push factors are investor-fear risk, liquidity risk and interest rate risk. The investor-fear factor is proxied by the VXO volatility index which is compiled by the Chicago Board Options Exchange. VXO measures implied volatility using prices for a range of options on the S&P 100 index and captures overall “economic uncertainty” or “risk”, including both the riskiness of financial assets as well as investors’ risk aversion. The liquidity risk is proxied by year-on-year growth in US money supply (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). All data are sourced by *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. 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. Results are not reported to preserve space but are available from the authors upon request.

6. Conclusions

Motivated by the dramatic increase in international capital flows in recent years, and notably in cross-border bank credit flows during the period 2000-2007, which reached 60% of global GDP, we investigate whether the role of hot money in bank credit and portfolio flows has changed over the years. We deploy state-space models à la Kalman filter to measure the degree of temporariness or potential reversibility of capital flows, known as ‘hot money’ from the US to EMs over the period 1988 to 2012. In particular, we examine whether hot money in bank credit has increased in recent years reflecting the banking globalisation process.

A key finding 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 conclusion 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 findings confirm 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.

The paper provides evidence that hot money in bank credit and portfolio flows is a likely channel via which the Subprime Crisis in the US evolved into a global financial crisis.¹⁵ Our findings support the notion that bank lending played a major role in the transmission of the late 2000s GFC in line with the evidence, albeit from a different methodological framework, provided by Cetorelli and Goldberg (2011). Moreover, they 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).

¹⁵ This is not to say that we rule out other transmission channels. It is plausible that a number of 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.

References

- Acharya, V. V., Gale, D., and T. Yorulmazer (2011). Rollover risk and market freezes. *Journal of Finance* 66, 1177-1209.
- Acharya, V.V., and P. Schnabl (2010). Do global banks spread global imbalances? Asset-backed commercial paper during the financial crisis of 2007–2009. *IMF Economic Review* 58, 37-73.
- Agosin, M.R., and F. Huaita (2011). Overreaction in capital flows to emerging markets: Booms and sudden stops, *Journal of International Money and Finance* 31, 1140-1155.
- Aiyar, S. (2012). From financial crisis to great recession: The role of globalized banks, *American Economic Review* 102, 225-230.
- BIS (2009). *Capital flows and emerging market economies*. Bank for International Settlements Papers, January 2009.
- Bekaert, G., Harvey, C. R., and R. L. Lumsdaine (2002). The dynamics of emerging market equity flows. *Journal of International Money and Finance* 27, 295-350.
- Brogaard, J., Hendershott, T., and R. Riordan (2013). High frequency trading and price discovery. *University of Washington Working Paper*.
- Cetorelli, N., and L. Goldberg, (2011). Global banks and international shock transmission: evidence from the crisis. *IMF Economic Review* 59, 41–76.
- Cetorelli, N., and L. Goldberg (2012a). Banking globalization and monetary transmission. *Journal of Finance* 67, 1811–1843.
- Cetorelli, N., and L. Goldberg (2012b). Follow the money: Quantifying domestic effects of foreign bank shocks in the great recession. *American Economic Review* 102, 213-218.
- Chari, V. V., and P. J. Kehoe (2003). Hot money. *Journal of Political Economy* 111, 1262-1292.
- Chuhan, P., Claessens, S., and N. Mamingi (1998). Equity and bond flows to Latin America and Asia: The role of global and country factors, *Journal of Development Economics* 55, 439-463.
- Claessens, S., Dooley, M. P., and A. Warner (1995). Portfolio capital flows: Hot or cold? *World Bank Economic Review* 9, 153-174.
- Cuthbertson, K., Hall, S.G., and M. P. Taylor (1992). *Applied econometric techniques*. Harvester Wheatsheaf, Exeter.

- De Haas, R., and N. Van Horen (2013), Running for the exit? International bank lending during a financial crisis. *Review of Financial Studies* 26, 244-285.
- Ehrmann, M., Fratzscher, M., and A. Mehl (2009), What has made the current financial crisis truly global. *European Central Bank Working Paper* 20.
- Eichengreen, B., Mody, A., Nedeljkovic, M., and L. Sarno (2012). How the subprime crisis went global: evidence from bank credit default swap spreads. *Journal of International Money and Finance* 31, 1299-1318 .
- Forbes, K.J., (2012). The “Big C”: Identifying and mitigating contagion, *MIT Sloan School Working Paper* 4970-12.
- Forbes, K.J., and F.E. Warnock (2012), Capital flow waves: Surges, stops, flight, and retrenchment. *Journal of International Economics* 88, 235-251.
- Fratzscher, M., (2009). What explains global exchange rate movements during the financial crisis? *European Central Bank Working Paper* 1060.
- Fratzscher, M. (2012). Capital Flows, push versus pull factors and the global financial crisis. *Journal of International Economics* 88, 341–356
- Giannetti, M., and L. Laeven (2012). Flight home, flight abroad, and international credit cycles. *American Economic Review* 102, 219-224.
- Goldberg, L. (2009). Understanding banking sector globalization. *International Monetary Fund Staff Papers* 56, 171–97.
- Gray, H. P. (1964). Marginal cost of hot money. *Journal of Political Economy* 72, 189-192.
- Guo, F., and Y. S. Huang (2010). Does "hot money" drive China's real estate and stock markets? *International Review of Economics & Finance* 19, 452-466.
- Harvey, A.C. (1989). *Forecasting, structural time series models and the Kalman filter*. Cambridge Univ. Press, Cambridge, MA.
- He, Z., and W. Xiong (2012). Rollover risk and credit risk. *Journal of Finance* 67, 391-430.
- Hendershott, T., and A. J. Menkveld (2014). Price pressures. *Journal of Financial Economics*, forthcoming.
- International Monetary Fund (2011). *Recent Experiences in Managing Capital Inflow: Cross-Cutting Themes and Possible Policy Framework*. IMF Policy Paper, 14 February.
- Kaminsky, G. L. (1999). *Currency and banking crises: The early warnings of distress*. IMF Working Paper 99/178.
- Kaminsky, G. L., and C. M., Reinhart. (1998). Financial crises in Asia and Latin America: Then and now. *American Economic Review* 88, 444-448.

- Kaminsky, G. L., and C. M., Reinhart. (1999). The twin crises: The causes of banking and balance-of-payments problems. *American Economic Review* 89, 473-500.
- Korinek, A. (2011). Hot money and serial financial crises. *IMF Economic Review*, 59, 306-339.
- Kamin, S. B., and L. P. DeMarco (2012). How did a domestic housing slump turn into a global financial crisis? *Journal of International Money and Finance* 31, 10-41.
- Kester, A. Y. (1995). *Following the money: US finance in the world economy*, National Academies Press.
- Khwaja, A., and A. Mian (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review* 98, 1413–1442.
- Levchenko, A. A., and P. Mauro (2007). Do some forms of financial flows help protect against “sudden stops”? *World Bank Economic Review* 21, 389-411.
- Martin, M. F., and W. M. Morrison (2008). China's hot money problems. *Congressional Research Service Report 22921*.
- McCauley, R.N. (2010), Managing recent hot money inflows in Asia, in M. Kawai, M. Lamberte (Eds.), *Managing capital flows in Asia: Search for a framework*, Edward Elgar Publishing Ltd.
- McKinnon, R. (2013). *The unloved dollar standard: From Bretton Woods to the rise of China*, Oxford University Press.
- McKinnon, R. and Z. Liu (2013). Zero interest rates in the United States provoke world monetary instability and constrict the US economy. *Review of International Economics* 21, 49-56.
- McKinnon, R. and G. Schnabl (2009). The case for stabilizing China’s exchange rate: Setting the stage for fiscal expansion. *China and World Economy* 17, 1–32.
- Menkveld, A. J., Koopman S. J., and A. Lucas. (2007). Modeling around-the-clock price discovery for cross-listed stocks using state space models. *Journal of Business and Economic Statistics*, 25, 213–225.
- Milesi-Ferretti, G. M., and C. Tille. (2011). The great retrenchment: International capital flows during the global financial crisis. *Economic Policy*, 26, 289-346.
- Neumann, R.M., Penl. R., and A. Tanku (2009). Volatility of capital flows and financial liberalization: Do specific flows respond differently? *International Review of Economics and Finance* 18, 488-501.
- Ng. S. and P. Perron, (2001). Lag length selection and the construction of unit root tests with

- good size and power. *Econometrica*, 69, 1519-1554.
- Ostry, J.D., Chamon, M., Qureshi, M.S. Reinhart, D.B.S. Ghosh, A.R. and K.F. Habermeier (2010). *Capital inflows: The role of controls*. IMF Staff Position Note. Washington, D.C.: International Monetary Fund.
- Peek, J. and E. Rosengren (1997). The international transmission of financial shocks: The case of Japan. *The American Economic Review* 87, 495-505.
- Reinhart, C.M., and K.S. Rogoff (2009). *This time is different: Eight centuries of financial folly*. Princeton University Press.
- Sarno, L., and M. P. Taylor (1999a). Hot money, accounting labels and the permanence of capital flows to developing countries: An empirical investigation. *Journal of Development Economics* 59, 337-364.
- Sarno, L., and M. P. Taylor, (1999b). Moral hazard, asset price bubbles, capital flows, and the East Asian crisis: The first tests. *Journal of International Money and Finance*, 18, 637-657.
- Sarno, L., Tsiakas, I., and B. Ulloa (2013). What drives international portfolio flows? *Cass Business School Working Paper*.
- Schnabl, P. (2012). Financial globalization and the transmission of bank liquidity shocks: Evidence from an emerging market. *Journal of Finance* 67, 897–932.
- Tesar, L. L., and I. M. Werner (1994). International equity transactions and US portfolio choice. In J. Frankel (Ed.) *The Internationalization of Equity Markets* (pp. 185-215). Chicago: University of Chicago Press.
- Tesar, L. L., and I. M. Werner (1995). US equity investment in emerging stock markets. *World Bank Economic Review*, 9(1), 109-129.
- Tong, H., and S.-J. Wei (2011). The composition matters: Capital inflows and liquidity crunch during a global economic crisis. *Review of Financial Studies* 24, 2023-2052.
- World Bank (2011). *World Development Indicators 2011*, Washington DC: World Bank.

Table I. Descriptive statistics

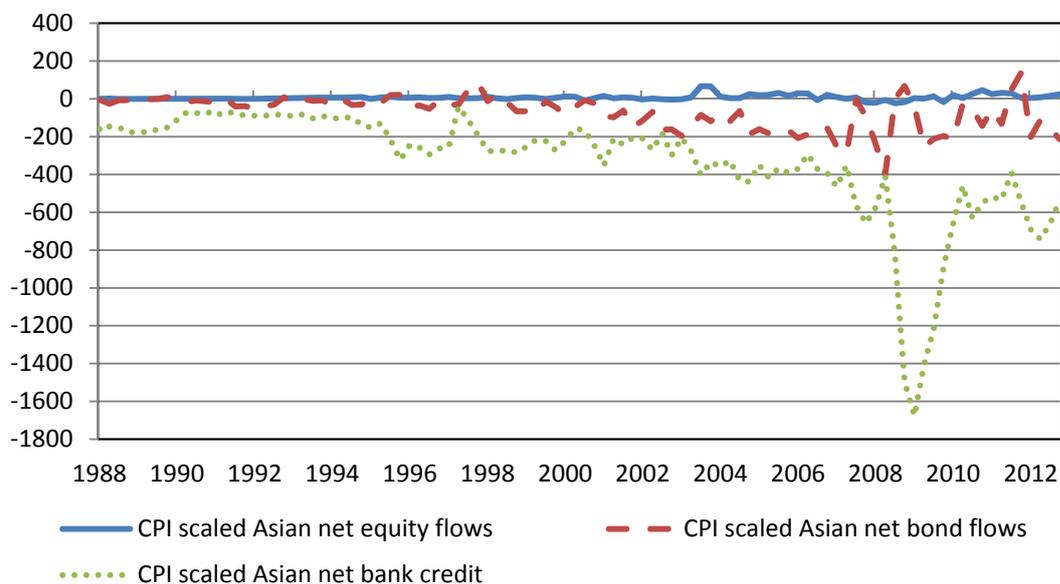
The table reports minimum, mean, maximum, and standard deviation (S.D.) of CPI scaled capital flows in US\$ million. The frequency of the data is quarterly for bank credit flows and monthly for equity and bond flows. The last column reports the Augmented Dickey Fuller (ADF) test statistic for the null hypothesis of unit root (non-stationary) behaviour against the alternative hypothesis of mean-reversion. The test augmentation lag order is selected using the modified AIC criterion (Ng and Perron, 2001). *, ** and *** indicate rejection of the null at the 10%, 5% and 1% levels.

	Scaled Net bank credit flows					Scaled Net Equity flows					Scaled 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 China	-1,164	-141	-3.6272	198.83	-1.46	-13.837	0.093	21.161	2.468	-4.60 ***	0.013	119.350	524.810	113.390	-0.82
Taiwan China	-186	-89	-43.175	33.439	-2.97	-15.867	0.901	37.400	4.422	-5.69 ***	-0.455	25.946	105.090	17.321	-2.48
India	-158	-30	34.408	33.082	-1.45	-12.308	0.350	11.330	1.620	-3.68 ***	0.002	5.354	57.105	8.145	0.12
Indonesia	-143	-30	10.434	34.614	-2.40	-1.687	0.131	2.575	0.498	-1.89	-0.246	6.893	44.930	7.367	-0.08
South Korea	-67	20	86.722	29.301	-2.70	-7.757	0.660	9.072	2.028	-3.45 **	0.007	41.021	136.850	36.700	-0.43
Malaysia	-22	-6	10.541	4.6614	-1.73	-2.716	0.153	3.391	0.694	-3.76 **	-0.737	11.457	105.110	10.914	-1.73 *
Pakistan	-37	-7	4.416	8.3406	-0.70	-0.374	0.017	0.787	0.114	-3.69 **	0.000	0.118	4.054	0.342	-3.11
Philippines	-50	-9	9.5292	10.949	0.22	-1.242	0.053	1.389	0.216	-3.54 **	0.017	6.435	32.272	6.459	-0.31
Thailand	-212	-43	1.3388	47.214	0.07	-1.654	0.100	1.978	0.421	-1.98	0.022	9.627	41.692	7.349	-1.29
<i>Average</i>	<i>-226.636</i>	<i>-37.319</i>	<i>12.287</i>	<i>44.492</i>		<i>-6.382</i>	<i>0.273</i>	<i>9.898</i>	<i>1.387</i>		<i>-0.153</i>	<i>25.133</i>	<i>116.879</i>	<i>23.110</i>	
<i>Total</i>	<i>-2,039.721</i>	<i>-335.869</i>	<i>110.587</i>	<i>400.431</i>		<i>-57.441</i>	<i>2.457</i>	<i>89.083</i>	<i>12.481</i>		<i>-1.378</i>	<i>226.201</i>	<i>1,051.913</i>	<i>207.988</i>	
Panel B: Latin America															
Argentina	-75	-28	65.247	26.548	-3.06	-4.601	0.034	9.487	0.943	-3.16 *	-0.458	13.527	106.070	18.945	-2.33
Brazil	-136	41	257.07	82.536	-1.73	-9.848	1.555	41.563	4.029	-2.37	-0.264	61.230	383.670	58.739	-1.16
Chile	-48	0	33.963	16.768	-2.36	-4.509	-0.023	4.371	0.826	-3.69 **	0.027	11.660	62.124	12.280	-0.90
Colombia	-74	-13	25.653	21.25	-1.01	-2.117	-0.024	2.237	0.348	-3.60 ***	0.004	9.655	49.832	9.003	0.42
Ecuador	-16	-6	10.235	6.7393	-2.39	-1.721	-0.022	2.462	0.235	-4.40 ***	-0.433	1.159	7.824	1.373	-2.13
Jamaica	-5	-2	1.4477	1.2221	-2.30	-0.738	-0.012	0.105	0.060	-4.65 ***	0.000	1.291	9.470	1.703	-2.05
Mexico	-203	-75	115.92	75.641	-2.53	-7.170	-0.072	11.708	2.279	-3.40 **	0.018	38.902	171.500	29.127	-1.41
Uruguay	-43	-17	-4.4866	10.44	-0.16	-1.208	-0.091	1.902	0.220	-2.40 **	0.024	5.583	31.627	4.936	-0.95
Venezuela	-138	-85	14.217	35.764	-0.90	-2.411	-0.041	4.061	0.482	-4.33 ***	-0.234	4.878	30.199	3.940	-0.94
<i>Average</i>	<i>-82.050</i>	<i>-20.644</i>	<i>57.696</i>	<i>30.768</i>		<i>-3.814</i>	<i>0.145</i>	<i>8.655</i>	<i>1.047</i>		<i>-0.146</i>	<i>16.432</i>	<i>94.702</i>	<i>15.561</i>	
<i>Total</i>	<i>-738.45</i>	<i>-185.80</i>	<i>519.27</i>	<i>276.91</i>		<i>-34.32</i>	<i>1.30</i>	<i>77.90</i>	<i>9.42</i>		<i>-1.32</i>	<i>147.88</i>	<i>852.32</i>	<i>140.05</i>	

Figure I. Evolution of capital flows

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

Panel A: Net capital flows to Asia



Panel B: Net capital flows to Latin America

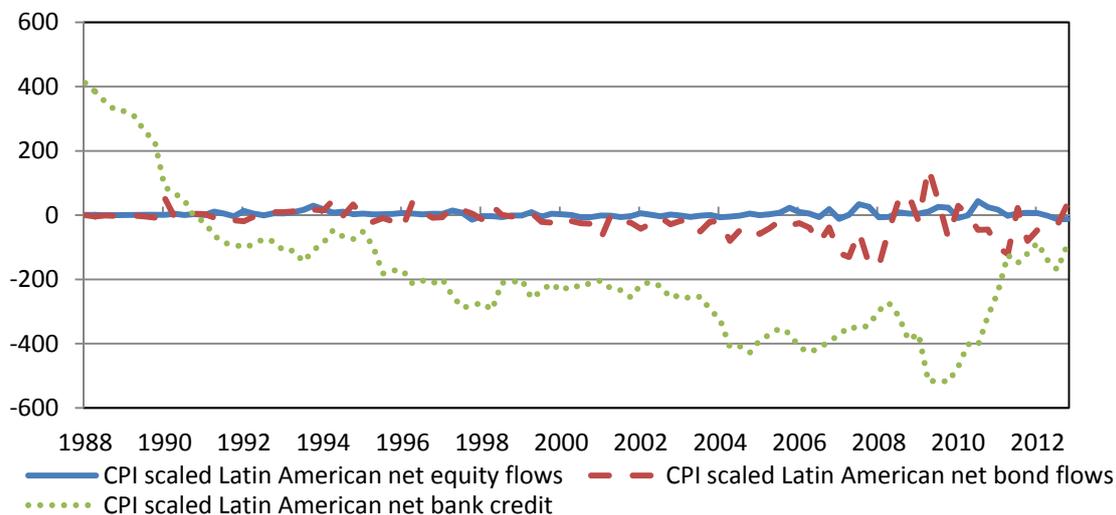


Table II. State-space model for bank credit flows.

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 (S.D.) of the each component over the largest S.D. across components, computed from the variance-covariance matrix of disturbances, and provides a scaled measure of the relative importance of each component. RMSE means estimated root mean square error and *(**) indicates statistical significance at the 5% (1%) level. The last column reports the p -value of the Ljung–Box test for the null hypothesis of no residual autocorrelation.

Country	Selected model	Q -ratios of unobserved components			Final level of stochastic trend component [RMSE]	Persistence of AR component $\rho_1 + \rho_2$	R^2	Ljung-Box
		Permanent Stochastic trend	Temporary					
			Irregular ε_t	AR v_t				
		μ_t						
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	Selected model	Q -ratios of unobserved components			Final level of stochastic trend component [RMSE]	Persistence of AR component $\rho_1 + \rho_2$	R^2	Ljung-Box
		Permanent Stochastic trend	Temporary					
			Irregular ε_t	AR v_t				
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.

For each country, quarterly 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 (S.D.) of the each component over the largest S.D. across components, computed from the variance-covariance matrix of disturbances, and provides a scaled measure of the relative importance of each component. RMSE means estimated root mean square error and $(**)$ indicates statistical significance at the 5% (1%) level. The last column reports the p -value of the Ljung–Box test for the null hypothesis of no residual autocorrelation.

Country	Selected model	Q -ratios of unobserved components			Final level of stochastic trend component [RMSE]	Persistence of AR component $\rho_1 + \rho_2$	R^2	Ljung-Box
		Permanent Stochastic trend	Temporary					
			Irregular	AR				
		μ_t	ε_t	v_t				
Panel A: First subperiod 1988Q1-1997Q4								
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 1988Q1-2012Q4								
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	Selected model	Q -ratios of unobserved components			Final level of stochastic trend component [RMSE]	Persistence of AR component $\rho_1 + \rho_2$	R^2	Ljung-Box
		Permanent		Temporary				
		Stochastic trend	Irregular	AR				
		μ_t	ε_t	v_t				
Panel C: Recent 1998Q1-2012Q4								
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, quarterly 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. $0 \leq Q\text{-ratio} \leq 1$ is the standard deviation (S.D.) of the each component over the largest S.D. across components, computed from the variance-covariance matrix of disturbances, and provides a scaled measure of the relative importance of each component. RMSE means estimated root mean square error and $(**)$ indicates statistical significance at the 5% (1%) level. The last column reports the p -value of the Ljung–Box test for the null hypothesis of no residual autocorrelation.

Country	Selected model	Q -ratios of unobserved components			Final level of stochastic trend component [RMSE]	Persistence of AR component $\rho_1 + \rho_2$	R^2	Ljung-Box
		Permanent Stochastic trend	Temporary					
			Irregular ε_t	AR v_t				
μ_t								
Panel A: First subperiod 1988Q1-1997Q4								
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 1988Q1-2012Q4								
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	Selected model	Q-ratios of unobserved components			Final level of stochastic trend component [RMSE]	Persistence of AR component $\rho_1 + \rho_2$	R^2	Ljung-Box
		Permanent Stochastic trend μ_t	Temporary					
			Irregular ε_t	AR v_t				
Panel C: Recent period 1998Q1-2012Q4								
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.

This table reports the estimates and diagnostics of the state-space Model 5 in Appendix D with pull and push factors added both in the permanent and temporary 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. The (seasonally unadjusted) short-term interest rates and foreign exchange rates are obtained from *DataStream*. All push factors and pull factors are entered one-period lagged. Bank credit flows are scaled by US core CPI. “+/-” denotes that we expect the factor of interest has a positive or negative impact on the capital flows from the US to the EMs. $0 \leq Q$ -ratio ≤ 1 is the standard deviation (S.D.) of each component over the largest S.D. across components and provides a scaled measure of the relative importance of each component. RMSE means estimated root mean square error and *(**) indicates statistical significance at the 5% (1%) level. The last column reports the p -value of the Ljung–Box test statistic for the null hypothesis of no residual autocorrelation.

	Q -ratios		Final level of stochastic trend component [RMSE]	Coefficients of push factors				Coefficients of pull factors						R^2	Ljung-Box
	Permanent	Temporary (AR)		Permanent		Temporary		Permanent			Temporary				
				US equity index (+)	US interest rate (-)	US equity index (+)	US interest rate (-)	EM interest rate (+)	EM equity index (+)	FX rate (-)	EM interest rate (+)	EM equity index (+)	FX rate (-)		
India	0.929	1.000	155.502 [2.325]**	0.022 [0.000]**	-3.100 [0.051]**	0.002 [0.001]	3.450 [0.444]**	0.003 [0.000]**	2.062 [0.060]**	-0.701 [0.009]**	0.043 [0.003]**	-1.555 [0.196]**	-4.472 [0.149]**	0.207	0.191
Malaysia	0.243	1.000	14.387 [0.805]*	0.001 [0.001]	-0.176 [0.218]	-0.011 [0.011]	0.084 [1.004]	0.000 [0.003]	-0.199 [0.667]	-0.291 [0.291]	0.045 [0.026]	-0.893 [0.614]	-3.131 [9.489]	0.369	0.585
Philippines	0.202	1.000	-57.847 [0.951]**	-0.007 [0.013]	0.752 [1.081]	-0.002 [0.014]	0.331 [1.723]	0.011 [0.021]	0.023 [0.577]	0.057 [0.185]	-0.011 [0.038]	-0.186 [1.739]	0.422 [0.890]	0.767	0.673
Thailand	0.813	1.000	-223.076 [1.522]**	-0.012 [0.000]**	1.210 [0.044]**	0.014 [0.001]**	2.343 [0.146]**	0.024 [0.000]**	-0.544 [0.073]**	0.179 [0.002]**	-0.024 [0.005]**	-1.470 [0.110]**	1.230 [0.075]**	0.889	0.236
Argentina	0.202	1.000	-83.005 [1.574]**	0.009 [0.005]	-1.034 [0.866]	0.005 [0.011]	0.002 [1.442]	0.001 [0.001]	-0.227 [0.153]	-2.666 [1.032]**	-0.002 [0.002]	-0.047 [0.202]	7.319 [6.675]	0.182	0.328
Brazil	0.391	1.000	-142.268 [10.058]**	0.063 [0.015]**	-11.078 [4.361]**	-0.004 [0.082]	0.218 [9.477]	-0.007 [0.005]	0.788 [2.182]	-19.915 [10.418]	0.041 [0.018]*	-0.827 [2.285]	10.725 [33.373]	0.889	0.762
Chile	0.340	1.000	172.306 [2.376]**	-0.010 [0.017]	1.344 [1.529]	-0.012 [0.019]	-0.273 [2.447]	0.003 [0.004]	-0.096 [0.632]	0.373 [1.649]	-0.006 [0.009]	-0.630 [1.283]	-6.596 [14.997]	0.426	0.256
Mexico	0.202	1.000	-151.468 [3.802]**	-0.027 [0.001]	-0.668 [1.957]	-0.083 [0.071]	9.512 [4.452]*	0.003 [0.001]**	1.245 [0.811]	0.689 [1.358]	0.012 [0.016]	-2.267 [2.092]	4.085 [8.721]	0.461	0.311

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" which are available, respectively, at <http://www.treas.gov/tic/forms-s.shtml> and <http://www.treas.gov/tic/forms-b.shtml>.

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 Depository Receipts (ADR) transactions are included in the figures. 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 from 1988M1 to 2012M12.

The table reports minimum, mean, maximum, and standard deviation of monthly net bond flows in US\$ million. The last column reports the Augmented Dickey Fuller (ADF) statistic to test the null hypothesis of (unit root) non-stationarity against the alternative of mean-reversion. *, ** and *** represent rejection of the unit root null at the 10%, 5% and 1% levels, respectively.

	Scaled Net bond flows				
	Min	Mean	Max	S.D.	ADF test
Panel A: Asia					
Mainland China	-170.050	-17.001	164.590	33.394	-2.78
Taiwan China	-33.114	-3.759	31.993	8.698	-3.68 **
India	-16.563	-0.190	14.684	2.978	-15.34 ***
Indonesia	-10.603	-0.072	11.396	2.668	-3.30 *
South Korea	-29.134	-2.186	59.259	8.744	-4.69 ***
Malaysia	-19.742	-0.448	10.613	3.589	-3.43 *
Pakistan	-0.414	0.044	4.014	0.289	-3.82 **
Philippines	-11.193	-0.114	7.049	2.003	-4.20 ***
Thailand	-29.640	-0.471	21.046	4.102	-3.43 **
<i>Average</i>	<i>-35.606</i>	<i>-2.689</i>	<i>36.072</i>	<i>7.385</i>	
<i>Total</i>	<i>-320.453</i>	<i>-24.198</i>	<i>324.644</i>	<i>66.464</i>	
Panel B: Latin America					
Argentina	-21.356	-0.236	14.934	2.786	-5.67 ***
Brazil	-114.870	-2.972	92.673	16.463	-3.73 **
Chile	-14.998	-0.457	9.778	2.697	-6.08 ***
Colombia	-13.178	-0.227	15.589	2.621	-3.74 **
Ecuador	-2.481	-0.088	4.068	0.524	-2.58
Jamaica	-1.043	-0.041	2.130	0.319	-2.75
Mexico	-74.646	-1.330	51.686	10.576	-2.94
Uruguay	-3.877	-0.232	5.464	1.070	-4.52
Venezuela	-8.299	-0.087	25.167	2.615	-3.37 *
<i>Average</i>	<i>-28.305</i>	<i>-0.630</i>	<i>24.610</i>	<i>4.408</i>	
<i>Total</i>	<i>-254.75</i>	<i>-5.67</i>	<i>221.49</i>	<i>39.67</i>	

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 $\hat{\boldsymbol{\beta}}_{t|t}$ denote the best linear mean-squared estimate of $\boldsymbol{\beta}_t$ using all data up to time t . We can then obtain $\hat{\boldsymbol{\beta}}_{t|t}$ and its covariance matrix recursively via the Kalman-filter equations

$$\boldsymbol{\beta}_{t|t-1} = \mathbf{F}\boldsymbol{\beta}_{t-1|t-1}, \quad (\text{A.1})$$

$$\mathbf{P}_{t|t-1} = \mathbf{F}\mathbf{P}_{t-1|t-1}\mathbf{F}' + \sigma^2\mathbf{Q}, \quad (\text{A.2})$$

$$u_{t|t-1} = y_t - \mathbf{H}\boldsymbol{\beta}_{t|t-1} \quad (\text{A.3})$$

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

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

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

where

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

are the error covariance matrices for $1 \leq t \leq T$. The one-step-ahead prediction error, $u_{t|t-1}$, is used to perform the Ljung-box test. 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

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

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

$$\mathbf{J}_{t-1} = \mathbf{P}_{t-1|t-1} \mathbf{F}' \mathbf{P}_{t|t-1}^{-1} \quad (\text{A.9})$$

which is computed backward recursively for $t = T-1, T-2, \dots, 1$.

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

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

where $u_{t|t-1}$ and $\mathbf{f}_{t|t-1}$ 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, 1981).

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

Model 1: Random walk + irregular

$$y_t = \mu_t + \varepsilon_t$$

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

Model 2: Random walk + AR(1) + irregular

$$y_t = \mu_t + v_t + \varepsilon_t$$

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

$$v_t = \rho_1 v_{t-1} + \xi_t \quad |\rho_1| < 1$$

Model 3: Random walk + AR(2) + irregular

$$y_t = \mu_t + v_t + \varepsilon_t$$

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

$$v_t = \rho_1 v_{t-1} + \rho_2 v_{t-2} + \xi_t \quad (\rho_1 + \rho_2) < 1, (\rho_2 - \rho_1) < 1, |\rho_2| < 1$$

Model 4: Random walk + AR(1)

$$y_t = \mu_t + v_t$$

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

$$v_t = \rho_1 v_{t-1} + \xi_t \quad |\rho_1| < 1$$

Model 5: Random walk + AR(2)

$$y_t = \mu_t + v_t$$

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

$$v_t = \rho_1 v_{t-1} + \rho_2 v_{t-2} + \xi_t \quad (\rho_1 + \rho_2) < 1, (\rho_2 - \rho_1) < 1, |\rho_2| < 1$$

Model 6: Random walk with drift + irregular

$$y_t = \mu_t + \varepsilon_t$$

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

Model 7: Random walk with drift + AR(1) + irregular

$$y_t = \mu_t + v_t + \varepsilon_t$$

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

$$v_t = \rho_1 v_{t-1} + \xi_t \quad |\rho_1| < 1$$

Model 8: Random walk with drift + AR(2) + irregular

$$y_t = \mu_t + v_t + \varepsilon_t$$

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

$$v_t = \rho_1 v_{t-1} + \rho_2 v_{t-2} + \xi_t \quad (\rho_1 + \rho_2) < 1, (\rho_2 - \rho_1) < 1, |\rho_2| < 1$$

Model 9: Random walk with drift + AR(1)

$$y_t = \mu_t + v_t$$

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

$$v_t = \rho_1 v_{t-1} + \xi_t \quad |\rho_1| < 1$$

Model 10: Random walk with drift + AR(2)

$$y_t = \mu_t + v_t$$

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

$$v_t = \rho_1 v_{t-1} + \rho_2 v_{t-2} + \xi_t \quad (\rho_1 + \rho_2) < 1, (\rho_2 - \rho_1) < 1, |\rho_2| < 1$$