Essays on International Capital Flows

Thesis submitted to Lancaster University in fulfilment of the requirements of the degree of Doctor of Philosophy in Economics

Author: **Xichen Wang**

Supervisors: Professor Ivan Paya and Professor David Peel

Department of Economics

Lancaster University

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Declaration

I hereby declare that this thesis is my own work and that it has not been submitted for any other degree.

Xichen Wang

Date:

Signature:

Abstract

The thesis builds on recent developments of international economics and econometrics, so as to provide empirical investigations on international capital flows and their impact on emerging financial markets. Specifically, the main research topics discussed are as follows: first, determinants of capital flows towards emerging market economies (EMEs) conditional on different episodes (e.g., surges, tranquil times, and stops); second, evidence of rational bubbles in the emerging equity markets and its association with short-term speculative flows (equity, debt and bank flows); third, the link between international equity flows and predictability of emerging stock markets' returns.

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Chapter 1 Introduction

Over the last two decades, emerging markets economies (EMEs) have been significantly integrated to the international financial markets; the resulting increase in the level and volatility international capital flows and their impact on EMEs have been popular topics in international economics. This thesis seeks to investigate the determinants of such cross-border capital flows and their impact on emerging equity markets.

According to the neo-classical theory, reallocation of capital flows from capital-abundant countries (with lower marginal returns) to capital-scarce EMEs can bring considerable benefits: e.g., a reduction in capital cost, technology spill-over, improved domestic financial market, and others. However, it has also been well recognized that volatile capital flows also create economic distortions and policy challenges (Ahmed and Zlate, 2014). Therefore, understanding the dynamic determinants of international capital flows can help countries to design the most appropriate policies (Bussiere and Phylaktis, 2016).

A considerable amount of literature on international capital flows has tried to identify the respective role of global ("push") versus country-specific ("pull") factors (e.g., Forbes and Warnock, 2012; Byrne and Fiess, 2016; Sarno et al., 2016). Although global conditions tend to be suggested as playing a larger role, the literature has not yet reached a complete consensus (Montiel, 2014). Indeed, Ghosh et al. (2014) argue that it is hard to attribute the observed flows to one side or the other *during normal times*; from a policy perspective, it might be more sensible to investigate their determinants *conditional on* different episodes (of capital flows' rise and fall). This motivates the research in Chapter 2: would a picture emerge revealing a new pattern between push and pull factors, *conditional on* different periods such as sudden stops, tranquil times and capital surges? To conduct our empirical analysis, we collect panel data from 51 EMEs over 1990-2011 and employ a novel quantile regression model of Galvao (2011). In addition, we pay close attention to gross inflows to distinguish between foreign and domestic investors, as it has been strongly recommended by the literature (e.g., Alberola et al., 2016; Adler et al., 2016). The insights gained from making such a distinction are, in turn, exploited in the remaining chapters.

Chapter 3 investigates evidence of financial exuberance (e.g., rational bubbles) in the emerging equity markets and its (if there is any evidence) association with short-term speculative capital flows (portfolio equity flows, portfolio debt flows and bank flows). This chapter is motivated by the following observations: first, the bubble-like dynamic of emerging equity prices as a whole was particularly impressive during the 2000s—they went up by 43.6% in 2007 but dropped by 54.4% in late 2008, resulting in a more than $5.2 trillion loss since the peak (Bartram and Bodnar, 2009). Second, international capital flows experienced a similar pattern of rise and fall at the same time: they grew from less than 7% of GDP in 1998 to over 20% in 2007, but they also suffered large reversals at the end of 2008 (Bussiere and Phylaktis, 2016). Third, short-term capital flows—which are speculative and thus most likely to be connected with bubbles—were particularly active in the EMEs in the 2000s (Fuertes et al., 2016). Therefore, such observations lead to two key research questions: first, were there bubbles among EMEs before the onset of the global financial crisis? Furthermore, if there were any, would such bubbles be associated with international short-term speculative flows? To address such issues, we firstly employ the recent recursive Augmented Dickey-Fuller (ADF) procedure of Philips et al. (2015)—which process several advantages compared to traditional models—to identify evidence of bubbles among 22 emerging stock markets. Next, we use a pooled probit model to examine the association between episodes of exuberance and "short-term flows".

Chapter 4 examines the link between international equity flows and predictability of emerging stock markets' returns. Although earlier literature typically identifies equity flows as being stationary (e.g., Sarno and Taylor, 1999), recent studies have shown the difficulty of precisely identifying the exact degree of persistence, of which standard unit root tests hardly provide a firm guide (Lee, 2016). On other hand, a considerable number of studies suggest that international equity flows may be persistent (e.g., Froot and Donohue, 2002; Albuquerque et al., 2007; Ülkü, 2015); the (potential) persistence will give rise to invalid results if equity flows is employed as a predictor in a standard predictive regression. Specifically, Campbell and Yogo (2006) show that if the predictor is strongly persistent, empirical results based on standard regression models such as Ordinary Least Square (OLS) will suffer severe size distortion leading to an over-rejection of the null hypothesis of no predictability. To solve this problem, we employ a recent predictive regression model of Kostakis et al. (2015) based on IVX-filtering, which can handle predictor variables with various degrees of persistence. In addition, we employ the IVX-version of quantile regression (IVXQR) of Lee (2016), which enables us to examine the predictability of stock returns over its whole conditional distribution. Based on such techniques, we investigate both in-sample and out-of-sample predictability.

The final chapter summarizes the key results and discusses the contributions of this thesis.

Chapter 2 Determinants of Capital Flows to Emerging Market Economies: A Dynamic Panel Quantile Regression Approach

Abstract

The major goal of this paper is to characterize the determinants of capital flows towards emerging market economies (EMEs) conditional on different episodes of external financing (e.g., surges, tranquil times, and stops). Using a panel of 51 EMEs over 1990-2011, we conduct our empirical analysis with a recent quantile regression model for dynamic panel data with fixed effects. We focus on gross inflows and find that foreign investors are generally sensitive to global conditions—in particular, conditional on episodes of surges, push factors dominate. Nevertheless, when capital flows are relatively low, countries with better macro-fundamentals (e.g., higher real growth rate, better institutional quality) and more prudent fiscal and monetary policies (e.g., lower public debt and less credit expansion) may suffer less gross inflows' reductions. These findings may suggest that policy makers monitor capital flows' sustainability during capital surges and build up sound "pull conditions" to endure or recover from capital drought.

JEL codes: F21, F32

KEY WORDS: Capital Flows, Emerging Markets, Surges, Sudden Stops.

2.1 Introduction

Over the last two decades, emerging markets economies (EMEs) have been increasingly integrated to the international financial markets. According to neo-classical theory, the increasing cross-border capital flows—as a consequence of the growing financial globalization— is an efficient allocation of resources; reallocation of capital flows from capital-abundant countries with lower marginal returns to capital-scarce EMEs can bring considerable benefits, such as a reduction in capital cost, technology spill-over, improved domestic financial market, and others. Nevertheless, the literature also shows that volatile capital flows also trigger considerable macroeconomic distortions and raise financial-stability concerns. In bad times, abrupt reductions of capital flows that cut off EMEs from the international capital markets—namely sudden stops—inflict a great deal of pain: their frequent occurrences lead to crisis such as sharp currency depreciations and economic recessions (Rothenberg ad Warnock, 2011). Even in good times, surges can also be worrying because they potentially lead to troubles such as financial overheating, loss of competitiveness as a result of real currency appreciation, and increased vulnerability to crisis (IMF, 2007). Therefore, given the policy challenges posed by the euphoria and drought in external financing flows, unearthing their characteristics and determinants—which is the major goal of this paper—can help EMEs design the most appropriate policies (Bussiere and Phylaktis, 2016).

Are large and volatile capital flows to EMEs mainly driven by global 'push' factors or domestic 'pull' factors? Numerous papers have been discussing this question over the past decades. In particular, the recent global financial crisis has spurred a resurgence of studies on this topic (Forbes and Warnock, 2012). Nevertheless, it seems that researchers have not yet reached a consensus (Montiel, 2014). Ghosh et al. (2014) argue that it is hard to attribute the observed flows to one side or the other during normal times, because capital flows must reflect the confluence of supply (push) conditions and (pull) conditions in equilibrium. Therefore, from a policy perspective it might be more sensible to investigate their determinants *conditional on* different episodes of capital flows' rise and fall. In other words, would a new picture emerge revealing the factors driving capital flows, *conditional on* different periods such as sudden stops, tranquil times and capital surges? This is the key question that this study investigates by employing a recent quantile regression model.

To conduct our empirical analysis, we use annual data from 51 EMEs over 1990-2011 when emerging markets became more integrated to the international financial system (Aizenman et al., 2013).[1] Among the different types of aggregate capital flows, we focus on gross flows rather than net flows[2], for this choice has become increasingly recommended by the recent literature (see, e.g., Alberola et al., 2016; Adler et al., 2016; Bussiere and Phylaktis, 2016). The main reasons are, firstly, foreign and domestic investors have different motivations and thus different responses to shocks and policies. Besides, gross outflows driven by domestic investors have increased significantly since the 2000s. It is, therefore, no longer appropriate to consider net flows as a mirror of gross inflows, which was a common option among the early literature when gross outflows were negligible (Forbes and Warnock, 2012). Furthermore, sudden stops in net flows might actually result from cross-border portfolio diversification of the domestic agents, which is not necessarily in line with the "true sudden stops" suggesting EME's loss of access to international capital market (Rothenberg and Warnock, 2011). For these reasons, we employ gross inflows.

Our key findings can be summarized as follows: as a preliminary analysis of investigating capital flows' determinants, we start with a conditional-mean regression by employing a standard dynamic panel approach (Arellano and Bond, 1991). In line with the suggestions from Ghosh et al. (2014), we find no massive evidence of factors significantly driving capital flows. Next, we proceed to our main empirical analysis with a quantile regression model for dynamic panel data with fixed effects (Galvao, 2011). A new picture emerges as we investigate the whole conditional distribution of gross inflows—the relative importance between "push" and "pull" factors is different *conditional on* various episodes of capital waves. In the upper quantiles where EMEs

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[1] Cavallo and Frankel (2008) also find that sudden stops have been more likely to happen starting since the 1990s. Apart from this concern, the sample period is limited by data availability of some key control variables in this study such as VIX, domestic credit expansion.

[2] Following Forbes and Warnock (2012), we define gross inflows as "the net of foreign purchases of domestic assets and foreign sales of domestic assets"; a positive entry suggests net foreign capital inflow. Similarly, gross outflows "is the net of domestic residents' purchases of foreign assets and domestic residents' sales of foreign assets"; a positive entry implies domestic capital outflow. Finally, "net flows", as defined by the early literature, is the net of gross inflows and gross outflows.

typically experience large inflows, global factors dominate—surges in gross inflows are strongly associated with more abundant global liquidity conditions, less global risk aversion, higher world growth rates and stronger regional contagion. In the lower quantiles, push factors remain important, but a distinctive cross-country heterogeneity appears, which is not shown in the right tail. In particular, we find that EMEs with higher return rates, better macro-fundamentals (higher real growth rate, better institutional quality), more prudent macro policy (lower public debt and less credit expansion) could experience less gross inflow reductions during episodes of relatively low gross inflows. Such findings are novel in the literature, to the author's knowledge at the time of writing. Furthermore, we show that our findings are robust to a range of sensitivity tests, including alternative specifications and additional regressors. Finally, we apply the same quantile regression model to net flows and gross outflows, and find that net flows are relatively more stable and less sensitive to external shocks compared to gross inflows, possibly due to the strong offsetting co-movement between gross inflows and outflows (Broner et al., 2013; Adler et al., 2016).

Our results hold some important policy implications. First, during periods of large capital inflows, cross-border capital movements into EMEs are strongly affected by push factors which are largely beyond EMEs' control (Broto, et al. 2011). This may suggest that capital surges may be reversed abruptly if global conditions suddenly change. On the other hand, Kaminsky et al. (2004) argue that the roots of most debt crisis in EMEs are public over spending and borrowing when times are favourable (e.g., international capital is plentiful). Policymakers, therefore, need to watch out for the sustainability of their external financing and consequently their expenses and indebtedness during booms. Second, despite the overall importance of global conditions, strong fundamentals and prudent macro policy could make reductions of capital flows less severe during "capital drought". Therefore, policy makers should still aim to build up sound pull conditions, whose role tends to be overlooked by recent literature.

The first contribution of this paper is methodological: we introduce to the literature of capital flows a novel quantile regression model of Galvao (2011), which allows for dynamic panel data controlling for fixed effects. The benefit of applying this method is that its estimation provides a novel answer to the debate on the relative importance between push and pull factors. For instance, a number of papers—such as

Forbes and Warnock (2012), Caderon and Kubota (2013), and Ghosh et al. (2014)—use binary outcome models to investigate the probabilities of extreme capital episodes (surges or stops) and find a dominating importance of push factors. On the other hand, Fratzscher (2012) finds that pull factors are important during recoveries after the recent global financial crisis. Our results seem to reconcile these findings by suggesting an important role of push factors over *the whole conditional distribution* but significance of pull factors over the *lower quantiles only*. Such a finding is novel to the literature. Another contribution is that we confirm the distinction between gross and net capital flows to be important for evaluating the impact of capital flows, as pointed out by the recent literature (e.g., Bussiere and Phylaktis, 2016). We show that merely investigating net flows—as the early literature did—might overlook the ongoing dynamics of gross flows and misinterpret the empirical results.

The rest of this paper is organized as follows: Section 2 shows the model specification and data source; Section 3 provides the stylized facts of capital flows; Section 4 introduces our empirical strategy; Section 5 presents our core empirical results; Section 6 summarizes the results from the robustness checks; and Section 7 concludes.

2.2 Model specification and Data

The data for capital flows is from 51 EMEs over 1990-2011 from Bluedorn et al. (2013), which builds its database based on International financial statistics (IFS). We choose Bluedorn et al. (2013) (rather than IFS) because the former extends IFS's missing data from other possible sources (e.g., Haver Analytics, CEIC and EMED databases).[3] Following the standard practice of the literature (e.g., Yan et al., 2016), annual capital flows are expressed as a percentage of domestic GDP. As there are different types of capital flows, first, we focus on private capital flows that exclude flows to official sectors. Second, we concentrate on "total flows" rather than "individual flows" (e.g., foreign direct investment flows, portfolio flows and so forth), because total flows are arguably the most relevant type to policy makers (Broto et al., 2011).[4] Third, we focus on the *level* rather than the *first difference* of capital flows, for

[3] See Bluedorn et al. (2013) for a detailed discussion on the origin of its database.

[4] We also perform the same analysis on the disaggregated capital flows such as foreign direct investment, portfolio equity flow and so forth; see our robustness check section of 2.8.1.4.

first difference might neglect the dynamics of capital flows.[5] Forth, as mentioned in the introduction, we focus on gross rather than net flows.

Based on the discussions of the recent literature, we model the magnitude of capital flows, $K_{i,t}$, as a function of vectors of real interest rate return parity, $r_{i,t}^{d}$; global push factors, $g_{i,t}'$; and domestic pull factors, $d_{i,t}'$.

$$K_{i,t} = K_{i,t-1}\beta_0 + r_{i,t}^{d}\beta_1 + g_{i,t}'\beta_2 + d_{i,t}'\beta_3 + \varepsilon_{i,t}. \tag{1}$$

2.2.1 Real interest rate parity ($r_{i,t}^{d}$)

Real interest rate parity is the starting point of capital flows' determinants. Neo-classical theory suggests that investment could flow from capital-abundant countries (with a lower return) to capital-scarce countries (with a higher return). In this sense, developing countries with relatively higher returns are more attractive to investors responding to real interest rate differential, until the marginal returns are equalized. To see this relationship more clearly in a simple model, we follow Zalduendo et al. (2012) and start with the nominal interest rate differential given by standard uncovered interest rate parity condition: [6]

$$i_{i,t}^{d} = i_{i,t} - (i_t^{*} + \left(e_{i,t+1}\right) - e_{i,t}), \tag{2}$$

where $i_{i,t}^{d}$ is the nominal interest rate differential for country i at time t, $i_{i,t}$ is the domestic nominal rate, i_t^{*} is the world rate, and $e_{i,t}$ is the domestic nominal exchange rate (as defined by domestic currency unit per unit of foreign currency). Subtracting inflation rate from both sides of (2) yield:

$$r_{i,t}^{d} = i_{i,t} - \left(p_{i,t+1} - p_{i,t}\right) - \{i_t^{*} - (p_{t+1}^{*} - p_t^{*}) + \left(p_{i+1}^{*} + e_{i,t+1} - p_{i,t+1}\right) - (p_t^{*} + e_{i,t} - p_{i,t}),$$
(3)

where $p_{i,t}$ and p_t^{*} represent the domestic and world price level, respectively. Simplify the notation at (3):

[5] For example, as capital flows could be persistent during booms, suppose capital flow to Argentina is 6% of GDP in year *t*, 7% in year *t+1*, and 5% in year *t+2*. The first difference would yield 1% between year *t* and *t+1*, and -1% between year *t+1* and *t+2*. It is clear that measurement based on first difference would neglect the dramatic persistence of booms.

[6] Zalduendo et al. (2012) is a working paper version of Ghosh et al. (2014)

$$r_{i,t}^{d} = r_{i,t} - r_{t}^{*} - \Delta q_{i,t+1}^{e}, \quad (4)$$

where $r_{i,t}^{d}$ represents the real interest rate differential, $r_{i,t}$ and r_{t}^{*} denote the domestic and world real rates, respectively; and $\Delta q_{i,t+1}^{e}$ is the expected real exchange rate depreciation. As for the empirical measurement of these variables, first, we choose the average value of available interest rates (money market rate, treasury-bill rate, and etc.; subject to data availability) deflated by inflation as a proxy $r_{i,t}$.[7] Second, real world interest rate r_{t}^{*} is measured as U.S. 3-month treasury-bill rate. Expected depreciation or implied overvaluation, $\Delta q_{i,t+1}^{e}$, is captured as the log difference of current real effective exchange rate and its long term-trend (Ghosh et al., 2014). Overall, Equation (4) shows that more capital inflow towards an EME can be associated with a higher real domestic return, a lower real world return, or less domestic currency overvaluation.

Early literature highlights the importance of real interest rate parity. For example, Taylor and Sarno (1997) find that the noticeable fall of U.S. interest rate is associated with a sharp increase of U.S. capital flows towards EMEs in the late 1980s. However, a number of studies also show the failure of this mechanism. For example, Lucas (1990) argues that the marginal product of capital in India is roughly 58 times as that of United States in 1988. Nevertheless, in reality, one has never observed such a dramatic cross-border capital flow. To eliminate this so called "Lucas Paradox", other factors should be controlled; recent literature has identified a broad array of factors and classified them into global (push) factors and domestic (pull) factors.

2.2.2 Push factors ($g_{i,t}'$)

'Push factors' are those determinants that affect the supply conditions from creditor countries (Montiel, 2014). We choose a few of highly relevance according to the recent literature: first, a rise of uncertainty of global economic conditions could trigger a "flight to safety", encouraging capital flows towards countries perceived to be safe havens—typically the advanced economies such as the United States. To measure this global risk appetite, we choose the VIX index—which has been widely used in the literature (e.g., Ghosh et al., 2014)—from Chicago Board Options

[7] Ghosh et al. (2014) use only money market rate or treasury bill rate subject to data availability. Although we could also find data for both of these two interest rates from IFS , we find a dramatic drop of sample size due to missing values when we follow this specification.

Exchange. This index is calculated as the implied volatility of S&P 500 options prices; its increase implies a higher expected near-term risk in financial assets and thus a lower risk appetite among investors (Forbes and Warnock, 2012). Moreover, a global liquidity squeeze could exacerbate a financial crisis, and thereby promote capital flights from EMEs; following Fratzscher (2012), we use TED spread as a measure of global liquidity condition. Besides, as pointed out in business cycle models, global productivity shocks—which could result in variations in global growth rates—might lead to lending booms and busts and thus variations in cross-boarders capital flows (Aguiar and Gopinath, 2007; Forbes and Warnock, 2012); we capture foreign trade shocks as real U.S. growth rate (Broto et al, 2011). Finally, as recent literature also highlights the increasingly important role of regional contagion, we capture this effect by following Ghosh et al. (2014) and we measure contagion as the average net capital flow (in percentage of GDP) to other countries in the region.

2.2.3 Pull factors ($\boldsymbol{d'_{i,t}}$)

Pull factors are those demand-side conditions that reflect the recipient country's characteristics (Montiel, 2014). Again, we choose our pull factors based on the suggestions of the following literature: the first group of domestic conditions of our interest is related to macro fundamentals. Specifically, first, improving economic performance appears an attractive pull condition to foreign investors—we measure it by real GDP growth rate. Second, countries with worse institutional quality or higher political risk would depress capital inflows; thus we collect data from International Country Risk Guide and calculate the institutional quality index as the average value of all components in the table of political risk (Ghosh, et al., 2014).

The second group to which we pay close attention is associated soundness of domestic policies—both in monetary and fiscal terms. To empirically measure these variables, we firstly choose inflation rate as a proxy of soundness of monetary policy, for high inflation can be a result of erratic and distortionary monetary condition (Broto et al., 2011). In addition, excessive private credit expansion is a sign of the frangibility of domestic financial systems, which will shift investors' sentiment towards leaving the country; we measure this as bank credit to private sector as a ratio of GDP (Calderon and Kubota, 2013). Furthermore, as expansionary fiscal policy is usually associated with increasing public spending, we include public debt to GDP from Abbas et al. (2010) to investigate a country's indebtedness.

Besides, we follow the literature and include another set of relevant pull conditions to control for the cross-country heterogeneity: first, Ghosh et al. (2014) argue that an implicit guarantee of a more rigid exchange rate regime may encourage greater cross-border borrowing and lending (thus larger international capital flows). Therefore, we include exchange rate flexibility as measured by ilzetzki et al. (2008), which provides an index ranging from 1 to 15 with a higher value implying less exchange rate rigidity.[8] Second, larger current account deficit may signal greater external financial need which may attract more inflows; we capture this external position as current account balance relative to GDP. Third, we control for GDP per capita to allow for the possibility of "Lucas paradox" (Lucas, 1990)—that is, capital does not flow from rich to poor countries. Last, we also consider the openness—both in financial and trade terms—to see whether countries with larger financial or trade exposure to the world will suffer more severe capital flow reductions during bad times: the data for financial openness is collected from Ito and Chinn (2008), where a higher value of the index implies less capital control; the degree of trade openness is measured by the ratio of total trade to GDP—a higher value of which suggests greater trade openness (Broto et al., 2011).

Finally, Table 2.1 presents the summary statistics as well as data source for all the variables mentioned above.

<Insert Table 2.1 here>

2.3 Stylized facts of Capital Flows

<Insert Figure 2.1 here>

To illustrate the advantages of focusing on *gross inflows*, Figure 2.1 plots both the average net and gross flows towards EMEs. We begin by discussing net flow. In the early 1990s, capital flows started with a relatively low level, which might be a consequence of the collapse during the debt crisis in 1980s (Montiel, 2014). Net flows kept on increasing until the onset of the Asian financial crisis during 1997-1998 (shown as the first interval between the red lines), which reduced capital flows dramatically, and net flow stayed depressed until the late 1990s. However, capital flows revived in the early 2000s, growing substantially until reaching their peak in

[8] In the robustness check, we also use exchange rate classification of Shambaugh (2004), which is a dummy variable taking the value of 1 if the exchange rate stays within a +/- of 2% band in a year and zero otherwise.

2007, but they collapsed during the recent global financial crisis. After 2009, capital flows retrenched towards EMEs.

The dynamics of gross flows tell some different stories: before the late 1990s, net flows mirrored gross inflows because gross outflows were not sizable; to focus on net flows alone—as many early empirical literature did—can, therefore, reveal the main story (Forbes and Warnock, 2012). However, this approximation is no longer appropriate during the recent decade. As shown in Figure 2.1, net flows were relatively stable during the recent financial crisis, but both types of gross flows were strongly volatile; focusing on net flows will miss their underlying volatile nature.

Moreover, gross inflows behave differently from gross outflows,[9] and their strongly negative co-movement becomes even more prominent during episodes of crisis, when gross inflows drop as foreign investors retreat their funds, and gross outflows decline as domestic investors retrench investments from abroad (Broner et al., 2013).[10] As a complement, Figure 2.2 displays the time-series plots of capital flows from a number of individual EMEs (Argentina, Brazil, Mexico, South Korea, Thailand and Turkey) that experienced massive capital drought during financial crisis over the recent two decades. One can see that this pattern is present in most of these individual countries during the recent global financial crisis.

<Insert Figure 2.2 here>

Furthermore, a large gross outflow might not necessarily be associated with financial drought, even though the early literature defines 'capital flight' as periods during which domestic investors escape to safety heavens because of deteriorating domestic conditions. Figure 2.1 shows a sizable gross outflow after the mid 2000s, which might in turn be associated with the release of outflow restrictions in the EMEs (Aizenman and Pasricha, 2013). Furthermore, Calderon and Kubota (2013) argue that 'flight episodes' might not always be associated with situations in which EMEs were cut off from the international market. Rather, stock of capital might be abundant in those domestic markets such that domestic agents invest them abroad. Therefore, such

[9] The correlation coefficient between gross inflow and gross outflow is -0.74 over 1990-2011. The negative sign is due to the accounting principle.

[10] The decline in gross outflow is shown as a positive entry in balance of payment.

dynamics of gross outflows may be overlooked if the researchers merely investigate net flows.

For these reasons, we choose to focus on gross flows, which will lead to more accurate empirical results and better informed policy prescriptions (Rothenberg and Warnock, 2011).

2.4 Empirical methodology

2.4.1 Dynamic panel data approach

Although we are particularly interested in the determinants of capital flows *conditional on different episodes* through looking at the quantile regression, it is, nevertheless, reasonable to start with the *conditional mean regression* as a benchmark model. To that end, we employ the dynamic panel data approach (DPD) proposed by Arellano and Bond (1991). In particular, we utilize system GMM proposed by Blundell and Bond (1998) to simultaneously explore extra moment conditions. Moreover, we employ standard errors robust to any pattern of heteroscedasticity and autocorrelation within panels. Regarding the potential endogeneity of the push and pull factors, we follow Ghosh et al. (2014) and lag all pull factors by one period. Overall, following the specification in Eq.(2), our model is estimated as:

$$K_{i,t} = K_{i,t-1}\alpha_0 + r_{i,t}^d\beta_1 + g_{i,t}'\beta_2 + d_{i,t-1}'\beta_3 + \eta_i + \varepsilon_{i,t}, \tag{5}$$

where η_i captures the fixed effects.

Notice that our panel data has relatively small cross-sectional units "*N"* (51 in total) relative to time observations per unit "T" (17 on average); based on such a data-structure traditional DPD approach might result in a large instrument collection, which would over-fit endogenous variables and thereby yield invalid results. To avoid this issue, we utilize the "collapsed instruments" method of Roodman (2009).[11]

2.4.2 Quantile regression

This section briefly describes our primary empirical tool: quantile regression model for dynamic panel data with fixed effects proposed by Galvao (2011). Quantile regression is introduced by Koenker and Bassett (1978), which estimates "models in

[11] The "collapsed instruments" is implemented in stata's package *xtabond2* by giving the *collapse* option. Moreover, we only choose $K_{i,t-2}$ and other repressors lagged by 2 periods as instruments of $K_{i,t-1}$.

which quantiles of the conditional distribution of the response variable are expressed as functions of observed covariates" (Koenker and Hallock, 2001). In our study, the quantile regression version of model specification in equation (5) can be rewritten as:

$$Q_{K_{i,t}}\left(\tau \middle| K_{i,t-1}, X_{i,t\ or\ t-1}\right) = \eta(\tau)_i + \alpha(\tau)K_{i,t-1} + \ \beta(\tau)X'_{i,t\ or\ t-1} + \varepsilon_{i,t}, \tag{6}$$

where τ is the quantile index such that $\tau\ \in (0, 1)$, X is the vector of other regressors, and η represents the individual effects.

To account for individual effects of quantile regression is not straightforward. First, traditional panel data methods (e.g., first difference and de-mean) are not able to remove the individual effects in quantile regression because of its non-linearity. Second, the introduction of cross-section dummy variables as a compromise is invalid either when the number of groups of the panel is large, for the inclusion of numerous dummies may inflate the variability of other regressors' estimated coefficients. Based on these considerations, Koenker (2004) provides a solution—it proposes a penalty method that shrinks the individual effects towards a common value, which can be expressed as:

$$\left(\hat{\eta}, \hat{\alpha}, \hat{\beta}\right) = \min_{\eta,\alpha,\beta}\ \sum_{i=1}^{N}\sum_{t=1}^{T}\rho_\eta \times (K_{i,t} - \eta(\tau)_i - \alpha(\tau)K_{i,t-1} - \ \beta(\tau)X'_{i,t\ or\ t-1}), \tag{7}$$

where $\rho_\eta(u) \coloneqq u(\eta - I(u < 0))$ is the "checked function" as defined in Koenker and Bassett (1978). Galvao (2011) incorporates this penalty method to deal with fixed effects in his model.

To apply dynamic panel techniques in quantiles regression, another typical problem remains: the presence of lagged dependent variable ($K_{i,t-1}$) leads to the same bias as in the least square case. Galvao (2011) provides a solution by following the literature on instrumental variable quantile regression (e.g., Chernozhukov and Hanson, 2006 and 2008). To show this method in detail, we firstly assume for clarity and simplicity $K_{i,t-1}$ as the only endogenous variable in our regression (Huo et al., 2015). In addition, following Galvao (2011), we employ $K_{i,t-2}$ as the instrumental variable (IV), namely $W_{i,t}$.[12] In Equation (6), the coefficient for the lagged dependent, α, can be estimated as:

$$\hat{\alpha} = \min_{\alpha} ||\hat{\gamma}(\alpha)||_A, \tag{8}$$

where

$$(\hat{\eta}(\alpha), \hat{\beta}(\alpha), \hat{\gamma}(\alpha)) = \min_{\eta,\alpha,\gamma} \sum_{i=1}^{N}\sum_{t=1}^{T}\rho_\eta \times \left(K_{i,t} - \eta(\tau)_i - \alpha(\tau)K_{i,t-1}X_{i,t\ or\ t-1}^{'}\beta(\tau) - W_{i,t}^{'}\gamma(\tau)\right), \tag{9}$$

with $||X||_A = \sqrt{x'Ax}$, and A is a positive definite matrix. Therefore, the final parameter estimates of interest are

$$\hat{\theta}(\tau) \equiv \left(\hat{\beta}(\tau), \hat{\alpha}(\tau)\right) \equiv \left(\hat{\beta}(\hat{\alpha}(\tau), \tau), \hat{\alpha}(\tau)\right). \tag{10}$$

The intuition is that if the IV, namely w, is valid and thus independent of the error term, its presence in the model should lead to a zero coefficient. Therefore, "the estimator (10) finds parameter values for α and β through the inverse step (8) such that the value of the coefficient $\gamma(\alpha, \tau)$ on the instrument in the ordinary QR step (9) is driven as close to zero as possible. Hence, by minimizing the coefficient of the IV one can recover the estimator of α" (Galvao, 2011)[13].

2.5 Empirical results

2.5.1 Results for conditional-mean regression

<Insert Table 2.2 here>

Table 2.2 (columns [1] - [4]) reports the empirical results of our benchmark conditional-mean regression estimated by DPD. The first row shows that gross inflows are persistent—their AR (1) coefficients consistently display positive and strongly significant estimates from Columns [1] to [4]. As for the push and pull factors—which are of our major interest—it appears that the majority of determinants are insignificant. First, among the components of real interest rate differentials,

[12] Using the other lagged values of explanatory variables as IVs as well as K_{t-2} will greatly increase the computational burden of this model. Nevertheless, as a robustness check, we also try to compute the instrument variable the predicted value from a OLS projection of K_{t-1} on K_{t-2} and other explanatory variables, following the suggestion of Chernozhukov and Hansen (2008). The empirical results that follow are similar, and they are available on request.

[13] I am grateful to Dr. Antonio F. Galvao Jr. for sharing his code of this dynamic quantile panel approach.

neither world interest rate, domestic interest rate nor REER deviation from trends appears significant. Second, regarding the other determinants, push factors seem to be more important: Global risk appetite as measured by VIX is consistently significant, and ten units' rise of the index is associated with a 1.57% reduction of gross inflow relative to domestic GDP. In addition, contagion factor is the most significant push factor in col. [4]—one percent increase of the average net flow in neighbour countries within the same region may yield 0.460% of increase in gross inflow over GDP. Third, pull factors are generally insignificant. One exception is that institutional quality index displays a negative coefficient, suggesting countries with worse institutional quality might receive higher gross inflows, for they are generally less developed countries. However, it is not strongly conclusive since the estimated coefficient is only marginally significant at 10% level.[14] Finally, the results of diagnostic tests in the bottom rows are favourable—all regressions have passed Arellano-Bond test for AR(2) and Hansen's over-identification test. As a rule of thumb, instrument count should be below the number of panel units; we observe that the number of instruments are controlled in a reasonable level because of employing the "collapsed instruments" method of Roodman (2009)—

Overall, our results may imply that "Lucas Paradox" holds, for capital flows to EMEs are not driven by return differentials or even favourable pull conditions but global risk appetite and regional contagion.

2.5.2 Quantile regression

In what follows we present the core part of our empirical results, which will reveal a novel pattern between push and pull factors based on our *conditional-quantile* estimates.[15]

2.5.2.1 Episodes of booms in the upper quantiles

We start our report with the upper quantiles. For simplicity, we show results from only a selective amount of upper percentiles ($\tau = 50^{th}, 60^{th}, 70^{th}, 80^{th}$) through column (5) to (7) in Table 2.3.

[14] A stronger significance for VIX could be obtained if we alter the number of lags of instrument variable. Indeed, DPD is found to be sensitive to number of instruments (Roodman, 2009).

[15] For convenience of presentation, we firstly break down different components of real return differentials. Next, we merge world interest rate into push factors' group, domestic real return and currency overvaluation into pull factors' group, respectively.

In general, push factors seem to dominate over the right tail of gross inflows' conditional distribution—all external conditions display highly significant coefficients except that of real U.S. interest rate. In particular, an easing of global liquidity condition (indicated by lower TED spread) pushes foreign capital flows into EMEs, shown by its negative coefficients over all reported quantiles. Besides, gross capital inflows seem to be more elastic to global liquidity conditions during surges, for the magnitude of its estimated coefficient increases as the conditional quantile increases. VIX index shows a significant and negative coefficient in the upper quantiles, suggesting that foreign investors are risk averse—they retreat to safe havens when risk perception is higher. Moreover, world real growth rate is positively significant, but its magnitude of coefficient drops to around 0.250 compared to those in the lower quantiles. Last, gross private inflows to EMEs are sensitive to contagion effect: when the average net flow in the neighbour states is higher by 1% of GDP, the underlying median EME may receive 0.217% of GDP higher gross inflow.

In comparison, pull factors show a limited role over the right tail—the majority of them appear insignificant. Among the few significant estimates, first, real interest rate is significant only in the 50th quantile. Second, exchange rate overvaluation displays significant estimates when τ = 70th, 80th: a 10% of REER overvaluation is associated with an approximately 0.38% gross inflow drop. Moreover, interestingly, domestic indebtedness and credit expansion are significant in the right tail, but with different estimated signs compared to their negative signs in the left tail. Take public spending for instance, countries with 1% (of GDP) higher public debt are associated with 0.017% (of GDP) larger gross inflows, conditional on the 80th percentile. This observation shows that countries with more expansionary fiscal or monetary policy might in turn attract more gross inflows when capital flows are relatively abundant.

In summary, our empirical results over the upper quantiles suggest that push factors seem to dominate over the pull factors. This finding is in line with that of a number of recent literature (e.g., Forbes and Warnock, 2012; Sarno et al., 2016).

2.5.2.2 Episodes of busts in the lower quantiles

<Insert Table 2.3 here>

Next, from column (2) - (4) of Table 2.3, we report our empirical results over the lower percentiles (τ = *20^{th}*, *30^{th}*, *40^{th}*), where EMEs experience episodes of relatively low capital flows.

Push factors are still significant in general. Both global risk appetite (as measured by VIX index) and global growth rates (as measured by U.S. growth rate) remains significant across all lower quantiles reported; Global liquidity (as measured by TED spread) and regional contagion are also significant when τ = *40^{th}*. Moreover, world interest rate (as captured by U.S. real rate) turns significant in the lower quantiles (τ = *20^{th}, 30^{th}, and 40^{th}*) as well. Therefore, similar with the situation from the upper quantiles, it seems that gross inflows are still generally sensitive to the global economic climate even when capital flows are relatively low.

On the other hand, an interesting finding is that the pull factors—which are mostly insignificant across the upper quantiles—show a considerable number of significant estimates across the left tail. In particular, first, regarding real interest rate parity, domestic real interest rate is significant: one percent rise may lead to 0.028% (relative to GDP) larger gross inflow. Its coefficient's magnitude decreases to 0.018% as the conditional quantile increases to the 40^{th}, after which its significance disappears. Second, macro-fundamentals are also significant in the left tail: real growth rate are also highly significant over the lower quantiles—a higher real growth rate may lead to 0.186 % less foreign capital reduction during bad times (e.g., τ = *20^{th}*), and this effect decreases to 0.086% when τ = *40^{th}*. Besides, institutional quality also displays positive and significant coefficients over the lower quantiles: countries with a higher unit of intuitional quality index are associated with 0.637% (relative to GDP) lower reduction of gross inflows at the 20^{th} percentile; its coefficient decreases as the conditional quantile increases (e.g., reduce to 0.345 % when τ = *40^{th}*), and eventually it becomes insignificant when τ > *40^{th}* where external financial turbulence is eased. Third, EMEs with more reckless fiscal policy (as measured by a higher degree of indebtedness) and fragile financial systems (as proxied by more excessive credit expansion) are more vulnerable to sudden stops—this finding is in line with that of the literature (e.g., Honig 2008, Calderon and Kubota 2013). Specifically, 10% higher public deficit is correlated with 0.16% (over GDP) reduction of 20^{th} quantile, and this effect shrinks to 0.08% at the 40^{th} percentile. Similarly, excess credit boom is significantly associated with a larger gross inflow stop in the left tail.

As for the other control variables, first, a more flexible exchange rate regime—indicated by a unit increase in the annual fine class index—is associated with larger *reduction* of gross inflows at the 30th and 40th percentile, respectively; such a connection agrees with the finding of Ghosh et al. (2014) arguing that a fixed rate regime might provide implicit guarantee of cross-border borrowing and lending and therefore encourage more capital flows (especially during turbulent times). Second, countries with greater financial need (as measured by higher current account deficit) lower gross inflows' reductions at the 20th and 30th conditional quantile, respectively; this negative coefficient estimate is also in line with that of Ghosh et al. (2014). Last, exchange rate overvaluation, inflation rate, trade and financial openness are all insignificant across lower percentiles.

In summary, these results seem to suggest that EMEs with higher return rate, better macro-fundamentals (higher real growth rate and better institutional quality), more prudent fiscal (lower public debt) and monetary policy (less excessive credit expansion), larger external financial need (larger current account deficit), and more fixed exchange rate regime could experience less gross inflow reductions or pull back more foreign investments during episodes of relatively low capital flows. This finding disagrees with Forbes and Warnock (2012) that reports a trivial role of domestic conditions, but is in line with that of Fratzscher (2012) which finds a cross-country heterogeneity among EMEs during the recovery episodes of the recent financial crisis. Besides, a final note is that all components of real interest rates differentials display expected signs in our quantile estimations—world interest rate is significant in lower quantiles; domestic interest rate and currency overvaluation appear significant around median and upper percentiles. This may imply that in order to eliminate the "Lucas Paradox", one might need to take different episodes of capital flows into account.

2.5.2.3 Policy Implications from Quantile Estimates

First of all, as push factors consistently display significant estimates over the whole conditional distribution, our quantile regression estimates confirm the overall importance of push factors. This implies a challenge for policy makers in EMEs to stabilize capital flows, for the global economic climate is largely beyond their control.

Nevertheless, pull factors are not always as suggested by some literature (e.g., Forbes and Warnock, 2012), our results based on quantile regression reveal a new picture: they are significant over the lower quantiles. This in turn indicates that countries should still aim to build up attractive domestic economic conditions (e.g., high domestic, fast real growth rate, sound institutional quality, prudent fiscal and monetary policy), which will make them suffer less inflow reductions or pull back more foreign investment during turbulent times.

Moreover, our results—together with some recent literature—may suggest that policy makers watch out for capital flows' sustainability. First, the dominating role of push factors *conditional on episodes of high gross inflows* may sometimes be worrying: if global climate changes unexpectedly, a typical sudden stop—an 'abrupt and major reduction in capital inflows to a country that up to that time had been receiving large volumes of foreign capital' (Mendoza, 2006)—can happen. Second, capital flows to EMEs tend to overreact, such that a capital boom is a robust predictor of sharp contraction in the future (Agosin and Huaita, 2012). Third, capital flows can be pro-cyclical: our results from the upper quantiles suggest that more expansionary fiscal or monetary policy may attract more gross inflows. A number of studies (e.g., Kaminsky et al., 2005; Reinhart and Reinhart, 2008) agree with this suggestion by showing that EMEs tend to over-spend and over-borrow during good times when international capital is plentiful, which in turns attracts more foreign investment. However, this situation is reversed over the lower quantiles: higher public indebtedness and more excessive credit expansion—which are signs preceding financial crisis, as suggested by Lane and MaQuade (2014)—in turn are associated with larger inflow reduction. Therefore, policy makers should be prudent even when capital flows are abundant.

2.5.3 Analysis based on Net Flows and Gross Outflows

Although our core empirical analysis focuses on gross inflows that is more relevant to 'true sudden stops', it might also be interesting to investigate net flows and gross outflows using the same dynamic quantile regression to see how the results will differ.

Before we report our empirical results, it is important to note that the distributional property of *gross outflows* is completely different from that of *gross inflows*: for *gross outflows*, the right tail of its conditional distribution should be regarded as episodes of retrenchments resulted from an unfavourable global climate, while the left tail as good times during which domestic agents invest funds aboard.

This opposite interpretation compared to that of *gross inflows* is also supported by the strong negative correlation between *gross inflows* and *outflows* as discussed in stylized facts (Section 3 of the main paper).

<Insert Table 2.4 here>

Table 2.4 reports the empirical results of both *net flows* and *gross outflows*. First of all, push factors' significance seems to be weakened in net flows; this might be a result of the offsetting co-movements between *gross inflows* and *gross out flows*. For instance, TED spread consistently displays significant and positive coefficients for gross outflows (e.g., Columns 5 to 7 in Table 2.4); In contrast, TED's sign is negative in our regression based on *gross inflows* (as shown in Table 2.3). This observation implies that during episodes of liquidity squeeze, domestic agents bring their funds back home from abroad, while foreign agents cut down their investments in EMEs and escape to safe havens (e.g., advanced economies) where they have relatively information advantage (Broner et al., 2013). Moreover, we can also observe different signs for global risk aversion and contagion effect from regression based on *gross outflows* (as shown in Table 2.4) and *inflows* (as shown in Table 2.3). Nevertheless, as for *net flows*, most push factors' estimated signs are still in line with those of *gross inflows'* estimates, so do their significance—perhaps because gross inflows dominate the pattern of net flows due to their relatively larger volumes, which can be observed in Figures 2.1 and 2.2 (of the main paper).

Turning to the pull factors, they are still significant in the lower quantiles of net flows, and their estimated signs are similar with those of gross inflows' estimates. Nevertheless, there are some new stories: lower REER overvaluation, a more flexible exchange rate regime, and a lower inflation rate may result in lower net flows reductions over the lower quantiles (e.g., Column 1 of Table 2.4); Columns 5 to 8 may show that these coefficients are associated with lower gross outflows (recorded as positive entries) indicating retrenchment of domestic investments back home.

In summary, first, net flows seem to be less sensitive to external shocks compared to gross inflows; we show that this is because of the strong correlation between *gross inflows* and *gross outflows*. Second, some pull factors become significant once we take into account *gross outflows*. Overall, the findings in this section confirm the importance of investigating different types of flows which are of a different nature separately; merely investigating net flows as the early literature did might overlook the ongoing dynamics of gross flows and misinterpret the empirical evidence (Calderon and Kubota, 2013).

2.6 Robustness Checks

We perform a number of robustness checks by altering the specifications of capital flows' determinants such as world interest rate, world growth rate, global liquidity and exchange rate regime; including additional regressors (e.g., time trend, default dummies, international reserves, and liability dollarization); comparing the performance between gross flows and net flows. Below is a summary of the results.

First, the pattern between push and pull factors emerging from our core empirical results remains—global factors consistently display significant estimates across the whole conditional distribution, and they still dominate over the upper quantiles; pull factors are significant in only the left tail.

Second, there are indeed some variables which are consistently insignificant in our test. For example, in line with the finding of Forbes and Warnock (2012), there is no evidence that financial openness is significantly associated with gross inflows, even though the discussion on capital control has been popular in the literature (Aizenman and Pascricha, 2013). Moreover, both trade openness and inflation rate fail to show significant estimates generally.

Third, we perform the same quantile-regression techniche on disaggregated captial flows (FDI, equity, debt and bank flows). We find global factors seem to have heterogonous impacts on different types of disaggregated capital flows. Futhermore, some of pull factors show a similarly heterogonous impact as the push factors do.

In addition, we also examine estimates based on traditional fixed effect models; county and time distribution of capital flows; and diagnostic tests on multi-collinearity. Readers are referred to the supplementary data in the Appendix for more details.

2.7 Conclusions

This paper investigates the determinants of capital flows to EMEs conditional on different episodes—stops, tranquil periods, and surges. We use a panel data of 51 EMEs over 1990-2011, and conduct our empirical analysis using a recent quantile regression for dynamic panel data with fixed effects. We focus on gross inflows rather than net flows, and our descriptive analysis from stylized facts also shows that net flows is no longer an appropriate approximation of foreign investment flows, since domestic agents' investments abroad have become significant since the 2000s.

We start our empirical investigation through the conditional mean regression, whose results show no clear pattern between push and pull factors. On the other hand, our quantile estimates deliver a new picture: push factors are generally significant across the whole conditional distribution, and their effects dominate compared to those of the pull factors in the upper quantiles of gross inflows' conditional distribution. Nevertheless, over the lower quantiles, pull factors become significant; they suggest that when foreign investments are relatively low, EMEs with higher return rate, better macro-fundamentals, better institutional quality, more prudent fiscal and monetary policy may experience less gross inflow reductions or pull back more foreign investments during episodes of relatively low capital flows. Such findings are novel to the literature.

Our results can be used to draw policymakers' attention to several issues. First, policy makers may need to watch out for capital flows' sustainability even when they are abundant. For as push factors dominate over the upper quantiles, a sudden change in the global economic climate would lead to a sudden stop of gross inflows. Second, despite push factors' overwhelming effect, policy makers should still aim to build up more attractive "pull conditions", which are especially significant when EMEs are suffering a capital drought.

Table 2-1 Summary statistics

	Unit	observations	mean	sd	min	max	source
Gross capital inflows	% of GDP	1083.0	6.19	10.13	-49.3	124	Bluedorn et al. (2013) and IFS
Gross capital outflows	% of GDP	1080.0	-3.33	9.43	-159.2	64	Bluedorn et al. (2013) and IFS
Net capital inflows	% of GDP	1083.0	2.86	7.03	-34.9	49	Bluedorn et al. (2013) and IFS
US real interest rate	in %	1193.0	0.14	0.56	-0.8	1	IFS
Domestic real interest rate	in %	1072.0	0.29	10.87	-285.7	133	IFS
REER deviation from trend		1188.0	0.14	27.36	-200.5	255	Author's calculation,
TED spread	bps	1193.0	53.85	30.01	19.0	155	Darvas (2012)
Real growth rate of advanced economies	in %	1193.0	2.25	1.52	-3.4	4	OECD data, IMF
VIX index		1193.0	19.11	6.24	11.0	36	Datastream
Contagion index		1082.0	2.98	3.40	-19.2	19	Bluedorn et al. (2013) and IFS
Real domestic growth rate	in %	1123.0	3.93	5.45	-41.0	51	Bluedorn et al. (2013) and IFS
Institutional quality index		1052.0	5.49	0.83	2.4	7	International country risk guide
GDP per capita	in logs	1159.0	8.29	0.91	6.0	10	IFS
Domestic inflation rate	in %	1145.0	60.30	381.65	-9.8	7482	IFS
Public debt	% of GDP	1119.0	48.71	34.44	0.0	290	Abbas et al. (2010)
Bank credit to private sector	% of GDP	1057.0	3.39	0.85	0.1	6	Global Financial Development Database
Exchange rate regime		1090.0	8.07	3.95	1.0	15	Ilzetzki et al. (2009)
Financial openness		1107.0	0.27	1.52	-1.9	2	Ito and Chinn (2008)
Trade openness		1145.0	62.92	33.04	0.0	196	Author's calculation, IFS
Current account balance	% of GDP	1143.0	-0.98	10.60	-240.5	45	IFS
Expected U.S real interest rate	in %	1193.0	0.06	0.80	-2.8	1	Survey of professional forecasters
Expected U.S. growth rate	in %	1193.0	5.19	5.64	-0.9	22	Survey of professional forecasters
Average money growth rate	in %	1193.0	1.30	0.46	0.7	2	IFS
IMF exchange rate regime		1015.0	2.65	1.14	1.0	4	Ilzetzki et al. (2009)
Sovereign crisis		1193.0	0.01	0.10	0.0	1	Laeven and Valencia (2013)
Reserves in months of import		1116.0	7.09	10.87	0.1	157	Author's calculation, IFS
Dollarized liability in financial system		771.0	24.83	20.34	0.0	89	Levy-Yeyati (2006)

Table 2-2 Dynamic panel-data estimate of capital flow (Level)

	(1) Return differential	(2) Plus push factors	(3) Plus pull factors	(4) Full specification	(5) + Year dummies
Lagged gross capital inflow	0.690***	0.628***	0.630***	0.546***	0.555***
	(0.152)	(0.154)	(0.155)	(0.169)	(0.171)
World interest rate (US real interest rate, %)	0.009	0.651	0.573	1.073	3.352***
	(0.378)	(0.744)	(0.846)	(0.957)	(0.772)
Domestic real interest rate (in %)	-0.001	0.004	0.001	-0.008	-0.010
	(0.006)	(0.007)	(0.008)	(0.014)	(0.010)
REER deviation from trend	-0.025*	0.010	0.008	-0.021	-0.021
	(0.015)	(0.026)	(0.032)	(0.022)	(0.020)
Global Liquidity (TED spread, bps)		0.017	0.014	0.013	0.013
		(0.022)	(0.021)	(0.022)	(0.014)
`Global growth rate (Advanced economies, %)		-0.138	0.022	0.250	-2.023
		(0.485)	(0.389)	(0.462)	(3.278)
Global risk appetite (VIX)		-0.245**	-0.224**	-0.157*	-0.873
		(0.104)	(0.089)	(0.085)	(0.832)
Contagion factor		0.289	0.209	0.460**	0.371*
		(0.200)	(0.203)	(0.223)	(0.218)
Real domestic growth rate			0.042	0.140	-0.008
			(0.092)	(0.089)	(0.139)
Institutional quality index			-0.927	-2.505*	-1.293
			(0.660)	(1.464)	(1.632)
Exchange rate regime				-0.054	-0.288
				(0.261)	(0.323)
Current account balance (% GDP)				-0.129	-0.185*
				(0.104)	(0.105)
GDP per capita (in logs)				-1.995	-2.517
				(2.049)	(2.175)
Public debt (% GDP)				-0.008	0.020
				(0.027)	(0.034)
Bank credit to private sector (% GDP)				2.325	-1.000
				(1.848)	(1.679)
Domestic inflation rate				0.000	-0.000
				(0.001)	(0.001)
Trade openness				0.004	-0.024
				(0.036)	(0.043)
Financial openness				1.479	0.632
				(1.155)	(1.109)
Hansen pvalue	0.512	0.785	0.540	0.243	0.833
AR(2) pvalue	0.266	0.307	0.319	0.470	0.476
R squared	0.338	0.366	0.352	0.302	0.422
Observations	1005	1001	943	872	872
No. of countries	52	52	51	51	51
No. of instruments	6	17	21	37	58

Notes: The dependent variable is gross private capital flow relative to GDP. The results for constant are omitted. Robust standard errors are employed.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors reported in parentheses. In Col (5), the results for year dummies are omitted.

Table 2-3 Determinants of gross capital inflow, 1990-2010

Estimation for gross capital inflow	Quantile regression (percentiles)						
	20th	30th	40th	50th	60th	70th	80th
	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged gross capital inflow	0.130	0.205*	0.575***	0.755***	0.810***	0.895***	1.010***
	(0.109)	(0.106)	(0.041)	(0.16)	(0.168)	(0.140)	(0.120)
External factors							
World interest rate	-1.319***	-0.809**	-0.612**	-0.277	0.008	0.267	0.733*
(US real interest rate, %)	(0.484)	(0.361)	(0.305)	(0.252)	(0.243)	(0.311)	(0.436)
Global Liquidity	0.006	0.002	-0.010**	-0.016***	-0.017 ***	-0.018***	-0.018***
(TED spread, bps)	(0.007)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Global Risk Aversion	-0.089**	-0.083**	-0.069**	-0.067***	-0.080***	-0.065**	-0.081**
(VIX)	(0.039)	(0.035)	(0.028)	(0.021)	(0.029)	(0.032)	(0.033)
Global growth rate	0.563***	0.404***	0.407***	0.288**	0.222**	0.261**	0.229**
(advanced economies, %)	(0.202)	(0.151)	(0.147)	(0.122)	(0.110)	(0.119)	(0.137)
Contagion factor	0.188*	0.173	0.229***	0.217***	0.166**	0.163 *	0.190**
	(0.101)	(0.109)	(0.073)	(0.064)	(0.068)	(0.085)	(0.084)
Domestic factors							
Domestic real interest rate	0.028***	0.030***	0.022***	0.018**	0.015	0.013	0.013
(in %)	(0.009)	(0.010)	(0.008)	(0.008)	(0.011)	(0.014)	(0.021)
REER deviation from trend	-0.008	-0.013	-0.011	-0.016	-0.022	-0.040**	-0.036**
	(0.020)	(0.015)	(0.018)	(0.018)	(0.017)	(0.018)	(0.018)
Exchange rate regime	-0.037	-0.124*	-0.094**	-0.050	-0.012	-0.050	-0.041
	(0.062)	(0.065)	(0.041)	(0.043)	(0.046)	(0.066)	(0.091)
Real domestic growth rate	0.186***	0.165***	0.086**	0.037	0.033	0.001	-0.089
	(0.056)	(0.056)	(0.041)	(0.035)	(0.051)	(0.063)	(0.068)
Institutional quality index	0.637**	0.518**	0.345**	0.071	0.012	-0.003	-0.137
	(0.300)	(0.239)	(0.145)	(0.147)	(0.174)	(0.240)	(0.385)
Current account balance	-0.206**	-0.142**	-0.043	0.007	-0.006	0.022	0.054
(% GDP)	(0.072)	(0.060)	(0.037)	(0.022)	(0.022)	(0.035)	(0.038)
GDP per capita (in logs)	0.039	0.227	0.124	0.228	0.279	0.241	0.175
	(0.244)	(0.267)	(0.169)	(0.152)	(0.179)	(0.228)	(0.295)
Public debt	-0.016**	-0.018***	-0.008**	-0.003	0.001	0.002	0.017**
(% GDP)	(0.007)	(0.007)	(0.004)	(0.004)	(0.005)	(0.007)	(0.008)
Bank credit to private sector	-0.615**	-0.343	-0.135	0.044	0.096	0.297	0.589*
(% GDP)	(0.287)	(0.230)	(0.182)	(0.175)	(0.190)	(0.250)	(0.335)
Domestic inflation rate	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Trade openness	-0.002	0.001	0.001	0.007	0.008	0.008	0.019
	(0.007)	(0.006)	(0.005)	(0.005)	(0.006)	(0.009)	(0.013)
Financial openness	-0.052	-0.174	-0.125	-0.074	0.090	0.095	0.164
	(0.171)	(0.179)	(0.103)	(0.115)	(0.130)	(0.173)	(0.208)
Observations	872	872	872	872	872	872	872

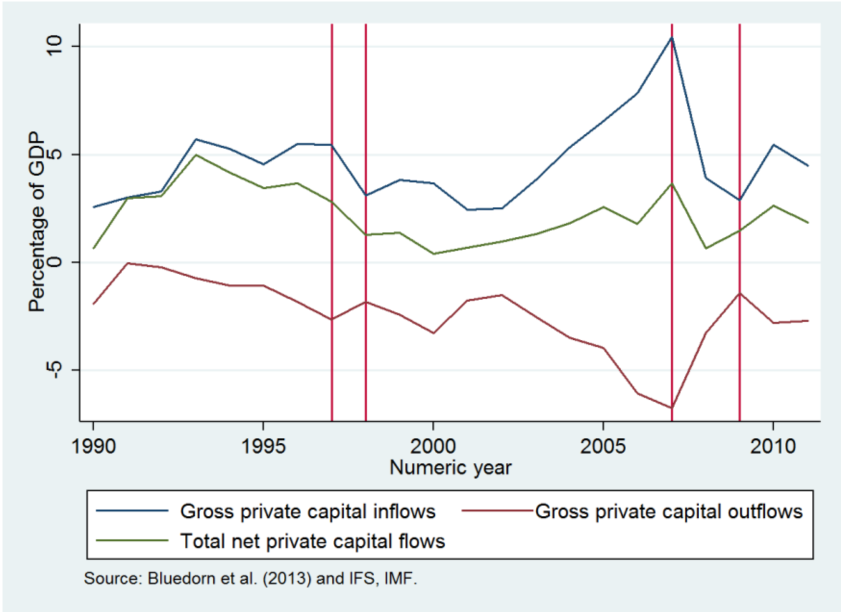
Notes: The dependent variable is gross private capital flow relative to GDP. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All domestic factors are lagged by 1 period.

Table 2-4 Determinants of net capital inflow and gross outflow, 1990-2010

	Net capital flows				Gross capital outflows			
	20th	40th	60th	70th	20th	40th	60th	70th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged net capital inflow	0.505***	0.68***	0.880***	1.02***	0.775***	0.700***	0.565***	0.190**
	(0.193)	(0.168)	(0.184)	(0.171)	(0.125)	(0.172)	(0.096)	(0.096)
World interest rate	-1.507	-0.842**	-0.298	-0.176	-0.745**	-0.300	-0.119	-0.150
(US real interest rate, %)	(0.493)	(0.351)	(0.317)	(0.317)	(0.329)	(0.279)	(0.177)	(0.194)
Global Liquidity	0.004	-0.007	-0.008	-0.002	0.011**	0.011**	0.011***	0.001
(TED spread, bps)	(0.007)	(0.004)	(0.006)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)
Global risk aversion	-0.022	-0.003*	-0.050***	-0.077***	0.035*	0.025	-0.004	0.020
(VIX)	(0.031)	(0.028)	(0.025)	(0.023)	(0.021)	(0.017)	(0.012)	(0.019)
Global growth rate	0.640**	0.297**	0.157	0.048	-0.084	-0.039	-0.094	-0.069
(Advanced economies, %)	(0.248)	(0.154)	(0.098)	(0.104)	(0.108)	(0.091)	(0.078)	(0.114)
Contagion factor	0.136	0.155**	0.058	0.011	-0.023	-0.072	-0.062*	-0.058
	(0.086)	(0.075)	(0.070)	(0.051)	(0.072)	(0.052)	(0.032)	(0.056)
Domestic real interest rate	0.022	0.037	0.040***	0.037***	0.012	0.018	0.014*	0.023**
(in %)	(0.021)	(0.019)	(0.009)	(0.011	(0.015)	(0.014)	(0.007)	(0.013)
REER deviation from trend	-0.084***	-0.038	-0.030	-0.040*	-0.027**	-0.019*	-0.013*	-0.007
	(0.032)	(0.031)	(0.028)	(0.024)	(0.013)	(0.008)	(0.007)	(0.007)
Exchange rate regime	0.161**	0.027	-0.048	-0.031	0.155	0.096	0.047*	0.085*
	(0.071)	(0.052)	(0.047)	(0.052)	(0.112)	(0.068)	(0.027)	(0.040)
Real domestic growth rate	0.179***	0.048	-0.012	-0.076	-0.001	0.026	0.022	-0.016
	(0.057)	(0.035)	(0.046)	(0.057)	(0.046)	(0.030)	(0.022)	(0.026)
Institutional quality index	0.777**	0.307	0.127	0.039	0.460	0.098	0.060	0.200
	(0.344)	(0.192)	(0.214)	(0.263)	(0.346)	(0.202)	(0.109)	(0.146)
Current account balance	-0.242***	-0.107**	0.023	0.102***	-0.085*	-0.049*	-0.048***	-0.124***
(% GDP)	(0.066)	(0.042)	(0.029)	(0.029)	(0.049)	(0.029)	(0.014)	(0.028)
GDP per capita (in logs)	-0.967***	-0.260	0.278	0.393**	-0.744**	-0.266	-0.133	-0.366**
	(0.275)	(0.208)	(0.173)	(0.179)	(0.337)	(0.193)	(0.096)	(0.180)
Public debt	-0.001	-0.001	0.005	0.005	0.005	0.005	0.007***	0.011**
(% GDP)	(0.007)	(0.005)	(0.004)	(0.005)	(0.007)	(0.004)	(0.003)	(0.004)
Bank credit to private sector	-0.146	-0.080	-0.266	-0.110	-0.258	-0.269	-0.104	0.031
(% GDP)	(0.337)	(0.222)	(0.173)	(0.237)	(0.363)	(0.249)	(0.122)	(0.174)
Domestic inflation rate	-0.002	-0.001	0.001	-0.001	-0.001*	-0.001**	-0.001	0.001
	(0.003)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Trade openness	-0.019*	-0.001	0.009*	0.010	-0.019*	-0.008	0.001	-0.003
	(0.010)	(0.006)	(0.005)	(0.008)	(0.010)	(0.006)	(0.003)	(0.003)
Financial openness	0.086	-0.137	-0.128	-0.118	-0.325	-0.106	0.090	0.096
	(0.157)	(0.108)	(0.093)	(0.116)	(0.224)	(0.134)	(0.060)	(0.076)
Observations	872	872	872	872	865	865	865	865

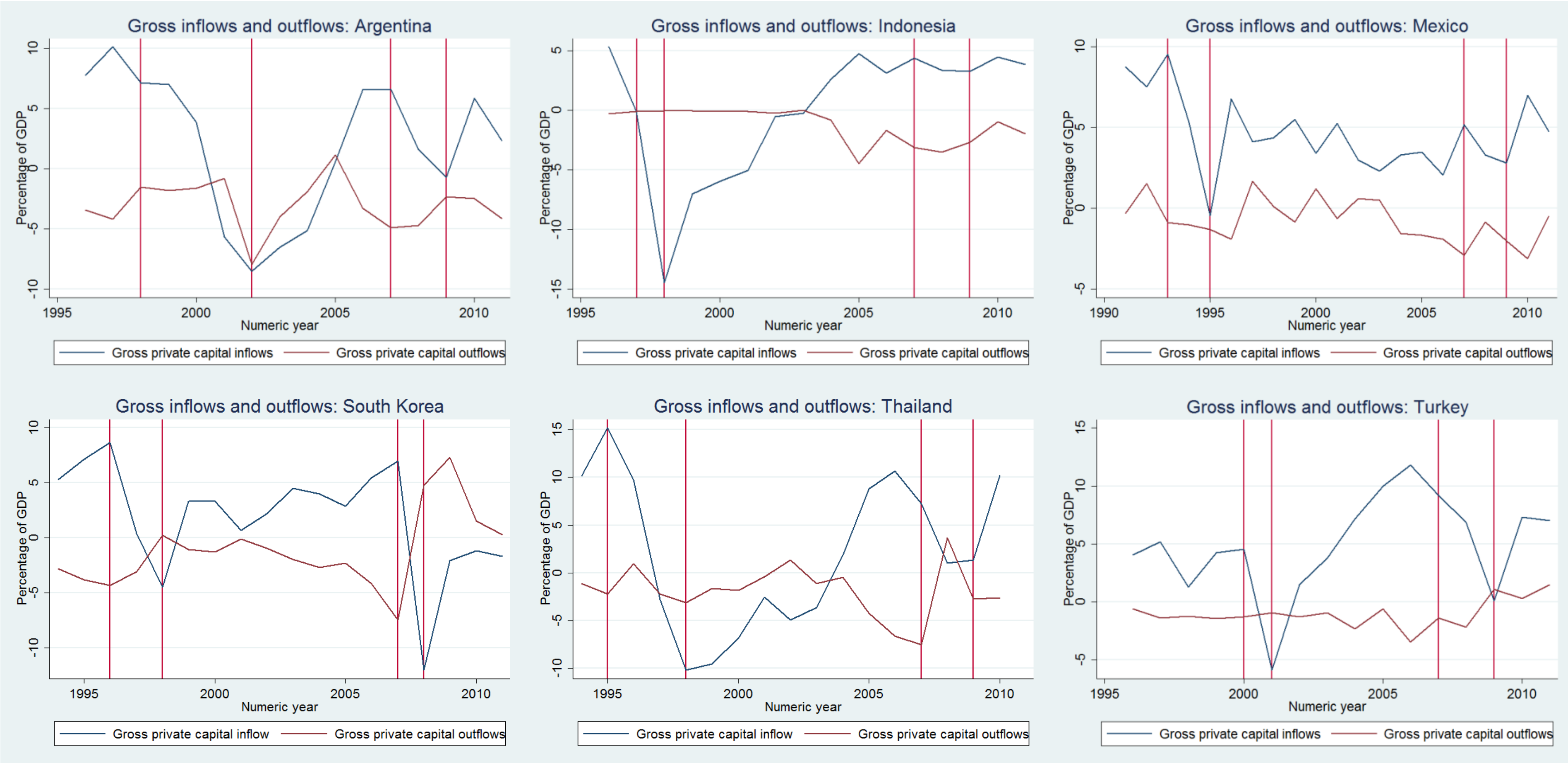
Notes: The dependent variables are net capital flows through column (2)-(9), and gross outflows through (10)-(14). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2-1 Net and gross private capital flows to EMEs, 1990-2010



Notes: The first span marked by red lines shows the Asian financial crisis during 1997-1998. The second display the recent global financial crisis.

Figure 2-2 Gross inflows and outflows of selected EMEs, 1990-2011



Notes: The span between the first two red lines (in all these countries) shows a domestic financial crisis, and the latter span implies the recent global financial crisis during 2007-2009.

2.8 Appendix

2.8.1 Robustness Checks of the Conditional Quantile Estimates

To check the robustness of our empirical results based on gross inflows, we conduct a range of sensitivity tests with different specifications of control variables and additional regressors. Tables 2.5-2.7 report our estimations from three selected quantiles over the conditional distribution (τ = *20th, 50th, 80th*), respectively.

<Insert Table 2.5 to 2.7 here>

2.8.1.1 Alternative Specification

We begin by using a number of different measures of control variables: First, foreign investmen ts in EMEs could be forward-looking. Therefore, we use U.S. expected real interest and real growth rate from surveys of professional forecasters, instead of ex-post real world return rate and growth rate. Second, to alter the definition of global liquidity, we use the average money growth rate in U.S., Japan, France, Germany, and U.K., following Forbes and Warnock (2012). A higher money growth rate might indicate an ill-liquidity state ex-post, but might imply an improved liquidity ex-ante. Third, we use another specification of exchange rate regime from Shambaugh (2004), which is a dummy variable taking the value of 1 if the exchange rate stays within 2% variation band in a year and zero otherwise.

The results are shown over columns 1 – 4 over Tables 2.5-2.7. First, the expected real U.S. interest rate still shows significantly negative coefficients when $\tau = 50^{th}$ (as show in Column 1 of Table 2.6), $\tau = 80^{th}$ (as shown in Column 1 of Table 2.7). Compared to the significant estimation of ex-post rate (as shown in Table 2.5) reported in the lower quantiles, it suggests that ex-ante rate is more relevant during good times, that is, over the upper quantiles. Second, a higher money growth rate in major advanced countries, which possibly signals a need to boost global ill-liquidity conditions ex-post, is reported to be negatively associated gross capital inflow around the median quantiles (as shown in Column 3 of Tables 2.5 to 2.7).[16] Third, expected U.S. growth rate appears insignificant in all selected percentiles; it seems that ex-post growth rate rather than expected growth rate matters. Forth, the significance of

[16]Apart from the 50th quantile, It also shows a negative coefficient significant at 5% when $\tau=60^{th}$, which is reported here.

exchange rate regime disappears when its data from Shambaugh (2004) is employed (as displayed in Column 4 of Tables 2.5 to 2.7)

Finally, despite alternative specifications, the main pattern between "push and pull" as shown in our core results in Table 2.3—push factors are generally significant especially over upper quantiles; pull factors are significant only in the left tail—remains.

2.8.1.2 Additional Controls

Next, we test the robustness of our results by including some additional control variables as suggested from the literature. First, capital flows towards EMEs might be relatively high in the mid-2000s (Yan et al., 2016). To take this effect into account, we add a dummy variable taking the value of one if capital flows is realized during 2003 to 2007 and zero otherwise. Second, we test whether sovereign default could trigger outflows by including a dummy variable equal to one indicating the occurrence of a sovereign crisis. The dummy variable's data is from Laeven and Valencia (2013). Third, we test the possibility that international reserves acts as a stabilizer of capital flows, especially during times of global financial distress (Alberola et al., 2016). We measure international reserves as reserves in months of imports (Broto et al., 2011). Moreover, it is reported that high external liabilities play an important role in triggering financial crisis including sudden stops (Catão and Milesi-Ferretti, 2014); we control external liability as foreign currency deposits over total deposits in local banks (Levy-Yeyati, 2006).

The modified results with additional regressors are reported from columns 5 to 8 over Tables 2.5 to 2.7. First, the time dummy (of mid-2000s) seems to be significant in all quantiles selected, but its inclusion does not affect the results of other variables. Second, the dummy indicating the occurrence of sovereign crisis appears insignificant over all estimations, which can be seen in column 6 throughout Table 2.5 to 2.7 Third, a higher stock of international reserve is positively significant in the 20th quantile (as shown in Column 7, Table 2.5), implying a buffer that reduces net foreign capital outflows in bad times, which agrees with the findings of Alberola et al. (2016). Forth, we could not find evidence of significant and negative estimate of domestic liability dollarization as expected from the literature, as displayed in Column 8 over Table 2.5 to 2.7.

In summary, throughout different kinds of robustness tests, it seems that the major story revealed from the core quantile regression (displayed from Table 2.3) remains: first, global factors consistently display significant estimates over Table 2.5 to 2.7, highlighting their dominating role during all kinds of situations, especially during good times. Among the push factors, real world return measured by real U.S. 3-month treasury bill rate is consistently significant in the lower quantile (Table 2.5), but insignificant in the median quantile (Table 2.6). Its significance appears again in the right tail (Table 2.7). Global liquidity measured by TED spread is consistently significant over the median and upper quantile (Tables 2.6 and 2.7), which proves to be a robust control for capital booms towards EMEs. Moreover, in line with recent literature suggesting a strong role of global risk aversion (e.g., Forbes and Warnock, 2012; Fratzscher, 2012), VIX index reports consistently significant and negative coefficients over all selected quantiles. Moreover, gross inflows are also robustly positively associated with world productivity shocks over all selected quantiles. Finally, in line with Forbes and Warnock (2012), we also find strong evidence of regional contagion over Table 2.5 to 2.7. These findings highlight the danger of abrupt reversals during surges given the overwhelming importance of global factors, especially expected world interest rate, TED, and VIX are forward-looking and based on perceptions. Second, turning to pull factors, consistent with our core quantile estimates, they are robustly significant over the lower quantiles in general. During episodes of external financial stress (e.g., τ = *20th* shown in Table 2.5), EMEs with higher growth rates, better institutional qualities, higher external financial needs, less indebtedness, and less credit booms are robustly shown to experience less reductions in gross inflows.

Last, there are indeed some variables which are consistently insignificant in our test. First, in line with Forbes and Warnock (2012), we could not find any evidence of the effect of financial openness on gross inflows. Moreover, trade openness and inflation rate also fail to show significant estimates generally.

2.8.1.3 Analysis based on Disaggregated Capital Flows

Our main empirical analysis is based on the *total* (*aggregated)* capital flows.[17] Nevertheless, the literature argues that (disaggregated) capital flow may differ in nature and therefore respond differently to variations of both push and pull factors. For instance, portfolio equity or debt flow might be more speculative than foreign direct investment (e.g., Stiglitz, 2000). As a result, their determinants could be different. To that end, we apply the same quantile regression technique of Galvao (2011) to FDI, portfolio debt flow, portfolio equity flow and back flow. The estimated results are presented from table 2.8 - 2.11; their key results are summarized as follows:

<Insert Table 2.8 – 2.11 here>

Firstly, global factors seem to have heterogonous impacts on different types of disaggregated capital flows. For instance, global liquidity condition—as measured by TED spread—seems to be more significantly associated with both portfolio equity and debt flows: its estimated coefficients are significant across almost the whole conditional distributions of these two flows (as shown in Table 2.9 and 2.10). In contrast, global risk aversion (as measured by VIX index) display a stronger impact on FDI and bank flows (as shown in Table 2.8 and 2.11). Such an observation seems to complement the main empirical results based on aggregated flows—almost each global factor contributes as a significant determinant of the aggregated capital flows (as shown in Table 2.3). Nevertheless, each push factor might have a heterogonous effect on disaggregated components (Such as FDI) of the total flows.

Secondly, some of pull factors show a similarly heterogonous impact as the push factors do. For example, countries with higher domestic growth rate may retain more FDI and bank flows (in their lower quantiles). In addition, a higher domestic return may be associated with a higher debt flow at its 20th conditional quantile (as shown in column 2 of Table 2.9). Nevertheless, results of pull factors such as institutional quality and exchange rate regime are not quite in line with those from the main analysis based on aggregated flow (as show in Table 2.3)—such domestic conditions lack significance in almost every type of the disaggregated flow. Such a divergence may result from a significant drop of sample size when we analyze disaggregated flows: for example, the total observations drops from 872 by nearly one

[17] See section 2.2 for more discussions.

third to 578 when we shift our empirical investigation from total capital flow to equity flows (as shown in the last rows of both Table 2.3 and 2.10). Therefore, such a difference in sample size hinders a decent comparison of our empirical results.

2.8.2 Robustness checks of the Conditional Mean Estimates

2.8.2.1 Fixed Effects(FE) Estimates

In section 2.5.1, we conduct our empirical analysis of conditional mean regression by the dynamic panel data approach (DPD) of Arellano and Bond (1991). Nevertheless, Judson and Owen (1999) argue that when T (average observations of each panel unit) is relatively large, the "Nickell bias" in DPD is less of a problem than when T is small. In that case, conventional fixed effect (FE) model might work reasonably well. In our study, the average observation per country is 17, which could be regarded as a relatively large amount of T in empirical studies based on DPD. Hence, it will be interesting to investigate whether FE estimations would deliver a significantly different result.

<Insert Table 2.12 here>

Table 2.12 presents our results based on FE estimations. In summary, the key results are: firstly, FE estimate delivers a smaller coefficient of lagged gross inflows—it drops from 0.546 based on DPD (as shown in column 4 in Table 2.2) to 0.359 (as shown in column 1 in Table 2.12). Such a drop of magnitude may imply the presence of "Nickell bias" even though T (in our study) is relatively large, because our FE estimate is likely to be downwardly biased. Secondly, none of the interest rate differential components—that is, world interest rate, domestic interest rate, and REER deviation from trend—display strongly significant estimates. Such a result may echo the presence of "Lucas Paradox" which was argued in our discussion of empirical results based on DPD.[18] Thirdly, reginal contagion turns to be the most significant push factor. Its estimated coefficient suggests that when the average capital flow of the region increase by 1% (of GDP), domestic total flow may also raise by 0.473 % (of domestic GDP). Finally, our FE estimations seem to suggest more significant pull factors: countries with a higher domestic growth rate, a larger external financial need (as measured by a higher current account balance or equivalently a higher financial

[18] See our discussion in section 2.5.1 for details.

account deficient), higher GDP per capital, and higher financial openness may attract more capital flows.

2.8.3 Comparison between conditional mean and quantile estimates

In section 2.5, we conduct our main analysis by employing both the conditional mean and quantile regressions. The results of such two estimates are significantly different: In section 2.5.1, our results show that none of return differentials factors are significant; most pull conditionals are insignificant; and only global risk appetite and reginal contagion are significant. Nevertheless, in section 2.5.2, our conditional quantile estimates based Galvao (2011) are significantly different—almost all push factors are significant over the whole conditional distribution; a considerable number of pull factors display significant estimates over the lower quantiles.

Such a significant difference between these two estimates raises one concern: if capital flow is normally distributed, the conditional mean estimates should be similar with the conditional median estimates. Alternatively, if the conditional distribution of capital flow is skewed to the right (left), the conditional mean regression should display a result similar with that of the upper (lower) quantiles. Nevertheless, in this study, both the conditional mean estimates from DPD (as discussed in Section 2.5.1) and FE (as discussed in Section 2.8.2.1) are significantly different from any of the conditional quantile estimates in 2.5.2.

One might possibly suspect the validity of Galvao (2011)—it is a relatively new model and therefore it might have some flaws. To rule out this possibility, we conduct the same analyse with a traditional quantile regression model of Koenker and Bassett (1978), which does not consider the dynamic panel structure; the results are shown below:

<Insert Table 2.13 here >

Table 2.13 shows a result similar with that of section 2.5.2: a consider amount of push factors are significant over the whole conditional distribution; pull factors display significant estimates particularly over the lower quantiles. Once again, none of the results from any quantiles are similar with the conditional mean estimates (as shown in Section 2.5.1 and 2.8.2).

Overall, it seems that the unexpected difference between conditional mean and quantile estimates is irrelevant with the potential flaws of Galvao (2011). It is more likely a consequence of the different estimation techniques.

2.8.4 Country and Time Distribution of Gross Inflows

2.8.4.1 Country Distribution

In our main empirical analysis, although gross inflows are scaled by the domestic GDPs to account for each country's economic size—which is a standard practice in the literature—the country distribution of such capital flows need more investigations. For example, the ratio of capital flows over GDP might be consistently low in countries such as China and India because of the large size of their economies. Therefore, their capital flows are more likely to stay in the lower quantiles. Similarly, capital flows to small EMEs are more likely to appear in the upper quantiles. To further investigate this issue, we examine the country distribution of gross inflows.

<Insert Table 2.14 here>

The country distribution of gross inflows is summarized in Table 2.14—its upper panel shows the value from the 20th, 40th, 60th and 80th quantiles of the whole sample. One may find that its conditional distribution is skewed to the right (compared to a standard normal distribution), because even the 20th percentile shows a level at 1.795 % (over GDP). This implies an abundant movement of capital flows towards EMEs during the last two decades.

The lower panel shows the country-specific statistics for gross inflows; 15 representative EMEs are chosen from different regions. The key observations are: first, average gross inflows towards large economies are relevantly lower. For instance, the mean gross inflows to China is 3.886, which is significantly lower than that of the whole sample, 6.72. Secondly, average gross inflow towards small economies (such as those from East Europe) tend to be relatively higher—the average value for Czech and Hungary, for instance, is 8.68 and 9.376, respectively. Third, apart from the two huge economies—China and India—the standard deviations of capital flows to the other EMEs are high. Overall, our results may confirm the expectation that capital flows to large (small) EMEs are more likely to appear in the lower (upper) quantiles. Nevertheless, since the standard deviations are generally high, most observations may be scattered over the a considerably wide interval across capital flows' conditional distribution.

2.8.4.2 Time Distribution

The literature reports a high level of capital flows towards EMEs before the onset of global financial crisis in 2008 (e.g., Fuertes et al., 2016; Yan et al., 2016). Therefore, regarding the conditional distribution of capital flows, observations during the mid-2000s are more likely to appear in the upper quantiles. To investigation this issue in details, we plot the average gross inflows towards all EMEs each year in Figure 2.3, where the shaded area represents the 95% confidence interval.

<Insert Figure 2.3 here>

As expected, Figure 2.3 shows a spike during the mid-2000s—average gross inflows increase from less than 5% (of GDP) in 20002 to nearly 15% (of GDP) in 2007. Nevertheless, they collapse in 2008—the onset of the crisis. Hence, capital flows occurred during the mid-2000s are more likely to appear in the upper quantiles.

We take this consideration into account in our robustness check (in Section 2.8.1.2)—we set a dummy variable taking the value of one if capital flow is observed from 2003 to 2007 and zero otherwise. The results in 2.8.1.2 show that its inclusion does not change the estimated results of the other coefficients and therefore the main story of our empirical findings.

2.8.5. Diagnostic Tests on Multi-collinearity

<Insert Table 2.15 here>

Table 2.15 shows the results of our diagnostic test for multi-collinearity—Variation Inflation Factors (VIF) test. The VIF statistics for all the estimated coefficients are significantly below 10, which as the rule of thumb is the tolerance VIF. Therefore, severe multi-collinearity is not present.

Table 2-5 Determinants of gross capital inflow, 1990-2010: sensitivity test at the 20th conditional quantile

τ = 20th	Alternative specifications				Additional control variables			
	Expected world interest	Expected world growth	Money growth	Shambaugh (2004)	Time Trend	Default Dummy	Reserves	Liability dollarization
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged inflow	0.005	0.035	0.120	0.110	0.125	0.055	0.005	0.340
	(0.974)	(0.142)	(0.111)	(0.109)	(0.111)	(0.129)	(0.161)	(0.267)
World interest rate	-0.662	-0.781**	-1.113**	-1.427**	-1.189*	-1.362***	-1.198***	-1.985***
(US real interest rate, %)	(0.433)	(0.389)	(0.474)	(0.558)	(0.622)	(0.454)	(0.457)	(0.634)
Global Liquidity	0.010	0.005	0.576	0.005	0.007	0.005	0.003	0.001
(TED spread, bps)	(0.009)	(0.007)	(0.418)	(0.006)	(0.006)	(0.006)	(0.005)	(0.007)
Global Risk Aversion	-0.139***	-0.151***	-0.097**	-0.084***	-0.099**	-0.095**	-0.101**	-0.071*
(VIX)	(0.046)	(0.037)	(0.039)	(0.039)	(0.040)	(0.038)	(0.043)	(0.037)
Global growth rate	0.432**	0.010	0.475**	0.607*	0.548**	0.485**	0.435**	1.093**
(advanced economies, %)	(0.189)	(0.029)	(0.215)	(0.231)	(0.226)	(0.190)	(0.189)	(0.305)
Contagion factor	0.151	0.171	0.189**	0.193**	0.202*	0.148	0.213*	0.276***
	(0.121)	(0.110)	(0.087)	(0.106)	(0.114)	(0.096)	(0.114)	(0.113)
Domestic real interest rate	0.027**	0.032***	0.030**	0.029**	0.029***	0.017	0.032***	0.026***
(in %)	(0.013)	(0.012)	(0.015)	(0.013)	(0.009)	(0.020)	(0.012)	(0.010)
REER deviation from trend	-0.019	-0.007	-0.011	-0.010	-0.009	-0.009	-0.010	-0.022
	(0.015)	(0.018)	(0.022)	(0.020)	(0.016)	(0.020)	(0.017)	(0.023)
Exchange rate regime	-0.041	-0.043	-0.055	-0.164	-0.058	-0.045	-0.079	-0.113
	(0.064)	(0.063)	(0.064)	(0.178)	(0.072)	(0.067)	(0.069)	(0.078)
Real domestic growth rate	0.234***	0.211***	0.169***	0.194***	0.190***	0.237***	0.261***	0.144**
	(0.058)	(0.054)	(0.051)	(0.061)	(0.059)	(0.059)	(0.058)	(0.071)
Institutional quality index	0.506	0.682**	0.715***	0.591*	0.619*	0.682**	0.644**	0.819**
	(0.315)	(0.345)	(0.276)	(0.318)	(0.372)	(0.279)	(0.311)	(0.391)
Current account balance	-0.254***	-0.259***	-0.214***	-0.213***	-0.211***	-0.253***	-0.318***	-0.112**
(% GDP)	(0.083)	(0.080)	(0.067)	(0.078)	(0.065)	(0.077)	(0.076)	(0.055)
GDP per capita	0.278	0.310	0.038	0.069	-0.008	0.147	0.154	-0.203
(in logs)	(0.255)	(0.274)	(0.301)	(0.247)	(0.258)	(0.263)	(0.273)	(0.339)
Public debt	-0.015*	-0.014*	-0.015**	-0.018**	-0.016**	-0.013	-0.013	-0.015**
(% GDP)	(0.008)	(0.008)	(0.006)	(0.007)	(0.008)	(0.008)	(0.009)	(0.006)
Bank credit to private sector	-0.683*	-0.553	-0.668***	-0.551*	-0.627**	-0.725**	-0.947***	-0.500
(% GDP)	(0.349)	(0.343)	(0.255)	(0.309)	(0.311)	(0.338)	(0.354)	(0.311)
Domestic inflation rate	-0.001	-0.001	0.001	-0.001	0.001	0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Trade openness	0.001	-0.003	-0.004	-0.004	-0.002	-0.003	0.005	-0.010
	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)	(0.008)	(0.008)	(0.008)
Financial openness	-0.033	-0.149	-0.031	-0.073	-0.121	-0.075	-0.120	-0.185
	(0.201)	(0.208)	(0.175)	(0.180)	(0.192)	(0.197)	(0.174)	(0.190)
Additional regressor					0.046	-4.005	0.093***	0.007
					(0.042)	(5.047)	(0.034)	(0.012)
Observations	872	872	872	872	872	872	872	636

Notes for Tables 4-6: The dependent variable is gross private capital flow relative to GDP. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2-6 Determinants of gross capital inflow, 1990-2010: sensitivity test at the 50th conditional quantile

τ = 50th	Alternative specifications				Additional control variables			
	Expected world return	Expected world growth	Money growth	Shambaugh (2004)	Time Trend	Default Dummy	Reserves	Liability dollarization
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged inflow	0.755 ***	0.595***	0.725***	0.745***	0.735***	0.760***	0.735***	0.795*
	(0.158)	(0.038)	(0.143)	(0.158)	(0.150)	(0.162)	(0.130)	(0.445)
World interest rate	-0.528**	0.078	-0.464	-0.221	0.265	-0.263	-0.245	-0.477
(US real interest rate, %)	(0.252)	(0.218)	(0.284)	(0.258)	(0.349)	(0.256)	(0.264)	(0.409)
Global Liquidity	-0.014***	-0.013***	-0.494*	-0.018***	-0.018***	-0.017***	-0.016***	-0.016**
(TED spread, bps)	(0.004)	(0.004)	(0.258)	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)
Global Risk Aversion	-0.075***	-0.089***	-0.077***	-0.070***	-0.066***	-0.064***	-0.065**	-0.071***
(VIX)	(0.022)	(0.026)	(0.027)	(0.021)	(0.021)	(0.020)	(0.022)	(0.027)
Global growth rate	0.417***	-0.011	0.311**	0.299**	0.274**	0.292**	0.313**	0.454*
(advanced economies, %)	(0.144)	(0.024)	(0.154)	(0.125)	(0.129)	(0.147)	(0.138)	(0.234)
Contagion factor	0.219***	0.201***	0.197***	0.208***	0.242***	0.215***	0.224***	0.228***
	(0.070)	(0.076)	(0.074)	(0.068)	(0.071)	(0.067)	(0.074)	(0.077)
Domestic real interest rate	0.016**	0.024**	0.018**	0.018*	0.018**	0.007	0.018*	0.011
(in %)	(0.007)	(0.010)	(0.009)	(0.010)	(0.008)	(0.012)	(0.010)	(0.009)
REER deviation from trend	-0.016	-0.016	-0.014	-0.016	-0.013	-0.016	-0.017	-0.042*
	(0.019)	(0.019)	(0.018)	(0.017)	(0.020)	(0.018)	(0.019)	(0.023)
Exchange rate regime	-0.053	-0.053	-0.075	-0.172	-0.056	-0.047	-0.054	-0.049
	(0.043)	(0.049)	(0.048)	(0.130)	(0.042)	(0.045)	(0.046)	(0.043)
Real domestic growth rate	0.048	0.040	0.032	0.049	0.046	0.039	0.037	0.052
	(0.039)	(0.041)	(0.043)	(0.039)	(0.040)	(0.039)	(0.042)	(0.056)
Institutional quality index	-0.029	0.282*	0.137	0.149	-0.209	0.057	0.070	0.152
	(0.165)	(0.157)	(0.151)	(0.135)	(0.177)	(0.133)	(0.143)	(0.211)
Current account balance	0.001	-0.033	-0.008	-0.005	-0.006	0.008	-0.005	0.017
(% GDP)	(0.023)	(0.032)	(0.027)	(0.022)	(0.024)	(0.021)	(0.028)	(0.025)
GDP per capita	0.244	0.342**	0.229	0.221	0.253	0.222	0.228	0.105
(in logs)	(0.155)	(0.159)	(0.162)	(0.147)	(0.159)	(0.159)	(0.146)	(0.184)
Public debt	-0.001	-0.007	-0.004	-0.004	-0.001	-0.003	-0.002	-0.002
(% GDP)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Bank credit to private sector	0.057	-0.014	0.027	0.039	0.001	0.053	-0.004	0.001
(% GDP)	(0.182)	(0.207)	(0.221)	(0.169)	(0.185)	(0.196)	(0.206)	(0.191)
Domestic inflation rate	-0.001	-0.001	0.001	0.001	0.001	0.001	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Trade openness	0.009	0.007	0.008	0.005	0.011*	0.007	0.010	0.009
	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)
Financial openness	-0.050	-0.024	-0.090	-0.032	-0.053	-0.068	-0.085	-0.053
	(0.119)	(0.125)	(0.123)	(0.115)	(0.118)	(0.121)	(0.112)	(0.133)
Additional regressor					0.075**	-2.985	0.008	-0.002
					(0.033)	(5.905)	(0.015)	(0.011)
Observations	872	872	872	872	872	872	872	636

Table 2-7 Determinants of gross capital inflow, 1990-2010: sensitivity test at the 80th conditional quantile

τ = 80th	Alternative specifications				Additional control variables			
	Expected world return rate	Expected world growth rate	Money growth	Shambaugh (2004)	Time Trend	Default Dummy	Reserves	Liability dollarization
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged inflow	1.030***	0.990***	0.990***	0.930***	0.950***	1.020***	1.030***	1.330***
	(0.113)	(0.124)	(0.143)	(0.313)	(0.305)	(0.119)	(0.101)	(0.311)
World interest rate	-0.872**	0.974**	0.336	0.521	0.916*	0.861**	0.822***	0.511
(US real interest rate, %)	(0.414)	(0.375)	(0.451)	(0.458)	(0.472)	(0.413)	(0.399)	(0.594)
Global Liquidity	-0.014**	-0.019***	-0.750	-0.017***	-0.022***	-0.018***	-0.018***	-0.018**
(TED spread, bps)	(0.006)	(0.006)	(0.467)	(0.006)	(0.006)	(0.005)	(0.005)	(0.009)
Global Risk Aversion	-0.101***	-0.108***	-0.064*	-0.098***	-0.087**	-0.082***	-0.077**	-0.073*
(VIX)	(0.036)	(0.033)	(0.034)	(0.034)	(0.035)	(0.030)	(0.035)	(0.044)
Global growth rate	0.574***	-0.018	0.313**	0.183	0.289**	0.235	0.247*	0.342*
(advanced economies, %)	(0.174)	(0.039)	(0.137)	(0.142)	(0.134)	(0.145)	(0.135)	(0.175)
Contagion factor	0.288***	0.203**	0.201**	0.205**	0.246**	0.212**	0.179*	0.141
	(0.087)	(0.084)	(0.083)	(0.090)	(0.082)	(0.089)	(0.096)	(0.095)
Domestic real interest rate	0.013	0.014	0.011	0.017	0.014	0.003	0.011	0.006
(in %)	(0.022)	(0.019)	(0.018)	(0.023)	(0.022)	(0.035)	(0.022)	(0.019)
REER deviation from trend	-0.040**	-0.039**	-0.039*	-0.036	-0.037*	-0.038*	-0.041*	-0.047*
	(0.019)	(0.019)	(0.021)	(0.023)	(0.020)	(0.020)	(0.023)	(0.028)
Exchange rate regime	-0.015	-0.069	-0.022	-0.254	-0.021	-0.032	-0.032	0.115
	(0.109)	(0.103)	(0.094)	(0.255)	(0.101)	(0.090)	(0.102)	(0.094)
Real domestic growth rate	-0.125*	-0.097	-0.099	-0.129*	-0.109	-0.100	-0.123	-0.270**
	(0.075)	(0.067)	(0.073)	(0.070)	(0.071)	(0.066)	(0.083)	(0.095)
Institutional quality index	0.093	-0.202	-0.003	-0.026	-0.328	-0.205	-0.203	-0.183
	(0.343)	(0.390)	(0.433)	(0.373)	(0.403)	(0.376)	(0.383)	(0.511)
Current account balance	0.070*	0.047	0.047	0.043	0.047	0.052	0.066	0.179**
(% GDP)	(0.038)	(0.044)	(0.035)	(0.035)	(0.033)	(0.040)	(0.045)	(0.060)
GDP per capita	-0.099	0.419	0.107	0.209	0.101	0.197	0.222	-0.129
(in logs)	(0.294)	(0.315)	(0.316)	(0.301)	(0.272)	(0.292)	(0.278)	(0.392)
Public debt	0.016**	0.017*	0.011	0.004	0.013	0.016*	0.013	0.017*
(% GDP)	(0.008)	(0.009)	(0.009)	(0.009)	(0.010)	(0.008)	(0.012)	(0.010)
Bank credit to private sector	0.789**	0.522	0.409	0.914**	0.721*	0.584	0.581	0.795*
(% GDP)	(0.313)	(0.368)	(0.369)	(0.410)	(0.415)	(0.365)	(0.429)	(0.440)
Domestic inflation rate	-0.001	-0.001	-0.001	-0.001	0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001	(0.001)	(0.001)	(0.001)	(0.001)
Trade openness	0.014	0.018	0.020	0.015	0.020	0.019	0.019	0.016
	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)
Financial openness	0.136	0.043	0.093	0.160	0.178	0.163	0.149	-0.025
	(0.200)	(0.198)	(0.215)	(0.205)	(0.215)	(0.194)	(0.201)	(0.180)
Additional regressor					0.079**	-2.457	-0.006	0.016
					(0.037)	(16.008)	(0.029)	(0.016)
Observations	872	872	872	872	872	872	872	636

Table 2-8 Determinants of gross capital inflow (Foreign Direct Investment), 1990-2011

Estimation for FDI	Quantile Regression (Quantiles)			
	20th	40th	60th	80th
(1)	(2)	(3)	(4)	(5)
Lagged gross capital inflow	0.615	0.765*	0.94**	1.19***
	(0.655)	(0.413)	(0.379)	(0.262)
External Factors				
World interest rate	-0.218*	-0.242 **	-0.164	0.165
(US real interest rate, %)	(0.119)	(0.095)	(0.106)	(0.198)
Global Liquidity	0.003**	0.002	0.001	-0.002
(TED spread, bps)	(0.001)	(0.001)	(0.002)	(0.003)
Global Risk Aversion	-0.011	-0.014*	-0.022***	-0.040***
(VIX)	(0.010)	(0.008)	(0.009)	(0.012)
Global growth rate	0.060	0.110**	0.107***	0.149**
(advanced economies, %)	(0.055)	(0.030)	(0.031)	(0.071)
Contagion factor	0.045*	0.043	0.051**	-0.012
	(0.024)	(0.017)	(0.020)	(0.033)
Domestic Factors				
Domestic real interest rate	-0.007	-0.004	-0.004	-0.008
(in %)	(0.006)	(0.006)	(0.007)	(0.006)
REER deviation from trend	0.002	0.001	0.001	0.004
	(0.003)	(0.002)	(0.005)	(0.007)
Exchange rate regime	0.022	0.002	-0.021	-0.010
	(0.017)	(0.014)	(0.018)	(0.030)
Real domestic growth rate	0.036***	0.013	0.021	0.014
	(0.004)	(0.011)	(0.019)	(0.029)
Institutional quality index	0.141	0.098	0.136*	0.157
	(0.099)	(0.068)	(0.072)	(0.177)
Current account balance	0.006	-0.002	0.013	0.006
(% GDP)	(0.009)	(0.014)	(0.015)	(0.014)
GDP per capita (in logs)	-0.160**	-0.076	0.008	-0.011
	(0.080)	(0.057)	(0.064)	(0.109)
Public debt	0.000	0.001	0.003	0.004
(% GDP)	(0.001)	(0.001)	(0.002)	(0.004)
Bank credit to private sector	0.062	0.062	-0.157**	-0.064
(% GDP)	(0.109)	(0.058)	(0.078)	(0.162)
Domestic inflation rate	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Trade openness	-0.004	0.000	0.002	0.012**
	(0.004)	(0.002)	(0.003)	(0.006)
Financial openness	-0.046	-0.009	0.025	0.009
	(0.054)	(0.031)	(0.044)	(0.074)
Observations	860	860	860	860

Notes: The dependent variable is gross private capital flow relative to GDP. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
All domestic factors are lagged by 1 period.

Table 2-9 Determinants of gross capital inflow (Portfolio Debt Flow), 1990-2011

Estimation for debt flow	Quantile Regression (Quantiles)			
	20th	40th	60th	80th
(1)	(2)	(3)	(4)	(5)
Lagged gross capital inflow	0.41***	0.815***	1.09***	1.18***
	(0.057)	(0.128)	(0.106)	(0.085)
External Factors				
World interest rate	0.238*	0.171	0.213	0.230
(US real interest rate, %)	(0.136)	(0.110)	(0.186)	(0.299)
Global Liquidity	-0.010***	-0.009***	-0.007***	-0.011***
(TED spread, bps)	(0.002)	(0.003)	(0.002)	(0.003)
Global Risk Aversion	0.005	0.004	0.009	-0.002
(VIX)	(0.010)	(0.007)	(0.008)	(0.018)
Global growth rate	0.036	-0.038	-0.139**	-0.239**
(advanced economies, %)	(0.054)	(0.042)	(0.064)	(0.118)
Contagion factor	-0.010	0.005	0.023	0.022
	(0.021)	(0.018)	(0.017)	(0.038)
Domestic Factors				
Domestic real interest rate	0.009**	0.005	0.004	0.011
(in %)	(0.004)	(0.009)	(0.007)	(0.021)
REER deviation from trend	-0.005	-0.007	-0.010	-0.002
	(0.007)	(0.008)	(0.006)	(0.009)
Exchange rate regime	-0.007	0.019	0.004	-0.018
	(0.022)	(0.014)	(0.016)	(0.035)
Real domestic growth rate	0.019	0.017	-0.014*	-0.089**
	(0.018)	(0.018)	(0.020)	(0.035)
Institutional quality index	-0.155	-0.101	-0.033	0.054
	(0.129)	(0.064)	(0.080)	(0.196)
Current account balance	-0.011	0.002	-0.001	-0.006
(% GDP)	(0.012)	(0.006)	(0.015)	(0.023)
GDP per capita (in logs)	0.085	0.059	0.094	0.209
	(0.095)	(0.051)	(0.063)	(0.166)
Public debt	-0.008*	-0.002	0.001	0.003
(% GDP)	(0.004)	(0.002)	(0.003)	(0.004)
Bank credit to private sector	0.098	0.068	-0.023	0.112
(% GDP)	(0.074)	(0.051)	(0.098)	(0.162)
Domestic inflation rate	-0.001	-0.003***	-0.003***	-0.005*
	(0.002)	(0.001)	(0.001)	(0.003)
Trade openness	-0.002	-0.001	0.003	0.008
	(0.003)	(0.002)	(0.003)	(0.005)
Financial openness	0.042	0.023	-0.037	-0.033
	(0.060)	(0.033)	(0.040)	(0.089)
Observations	685	685	685	685

Notes: The dependent variable is gross private capital flow relative to GDP. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
All domestic factors are lagged by 1 period.

Table 2-10 Determinants of gross capital inflow (Portfolio Equity Flow), 1990-2011

Estimation for equity flow	Quantile Regression (Quantiles)			
	20th	40th	60th	80th
(1)	(2)	(3)	(4)	(5)
Lagged gross capital inflow	-0.21	0.245***	1.06***	1.980***
	(0.196)	(0.074)	(0.103)	(0.028)
External Factors				
World interest rate	0.195***	0.142**	0.132**	0.299*
(US real interest rate, %)	(0.072)	(0.057)	(0.060)	(0.171)
Global Liquidity	-0.004***	-0.002**	-0.002**	-0.002
(TED spread, bps)	(0.001)	(0.001)	(0.001)	(0.002)
Global Risk Aversion	-0.003	-0.003	0.003	0.005
(VIX)	(0.005)	(0.004)	(0.003)	(0.008)
Global growth rate	0.010	0.006	-0.021	-0.128**
(advanced economies, %)	(0.021)	(0.010)	(0.016)	(0.060)
Contagion factor	0.005	0.003	0.007	-0.009
	(0.012)	(0.009)	(0.007)	(0.013)
Domestic Factors				
Domestic real interest rate	0.000	0.000	0.000	0.001
(in %)	(0.004)	(0.004)	(0.001)	(0.005)
REER deviation from trend	-0.004*	-0.003	-0.004	-0.002
	(0.002)	(0.002)	(0.003)	(0.008)
Exchange rate regime	0.006	0.012*	0.003	0.022
	(0.009)	(0.007)	(0.007)	(0.020)
Real domestic growth rate	0.013	0.007	-0.001	-0.006
	(0.009)	(0.006)	(0.005)	(0.016)
Institutional quality index	0.048	0.012	-0.014	-0.055
	(0.048)	(0.039)	(0.035)	(0.086)
Current account balance	-0.009	-0.001	0.004	0.023**
(% GDP)	(0.006)	(0.004)	(0.004)	(0.011)
GDP per capita (in logs)	0.005	-0.022	-0.010	-0.007
	(0.040)	(0.031)	(0.027)	(0.077)
Public debt	-0.002	0.000	0.000	0.003
(% GDP)	(0.002)	(0.001)	(0.001)	(0.002)
Bank credit to private sector	-0.001	0.057	0.061*	0.199**
(% GDP)	(0.051)	(0.039)	(0.033)	(0.088)
Domestic inflation rate	0.000	0.000	-0.001**	-0.001**
	(0.001)	(0.000)	(0.000)	(0.001)
Trade openness	-0.004***	0.000	0.001	0.006**
	(0.001)	(0.001)	(0.002)	(0.003)
Financial openness	-0.029	-0.010	0.001	0.036
	(0.020)	(0.012)	(0.015)	(0.033)
Observations	578	578	578	578

Notes: The dependent variable is gross private capital flow relative to GDP. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
All domestic factors are lagged by 1 period.

Table 2-11 Determinants of gross capital inflow (Bank Flow), 1990-2011

Estimation for bank flow	Quantile Regression (Quantiles)			
	20th	40th	60th	80th
	(2)	(3)	(4)	(5)
Lagged gross capital inflow	-0.81***	-0.58*	-0.345***	-0.1
	(0.0237)	(0.312)	(0.030)	(0.083)
External Factors				
World interest rate (US real interest rate, %)	-0.580**	-0.232	-0.230	-0.616**
	(0.247)	(0.181)	(0.272)	(0.295)
Global Liquidity (TED spread, bps)	0.003	0.003	0.003	0.006
	(0.003)	(0.003)	(0.005)	(0.007)
Global Risk Aversion (VIX)	-0.051**	-0.057***	-0.051**	-0.073**
	(0.023)	(0.015)	(0.022)	(0.028)
Global growth rate (advanced economies, %)	0.031	-0.010	-0.001	0.039
	(0.099)	(0.063)	(0.073)	(0.107)
Contagion factor	0.067*	0.067	0.093	0.107
	(0.040)	(0.057)	(0.067)	(0.082)
Domestic Factors				
Domestic real interest rate (in %)	0.006	0.007	0.006	0.008
	(0.012)	(0.019)	(0.022)	(0.018)
REER deviation from trend	-0.001	-0.002	-0.006	0.002
	(0.005)	(0.005)	(0.005)	(0.009)
Exchange rate regime	0.005	-0.055	-0.092*	-0.155
	(0.044)	(0.035)	(0.050)	(0.098)
Real domestic growth rate	0.155***	0.097***	0.080**	0.081
	(0.052)	(0.030)	(0.033)	(0.055)
Institutional quality index	0.044	-0.026	-0.055	-0.295
	(0.223)	(0.141)	(0.171)	(0.491)
Current account balance (% GDP)	-0.063**	-0.048*	-0.056**	-0.051
	(0.027)	(0.027)	(0.024)	(0.035)
GDP per capita (in logs)	0.021	0.165	0.236	0.394
	(0.200)	(0.139)	(0.185)	(0.394)
Public debt (% GDP)	-0.002	-0.005	-0.008*	-0.010
	(0.005)	(0.003)	(0.004)	(0.007)
Bank credit to private sector (% GDP)	-0.310	-0.114	-0.120	0.334
	(0.239)	(0.141)	(0.184)	(0.292)
Domestic inflation rate	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)
Trade openness	-0.002	0.005	0.010*	0.014*
	(0.006)	(0.005)	(0.006)	(0.008)
Financial openness	-0.050	0.102	0.191	0.398
	(0.108)	(0.087)	(0.144)	(0.281)
Observations	803	803	803	803

Notes: The dependent variable is gross private capital flow relative to GDP. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
All domestic factors are lagged by 1 period.

Table 2-12 Fixed effect estimate of capital flow (Level)

	(1) Full specification
Lagged gross capital inflow	0.359***
	(0.065)
World interest rate (US real interest rate, %)	0.119
	(0.425)
Domestic real interest rate (in %)	-0.001
	(0.009)
REER deviation from trend	-0.034*
	(0.020)
Global Liquidity (TED spread, bps)	0.011
	(0.012)
`Global growth rate (Advanced economies, %)	0.456
	(0.287)
Global risk appetite (VIX)	-0.087
	(0.065)
Contagion factor	0.473**
	(0.215)
Real domestic growth rate	0.170***
	(0.062)
Institutional quality index	-0.691
	(0.844)
Exchange rate regime	0.055
	(0.086)
Current account balance (% GDP)	-0.130**
	(0.055)
GDP per capita (in logs)	4.798**
	(1.928)
Public debt (% GDP)	0.008
	(0.019)
Bank credit to private sector (% GDP)	-1.206
	(0.801)
Domestic inflation rate	-0.001
	(0.001)
Trade openness	-0.001
	(0.025)
Financial openness	0.786**
	(0.360)
R-squared	0.287
Observations	872

Standard errors in parentheses
Notes: The depedent variable is gross private capital flow relative to GDP. Standard errors are clustered by countries.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2-13 Quantile regression (Koenker and Bassett, 1978) estimate of capital flow (Level)

	(1)	(2)	(3)	(4)
Quantiles	20th	40th	60th	80th
Lagged gross capital inflow	0.343***	0.558***	0.729***	0.849***
	(0.049)	(0.048)	(0.040)	(0.047)
Push Factors				
World interest rate (US real interest rate, %)	-1.502***	-0.671**	0.047	0.543
	(0.314)	(0.272)	(0.274)	(0.413)
Domestic real interest rate (in %)	0.003	-0.008**	-0.015***	-0.016***
	(0.004)	(0.003)	(0.004)	(0.005)
REER deviation from trend	0.787***	0.459***	0.226**	0.185
	(0.155)	(0.128)	(0.100)	(0.132)
Global Liquidity (TED spread, bps)	-0.070***	-0.057***	-0.062**	-0.087***
	(0.027)	(0.019)	(0.025)	(0.025)
`Global growth rate (Advanced economies, %)	0.190***	0.238***	0.216***	0.192***
	(0.052)	(0.042)	(0.037)	(0.057)
Global risk appetite (VIX)	0.021	0.023	0.017	0.020
	(0.037)	(0.027)	(0.092)	(0.075)
Contagion factor	-0.015	-0.009	-0.021**	-0.037
	(0.010)	(0.010)	(0.008)	(0.036)
Pull Factors				
Real domestic growth rate	0.158***	0.101***	0.066**	-0.015
	(0.040)	(0.031)	(0.031)	(0.057)
Institutional quality index	0.660***	0.404**	0.066	-0.160
	(0.228)	(0.187)	(0.230)	(0.277)
Exchange rate regime	-0.025	-0.072**	-0.000	-0.067
	(0.039)	(0.035)	(0.034)	(0.069)
Current account balance (% GDP)	-0.109***	-0.051*	-0.020	-0.024
	(0.036)	(0.026)	(0.023)	(0.038)
GDP per capita (in logs)	-0.019	0.209	0.328*	0.905***
	(0.205)	(0.164)	(0.192)	(0.262)
Public debt (% GDP)	-0.010**	-0.006	-0.000	0.014**
	(0.004)	(0.004)	(0.003)	(0.006)
Bank credit to private sector (% GDP)	-0.442**	-0.098	0.188	0.686***
	(0.178)	(0.173)	(0.159)	(0.144)
Domestic inflation rate	-0.000	0.000	0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.013)
Trade openness	-0.011*	0.002	0.011**	0.022***
	(0.007)	(0.005)	(0.005)	(0.008)
Financial openness	0.011	-0.135	0.071	-0.034
	(0.104)	(0.084)	(0.102)	(0.122)
Pesudo R2	0.180	0.240	0.313	0.400
Observations	872	872	872	872

(Robust) standard errors in parentheses

Notes: The depedent variable is gross private capital flow relative to GDP.

* p < 0.10, ** p < 0.05, *** p < 0.01

Table 2-14 Country distribution of gross capital inflow

Panel (a) Statistics of Gross Inflows over the whole Sample

Percentiles	20%	40%	60%	80%
Gross inflows (% of GDP)	1.795	3.981	6.237	10.147

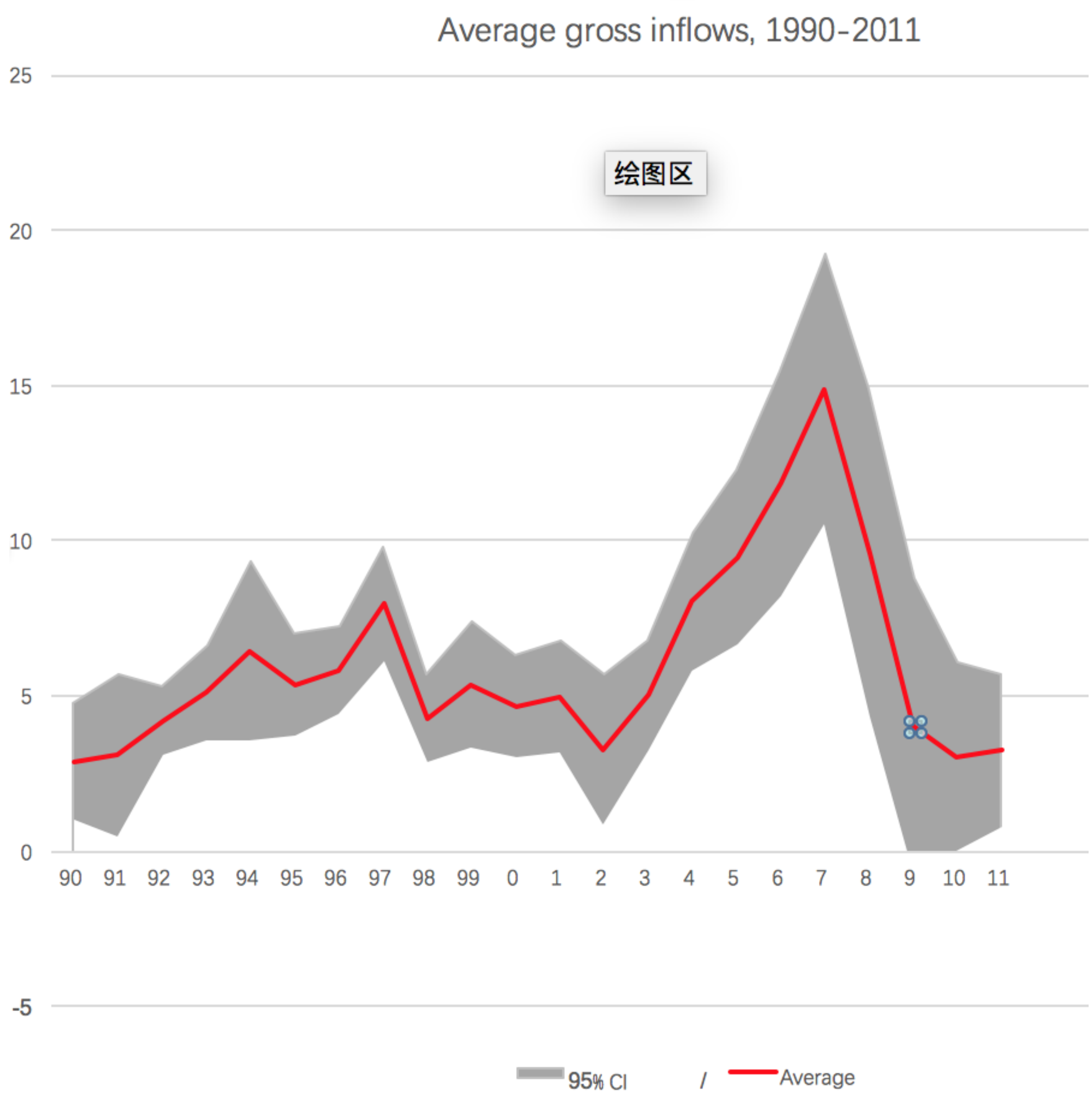
Panel (b) Country-specific Statistics

Countries	Mean	Std
Asia		
China	3.886	2.336
India	2.505	1.866
Indonesia	1.028	4.419
Malaysia	5.001	5.413
Thailand	3.952	7.176
Latin America		
Argentina	2.228	5.715
Brazil	2.757	3.401
Colombia	3.988	2.875
Mexico	3.273	3.770
Peru	4.314	4.721
East Europe		
Belarus	5.143	3.672
Czech	8.680	3.598
Hungary	9.376	16.830
Poland	5.798	4.351
Slovenia	7.000	5.826
Whole Sample	6.720	10.803

Table 2-15 Variance Inflation Factors (VIF) test of Multicollinearity

Variables	VIF
Global Factors	
World interest rate (US real interest rate, %)	1.24
Global Liquidity (TED spread, bps)	1.14
Global Risk Aversion (VIX)	1.70
Global growth rate (advanced economies, %)	1.64
Contagion factor	1.35
Domestic Factors	
Domestic real interest rate (in %)	1.50
REER deviation from trend	1.49
Exchange rate regime	1.30
Real domestic growth rate	1.24
Institutional quality index	1.98
Current account balance (% GDP)	1.37
GDP per capita (in logs)	2.05
Public debt (% GDP)	1.25
Bank credit to private sector (% GDP)	1.38
Domestic inflation rate	1.02
Trade openness	1.18
Financial openness	1.33
Mean VIF	1.42

Figure 2-3 Time Distribution of Gross Inflows



Chapter 3 Episodes of Exuberance in Emerging Stock Markets and International Short-term Capital Flows

Abstract

This paper investigates evidence of rational bubbles in a number of emerging stock markets and its association with international short-term flows (portfolio and bank flows). We adopt the generalized supremum Augmented Dickey-Fuller (*GSADF*) test of Phillips et al. (2015), to detect explosive time series from stock prices collected from MSCI. Our results suggest evidence of bubbles across a broad range of EMEs before the onset of the global financial crisis. Moreover, we show that the timeline of these bubbles was in line with the boom and bust of speculative capital flows towards EMEs. We further use a probit model and show that the occurrence of bubbles was significantly associated with international equity flows. For policy makers, this link might call for policy tools such as capital control to limit financial exuberance's transmission channel through portfolio equity flows. Moreover, our study can serve as a tool to monitor global financial over-heating in real time.

JEL Classification: C22, G12, G15, F34

KEY WORDS: Emerging Equity Markets, Rational bubbles, International Capital Flows.

"Emerging markets economies (EMEs) are plagued by episodes of bubble-like dynamics. These episodes begin with a 'bubble' phase where credit, investment, asset prices, and capital flows, all grow, and end with a bust phase when these variables collapse." (Caballero and Krishnamurthy, 2006)

3.1 Introduction

Although EMEs process significant growth potential, their financial underdevelopment usually results in a shortage of stores of values, which in turn becomes a key element for bubble formation (Caballero and Krishnamurthy, 2006). Historically, bubble-like dynamics were prevalent in EMEs—remarkable examples are debt crisis among Latin American countries in the 1980s, the Asian financial crisis in the middle 1990s, and the recent global financial crisis (GFC) in the late 2000s.This paper tries to examine the presence of bubbles in the *emerging stock markets* during the 2000s for the following reasons.

First, the boom and bust of emerging equity markets was particularly impressive in the 2000s. Bartram and Bodnar (2009) report that the stock prices in emerging markets went up sharply in 2007, but dropped even more than developed markets in 2008. In particular, emerging markets' portfolio experienced a significant rise in 2007 (up 43.6%) and stayed up around the same level through June 2008. However, at the end of 2008, prices collapsed (down 54.4%) which led to a more than $5.2 trillion loss since the market peaked in late 2007, and 45.9% of this decline occurred in the 31-day crisis period. Therefore, this dramatic boom and bust calls for a formal investigation of bubbles.

Second, the global financial market was significantly integrated in the last decade. Milesi-Ferretti and Tille (2011) report that gross capital flows, which represents the most prominent form of international financial integration, increased dramatically from less than 7% of the world GDP in 1998 to over 20% in 2007. This increasing financial linkage provides a possibility of simultaneous bubbles across different countries.

Third, short-term speculative capital flows (portfolio equity flows, portfolio debt flows and bank flows),[19] namely "short-term flows", were particularly active in

[19] We choose to focus on these short-term flows rather than foreign direct investment (FDI) because they are more likely to contribute to transmitting financial exuberance: theoretically, Foreign direct investment (FDI) could

the 2000s; for example, Fuertes et al. (2016) find that both portfolio flows and bank-credit flows were 'flooded' with reversible and temporary components in the 2000s. On the other hand, numerous studies have shown that the rushing in of such flows into an emerging economy gives rise to "asset bubbles" (Calvo 2011; Korinek, 2011). Take equity flows for instance, Froot and Ramadorai (2008) argue that foreign equity investors can generate movements in equity returns that are unrelated to underlying fundamentals: some of their trading patterns (e.g., positive feedback trading) can temporarily soak the available liquidity of an available asset, and thereby push up its asset price away from its fundamental value—such a disconnection is theoretically associated with the presence of rational bubbles, which we will show later in this paper. As for bank flows, Bruno and Shin (2015) formulate a model of international banking system that transmits financial conditions across borders through banking sector flows; this channel has been supported by a considerable amount of literature empirically (e.g., Cetorelli and Goldberg, 2011, 2012a, 2012b; Buch and Goldberg, 2015; Yan et al., 2016). Therefore, it would be interesting to empirically investigate whether these speculative capital flows contributed to the surge of speculative bubbles (if there were any).

These discussions lead to our key research questions: were there bubbles among EMEs before the GFC? More importantly, given the fact that global financial markets had significantly integrated through increasing international capital flows during the last decade, would the bubbles appear pervasive across different equity markets if they were detected? Moreover, were short-term capital flows associated with bubbles?

To answer these questions, we empirically investigate the performance of stock markets among EMEs. Although Calvo (2011) argues that asset bubbles might typically exist in the real estate sectors for EMEs, their data are not generally available. In contrast, our database collected from MSCI offers a comprehensive panel

be less volatile, speculative and disruptive, because it brings resources, technology, access to markets, valuable training, an improvement in human capital and among others (Stiglitzs, 2000); empirically, Jeanne et al. (2010) shows that FDI to EMEs was significantly more stable compared to short-term flows during the 2000s.

of stock prices for 22 EMEs, and thereby enables us to detect bubbles for a wide range of countries and regions.[20]

To achieve this goal, we follow Philips et al. (2011) by defining financial exuberance in a time series context as explosive autoregression behaviour. Among the available explanations of explosiveness in economic variables, the most prominent ones could be the rational bubble models (See, e.g., Blanchard, 1979; Blanchard and Watson, 1982; and Engsted, 2015). Such theories suggest that if rational bubbles were present in prices, they should display explosive time series characteristics that are not inherited from fundamentals.

To empirically detect explosive behaviour in stock prices, we primarily rely on the recent recursive Augmented Dickey-Fuller (ADF) procedure proposed by Philips et al. (2015). It is based on a repeated estimation of the right-tail variation of a standard ADF test on a forward expanding sample sequence with the alternative hypothesis of a mildly explosive process. The test statistic is obtained as the sup value of the corresponding ADF sequence. This procedure owns significant advantages over the conventional rational bubble tests: first, it possesses discriminatory power whenever bubbles are periodically collapsing and multiple, in which case standard methods such as unit root or co-integration tests perform poorly.[21] Second, it allows the researchers to date-stamp the beginning and termination of the episodes of exuberance. Third, this procedure could act as an *ex-ante* (or anticipative) as an early warning system, for it enables us to use data up to the point of analysis for ongoing assessment—this feature could be of particular interest to both market anticipates and regulators.

Following this empirical methodology, we find a strong evidence of financial exuberance across a broad range of EMEs synchronously. There was no precedent of such a global overheating, nor do we have such a sign in real time. In particular, our date-stamping strategy based on the Philips et al. (2015) suggests an interesting timeline: evidence of exuberance appeared among several Emerging European and

[20] We also report our results based on a MSCI index measuring the overall performance of emerging equity markets. See section 4 for more discussions.

[21] See Homm and Breitung (2012) for an empirical survey comparing the power properties of several rational bubble tests.

Latin American countries in late 2003, and then became pervasive across a considerable amount of EMEs after late 2005. This synchronization peaked in 2007, such that 15 out of 22 emerging stock markets in our database were in a “bubble stage”; such observations could have functioned as a strong warning of global overheating. Nevertheless, almost all explosive prices collapsed synchronously before September 2008, in which Lehman Brother declared bankruptcy.

We further show that the chronology of this synchronization was in line with the boom and bust of short-term capital flows towards EMEs. Based on such an observation, we use a pooled probit model to investigate the in-sample predictability of each speculative flow (equity, debt and bank flow). In line with the recent literature (e.g, Raddatz and Schmukler, 2012; Puy, 2016), we find that both equity and bank flow are significantly associated with the occurrence of bubbles. Nevertheless, equity flows appear more significant, especially conditional of episodes when bubbles had already become pervasive.

Therefore, this paper contributes to several main strands of literature. Firstly, this study extends the analysis of global financial exuberance to emerging markets. A recent paper, Pavlidis et al. (2015) investigates evidence of bubbles in the global housing markets (mainly from advanced economies). Interestingly, they find a similar chronology of exuberance: the boom in the U.S. housing market spread out to the other (mainly advanced) countries after 2003, and this synchronization also collapsed before the onset of GFC. This study finds similar observations even in the emerging stock markets, which might be somehow unexpected; for the literature (e.g., Milesi-Ferretti and Tille, 2011) argues that EMEs’ exposure to global financial risk was modest before the GFC. Nevertheless, this paper complements the findings of Pavlidis et al. (2015) by showing that the financial-overheating was global—even shown in EMEs.

Secondly, this study complements the prolific literature of international capital flows by associating them with bubbles. A recently popular research question is how international investors propagate financial shocks across borders. The literature mainly identifies three channels: a) transmission through bank flows (e.g., Cetorelli and Goldberg, 2012; Bruno and Shin, 2015; and Yan et al., 2016); b) through portfolio equity flows (e.g., Broner et al., 2006; Jotikasthira et al., 2012; Raddatz and

Schmukler, 2012; and Puy, 2016); and c) through portfolio debt flows (e.g., Milesi-Ferretti and Tille, 2011). Our paper shows that in the context of bubbles, both equity and bank flows were significant, and this conclusion is in line with the literature. However, conditional on the situation that bubbles had already become pervasive in the EMEs, equity flow seemed to play a more significant role.

Thirdly, we apply the state-of-the-art bubble-detecting technique of Phillips et al. (2015); such an application yields several new insights—e.g., when the bubbles became pervasive across different EMEs and how they were connected to the global financial exuberance then. Furthermore, since the observation of global overheating may happen again in the future, our study serves to monitor global financial exuberance and functions as an early warning mechanism useful to both market participants and regulators in real time.

The rest of the paper is organized as follows: Section 2 outlines a standard stock price determination model, and documents how explosive time series characteristics that are closely linked to the presence of rational bubbles may arise. Section 3 provides a detailed description of our empirical methodology primarily based on Philips et al. (2015). Section 4 presents our empirical findings and Section 5 concludes.

3.2 Rational Bubbles in Stock Markets

The concept of rational bubbles can be modelled with present value theory of finance, which suggests that fundamental asset prices are determined by the stream of present values of expected future fundamentals (e.g., dividends for stock markets). Assuming risk neutrality and a constant expected return on an alternative investment opportunity,[22] rearranging the no-arbitrage condition yields the standard model of stock price determination:

$$P_t = \frac{1}{1+R} E_t(P_{t+1} + D_{t+1}), \tag{1}$$

where $R > 0$ is the ex-ante one-period return, P_t is the (ex-dividend) stock price, and D_t is the dividends. Moreover, E_t is the conditional expectation operation based on all

[22] Assuming a time-varying return rate does not change the implication of submartingale (explosive) behaviour that is linked to the presence of bubbles given in (5), but complicates the analysis of the rational bubble solution (Philips et al., 2011). Hence, that is not our pursuit here.

information available up to time t. Overall, equation (1) implies that current stock price, P_t, is determined by the present value of its expected future dividends, D_{t+1} and its re-sale value, P_{t+1}.

Recursively solving equation (1) T periods forward, stock price (P_t) can be shown as:

$$P_t = \varepsilon_t \left[\sum_{i=1}^{T} \left(\frac{1}{1+r}\right)^i D_{t+i}\right] + \varepsilon_t[\left(\frac{1}{1+r}\right)^T P_{t+T}] \, . \quad (2)$$

Equation (2) shows that stock price includes: a) a stream of discounted dividends up to time *T*, and b) present value of the re-sale price at time *t+T*.

Applying the transversality condition when *T* goes to infinity yields:

$$\lim_{T \Rightarrow \infty} \varepsilon_t[\left(\frac{1}{1+r}\right)^T P_{t+T}] < \infty, \quad (3)$$

then the no-bubble solution, P_t^*, which could be referred as the fundamental value of stock prices, can be written as:

$$P_t^* = \varepsilon_t \left[\sum_{i=1}^{\infty} \left(\frac{1}{1+r}\right)^i D_{t+i}\right]. \quad (4)$$

Equation (4) suggests that the fundamental component of stock price is the stream of expected dividends $E_t D_{t+i}$ for all $i \geq 1$.

When the transversality condition in (3) is not imposed, the bubble component in stock price emerges. In that case, stock price is not only determined by its fundamental value, P_t^*, but also by a nonstationary process as:

$$P_t = P_t^* + (1+r)^t b_t. \quad (5)$$

In particular, the martingale process b_t in Equation (5) leads to explosiveness in stock prices P_t regarding its time series properties (Diba and Grossman, 1988): defining the non-stationary component in (5) as $B_t = (1+r)^t b_t$, its explosive behaviour can be shown by

$$E_t(B_{t+1}) = (1+r)B_t, \quad (6)$$

as c_t is a martingale and $r>0$. Furthermore, B_t is usually characterized as the rational bubble term, for investors might expect B_t to be growing at a constant rate r (as shown in Equation 6), even if the bubble term's presence leads to a disconnection between stock price P_t and its fundamental value P_t^*. Indeed, this is profitable as long as investors sell their stocks before the bubble busts, even if B_t constantly drives up future stock price. What is more, the popularity of this belief among investors can increase stock prices, which further confirms the expectation of future price increase as a self-fulfilling prophecy, regardless of the fundamental values (Engsted and Nielsen, 2012; Pavlidis et al., 2015).

The disconnection between stock price P_t and its fundamental component P_t^* due to the presence of rational bubble B_t can be more clearly seen if we rearrange equation (5) as:

$$B_t = P_t - P_t^*. \tag{7}$$

Therefore, if $B_t = 0$ we might conclude there is no bubble in stock price—stock prices reflect the fundamental value P_t^* only, which is ultimately determined by the discounted fundamentals (dividends) only (Philips et al., 2011). In this case, stock prices should not display any explosive behaviour, since it is difficult to argue for explosiveness in expected dividends (Engsted, 2015). On the other hand, the presence of bubble, $B_t > 0$, gives rise to explosiveness in stock prices P_t. In that case, the presence of B_t will shift stock price from *I(1)* (regarding its time series characteristics) to an explosive regime. Based on such theoretical discussions, we present our empirical methodology to detect this change or regime—which is highly likely due to the presence of rational bubble—in our next section.

3.3 Empirical Methods

In order to detect the explosive behaviour in stock price that is linked to the presence of rational bubble, we employ the generalized recursive Augmented Dickey-Fuller (ADF) unit root test recently proposed by Phillips et al. (2015), which owns significant advantages compared to conventional rational bubble tests. First, it presents discriminatory power in detecting periodically collapsing bubbles, to which traditional ADF test and the associated co-integration studies have extremely low power (Evans, 1991). Second, it generalizes the earlier version of sup ADF test (Phillips et al., 2011), and thereby allows us to detect multiple bubbles, which might be more typical for volatile stock prices. Third, it provides a consistent date-stamping strategy for the origination and termination of multiple bubbles in real time, which could be of particular interest to policy makers.

To formally present this method, we start with the standard Augmented Dickey-Fuller (ADF) regression shown as:

$$\Delta y_t = \alpha_{r_1,r_2} + \beta_{r_1,r_2} y_{t-1} + \sum_{i=1}^{k} \psi_{r_1,r_2}^{i} \Delta y_{t-i} + \varepsilon_t, \varepsilon_t \sim NID(0, \sigma_{r_1,r_2}^2), \tag{8}$$

where y_t represents stock prices in this study, Δ is the difference operator, k is the maximum number of lag in our specification, and ε_t is the error term. Based on this model, Philips et al. (2011) suggests a recursive implementation on a forward expanding sample sequence to more effectively detect bubbles especially when it is periodically collapsing. Formally, for a subsample that starts from the r_1^{th} fraction of the total sample (T) and ends at the r_2^{th} fraction, the estimated coefficient β_{r_1,r_2} for y_{t-1} (as shown in Equation 8) is of particular interest, and denote its test statistic as:[23]

$$ADF_{r_1}^{r_2} = \frac{\hat{\beta}_{r_1,r_2}}{s.e.(\hat{\beta}_{r_1,r_2})}. \tag{9}$$

As discussed in the preceding section, the emergence of a bubble could shift the stock price series from a random walk to an explosive process. Therefore, our empirical strategy aims to detect explosiveness by rejecting the null hypothesis of a unit root in y_t, $H_0: \beta_{r_1,r_2} = 0$, against the alternative of mildly explosive behaviour, $H_1: \beta_{r_1,r_2} > 0$. The test statistics is obtained as the sup value of the corresponding ADF statistic sequence estimated from each subsample. Formally, fixing the starting point r_0 of the sample sequence at 0 and increasing the end point r_2 from r_0 (the minimum window size) to 1, the test statistic (namely *PWY* or *SADF* test) is defined as:

$$SADF(r_0) = \sup_{r_2 \in [r_0, 1]} ADF_0^{r_2}. \tag{10}$$

[23] This test statistics is identical to that of standard ADF test when $r_1 = 0$ and $r_2 = 1$.

The disadvantage of *SADF* test is its poor power to detect multiple bubbles in the sample. To solve this problem, Philips et al. (2015) propose a *general* version of *SADF* (*GSADF*) test by allowing the starting point $r_1$to vary within a feasible range, i.e., $[0, r_1]$. To formally present this idea, we define the *GSADF* test statistics as the sup value of *ADF* statistic sequence obtained from this double recursion over all feasible ranges of r_1 and r_2, formally shown as:

$$GSADF(r_0) = \sup_{r_1 \in [0, r_2 - r_1],\ r_2 \in [r_0, 1]} ADF_0^{r_2}. \tag{11}$$

Equation (11) shows that rejecting the null hypothesis (that is, unit root) of *GSADF* test suggests the evidence of explosiveness.

Furthermore, as policy makers may be even more interested to pin down the start and end of bubbles, Philips et al. (2015) suggest a date-stamping algorithm based on backward sup *ADF* statistics defined as:

$$BSADF_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} BADF_{r_1}^{r_2}, \tag{12}$$

Where the end point of each subsample is fixed at r_2 and the starting point varies from 0 to $r_2 - r_0$. In this case, the starting of a bubble is defined as the first observation that *BSADF* statistic exceeds its critical value, which is shown as:

$$\widehat{r_e} = \underset{r_2 \in [r_0, 1]}{inf} \{r_2 \colon BSADF_{r_2}(r_0) > scu_{r_2}^{\alpha}\}. \tag{13}$$

Similarly, the end is identified as the first observation of $\widehat{r_e}$ that falls below the critical value:

$$\widehat{r_f} = \underset{r_2 \in [\widehat{r_e}, 1]}{inf} \{r_2 \colon BSADF_{r_2}(r_0) < scu_{r_2}^{\alpha}\}, \tag{14}$$

where the critical value, $scu_{r_2,}^{\alpha}$ is the $100(1 - \alpha)\%$ critical value of the *GSADF* test based on the selected subsample with $[r_2 T]$ observations, and α is the chosen significant level, i.e., 5%.

As for other technical details, first, researchers can choose a minimal duration period (e.g., by $\log(T)$ where T denotes the sample size) to exclude occasional episodes of explosiveness. Second, finite sample critical values of *SADF*, *BSADF* and *GSADF* test statistics are generated by Monte Carlo simulations, as the their limit distributions are non-standard and depend on the minimum window size. Third, we follow Philips et al. (2015) by choosing the minimum size, r_0 equal to 36 observations. Moreover, we set the autoregressive lag length $k=4$ such that the computational cost of estimation could be reduced (Pavlidis et al., 2015).[24]

3.4 Empirical Findings

3.4.1 Data

We collect Morgan Stanley Capital International data (MSCI) through Bloomberg, which provides us with a broad coverage of major EMEs. Our sample includes 22 emerging countries, together with an overall index: MSCI emerging markets index; [25] our sample covers the period from January 1995 to December 2015.[26] We collect monthly observations on price index in order to investigate the presence of rational bubbles. Since all data are measured in U.S. dollars, we deflate each price series by U.S. Consumer Price Index (CPI), which is obtained from the Federal Reserve Bank of St. Louis, in order to avoid money illusion.

Notice that data for fundamentals (dividends) are missing in our sample, because we are not confident to use these EMEs' dividends' data. We suspect that there might be a problem of misreporting, for we could observe a considerable amount of zero dividends for some countries. For example, Pakistan's dividends data start with January 1995, but it shows a series of zeros between November 1996 and May 1998—it might be unlikely for a whole nation to experience zero dividends for such a long time. For this reason, we use data of prices only. We fully acknowledge the limitations of this study as a consequence of missing dividends' data: explosiveness (if detected) may be inherited from dividends. Nevertheless, as Engsted (2015) suggests, it might be difficult to argue for explosiveness in dividends: first, the literature usually assumes that dividends follow a random walk with drift (e.g., Homm

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[24] Besides computational burdens, more sophisticated lag length selection procedures might also own other disadvantages (see Philips et al., 2015 for more technical discussions).

[25] To enlarge our sample, we choose as many countries as possible from both the MSCI Emerging and Frontier Markets groups. Nevertheless, a number of countries are dropped for the following reasons: first, some countries (e.g., Qatar, UAE, and so forth) are not chosen because of their small sample sizes, which would hinder us from conducting the recursive ADF test. Second, Greece, Taiwan and South Korea are excluded because of the controversy of classifying them as EMEs.

[26] We choose to start from January, 1995 mainly because data for countries such as Czech, Hungary and so forth is unavailable before this date.

and Breitung, 2012); second, a considerable number of empirical studies investigating other markets find no evidence of explosiveness in dividends (e.g., Engsted, 2006; Phillips et al., 2011; and Engsted and Nielson, 2012).

<insert Figure 3.1 here>

Figure 3.1 displays the time series trajectories of MSCI emerging market real price index. It shows that the stock prices in EMEs have been generally volatile during the past two decades, and the bubble-like dynamic during the mid-2000s was most outstanding. In particular, the first bubble-like dynamics occurred around 1999, reaching its peak in 2000, at which the dot.com bubble was present in the U.S. (Philips et al., 2011). Moreover, the boom-and-bust that emerged in the early 2000s appeared much more sustained and volatile: stock prices increased sharply after 2003, but it was after September 2008 when they started to collapse. Although stock prices revived after 2009, their trajectories no longer display such a noticeable bubble-like dynamic observed before the crisis. Such an observation motivates our interest to test the presence of rational bubbles using method of Philips et al. (2015).

3.4.2 Financial Exuberance in the Emerging Stock Markets

3.4.2.1 MSCI Emerging Markets Index

<Insert Table 3.1 here>

We start our empirical investigation with MSCI Emerging market composite index to have an overview in the first place. Table 3.1 reports the empirical results of real stock prices based on the *GSADF* test of Philips et al. (2015). The test statistics is significant at 1%, suggesting that the prices have been explosive in our sample, which could be a strong indication of the presence of rational bubble (Engsted, 2015).

From a policy perspective, it may be more important to date-stamp the periods at which bubbles were present; we follow the algorithm proposed by Philips et al. (2015) and identify periods of explosiveness whenever the *BSADF* statistics exceed the 95% *GSADF* critical value sequence in the finite sample. In addition, we only define a bubble when the length of its explosive regime exceeds 3 months to exclude occasional explosive observations.[27]

[27] Following Philips et al. (2015), we set the minimum duration by *log (T)* where *T* is the sample size.

<Insert Figure 3.2 here>

Figure 3.2 displays the estimated *BSADF* statistics and 95% critical values. It shows a uniquely sustained period of explosiveness in 2007, which is associated with the peak of stock prices shown in Figure 3.1, shaded in orange areas. Indeed, a number of other studies also report this unusual boom: for example, Bartram and Bodnar (2009) find that emerging stock markets experienced a significant rise of 43.6% in 2007.

This period of explosive regime appeared in April 2007 and lasted until February 2008; this implies that the whole emerging market could be in a bubble stage during this period. On the other hand, the results in Figure 3.2 suggest that MSCI composite index has few other explosive regimes: the first group of observations occurred at the start of the sample, but they did not last long enough to form a bubble; Episodic explosiveness emerged again in January, 2006 but disappeared after April, 2006.

In summary, we may find evidence of rational bubbles in the overall emerging stock market—we detect explosive behaviours in MSCI emerging market composite price index, and we further date-stamp that bubbles occurred between April 2007 and February 2008. This bubble-like dynamic was unique, compared to other occasional explosive regimes that were all short-lived. Nevertheless, to have a more specific view of bubbles in emerging stock markets, we will investigate each individual market in the next section.

3.4.2.2 Individual countries

In what follows we present our empirical results for the 22 EMEs individually. Table 3.2 shows that 16 out of 22 EMEs' *GSADF* statistics are above 99% critical values, while the other two are higher than 95%. Hence, our empirical results signal a widespread explosiveness—which could be a strong indicator of the presence of rational bubbles (Engsted, 2015)—among these EMEs over the past two decades.

<Insert Table 3.2 and Figure 3.3 to3. 8 here>

Next, we date-stamp the timeline of such bubbles; Figure 3.3 displays the periods of financial exuberance for all countries in our sample.[28] In addition, through Figures 3.4 to 3.7, we also display the *BSADF* test statistics sequence against the critical values for each individual stock market.

As an overall picture, Figure 3.3 shows a concurrent episode of financial exuberance — which appeared after 2003 and peaked in 2007—among a large number of EMEs. The majority of these booms collapsed simultaneously before the onset of the recent global financial crisis (GFC) in late 2008. This synchronization had no precedents, nor could we observe any such phenomenon after 2008. Therefore, this finding echoes the result of our previous empirical investigation with the MSCI emerging markets composite index.

We now turn to the chronology of exuberance. Figure 3.3 shows that explosiveness hardly exists before 2003—only South Africa displayed explosiveness during June 1998 and December 1998. The surprising picture appeared in the middle 2000s: starting from late 2003, evidence of bubbles appeared in different continents—Latin America (e.g., Colombia and Peru), East Europe (e.g., Czech and Hungary) and Asia (e.g., Thailand). In 2004, some countries in the middle-east (e.g., Egypt and Jordan) also exhibited explosive behaviours.

Observations of financial exuberance became more pervasive after early 2006. More countries from Asia (e.g., India and Pakistan), Latin America (e.g., Argentina, Brazil, Chile and Mexico), East Europe (e.g., Poland and Russia), Middle-east (e.g., Morocco and Turkey), and Africa (e.g., South Africa) displayed explosive dynamics which lasted long enough to be identified as bubbles, as displayed in Figure 3.3. In fact, 15 out of 22 EMEs in our sample were in explosive regimes in early 2006. This is in line with our previous result on the composite index, which suggests an explosive period over the whole emerging market in early 2006. But explosiveness in a number of countries (e.g. India, Brazil, Turkey and South Africa) disappeared after early 2006, leading to a break of overall exuberance (shown as the red block in Figure 3).

[28] In Figure 4.3, we combine adjacent periods of exuberance when the length of gap between them is short than *log T*, that is, 3 months given our sample size.

Synchronous bubbles across different EMEs became most prominent in 2007—15 out of 22 countries displayed explosive behaviour in 2007. Although the "participation rate" (68%) is the same compared to the synchronization in early 2006, bubbles were much more sustained in 2007, for Figure 3.3 shows significantly less gaps of explosive episodes in 2007. This result also agrees with the findings based on the composite index, which suggests the presence of a bubble over the whole EMEs between April 2007 and February 2008.

Nevertheless, these bubbles collapsed simultaneously before the onset of the GFC in 2008. In particular, the date-stamping technology of Philips et al. (2015) suggests that the latest collapse happened in Brazil in August 2008. In other words, all bubbles disappeared before September 2008 when Lehman Brothers declared bankruptcy, which is generally acknowledged as the benchmark of the GFC's outbreak.

As a consequence of this global depression, the stock prices among EMEs stayed low during 2008-2009. The recent recovery from the GFC resurrected the stock prices, raising concerns of financial overheating again. Nevertheless, our findings shown in Figure 3.3 suggest that such worries might be somehow unnecessary, for by the end of 2014 we can detect explosiveness in Pakistan only—this is a much weaker evidence of overheating compared to that of the pre-crisis era.

In summary, our study identifies a synchronization of bubbles across a large number of EMEs during the mid- 2000s; this phenomenon has no precedent, nor could we observe such a synchronization after 2008. In particular, these simultaneous bubbles appeared in a few EMEs in late 2003, became pervasive after 2005, peaked in 2007 and collapsed in late 2008. This timeline echoes the finding of Pavlidis et al. (2015), which finds a similar chronology of financial exuberance in the global housing market: the boom in U.S. housing markets spread out to the other (mainly advanced) countries after 2003; such a synchronization of bubbles also collapsed before the onset of the GFC. Our study is a complement to Pavlidis et al. (2015) because it completes the picture of global overheating.[29]

[29] It would be ideal to investigate the emerging housing markets, but the availability of data is the constraint.

3.4.3 Synchronization of Bubbles and International Capital Flows

3.4.3.1 Stylized Facts and Main Results

The previous section reports an unusual synchronization of bubbles across the EMEs during the mid-2000s (before the onset of the global recession); this timing might be interesting because it happened when the global financial market was being significantly integrated. In particular, as we mentioned before, gross capital flows, which represents the most prominent form of international financial integration, dramatically increased from less than 7% of the world GDP in 1998 to over 20% in 2007 (Milesi-Ferretti and Tille, 2011). This increasing financial linkage could provide a transmission channel of financial exuberance; we, therefore, proceed to empirically investigate the link between bubbles detected in our sample and international capital flows.

<Insert Figure 3.9 here>

The lower panel of Figure 3.9 presents the annual average short-term capital flows relative to GDP towards the EMEs in our sample.[30] It shows that "short-term flows" to EMEs have been volatile since the early 2000s. More interestingly, their dynamics seem to associate with the boom and bust of their stock markets (as shown in the upper panel of Figure 3.9): in the early 2000s, the volume of short-term flows stayed low; there was no significant evidence of financial exuberance over the emerging stock market at the same time. Next, speculative flows increased by more than 1% of GDP in 2003, and then explosiveness emerged in some Latin American and East European countries. Thirdly, speculative flows kept on booming until 2007, and during the same period we also observe a jump of stock prices (as shown in the upper panel of Figure 3.9) and increasingly massive indications of bubbles across the EMEs (as shown in Figure 3.3). Finally, both short-term flows and stock market' exuberance collapsed in the late 2008.

Based on such an observation, we use a pooled probit model to more formerly investigate the association between short-term flows and the occurrence of bubbles. The model is:

[30] We exclude Argentina, Jordan, Morocco and Pakistan from this section's analysis because of problems of data availability.

$$\Pr(EXU_{i,t} = 1) = F(STF_{i,t-1}\beta), \tag{15}$$

where $EXU_{i,t}$ is a dummy taking the value of 1 if the country is identified as being in an explosive regime; $STF_{i,t}$ represents short-term capital flows: portfolio equity flow, portfolio debt flow, and bank flow. In addition, we focused on gross capital inflow dominated by foreign investors rather than net capital flows. Recent literature has shifted its focus from net flows to gross flows, and this concept has become increasingly significant in EMEs (Calderon and Kubota, 2013). The main reason is that observed sudden stops in net flows might result from portfolio diversification aboard by domestic agents, which is not necessarily consistent with the threat that domestic country loses its access to the international capital market. Therefore, focusing on gross inflows rather than net flows could lead to more accurate empirical results and better informed policy prescriptions (Rothenberg and Warnock, 2011).[31] Capital flows' data are collected from Bluedorn et al. (2013) and International Financial Statistics (IFS), and compute each type of flow as the sum of the last four quarters, because quarterly capital flows might be too noisy to be associated with bubble's occurrence. Subject to data availability, our sample covers quarterly observation from 1998 to 2011. Since the frequency of our empirical analysis in Section 3.4.2 is monthly, we convert monthly observations of exuberance into quarterly dummy variables with the value of 1 if at least two months within that quarter are in a bubble stage. When running our regressions, we include country dummy variables and use the Huber-White sandwich (robust)standard errors.

<Insert Table 3.3 here>

The results in Table 3.3 show the association between emerging stock markets' exuberance and the short-term capital flows. Firstly, portfolio equity flows have consistently shown significance: for example, results from Column 1 indicate that a 1% rise in equity flow relative to GDP is associated with a 4.9% higher likelihood of an explosive episode. In the full specification shown in Column 6, although the magnitude of equity flows' marginal effect slightly decreases to 4.0%, its significance remains at 1% level. Moreover, in Column 7, we report our results based on the

[31] Readers are referred to Chapter 2 for more detail about issues such as the difference between net and gross flows, and the advantage of employing gross flows.

subsample which starts in the 2^{nd} Quarter of 2003 (when bubbles began to emerge across a number of countries) and ends in the 2^{nd} Quarter of 2009 (when the global financial crisis was over); one could observe that equity flow's marginal effect goes up to 7.8%, implying a larger impact when bubbles had already been transmitted across different emerging stock markets.

Turning to the two other types of capital flows, firstly, portfolio debt flow is significant when it is the single type of flow included in regression (as shown in Column 1). In addition, it is also significant the full specification shown in Column 6. Furthermore, bank flows are also significant: when bank flow is the single regressor (apart form the country dummies, as shown in Column 3), a 1% rise in average bank flows over the past 4 quarters (relative to domestic GDP) is associated with a 2.1% higher likelihood of bubble's presence. Column 6 (with model of full specification) confirms a significant result, and its magnetite remains at 2.2%. Nevertheless, in the subsample analysis whose results are shown in Column 7, bank flows' marginal effect turns to be insignificant; such a result might indicate that when bubbles became massive (e.g., during the mid-2000s), bank flows no longer played an important role as portfolio equity flow did.

In summary, our results based on pooled probit regression seem to suggest a strongest association between portfolio equity flows and episodes of financial exuberance—this link is even more prominent in the sub-sample analysis when the time window is limited to the 2nd Quarter of 2003 and the 2nd Quarter of 2009, during which bubbles were pervasive across different EMEs, for the other two types of short-term flows lack significance.

3.4.3.2 Robustness Checks (with Domestic Variables)

To check the robustness of the association between short-term flows and bubbles, we run the same pooled probit regressions but controlling for additional domestic variables in this section. We choose the following domestic conditions: first, we include indicators measuring business cycle: productivity (as measured by real GDP growth rate) and inflation (as measured by percentage change of CPI index). The rationale behind is that a boom or expansion of business cycle might predict a sudden appreciation of asset prices and even the presence of bubbles (Pavlidis et al., 2015). Second, we also control for institutional quality (as measured by a politic risk index), because less developed EMEs with weak institutional structure might be fertile ground of asset bubbles (Caballero and Krishnamurthy, 2006). Third, we control for exchange rate regime because EMEs with more rigid exchange rate regimes are more susceptible to speculative attacks (Obstfeld, 1996). Finally, as our results in Section 3.4 suggests a similar timeline of emerging stock bubbles with that of the advanced housing markets (as found by Pavilidis et al. (2015)), it is possible that EMEs with higher openness could be more exposed to global transmission of financial exuberance. Hence, we control for both trade and financial openness, expecting a higher possibility of bubbles present in EMEs with higher external exposures—both in trade and financial terms—to the global market.[32] Their results are presented in table 3.4, 3.5 and 3.6:

<Insert Table 3.4, 3.5, and 3.6 here>

Table 3.4 shows the results of robustness checks for equity flows. As for the domestic control variables, Table 3.4 suggests that EMEs with a higher GDP growth rate, a lower inflation rate and a more flexible exchange rate regime are more likely to be associated with explosive episodes. More importantly, Table 3.4 shows that equity flows remain significant throughout different specifications, as shown from Columns 1 to 4. Interestingly, when we (again) limit the sample's time window to the 2nd quarter 2003 and the 4th quarter 2009, during which bubbles had become more pervasive across different EMEs, we find an even stronger association between equity flows and episodes of financial exuberance: the magnitude of the marginal effect almost quadruples from 4.4% to almost 10 %.

In contrast, the other two types of short-term flows show a smaller impact: the results from Table 3.5 suggest a lack of significance for bank flows across different specifications; bank flows again seem to play a less important role of transmitting financial exuberance across emerging stock markets compared to equity flows. Regarding debt flow, it is only significant at 10% in the full specification (Col 3 of Table 3.6). Although in the sub-sample analysis (as shown in Col 4) its significance goes up to 5%, the magnitude of its marginal effect is 3.1%, which is less than one third of that of equity flows.

[32] Readers are referred to Chapter 2 for the empirical specification and data source of these variables.

To summarize our robustness checks, we find equity flows seem the most robust type of short-term flows in transmitting explosive regimes. Such a finding echoes recent literature on the transmission of financial shocks, which report compelling evidence of both portfolio equity channel (e.g., Puy, 2016).

3.5 Conclusion

In this study we empirically investigate the presence of rational bubbles in various emerging stock markets and their association with international (short-term) capital flows. We are particularly interested in the the time window of the mid-2000s (before the onset of the GFC), during which the global financial market had been significantly integrated through increasing international capital flows. Our data is from MSCI which provides a broad data coverage for EMEs. We employ a novel test (*GSADF*) proposed by Philips et al. (2015), which processes significant advantages over the conventional bubble-detecting methods—it allows researchers to detect and date-stamp periods of explosive behaviours in stock prices, which could be a strong indication of rational bubbles (Engsted, 2015).

We start our empirical investigation with the MSCI emerging markets composite index, and find evidence of bubbles over the whole emerging markets in 2007. Furthermore, we extend our investigation to 22 individual emerging stock markets, and the empirical results confirm an unusual synchronization of bubbles among a considerable amount of EMEs in the early-to-mid 2000s. However, these bubbles collapsed almost simultaneously before September 2008 when Lehman Brothers announced bankruptcy, which is generally acknowledged as the start of global recession.

We further show that the timeline of bubbles is in line with the boom and bust of short-term flows (portfolio equity flows, portfolio debt flows and bank flows) towards EMEs. Therefore, we use a probit model to formerly investigate their associations. Our results suggest that both equity and bank flows are significantly associated with the occurrences of financial exuberance, which agrees with the findings of recent literature (e.g., Puy, 2016; Yan et al., 2016). Nevertheless, through various sub-sample analysis and robustness checks, we find that equity flows seem to play a more robust role in the particular context of transmitting explosive regimes.

For both policy makers and risk managers, the finding of concurrent bubbles among different risky emerging stock markets was by no means usual; it should have been viewed as an early-warning of financial overheating. Since such an observation may happen again in the future, our study might serve as a way to monitor global financial exuberance and function as an early warning mechanism useful to both market participants and regulators in real time. In addition, our findings point out a strong association between levels of gross equity flows and a possibility of bubble's presence; policy makers might consider tools such as capital control to limit the exuberance transmitted through this channel in due time (e.g., when bubbles are growing).

3.6 Appendix

3.6.1. Variation Inflation Factor (VIF) Test of multicollinearity of domestic factors

<Insert Table 3.7 here>

To account for the possibility of multicollinearity among the domestic factors in regressions in 3.4.3.2, we present the result of VIF test in Table 3.7. Our results suggest that both the average and individual VIF scores are far below 10, which is generally regarded as the tolerance VIF score. Therefore, multicollinearity might not be severe in our analysis.

3.6.2. Re-estimation using Logit Model

In our main empirical analysis, we use a probit model with country dummies. It is argued that country dummies in a panel probit may lead to biased results; we therefore re-estimate our models using a fixed-effect logit model to see whether our main conclusion would change. The empirical results for all three types of short-term flows are shown in Table 3.8:

<Insert Table 3.8 here>

Again, we are particularly interested at the associations between bubbles and short-term flows. The results in Table 3.8 once again suggest that equity flow remains the most significant type of speculative flows compared to bank and debt flows: the estimated odd ratio for equity flows is 1.896, which suggests that when the moving average equity flows (over GDP) is 1% higher, it is almost two times more likely to enter an explosive (bubble) regime. In contrast, the other two capital flows are insignificant.

3.6.3. Including Time dummies

<Insert Table 3.9 here>

To further check the robustness of equity flows, we include time dummies in both our probit and logistic estimations. The results are reported in Table 3.9, where we can see that equity flow remains a robust predictor of bubbles.

Table 3-1 GSADF statistics of MSCI Emerging Market (overall index)

Panel A: Test Statistics	
Country	*GSADF*
Emerging markets (Overall)	2.70***
Panel B: Critical Values	
95%	1.80
99%	2.39

Notes: **, P<0.1; **, P<0.05; ***, P<0.01.*All results are for autoregressive lag length k=4.

Table 3-2 *GSADF* statistics of MSCI index for all countries in the database

Panel A: Test Statistics	
Country	*GSADF*
Asia	
China	3.927***
India	4.123***
Indonesia	3.257***
Malaysia	3.085***
Pakistan	1.864**
Philippines	2.407***
Thailand	2.763***
Latin America	
Argentina	2.147**
Brazil	3.721***
Chile	2.031**
Colombia	5.159***
Mexico	3.176***
Peru	4.929***
Emerging Europe	
Czech	4.865***
Hungary	4.056***
Poland	2.577***
Russia	2.819***
Middle East and Africa	
Egypt	3.997***
Jordan	3.737***
Morocco	3.812***
Turkey	2.082**
South Africa	2.226**
Panel B: Critical Values	
95%	1.80
99%	2.39

Notes: **, P<0.1; **, P<0.05; ***, P<0.01.*All results are for autoregressive lag length k=4.

Table 3-3 Episodes of Bubbles and Their associations with "Short-term Flows".

Probit Regression: Marginal Effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Equity	Debt	Bank	Equity + debt	Equity + bank	Full specification	Sub sample: 03q2 - 09q2
Equity Flow	0.049***			0.044***	0. 044***	0.040***	0.078***
(% GDP)	(0.014)			(0.013)	(0.013)	(0.012)	(0.025)
Debt Flow		0. 022***		0.020***		0. 017**	0.029*
(% GDP)		(0. 069)		(0.007)		(0. 006)	(0.016)
Bank Flow			0.021***		0. 024***	0. 022***	-0.007
(% GDP)			(0.006)		(0.006)	(0.007)	(0.019)
Pseudo R2	0.14	0.132	0.142	0.152	0.164	0.174	0.248
Observations	814	814	759	814	759	759	375

Dependent variable: Dummy variables equal to 1 if country is in a bubble stage. Robust standard errors are emplyed. All three capital flows are measured as the moving average of the past four quarters. All regressors are lagged by 1 period. Sample time: 1998q3 – 2011q4. Country dummies are included in regressions.

* p<0.10, ** p<0.05, *** p<0.010

Table 3-4 Robustness Checks: Equity Flows

Probit Regression: Marginal Effect

	(1)	(2)	(3) Full specification	(4) Subsample: 03q2 - 09q2
Equity flow (% GDP)	0.032***	0.043***	0.044***	0.098***
	(0.012)	(0.013)	(0.013)	(0.029)
Institutional quality index	0.057*	0.037	0.035	0.158*
	(0.034)	(0.034)	(0.034)	(0.095)
Real domestic growth rate	0.037***	0.031***	0.030***	0.033**
	(0.005)	(0.004)	(0.004)	(0.014)
Domestic inflation rate (in %)		-0.015***	-0.014***	-0.011
		(0.004)	(0.004)	(0.011)
Exchange rate regime		0.027***	0.023***	0.039**
		(0.007)	(0.007)	(0.018)
Trade openness			0.001	0.003
			(0.001)	(0.003)
Financial openness			0.026	-0.069
			(0.019)	(0.065)
Pseudo R2	0.267	0.322	0.322	0.355
Observations	814	814	814	400

Dependent variable: Dummy variables equal to 1 if country is in a bubble stage. Standard errors are robust. All three capital flows are measured as the moving average of the past four quarters. All regressors are lagged by 1 period. Sample time: 1998q3 – 2011q4. Country dummies are included in regressions.
* p<0.10, ** p<0.05, *** p<0.01

Table 3-5 Robustness Checks: Bank Flows

Probit Regression: Marginal Effect

	(1)	(2)	(3) Full specification	(4) Subsample: 03q2 - 09q2
Bank flows (% GDP)	0.006	-0.001	-0.002	-0.036*
	(0.008)	(0.008)	(0.008)	(0.020)
Institutional quality index	0.076**	0.062*	0.057*	0.138
	(0.032)	(0.033)	(0.033)	(0.097)
Real domestic growth rate	0.036***	0.034***	0.033***	0.045***
	(0.005)	(0.005)	(0.005)	(0.014)
Domestic inflation rate (in %)		-0.013***	-0.011***	-0.008
		(0.004)	(0.004)	(0.010)
Exchange rate regime		0.023***	0.018***	0.031
		(0.006)	(0.007)	(0.027)
Trade openness			0.000	0.003
			(0.001)	(0.003)
Financial openness			0.028	-0.056
			(0.019)	(0.068)
Pseudo R2	0.288	0.291	0.291	0.251
Observations	759	759	759	375

Dependent variable: Dummy variables equal to 1 if country is in a bubble stage. Robust standard errors are employed. All three capital flows are measured as the moving average of the past four quarters. All regressors are lagged by 1 period. Sample time: 1998q3 – 2011q4. Country dummies are included in regressions.

* p<0.10, ** p<0.05, *** p<0.010

Table 3-6 Robustness Checks: Debt Flows

Probit Regression: Marginal Effect

	(1)	(2)	(3) Full specification	(4) Subsample: 03q2 - 09q2
Debt flows (% GDP)	0.017**	0.010*	0.010*	0.031**
	(0.007)	(0.006)	(0.006)	(0.016)
Institutional quality index	0.081**	0.061*	0.059*	0.143
	(0.034)	(0.032)	(0.032)	(0.095)
Real domestic growth rate	0.037***	0.033***	0.031***	0.040***
	(0.005)	(0.004)	(0.004)	(0.013)
Domestic inflation rate (in %)		-0.013***	-0.012***	-0.010
		(0.004)	(0.004)	(0.011)
Exchange rate regime		0.023***	0.021***	0.035*
		(0.006)	(0.006)	(0.018)
Trade openness			0.001	0.002
			(0.001)	(0.003)
Financial openness			0.017	-0.071
			(0.018)	(0.064)
Pseudo R2	0.266	0.303	0.305	0.264
Observations	814	814	814	400

Dependent variable: Dummy variables equal to 1 if country is in a bubble stage. Robust standard errors are employed. All three capital flows are measured as the moving average of the past four quarters. All regressors are lagged by 1 period. Sample time: 1998q3 – 2011q4. Country dummies are included in regressions.

* p<0.10, ** p<0.05, *** p<0.010

Table 3-7 Variation Inflation Factor (VIF) Test for Multicollinearity

Variable Names	VIF Score
Equity flow	1.14
Institutional quality index	1.58
Real domestic growth rate	1.24
Domestic inflation rate (in %)	1.53
Exchange rate regime	1.20
Trade openness	1.65
Financial openness	1.34
Mean VIF	1.42

Table 3-8 Results based on Fixed-effect Logit model

	(1) Equity Flow	(2) Debt Flow	(3) Bank Flow
Equity/Debt/Bank flow (%, GDP)	1.896***	1.144	0.942
	(0.401)	(0.108)	(0.098)
Institutional quality index	1.495	2.201	2.065
	(0.985)	(1.415)	(1.346)
Real domestic growth rate	1.512***	1.535***	1.572***
	(0.118)	(0.119)	(0.132)
Domestic inflation rate (in %)	0.821***	0.838***	0.851**
	(0.055)	(0.057)	(0.058)
Exchange rate regime	1.360**	1.326**	1.260
	(0.172)	(0.154)	(0.186)
Trade openness	1.005	1.002	0.995
	(0.021)	(0.020)	(0.020)
Financial openness	1.439	1.223	1.447
	(0.529)	(0.430)	(0.507)
Observations	814	814	759

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3-9 Results with Year Dummies

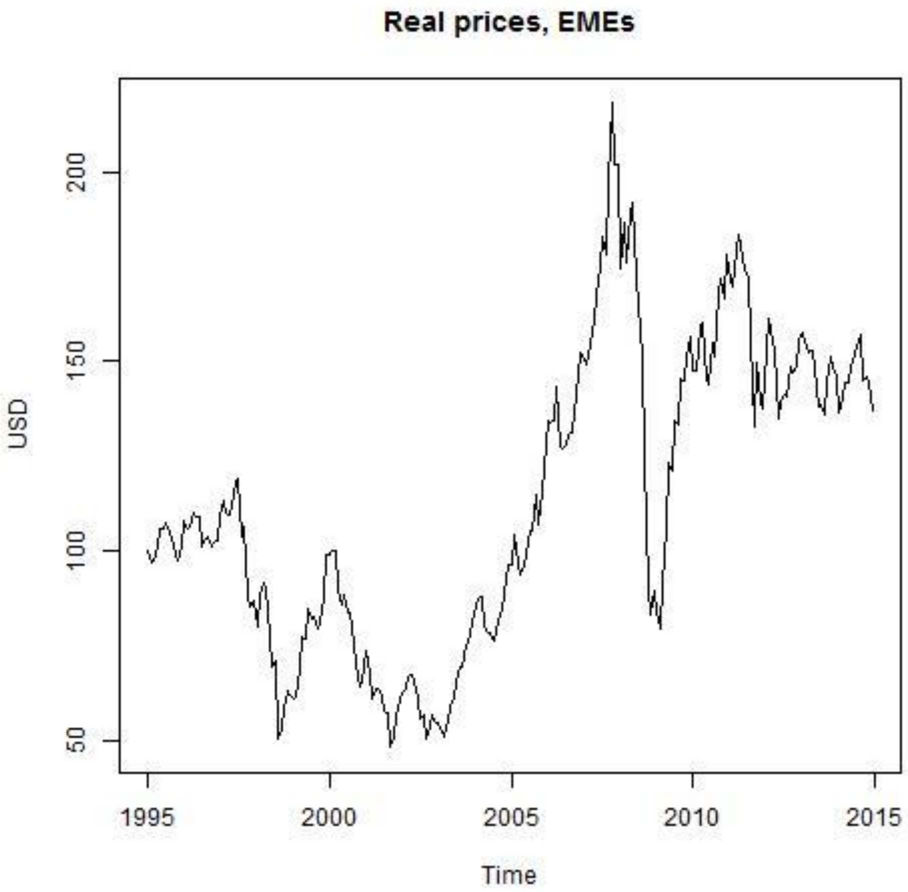
	(1) Fixed-effect Logit	(2) Probit
Equity flow	1.867**	0.056**
	(0.533)	(0.025)
Institutional quality index	1.890	0.099
	(2.367)	(0.098)
Real domestic growth rate	1.265	0.016
	(0.217)	(0.015)
Domestic inflation rate (in %)	1.036	-0.002
	(0.116)	(0.010)
Exchange rate regime	1.306	0.031**
	(0.228)	(0.014)
Trade openness	0.971	-0.001
	(0.042)	(0.004)
Financial openness	0.176*	-0.148*
	(0.171)	(0.079)
Observations	814	461

Notes:

1. Fixed-effect logit: odd ratios are reported. Standard errors in parentheses
2. Probit model: marginal effects are reported. Robust standard errors employed.
3. The empirical results of year dummies are omitted.

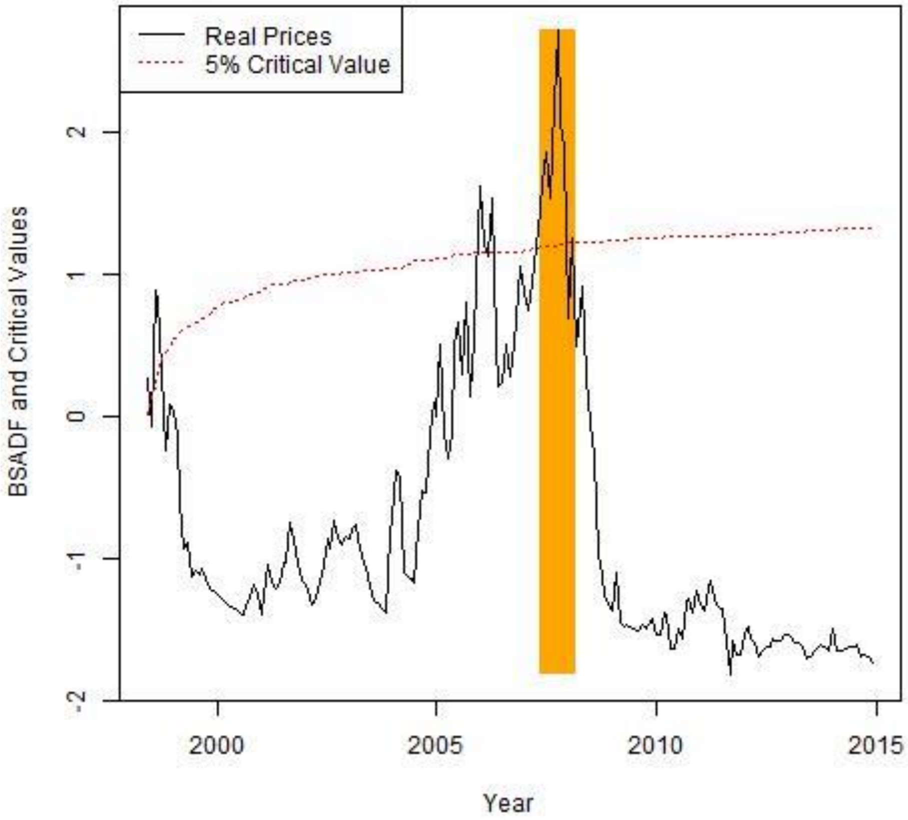
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 3-1 MSCI Emerging Market Index (Real Prices)



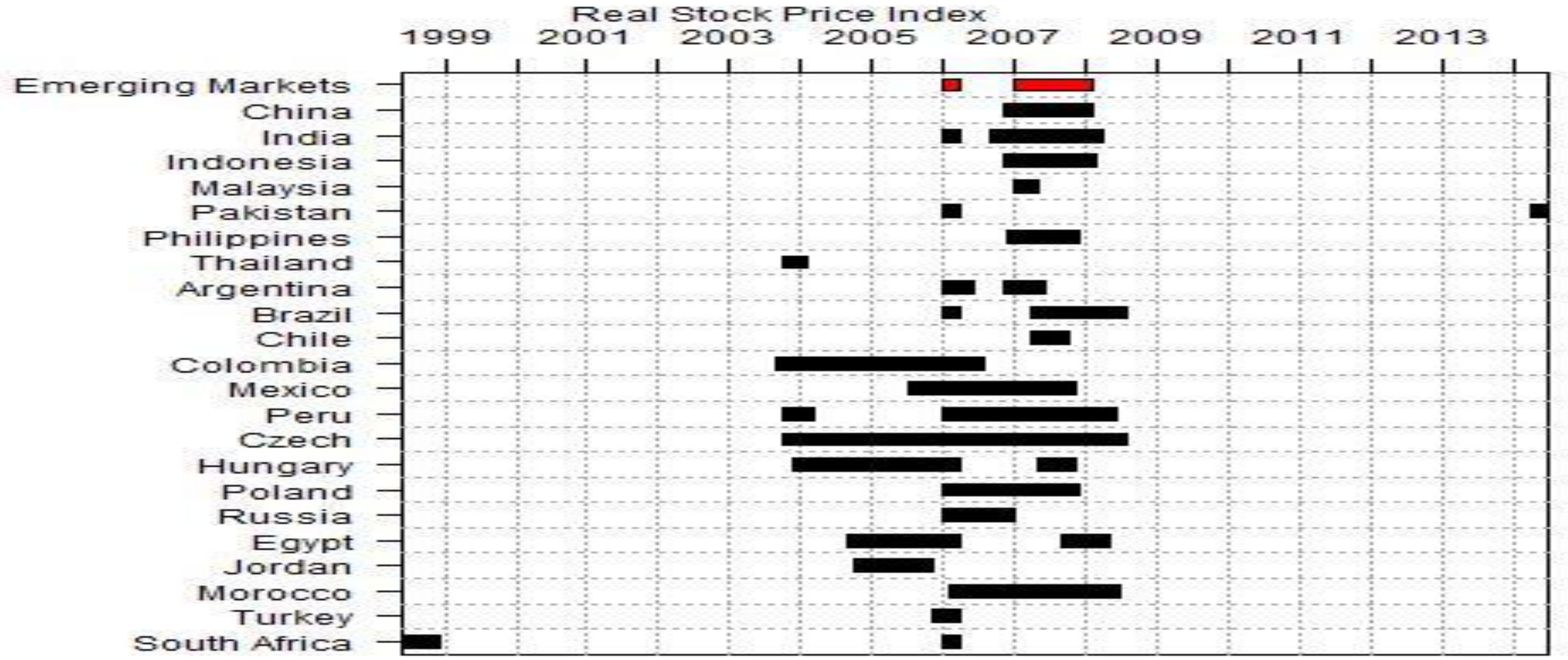
Notes: In US Dollars. 1995 M1=100. Data source: Bloomberg and MSCI.

Figure 3-2 Date-Stamping with Prices of MSCI Emerging Markets (Overall index)



Notes: Shaded areas indicate periods of exuberance detected by the GSADF test. Data source is from MSCI and Bloomberg.

Figure 3-3 Date-Stamping with Prices of MSCI Emerging Markets (Individual countries)



Notes: This diagram shows episodes of exuberance detected in real stock prices. Red areas indicate the bubble episode detected from the composite index. Length of exuberance exceed the threshold, $logT$ (T denotes sample size) to be identified as bubbles.

Figure 3-4 Exuberance in MSCI Index: Emerging Markets in Asia (a)

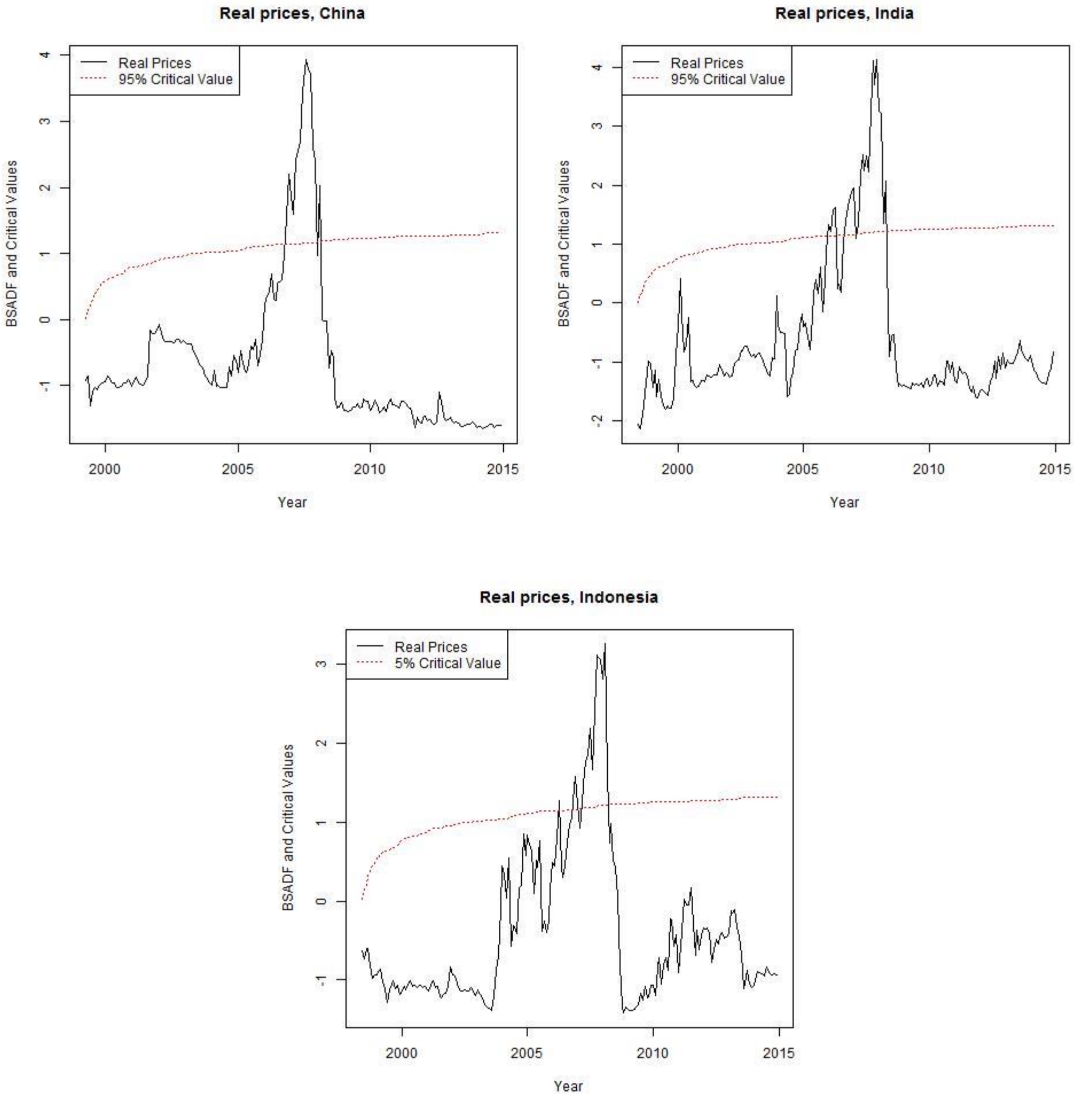


Figure 3-5 Exuberance in MSCI Index: Emerging Markets in Asia (b)

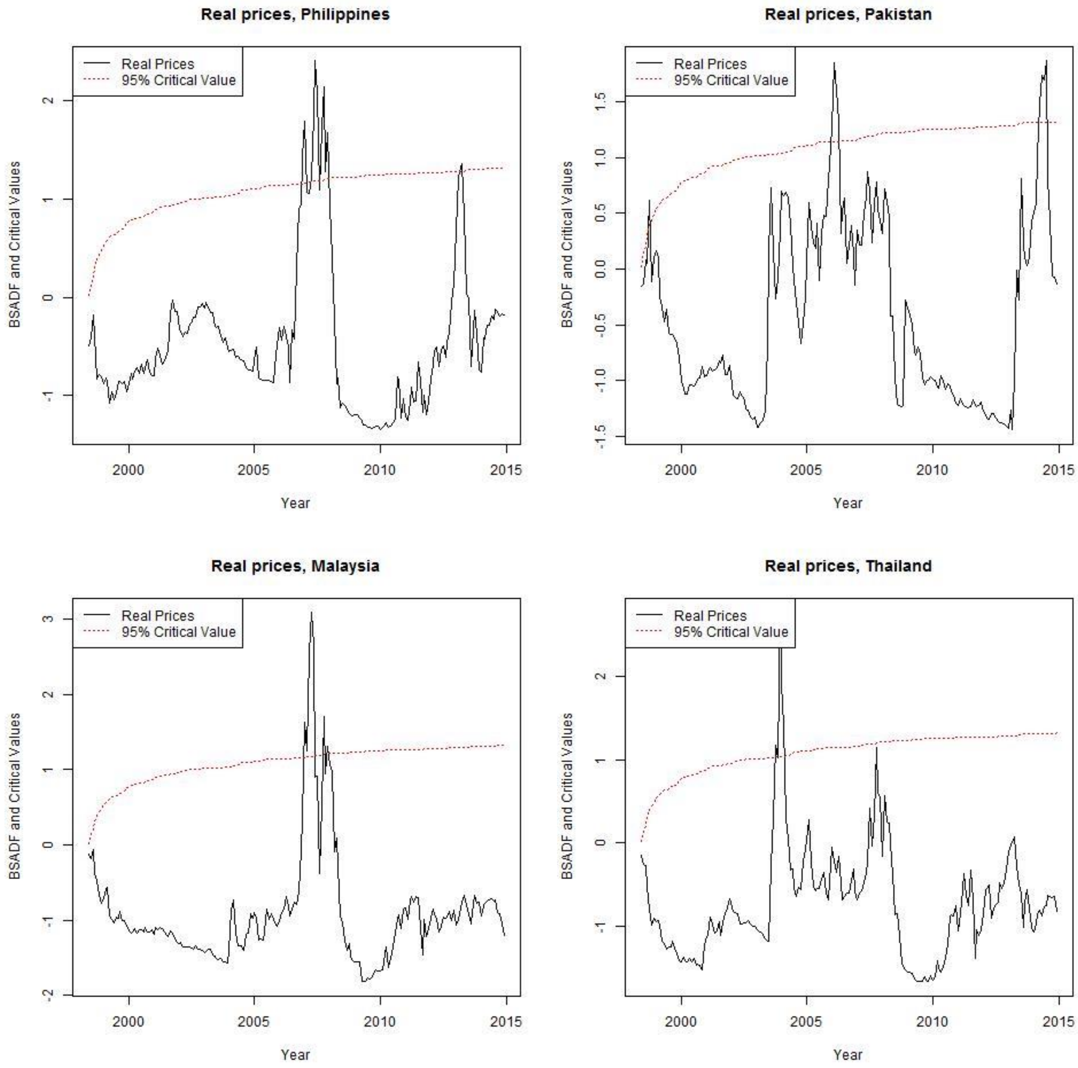


Figure 3-6 Exuberance in MSCI Index: Emerging Markets in Latin America

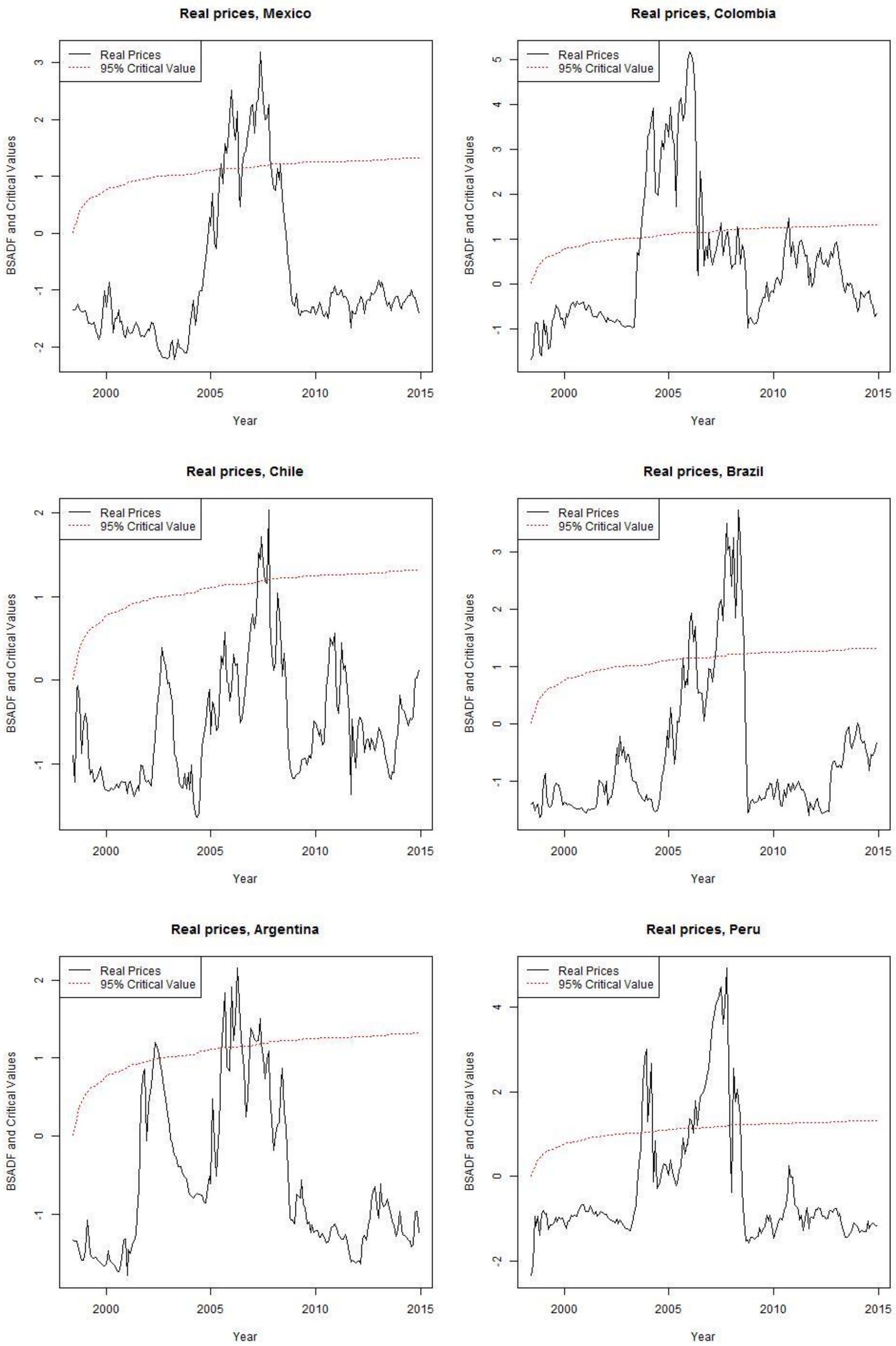


Figure 3-7 Exuberance in MSCI price index: Emerging Markets in Emerging Europe

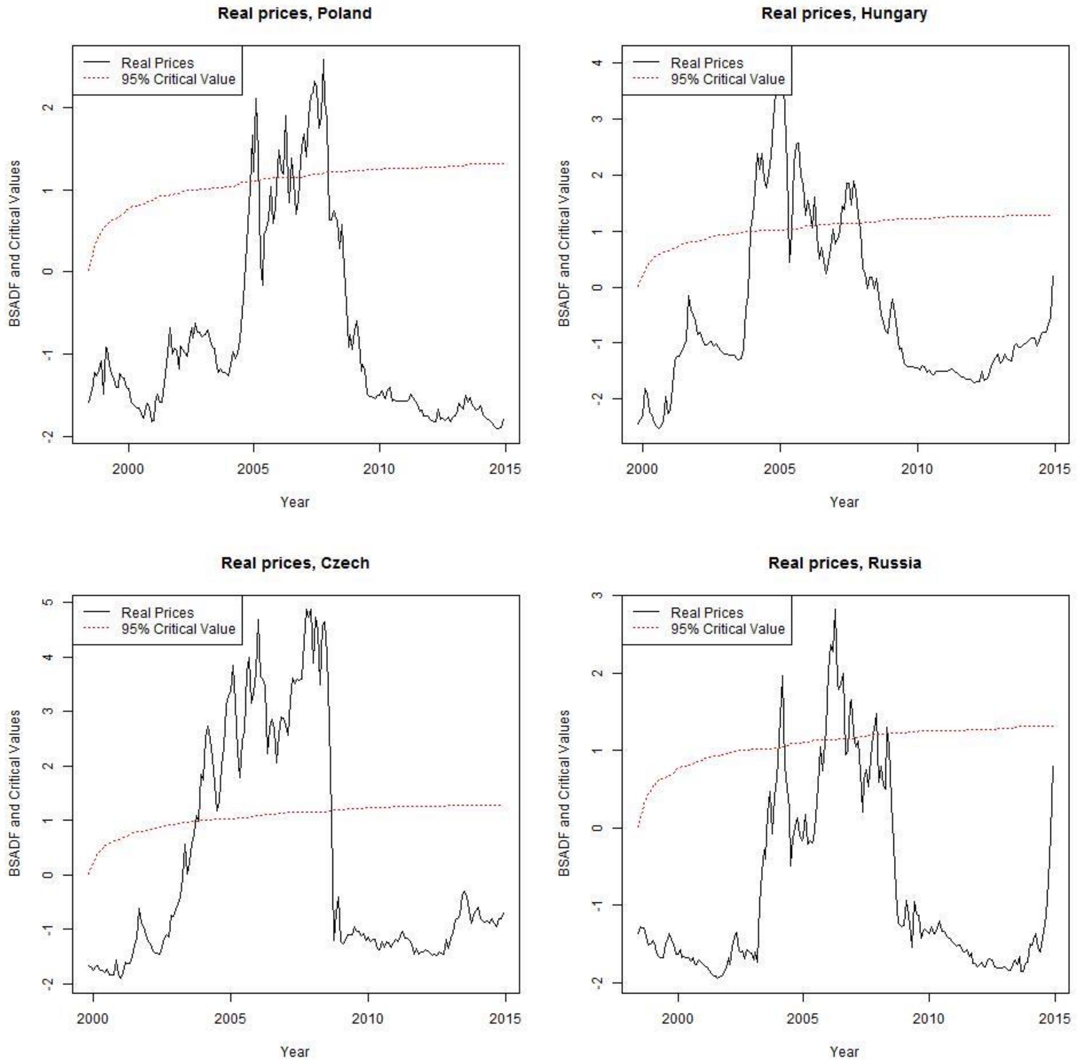


Figure 3-8 Exuberance in MSCI price index: Other EMEs

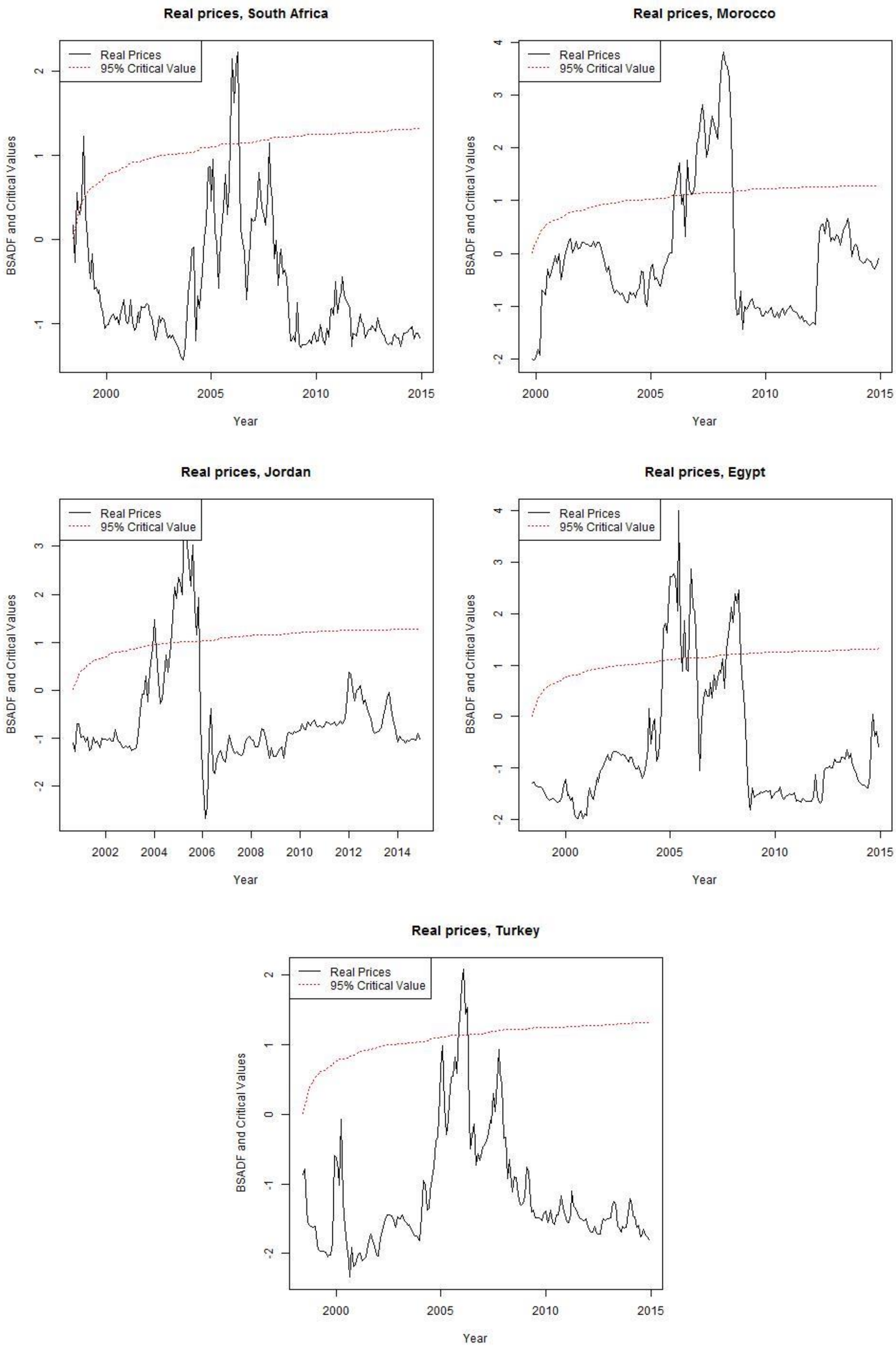
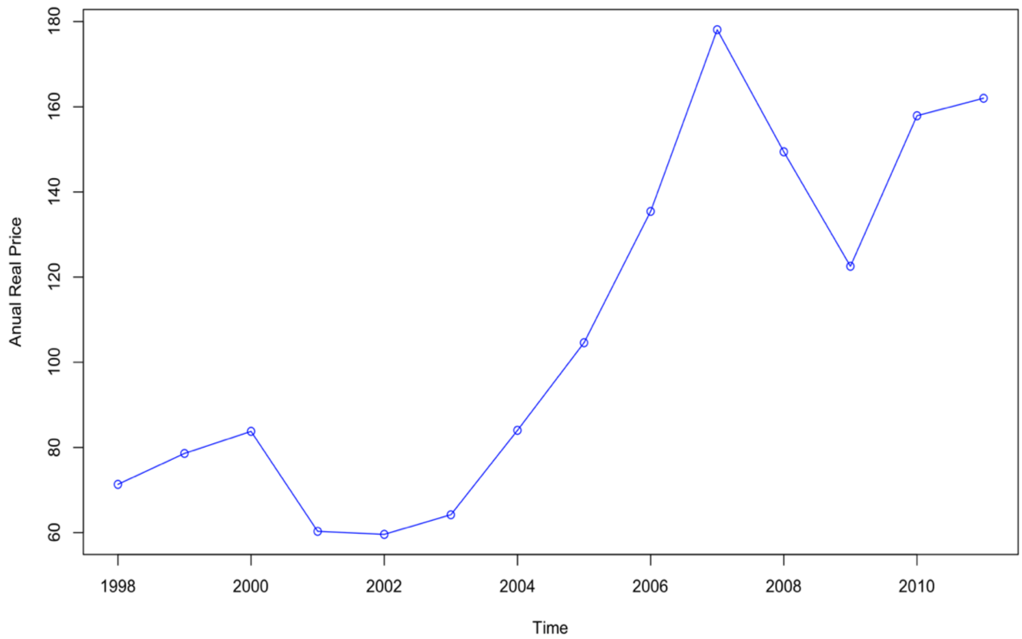
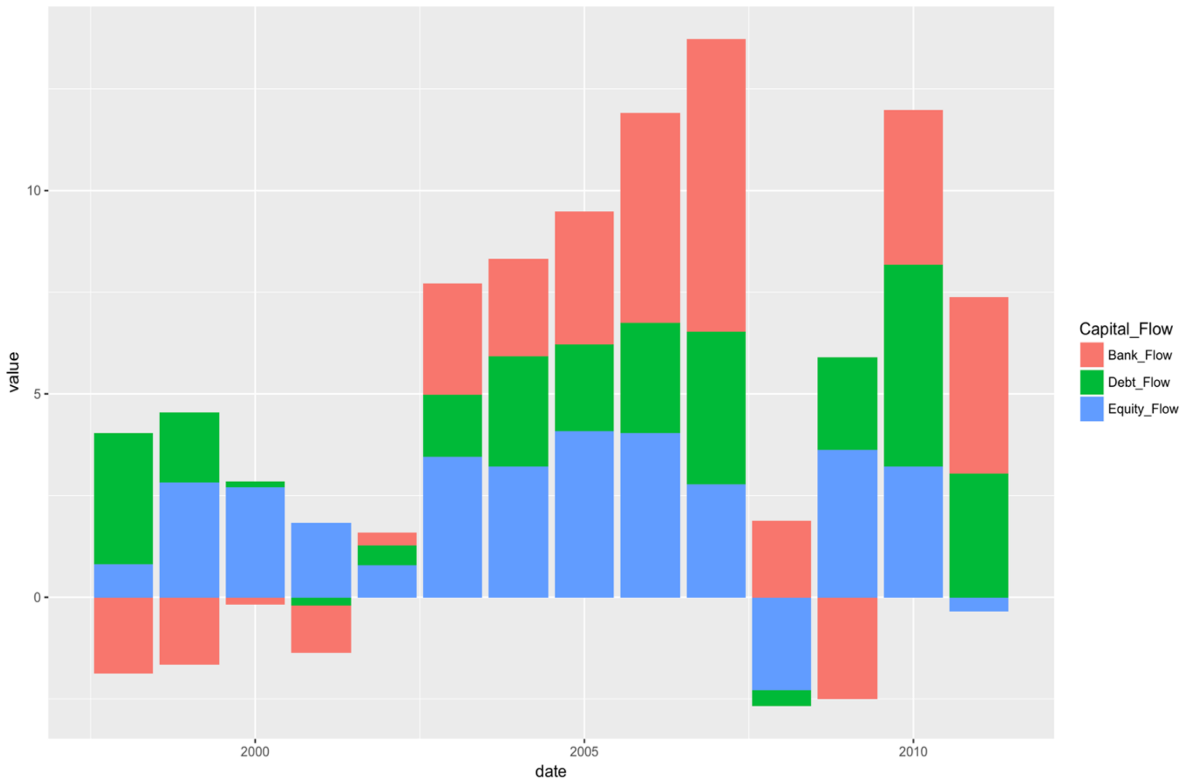


Figure 3-9 Stock Prices and Short-term Gross Capital Inflow

(a) Annual Real Prices of MSCI Emerging Market Index



(b) Annual Short-term Flows to Emerging Markets



Chapter 4 International Equity Flows and Predictability of Emerging Stock Markets' Returns

Abstract

International equity flows have significantly increased over the past decades, and they strongly affect the emerging financial markets as suggested by the recent literature. This observation raises our research question about whether international equity flows could help to predict stock returns. We employ the state-of-the-art predictive regressions of IVX-Wald (Kostakis et al., 2015) and IVX-Quantile regression (Lee, 2016) in order to ensure that our results will not be a statistical artefact of persistent regressor. We find a significant link between equity flows and contemporaneous stock returns among a large number of emerging equity markets (especially the Asian markets). However, there seems to be weak evidence that international equity flows can predict one-month-ahead stock returns (neither in-sample nor out-of-sample). Nevertheless, the strong contemporaneous association found in this study might still hint at the possibility of predictability if high-frequency (such as daily or weekly) data were employed. Future research along these lines might shed more light on this topic.

JEL Classification: C22, G12, G15

KEY WORDS: Emerging Equity Markets, International Capital Flows, Predictive regression, IVX filtering

4.1 Introduction

The growing cross-border capital flows represent the most prominent form of global financial integration, the degree of which has noticeably increased over the past decades. In particular, global capital flows increased from 7% of the world GDP in 1998 to over 20% in 2007 (Milesi-Ferretti and Tille, 2011). Although international capital flows collapsed largely after the global financial crisis, they surged again in the late 2000s. These sizable capital flows significantly affect the domestic financial markets (e.g., equity markets) of the emerging economies (Ahmed and Zlate, 2014).

A number of recent studies have focused on short-term capital flows, namely portfolio flows and bank flows (e.g., Fuertes et al., 2016), when they try to investigate the link between capital flows and local financial markets. Theoretically, short-term capital flows are different from foreign direct investment flows (FDI) in nature: they are more volatile and speculative, and thus they could rush into a country and then run out precipitously because of return chasing (Stiglitz, 2001). Therefore, these short-term speculative capital flows might have a larger impact on local financial markets. Empirically, there are a large number of studies which are in line with this view: for instance, Yan et al. (2015) find that these "short-term flows" (especially bank credit flows) help to transmit the recent financial crisis into the emerging equity markets. Apart from the bank industry, recent literature also identifies the mutual fund industry as another important vehicle of transmitting financial contagion (Puy, 2016). [33] For example, Jotikasthira et al. (2012) show that investor flows to funds domiciled in developed markets force significant changes in these funds' emerging market portfolio allocations. As a result, such forced trades or "fire sales" strongly affect emerging market equity prices. Therefore, these findings suggest that there may be a link between short-term capital flows and emerging capital markets such as the stock markets, which motivates our research question: could hot-money flows help to predict local stock returns?

To investigate this potential predictability, this paper chooses to focus on equity flows among all "hot-money flows". The main reasons are as follows: firstly, equity flows are available at higher frequencies (at least monthly) in comparison to

[33] Broner et al. (2006) show that there could be of other kinds of equity investors such as commercial and investment banks, but mutual fund flows could be a suitable representative of equity flows.

bank flows, which are usually quarterly or semi-annual (Fuertes et al., 2016). Predictive regressions with such low-frequency data will result in invalid results because of insufficient observations, and predictability may exist for short but not long horizons. Secondly, our choice of equity flow is a follow-up of the second chapter of this thesis, which finds that emerging equity markets' bubbles were most strongly associated with equity flows, compared to other types of short-term flows (Bond flows or Bank flows).

How do international equity flows affect domestic stock returns? First of all, the literature has found compelling evidence of a positive association between equity flows and returns *contemporaneously* (See, e.g., Brennan and Cao, 1997; Griffin et al., 2004; and Ülkü, 2015). Richard (2005) offers a simply story based on demand shocks to illustrate the mechanism: holding the portfolio preferences of domestic investors unchanged, decisions by foreigner investors to buy (sell) are demand shocks leading to an outward (inward) shift of aggregate demand curve and thereby an increase (a decrease) of stock prices. Nevertheless, equity flows' effects on future stock returns are relatively uncertain. A considerable amount of literature points out that foreign investors are return chasing, so a resulting higher returns will in turn attract more equity flows (see, e.g., Bohn and Tesar, 1996; Brennan and Cao, 1997; Raddatz and Schmukler, 2012; and Yan, 2015). Such a "positive feedback" channel will further drive up stock returns in the future. In contrast, other literature highlights equity flows' portfolio rebalancing channel, which implies a reduction of future stock prices. For instance, Hau and Rey (2004) show that when the local equity market appreciates, foreign investors might rebalance their portfolio by reducing their equity holdings in the underlying market to reduce their exchange-rate risk exposure. This behavior will result in future equity outflows and therefore local equity prices' reduction. In this study, we would investigate the link between equity flows and both contemporaneous and one-month-ahead returns, because it might provide more informative results.

<Insert figure 4.1 here>

To conduct our empirical analysis, we collect monthly data for 21 emerging markets economies (EMEs) over 1995-2014. Our data for stock prices are collected from Morgan Stanley Capital International (MSCI), and data for equity flows are from Treasury International Capital (TIC), which has been widely used by the literature of international finance. Figure 4.1 plots the data of both average equity flows and stock prices of all the EMEs in our sample to enable us to have a glimpse of the correlation between these two variables: the black solid line represents an overall price index of the whole emerging stock market obtained from MSCI; the blue dashed line shows the average equity flows towards all EMEs in our database, scaled by domestic GDP. Figure 4.1 seems to suggest a co-movement between these two variables, and this pattern becomes more obvious after the early 2000s, after which the global financial market had been significantly integrated. Specifically, both equity flows and stock prices rose before the millennium, around which the dot.com bubble was present in the U.S. stock market (Ljungqvist and Wilhelm, 2003). As this "information technology bubble" collapsed in the early 2000s, both equity flows and emerging stock prices dropped, reaching the bottom around late 2001. Nevertheless, a more noticeable pattern of co-movements appeared in the mid-2000s: both equity flows and stock prices surged until the outset of the global financial crisis. However, after 2008, both of these two time series collapsed sharply and semi-simultaneously. One might observe from Figure 4.1 that this drop is more sizable and prolonged than any other. Lastly, in the post-crisis era, equity flows and prices appear to co-move again: both of them revived. In sum, we observe several patterns of co-movements between equity flows and stock prices, which again motivate our interest in predictability.

Although earlier literature typically identifies equity flows as being stationary (e.g., Sarno and Taylor, 1999), recent studies show that it is actually difficult to precisely identify the exact degree of persistence, of which standard unit root tests hardly provide a firm guide (Lee, 2016). A considerable number of studies suggest that international equity flows are persistent. For instance, Albuquerque et al. (2007) develop a theoretical model predicting persistence as an enduring feature of foreign investors' trading, because of the heterogeneity within their group of accessing and responding to new information. Empirically, Froot and Donohue (2002) report strong evidence of persistence in net foreign flows, especially towards emerging markets. In a recent empirical study focusing on the Emerging European and Asian markets, Ülkü (2015), also show that equity flows are significantly persistent. It would be serious to neglect equity flows' persistence because it will give rise to invalid results if equity flows is employed as a predictor in a standard predictive regression. In particular, Campbell and Yogo (2006) show that if the predictor is strongly persistent, empirical results based on standard regression models such as OLS will suffer severe size distortion leading to an over-rejection of the null hypothesis of no predictability. To solve this problem, we employ a recent predictive regression model of Kostakis et al. (2015) based on IVX-filtering, which can handle predictor variables with various degrees of persistence. In addition, we employ the IVX-version of quantile regression (IVXQR) of Lee (2016), which enables us to examine the predictability of stock returns over its whole conditional distribution.

Our main findings can be summarized as follows. We firstly investigate the link between equity flows and *contemporaneous* returns. We start with OLS and find a significant association between these two variables among a large number of EMEs, especially among the Asian equity markets. The estimated coefficients of equity flows are mostly positive, and this finding is in line with that of the literature (e.g., Ülkü, 2015). Next, to rule out the invalidity of our results because of the potential size distortion resulted from equity flows' persistence, we employ the latest IVX models: based on the predictive mean regression of Kostakis et al. (2015), we confirm that our results are not a statistical artefact owning to a persistent regressor; based on the IVX-version of quantile regression, we also show that equity flows are generally significant across a wide range of quantiles. Secondly, we investigate the association between equity flows and *one-month-ahead* stock returns, at which investors might be more interested. Surprisingly, equity flows become largely insignificant to predict returns. Only a few countries, namely Poland and South Africa, show strongly significant estimates. The disappearance of equity flows' significance is in line with the findings of Richard (2005), which finds a significant price impact associated with foreigners' trading on six Asian emerging equity markets. However, this price pressure typically disappears within days. Similarly, in our study, it is likely that equity flows' price impact is short-term so that they contain limited information to predict *one-month-ahead* returns. In addition, equity flows' estimated signs are usually negative. Hartmann and Pierdzioch (2007) find exactly the same results when investigating the U.S. stock market, and they interpret it as an overshooting of stock returns in response to international equity flows, such that the price impact is gradually reversed in later months.[34] Finally, we also conduct an out-of-sample analysis, and find that only equity flows in Poland can outperform the benchmark model. In summary, this study finds significant *contemporaneous* association between equity flows and international equity flows. However, the monthly equity flows appear to contain limited (if any) information to forecast *one-month-ahead* stock returns in EMEs.

Our main contribution is that we apply the state-of-the-art predictive regression (based on IVX-instrumentation) to investigate the effect of persistence on the association between capital flows and predictability of stock returns—to our knowledge, this is the first paper that investigates this issue. Although no significant predictability is found in this study, our empirical tools could be a fascinating venue of future research especially those which would employ equity flows' data of higher frequency such as weekly or even daily, whose persistence could be significantly stronger (Ülkü, 2015). In that case, there will be a greater need to use the prediction regressions with IVX-instrumentation proposed by Kostakis et al. (2015) or Lee (2016) to ensure that the results would not a statistical artefact because of persistent predictor.

The reminder of this paper is organized as follows. Section 2 discusses our empirical methodology, and it gives a brief description of recent predictive regressions models based on IVX-filtering. Section 3 describes our database and summary statistics. Section 4 presents our empirical results. Section 5 concludes.

4.2 Empirical Methodology

4.2.1 Statistical Inference in the Presence of Persistent Regressors

We start our analysis with ordinary least squares (OLS) regression, which is standard in the literature of predicting stock returns. The regression model is shown as:

$$y_t = \mu + Ax_{t-1} + \varepsilon_t. \tag{1}$$

In this regression, y_t usually represents contemporaneous stock returns, and x_{t-1} denotes the lag of a vector of financial variables, which contains equity flows only in our case. A number of early findings based on such regressions report that the t-

[34] Cenedese and Mallucci (2016) find a similar result that equity flows' price impact is reversed latterly.

statistic is typically large enough to reject the null hypothesis that $A = 0$. Thus, they suggest a strong evidence of stock return predictability. However, Campbell and Yogo (2006) doubt the validity of such tests and further show that they tend to reject the null too frequently when the predictor variable is persistent and the innovations are highly correlated with returns.

Regarding the degrees of persistence of the predictor, we follow the presentations from Kostakis et al. (2015) and Lee (2016). We firstly assume that the vector of predictors x_{t-1} has the following autoregressive form:

$$x_t = R_n x_{t-1} + u_t, \tag{2}$$

$$R_n = I_K + \frac{C}{n^{\alpha}} \text{ for some } \alpha \geq 0, \tag{3}$$

where n is the sample size and $C = diag(c_1, c_2, c_3, \ldots, c_K)$ if we have K predictors. According to equation (3), the pair (α, C) determines predictors' persistence. In particular, Lee (2016) shows that x_t can belong to any of the following persistence categories:

(I0) Stationary: $\alpha = 0$ and $|1 + c_i| < 1$, $\forall i$,

(MI) Mildly integrated: $\alpha \in (0,\ 1)$ and $c_i \in (-\infty,\ 0)$, $\forall i$,

(I1) Local to unity and unit root: $\alpha = 1$ and $c_i \in (-\infty, \infty)$, $\forall i$,

(ME) Mildly explosive: $\alpha \in (0,\ 1)$ and $c_i \in (0, \infty)$, $\forall i$.

If any predictor falls into the category of (I1) or even (ME), its persistence will lead to serve size distortion of the empirical results, as reported by the literature. On the other hand, Section 1 (Introduction) of this paper has briefly introduced the persistent nature of equity flows and the difficulty to empirically identify the exact degree of their persistence. Next, we show our solution by employing recent predictive regression based on IVX-filtering instrumentation.

4.2.2 Solutions: IVX filtering

The literature has developed two major approaches to correct the nonstandard distortion caused by persistent predictors. The first approach focuses on the Bonferroni method (e.g., Stock et al., 1995; Campbell and Yogo, 2006). Its main idea is to find a confidence interval (CI) for R that incorporates confidence limits for c (shown in equation 3). In this way, the model can be independent of any particular value of c (Philips, 2015). However, this method has several disadvantages: firstly, such models usually allow for only one predictor in the regression. More importantly, Philips (2014) and Lee (2016) show that these models may lose validity when predictor persistence falls between (MI) and (I0). For this reason, it would be particularly difficult to employ models based on the Bonferroni method in our study, since it is empirically difficult to identify the exact degree of capital flows' persistence. Therefore, models retaining their validity over various degrees would be more desirable.

A solution to this problem is provided by the IVX filtering method of Magalinos and Philips (2009), which has been employed by recent studies such as Kostakis et al. (2015) and Lee (2016). These models can handle predictor variables with various degrees of persistence. The basic idea is to filter a predictor with strong persistence (e.g., belonging to the parameter space of I(1)) into an instrument with mildly integrated (MI) persistence. Specifically, following the presentation from Lee (2016), we filter persistent data x_t to generate $\widetilde{z_t}$:

$$\widetilde{z_t} = F\widetilde{z_{t-1}} + \Delta x_t. \tag{4}$$

When $F = 0_K$, $\widetilde{z_t} = \Delta x_t$. In this case, the instrument $\widetilde{z_t}$ is equivalent to the first difference of the persistent predictor, which is one of the most common ways to remove persistence. Although first difference could wipe out the nonstandard distortion, its sacrifice is a substantial loss of power. On the other hand, when $F = I_K$ then $\widetilde{z_t} = x_t$, we simply use level data without any filtering. In this case, the power is retained, but the resulting persistence would lead to a distorted inference as we discussed earlier.

To exploit advantages both from using level and the first difference of persistent predictor, the IVX-method filters x_t to generate $\widetilde{z_t}$ with (MI) persistence, intermediate between I(0) and I(1). Specifically, we choose $F = R_{nz}$ so that:

$$\widetilde{z_t} = R_{nz}\widetilde{z_{t-1}} + \Delta x_t, \tag{5}$$

$$R_{nz} = I_K + \frac{C_z}{n^\delta}, \tag{6}$$

where $\delta \in (0,1)$, $C_z = c_z I_K$, $c_z < 0$ and $\widetilde{z_t} = 0$.

Equations (5) and (6) show several advantages of this method. Firstly, since R_{nz} is constructed to be between 0_K (first differencing) and I_K (use of level data), this IVX-filtering enables us to preserve power and achieve size correction at the same time. Another advantage is that this model could automatically adjust several persistent predictors simultaneously. Therefore, this method is even valid for regressions with multivariate predictors with various degrees of persistence. In this study, although we consider equity flow as the only predictor, the uniform validity over the range of I(0) and I(1) would still make this method attractive: if equity flow is I(1), the IVX filtering reduces the persistence to (MI); if equity flow belongs to I(0) or (MI), the filtering maintains the original persistence. Although equity flows might hardly be explosive, Philips and Lee (2016) shows that models based on IVX instrumentation remain valid for regressors with local unit roots in the explosive direction and mildly explosive roots. In this way, this mechanism of self-generated instruments removes the worries of the unknown degree of capital flows' persistence.

4.2.3 Model estimations based on IVX

4.2.3.1 Mean regression: IVX-Wald (Kostakis et al., 2015)

For the conditional mean regression of stock return predictability, we use the model proposed by Kostakis et al. (2015). Denote all the demeaned variable as: $Y_t = y_t - \bar{y}_n$, $X_t = x_t - \bar{x}_{n-1}$, and $\xi_t = \varepsilon_t - \bar{\varepsilon}_n$, and then the resulting demeaned regression matrices would be: $\underline{Y} = (Y_1', \dots, Y_n')'$ and $\underline{X} = (X_1', \dots, X_n')'$. Similarly, we denote the (undemeaned) instrument matrix as $\underline{Z} = (Z_1', \dots, Z_n')'$. Then it is convenient to rewrite the model in equation (1) as follows:

$$Y_t = AX_{t-1} + \xi_t. \tag{7}$$

The IVX estimation of A from the predictive regression (7) is analogous to a two-stage least-squares estimator based on the instrument with (MI) persistence in (4). Formally, it is shown as:

$$\tilde{A}_{IVX} = \underline{Y'}\tilde{Z}(\underline{X'}\tilde{Z})^{-1}. \tag{8}$$

Kostakis et al. (2015) further show that IVX-estimators are asymptotically mixed normal, suggesting that linear restrictions on the coefficient matrix A from (1) or (7) could be tested by a standard Walt test. This is much easier to compute compared to earlier models based on the Bonferroni method.[35]

4.2.3.2 Quantile regression IVX-QR (Lee, 2016)

While the majority of the literature focuses on predicting the conditional mean of stock returns, it is interesting to investigate the predictability at each quantile across the whole conditional distribution of returns. Firstly, financial data are typically known as having heavy tails and skewed distributions. Such features might imply potentially greater predictability at certain quantiles rather than only the median (Lee, 2016). Secondly, in many areas of financial economics, it might be even more interesting to examine the entire return distribution or specific parts of the distribution such as tails. For instance, risk managers may pay more attention to the left tail (Pedersen, 2015). Thirdly, regarding our particular interest of equity flows, the literature reports that equity flows could be pro-cyclical. This implies that equity flows might have a larger impact on some particular quantiles (such as the two tails). For example, Broner et al. (2006) find that international mutual funds tend to increase (decrease) their weights of countries in which they have a large (small) portfolio weights when the funds are doing relatively well (badly). In addition, Raddatz and Schmukler (2012) also find that both investors and fund managers tend to take too much risk during good times. But they would run and retrench quickly when shocks hit the financial system. Therefore, it is interesting to examine whether equity flows exhibit a larger predictability conditional on turbulent episodes—two tails of returns distribution. To that end, the application of quantile regression (QR) proposed since Koenker and Basset (1978) will be attractive.

However, QR faces the same problem of non-standard distortion as the mean regression does if the regressor is highly persistent. To solve this problem, Lee (2016) adopts the same IVX instrumentation (Magdalinos and Philllips, 2009) and develops the IVX-quantile regression (IVX-QR) allowing for persistent predictors. To formally show this model, let us firstly consider a linear predictive QR model:

$$Q_{y_t}(\tau) = \mu_\tau + A_\tau x_{t-1} + \varepsilon_t, \tag{9}$$

[35] We obtain the Matlab code of this IVX-Wald procedure from Rapach et al. (2016).

where $Q_{y_t}(\tau)$ is a conditional quantile of the dependent variable (stock returns). Then the ordinary QR estimator has the form:

$$\hat{A}_{\tau}^{QR} = argmin_A \sum_{t=1}^{n} \rho_\tau (y_t - Ax_t), \tag{10}$$

Where $\rho_\tau (u) = u(\tau - 1(u < 0)), \tau \in (0,1)$ is the asymmetric QR loss function and u is QR the residual.

The IVX-QR estimation starts with a de-quantile procedure which is analogous to the demeaning process in the mean regression. Formally, we remove the intercept term in (9) and thereby transform (9) to:

$$y_{t\tau} = A_\tau x_{t-1} + \varepsilon_{0t\tau}, \tag{11}$$

Where $y_{t\tau} := y_t - \hat{\mu}_\tau^{QR}$. Then based on the IVX-instrument $\widetilde{z_t}$ from equation (5), the IVX-QR estimator can be shown as:

$$\hat{A}_{\tau}^{IVXQR} = \arg inf_A \frac{1}{2} (\sum_{t=1}^{n} m_t(A))' (\sum_{t=1}^{n} m_t(A)), \tag{12}$$

where $m_t(A) = \tilde{z}_{t-1}(\tau - 1(y_{t\tau} \leq A\, x_{t-1}))$. Lee (2016) further shows that the resulting test statistics also follows a chi-square limit distribution, which is empirically easy to compute. We obtain the Matlab code from the author's website to empirically implement this IVX-QR procedure.[36]

4.3 Data and descriptive statistics

Our dataset covers a total of 21 emerging market economies from January 1995 to December 2014. We start with January 1995 because some countries' data (e.g., Czech and Hungary) are not available before this time. We divide these countries into 4 groups according to their regions. The first group consists of 7 countries from Asia: China, India, Indonesia, Malaysia, Pakistan, Philippines and Thailand. The second group includes 6 Latin American countries: Argentina, Brazil, Chile, Colombia, Mexico and Peru. The third group contains 4 EMEs from emerging Europe: Czech, Hungary, Poland, and Russia. Finally, we classify the remaining countries in our sample into one group: Egypt, Morocco, Turkey and South Africa.

[36] We are grateful to the author of Lee (2016) who kindly shares his Matlab code on his personal website: https://sites.google.com/site/jihyung412/research.

For each of these countries, we compute stock returns based on MSCI equity index at monthly frequency collected through Bloomberg. As all price indexes are measured in dollars, we deflate each price series by U.S. CPI to control for any inflationary effects. Moreover, consistent with the existing literature, we focus on predicting excess return. We compute excess rate as the difference between monthly stock returns (of each country) and the one-month Treasury bill rate, and the data of the latter is obtained from Rapach et al. (2016).

This study uses data on monthly international equity flows from the U.S. to the 21 EMEs in our sample. We collect the data from the Treasury International Capital (TIC) database of the U.S. Treasury Department, which has been widely used in the literature (e.g., Sarno et al., 2015 and Fuertes et al., 2016).

We use gross flows rather than net flows in order to distinguish between foreign and domestic investors to get more accurate empirical results (Rothenberg and Warnock, 2011; Forbes and Warnock, 2012); readers are referred to Chapter 2 for more details regarding this choice. Moreover, as the literature mostly discusses the impact of investors domiciled in developed markets on emerging equity markets (e.g., Broner et al., 2006 and Jotikasthira et al., 2012), we also focus on gross inflows, defined as the net of U.S. purchases of domestic stocks and U.S. sale of domestic assets (Forbes and Warnock, 2012). Therefore, a positive entry indicates an inflow into an EME from the U.S. Finally, all flows are in millions of U.S. dollars, and we also deflate each time series by U.S. CPI to convert it into real values.

<Insert Table 4.1 here>

Table 4.1 reports the descriptive statistics for these data. Excess stock returns average about 0.506% across countries, and their standard deviations are on average 9.81%, indicating the high volatility of emerging equity markets. As for equity flows, they average about 25.306 million dollars and 0.006 % of nominal GDP across countries, and their high standard deviations also reveal equity flow's volatile nature. Across 21 EMEs, average standard deviations are 126.067 million dollars (when equity flows are measured in U.S. dollars) and 0.046 % (when flows are scaled by domestic GDP).

4.4 Empirical Results

To assess the predictability of stock returns from international equity flows, we present our empirical results in two parts. In the first part, we report our results of in-sample tests. In the second part, we show the out-of-sample tests' results.

4.4.1 In-sample tests

4.4.1.1 Contemporaneous returns
OLS

<Insert Table 4.2 here>

We start our empirical investigation with the contemporaneous relationship between equity flows and stock returns. Table 4.2 reports our results based on OLS. Our results suggest that international equity flows significantly affect emerging stock returns *contemporaneously*: equity flows in 9 out of 21 EMEs display significant estimates, and among them 7 are significant at 1% level. For these 9 countries, their estimated coefficients are all positive. Take India for example, if equity flows increases by 100 Million dollars (in real value), its domestic stock return is likely to increase by 0.7%. This positive sign is consistent with the theories arguing that the equity flows rush into an EME could drive up stock prices quickly (Hau and Rey, 2004).

In addition, our results in Table 2 suggest that equity flows have a heterogeneous impact among different regions. Specifically, it seems that the Asian countries are more severely affected. Among the 7 Asian emerging markets in our sample, 4 (India, Malaysia, Philippines and Thailand) display a significant slope estimate of equity flows. As for the other 14 EMEs, we also observe significant estimates from Brazil, Czech, Russia, Egypt and South Africa. But these countries are spread across different regions (Latin America, East Europe and others), and no other region contains such a considerable percentage of significant estimates as Asia does[37].

[37] A number of empirical literature—e.g., Richard (2005), Chai-Anant and Ho (2008), and Tillman (2013)—also support the observation that Asian equity flows significantly affect the local stock prices. Nevertheless, there seems to be little theoretical studies clarifying why this observation is particularly significant in Asia compared to other regions.

IVX-Wald

<Insert Table 4.3 here>

We previously mentioned that if equity flows are persistent or belong to the I(1) space, empirical results based on OLS would be invalid. Worse, it is also empirically difficult to identify the exact degree of persistence, which also confuses the validity of OLS estimates. Therefore, we employ the predictive regression based on IVX-filtering of Kostakis et al. (2015), which remains valid when handling predictors with various degrees of persistence. We report our results based on this method in Table 4.3.

One observes that the results in Table 4.3 are largely similar with those in Table 4.2. Again, 9 out of 21 EMEs show significant coefficient. Among them, 5 are still significant at 1% level, 3 significant at 5%, and 1 significant at 10%. Compared to the OLS results in Table 4.2, where 7 EMEs display significance at 1%, the general significance does slightly drop, but these results remain significant at conventional levels overall. In addition, the geographical pattern stays similar. Asian countries remain the largest group that displays significant estimates. This similarity suggests that the significant estimates of equity flows are not statistical artefacts due to the predictors' persistence. Therefore, our results (based on IVX-filtering technology) confirm the significant association between international Equity flows and contemporaneous emerging stock returns contemporaneously.

IVX-QR

<Insert Table 4.4 here>

Our empirical results based on predictive mean regression can be informative. However, given our previous discussion of equity flows' pro-cyclical nature, it might be even more interesting to examine the entire return distribution or specific parts of the distribution such as tails and centre.

Asian

Table 4.4 presents our empirical results from the 15th to the 85th quantile based on IVXQR. One can still observe that the equity flows' effect on stock returns is the strongest among the Asian emerging markets. Out of the 7 Asian countries in our samples, the 4 EMEs (India, Malaysia, Philippines and Thailand) where equity flows are significant in the conditional mean regression all display significant results across a wide range of quintiles. Equity flows in India appear significant through the 15th to 75th quantile of returns' conditional distribution. The magnitude of their estimated coefficient varies from 0.006 to 0.010, and it is slighter larger in the left tails (15th to 35th). This might signal that Indian equity inflows have a larger price impact conditional on episodes of relatively low returns. Equity flows into Thailand have positive and significant coefficients from the 25th to the 75th quantile. Moreover, we observe an even more pervasive effect from Malaysia and Philippines: equity flows towards these two countries possess positive and significant coefficient estimates across all quintiles reported (15th to 85th).

More interestingly, IVXQR detects predictability in some specific part of returns distribution, which has been overlooked by the conditional mean regression. For instance, equity flows to Indonesia lack significance in both of the conditional mean regressions, as shown in both Table 4.2 and Table 4.3. Nevertheless, our results based on IVXQR (in Table 4.4) report positive and strongly significant coefficients in the left tail (from 15th to 35th). In the 45th and 55th percentile, both the magnitude and significance of the coefficient decrease. Indonesian equity inflows eventually become insignificant in the upper quantiles. This finding based on quantile regression suggests a heterogeneous effect across different parts of returns' distribution, and thereby imply that the price impact of equity inflows into Indonesia might be larger when returns are relatively lower. This could be an interesting finding since Raddatz and Schmukler (2012) argue that international investors retreat from the local equity markets quickly during bad times (e.g., financial crisis); the heterogeneous price effect found in this study could be in line with this pro-cyclical nature.

In summary, our results suggest that equity flows towards Asian countries significantly affect the local stock returns contemporaneously. Among all the 7 countries, only China and Pakistan display no significant coefficient in any quantile reported. Furthermore, compared to the outcomes from the previous two conditional-mean regressions, our results based on IVX-QR show two additional implications: first, for some countries (especially those in Asia), equity flows affect equity prices during both booms and busts (throughout the whole conditional distribution of returns). Second, for a few other countries, predictability is only found during episodes of either expansion or contradiction. For instance, predictably in the Egyptian equity markets is only found in returns' lower quantiles; this shows the association between flows and returns only exists when returns are relatively low. Likewise, we could only observe predictability in the Moroccan equity markets during good times—that is, the upper quantiles.

Latin America

Table 4.4 also shows that equity flows into Latin America have a considerably smaller impact on returns, compared to their effect on the Asian market. Among the 6 Latin American EMEs in our sample, only equity flows to Brazil are generally significant across the whole conditional distribution. Moreover, those coefficients are all positive. This observation is once again in line with theory, as we previously discussed in Section 1. As for some other Latin American countries, equity flows appear with significant estimates in a few quantiles in one tail of returns' distribution. For example, equity flows to Chile are significant in the 15^{th} and the 25^{th} quantiles, which suggests that equity flows have a stronger contemptuous predictability of returns when returns are relatively low. However, the pattern in Peru is completely the opposite: equity flows are only significant when returns are relatively high ($\tau = 75th\ and\ 85th$). For these two countries, equity flows' price impact is significant only at the two tails of returns' conditional distribution, which again implies that equity flows might have a stronger impact on returns during good or bad times.

East Europe

Turning to the East European countries, Equity flows to Czech Republic and Russia are still significant across a considerable amount of quantiles. These observations are consistent with the results from the conditional mean regressions (shown in Table 4.2 and 4.3). In particular, equity flows to Russia are generally significant across the whole distribution: they possess positive and statistically significant coefficients from the 25^{th} to the 85^{th} quantile. However, equity flows' price impact is asymmetric in Czech, as we only observe significant estimates in the right part of the returns' conditional distribution implying episodes when the stock returns are booming.

Others

The bottom panel of Table 4.4 shows the results for the other EMES: mainly countries from the Middle East and Africa. Firstly, neither equity flows to Egypt nor those to Morocco are strongly significant in the conditional mean regressions (as shown in Table 4.2 and Table 4.3). However, our results based on IVXQR suggest that equity flows to these two EMEs might possess more predictability in some specific parts of the distribution. Start with Morocco, equity flows' effect (on returns' predictability) is not significant at the left tail of the conditional distribution. However, as quantile increases the effect also increases, and the magnitude of coefficients are relatively large compared with those of other countries. For instance, at the 75th percentile, a 10 million USD increase of equity flows would be associated with a 3.0% increase of return. This implies a significant price impact of equity flows to Morocco, which is a relatively small economy compared to the other EMEs in our sample. In contrast, we observe an opposite pattern in Egypt: equity inflow has a positive effect on returns conditional on episodes when returns are low (at lower quantiles), but this effect decreases and becomes insignificant after the 45th quantile. Overall, for Egypt and Morocco, quantile regression suggests more predictability in the two tails.

In summary, IVXQR provides us with more information about the relationship between equity flows and contemporaneous returns' predictability. In particular, equity flows' price impact appears the strongest in Asia, where flows significantly predict contemporaneous returns across a wide range of quantiles of returns' conditional distribution. In addition, for some countries (e.g., Indonesia, Egypt and Morocco), IVXQR reveals predictability in some specific part of returns' distribution, especially in the two tails. This observation might echo the pro-cyclical nature of equity flows.

4.4.1.2 One-month-ahead returns

For investors who want to forecast stock returns, our results of contemporaneous predictability might be informative. However, investors might be more interested to investigate whether international equity flows can help to predict future stock returns. To that end, we report the results of one-month-ahead predictability based on the same set of empirical models (OLS, IVX-Wald and IVXQR) employed in the previous section. We start our presentation with OLS estimate.

OLS

<Insert Table 4.5 here>

Table 4.5 shows the one-month-ahead results based on OLS. One might observe several noticeable findings: firstly, the predictability largely disappears. This is most prominent in Asian markets, that equity flows lack significance in all of the 7 Asian EMEs. This observation is a sharp contrast to our results reported in the previous section (Table 4.2), where contemporaneous equity flows display significantly positive estimates in 4 out of 7 Asian markets. How should one explain this difference? We argue that this is probably because of the short-term nature of equity flows' price impact. Richard (2005) uses daily data to investigate the link between net purchases of foreigners and returns in a number of Asian stock markets. He found that inflows have impacts on prices even beyond the day of inflow, but most of this impact is complete within a few days. This finding might help to explain our empirical results here: when international equity inflows enter the domestic stock markets, they drive up stock returns contemporaneously, but their impact might perish within days. Therefore, there is no significant link between equity flows and one-month-ahead returns.

Another somewhat surprising observation is that among the countries where equity flows are significant (Colombia, Poland and South Africa), the estimated coefficients for equity flows are all negative. Take Poland for instance: if foreign equity inflow goes up by 10 million U.S. dollars in real value, its domestic stock returns might decrease by 0.6%. Although this observation might not be very intuitive to interpret, a number of empirical studies found a similar story. For instance, Hartmann and Pierdioch (2007) investigated the possibility of whether equity flows to the U.S. could help to forecast U.S. stock returns. They report exactly the same pattern: a positive (negative) link between international equity flows into the U.S. market and its contemporaneous (one-month-ahead) stock returns. To interpret their results, Hartmann and Pierdioch (2007) suggest that there might be an overshoot of stock returns in response to international equity flows. In other words, this overshooting implies that equity flows might have a significant effect on contemporaneous prices. However, this effect might reverse gradually in later months. A recent finding of Cenedese and Mallucci (2016) might also support this argument. This study shows that the covariance between expected flows and returns turns negative in the long run, and this effect is especially strong for emerging economies.

IVX-Wald;

<Insert Table 4.6 here>

To ensure that our results are not a statistical artefact because of a persistent regressor, we again employ the IVX-Wald test of Kostakis et al. (2015), whose results are displayed in Table 4.5. Compared to OLS results from Table 4.4, firstly, we notice the weak significance of Colombian equity flows disappear. This might imply that its significance reported in Table 4.4 is resulted from size distortion owning to persistent equity flows. However, the significance of equity inflows into Poland and South Africa remain, and both of their estimated coefficients are negative. Therefore, their results might be valid and we may interpret them similarly as we did in the OLS estimates.

IVX-QR;

<Insert Table 4.7 here>

In order to explore more predictability from the whole distribution of one-month-ahead stock returns, we employ the IVXQR of Lee (2016) and present the results in Table 4.7. For the two countries (Poland and South Africa) where equity flows could significantly predict one-month-ahead stock returns in the conditional mean regressions, their equity flows again display significant and negative coefficients across a number of quantiles. Nevertheless, it seems that equity flows have a broader impact on South African future returns' distribution, for their coefficients are significant from the 25th to the 65th percentiles. In contrast, equity flows to Poland are only significant across a few quantiles around the median (from 35th to 55th). For the rest of the EMEs, equity flows are generally insignificant, and this is consistent with our preceding results.

In summary, the one-month-ahead predictability is surprisingly different from contemporaneous predictability. Firstly, equity flows' significance largely disappears. This observation is especially prominent among the Asian countries, where equity flows significantly affect contemporaneous returns. We argue that equity flows' price impact could be short-term. In other words, equity flows could drive up contemporaneous prices but their impact might perish quickly (Richard, 2005). Secondly, equity flows' estimated coefficients are generally found to be negative. We show that this observation might be an overshoot of returns in response to international equity flows (Hartmann and Pierdioch, 2007).

4.4.2 Out-of-sample tests

Next, we investigate equity flows' out-of-sample forecasting ability from the two countries where equity flows could help to predict one-month-ahead returns (in sample). Our motivation is that, firstly, a large number of literatures suggest that there is no necessary association between in-sample and out-of-sample predictability (see, e.g., Goyal and Welch, 2008). Secondly, investors might be much more interested in out-of-sample forecasting.

To conduct our empirical analysis, we employ the standard out-of-sample R-squared to see whether predictive regression of equity flows could outperform a prevailing-mean model. Specifically, corresponding to each country, we firstly compute the one-month-ahead forecast using equity flows as a predictor. This takes the form as:

$$\hat{y}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t x_t, \tag{13}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates of intercept and slope coefficient (for equity flows), respectively.[38] For each out-of-sample evaluation, the data is collected from the start of the sample through month t. Next, we compare the one-month-ahead forecasted return $\hat{y}_{t:t+1}$ from the benchmark model (prevailing mean), which is calculated as the average excess returns from the beginning of the sample through month t. Formally, it is shown as:

$$\hat{y}_{t+1} = average\ (\hat{y}_{1:t}), \tag{14}$$

In fact, the prevailing mean forecast is equivalent to the constant expected excess return model in equation (13) with $\beta = 0$. If the benchmark model outperforms our predictive regression with equity flows, it would suggest that equity flows might not help to forecast future returns, such that it might be even better to calibrate returns time series with a random walk with drift. We compare the performance of these two models by comparing their mean squared forecast error (MSFE), which is also called as the out-of-sample R-squared statistics (Rapach et al., 2016). The period for out-of-

[38] Newly-West standard errors are employed to account for serial correlation and heteroscedasticity.

sample evaluation is over 2003:1 to 2014:12. We use the statistics of Clark and West (2007) to test whether our predictive regression forecast delivers a significant improvement in MSFE. The null hypothesis of this test is that the benchmark (prevailing mean) MFSE is less than or equal to the predictive regression MSFE. If we could reject the null and accept the alternative hypothesis that the prevailing mean MFSE is greater than the predictive regression,[39] then we can conclude that our predictive regression with equity flows as the regressor can outperform the benchmark model, thus international equity flows might contain relevant information to forecast future emerging markets stock returns.

<Insert Table 4.8>

Table 4.8 shows our out-of-sample test results. In Column (1), we notice that the out-of-sample R-squared are almost all negative in all countries except Poland, which implies that equity flows to all these countries fail to outperform the prevailing mean benchmark model. In other words, equity flows to these countries might not be helpful to forecast future stock returns. Moreover, equity flows to South Africa lack significance in the out-of-sample test, even though the in-sample results are significant. Therefore, this observation confirms the conclusion of Goyal and Welch (2008) that in-sample predictability would not necessarily lead to out-of-sample forecasting ability, at which investors might be more interested. Finally, Poland seems to be the only remnant in our out-of-sample test. Yet, its significance is only at 10%, even though its test statistics of Clark and West (2007) is close to 5% critical value. To summarize our out-of-sample test's results, there seems to be weak association between equity flows and out-of-sample predictability of emerging stock returns.

4.4.3 Robustness checks

We conduct a few robustness checks by changing the specifications of equity flows into: (1) net flows; (2) gross inflows over domestic GDP. Furthermore, we also perform the unit root tests for equity flows since their persistence is the focus of this chapter.

The key results can be summarized as follows: first, we find even less predictability when net flows are employed as the predictor; this observation justifies

[39] This is corresponding to $H_0: R^2_{OS} \leq 0 \ against \ R^2_{OS} > 0$, where R^2_{OS}represents the out-of-sample R-squared statistics (Rapach et al., 2016)

our choice of gross flows. Second, measuring equity flows a percentage of GDP yields similar empirical results—which might imply a relatively small impact of wealth effect on our main analysis. Third, the unit-root tests show that equity flows to all countries are stationary. Nevertheless, recent literature unearths that such tests do not provide a firm guidance on discrepancy be between stationarity, near or exact unit root processes (Lee, 2016).

Readers are referred to the Appendix for more details.

4.5 Conclusion

Global capital flows have significantly increased during the past two decades. A considerable amount of literature suggests that short-term capital flows, especially international equity flows, have a strong impact on emerging equity markets. Motivated by this observation, this paper seeks to investigate the link between international equity flows and the predictability of emerging markets' stock returns.

To conduct our empirical analysis, we collect monthly data for 21 emerging markets economies (EMEs) over 1995-2014. We employ both in-sample and out-of-sample tests to investigate our research question. In particular, we employ the state-of-art predictive regression models based on IVX-instrumentation, in order to ensure that our empirical results would not be a statistical artefact due to a persistent regressor. Earlier literature typically identifies equity flows' degree of persistence as stationarity, recent studies show, however, that the exact degree of a predictor's persistence is not usually precisely identified, and standard unit root test might not provide a firm guide (Lee, 2016). Therefore, it might be better to employ predictive regressions which could handle various degrees of persistence. To that end, this paper employs the IVX-wald of Kostakis et al. (2015) and IVXQR of Lee (2016), which are the latest techniques of predictive regressions.

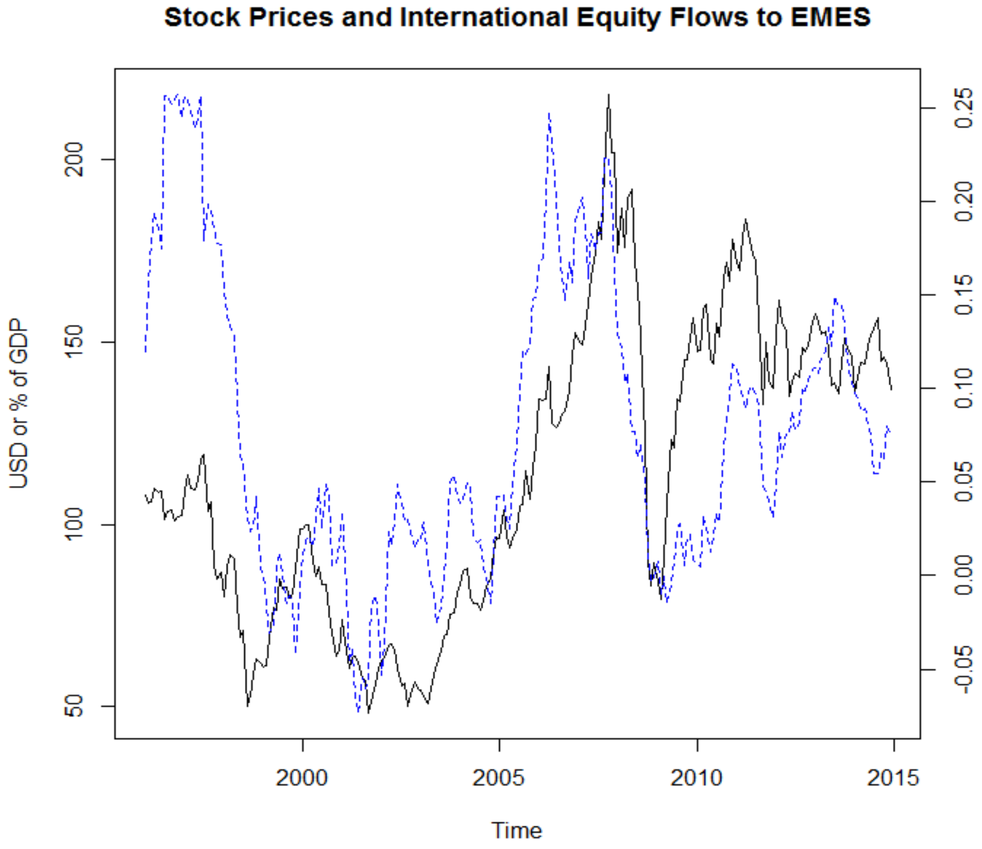
One of our main findings is that there seems to be a significant link between equity flows and contemporaneous stock returns among a large number of EMEs. This observation is especially prominent in Asian countries. Moreover, equity flows' estimated coefficients are mostly positive. All of these observations seem to confirm the immediate price impact of equity flows towards EMEs, as suggested by a number of literatures (see, e.g., Lou, 2012 and Yan, 2015).

However, there is only weak evidence that international equity flows could predict one-month-ahead stock returns (neither in-sample nor out-of-sample). In addition, among the few countries where equity flows display significant estimates, their coefficients are negative. Therefore, these observations imply that equity flows' price impact might not be persistent: when equity flows rush into one emerging equity market, they drive up prices contemporaneously, but the price impact can be eventually reversed. From the literature, there could be two main interpretations for the negative signs of equity flows' coefficient. Firstly, there could have been an overshooting of stock returns in response to equity flows, such that the price impact is gradually reversed in later months (Hartmann and Pierdzioch, 2007; Cenedese and Mallucci, 2016). Secondly, future stock returns' reduction might be a consequence of foreign investors' portfolio rebalancing. Specifically, when the local equity returns have been driven up by the international equity flows, foreign investors might rebalance their portfolio by reducing their equity holdings in the underlying market to hedge against foreign exchange risk. Such behaviours might lead to equity outflows, and thereby a reduction of stock returns (Hau and Rey, 2004).

Nevertheless, the strong contemporaneous association between equity flows and emerging markets' stock returns might still hint at the possibility of predictability, if we had access to higher-frequency data such as daily and weekly equity flows. In particular, it might still be possible to capture one-day-ahead or one-weak-ahead predictability (even in out-of-sample tests), despite our finding that equity flows' price impact disappears quickly. Therefore, it would be interesting to employ daily or weekly data and use the same empirical methods to investigate this topic again in the future.[40] Moreover, equity flows could be more persistent within such a daily or weekly time window (Ülkü, 2015), thus there could be a greater need to use prediction regressions with IVX-instrumentation proposed by Kostakis et al. (2015) or Lee (2016) in order to ensure that the results would not a statistical artefact because of persistent predictor. Therefore, future exploration along these lines could shed considerable light on the link between international equity flows and the predictability of emerging markets' stock returns.

[40] There have been a few studies using weakly or daily equity flows. See, e.g., Richard (2005) and Yan (2015). Unfortunately, we do not have access to their datasets.

Figure 4-1 Stock Prices and International Equity Flows to EMEs



Notes:

1) Black line: real MSCI EME stock index. Left axis: in USD.

2) Blue line: average equity flows to EMEs. Right axis: % of domestic GDP.

Table 4-1 Summary Statistics

	Excess return		Equity flows		Equity flows (% gdp)	
Countries	**mean**	**std**	**mean**	**std**	**mean**	**std**
Asia						
China	0.109	9.896	30.137	337.104	0.002	0.014
India	0.525	8.822	76.576	257.698	0.010	0.031
Indonesia	0.745	13.179	23.581	84.790	0.006	0.031
Malaysia	0.114	8.626	30.380	108.445	0.022	0.096
Pakistan	0.244	10.979	3.104	19.312	0.004	0.024
Philippines	0.006	8.629	9.100	31.519	0.010	0.034
Thailand	0.119	11.014	20.780	77.927	0.010	0.037
Latin America						
Argentina	0.604	11.498	1.857	137.226	0.001	0.048
Brazil	0.606	10.660	291.838	655.139	0.029	0.058
Chile	0.049	6.699	8.178	81.623	0.006	0.073
Colombia	0.642	9.086	5.300	60.974	0.003	0.034
Mexico	0.049	6.699	-35.686	253.960	-0.005	0.040
Peru	0.858	8.635	10.537	93.137	0.014	0.144
East EU						
Czech	0.498	8.279	-5.814	62.823	-0.007	0.099
Hungary	0.783	10.634	0.219	26.464	0.001	0.039
Poland	0.489	10.231	7.937	20.981	0.003	0.009
Russia	1.456	15.142	-1.178	73.542	0.000	0.012
Others						
Egypt	0.914	9.449	2.308	29.736	0.004	0.035
Morocco	0.157	5.484	0.350	3.372	0.001	0.007
Turkey	1.385	14.822	22.572	127.594	0.009	0.052
South Africa	0.288	7.680	29.356	104.053	0.017	0.060

Table 4-2 International equity flows and *contemporaneous* stock returns: OLS estimates

(1) Countries	(2) Coef	(3) T stat	(4) P value
Asia			
China	0.000	-0.172	0.864
India	0.007	3.400	0.001
Indonesia	0.011	1.307	0.193
Malaysia	0.015	4.035	0.000
Pakistan	0.021	0.793	0.428
Philippines	0.058	3.706	0.000
Thailand	0.025	3.642	0.000
Latin America			
Argentina	0.000	-0.113	0.910
Brazil	0.003	3.032	0.003
Chile	-0.008	-1.498	0.135
Colombia	-0.003	-0.327	0.744
Mexico	0.003	1.587	0.114
Peru	0.007	1.205	0.229
East EU			
Czech	0.021	3.124	0.002
Hungary	0.007	0.374	0.709
Poland	0.005	0.176	0.860
Russia	0.034	3.022	0.003
Others			
Egypt	0.032	1.794	0.074
Morocco	0.200	1.626	0.105
Turkey	0.011	1.182	0.239
South Africa	0.010	2.397	0.017

Notes: Stock returns are computed from MSCI Index. Equity flows are measured in millions of US dollars.

Table 4-3 International equity flows and *contemporaneous* stock returns: IVX-Wald Estimates

Countries	**Coef**	**IVX_Wald**	**P value**
Asia			
China	0.000	0.024	0.876
India	0.007	11.393	0.001
Indonesia	0.012	1.336	0.248
Malaysia	0.015	9.124	0.003
Pakistan	0.023	0.372	0.542
Philippines	0.061	12.140	0.000
Thailand	0.024	6.922	0.009
Latin America			
Argentina	0.000	0.000	0.995
Brazil	0.003	9.141	0.002
Chile	-0.008	2.293	0.130
Colombia	-0.003	0.068	0.795
Mexico	0.003	2.667	0.102
Peru	0.007	1.232	0.267
East EU			
Czech	0.021	6.087	0.014
Hungary	0.014	0.298	0.585
Poland	0.008	0.057	0.811
Russia	0.034	6.697	0.010
Others			
Egypt	0.033	2.549	0.110
Morocco	0.204	3.783	0.052
Turkey	0.011	2.041	0.153
South Africa	0.010	3.965	0.046

Notes: Stock returns are computed from MSCI Index. Equity flows are measured in millions of US dollars. Red: P<0.05; Blue: P<0.10.

Table 4-4 International equity flows and *contemporaneous* stock returns: IVX-QR Estimates

Countries/Quantiles	**0.15**	**0.25**	**0.35**	**0.45**	**0.55**	**0.65**	**0.75**	**0.85**
Asia								
China	0.000	-0.001	-0.002	-0.002	-0.001	0.000	-0.001	-0.002
India	0.009	0.009	0.010	0.007	0.006	0.007	0.002	0.003
Indonesia	0.037	0.034	0.025	0.017	0.016	0.003	0.000	0.005
Malaysia	0.016	0.015	0.012	0.012	0.013	0.013	0.015	0.013
Pakistan	0.027	0.011	0.002	0.002	0.005	0.031	0.043	-0.026
Philippines	0.068	0.062	0.052	0.049	0.062	0.062	0.043	0.067
Thailand	0.021	0.026	0.032	0.028	0.034	0.029	0.024	0.021
Latin America								
Argentina	0.004	0.001	-0.001	-0.003	0.003	0.003	-0.001	-0.008
Brazil	0.004	0.003	0.002	0.003	0.002	0.003	0.005	0.004
Chile	-0.018	-0.015	-0.009	-0.007	-0.002	-0.005	-0.002	-0.002
Colombia	-0.005	-0.009	0.007	0.008	0.003	0.009	0.003	-0.007
Mexico	0.004	0.002	0.001	0.001	0.002	0.001	0.003	0.001
Peru	0.009	0.006	0.005	0.001	0.006	0.009	0.018	0.029
East EU								
Czech	0.019	0.013	0.014	0.017	0.020	0.023	0.026	0.028
Hungary	0.028	0.010	-0.007	-0.005	-0.037	-0.028	0.005	-0.006
Poland	0.026	0.029	0.011	-0.020	0.008	0.025	0.061	-0.018
Russia	0.018	0.034	0.040	0.031	0.022	0.031	0.031	0.047
Others								
Egypt	0.072	0.055	0.060	0.048	0.035	0.017	0.018	-0.004
Morocco	0.139	0.137	0.218	0.180	0.298	0.223	0.305	0.362
Turkey	0.002	0.009	0.010	0.007	0.003	0.005	0.007	0.018
South Africa	0.010	0.007	0.005	0.003	0.004	0.011	0.008	0.011

*Notes: This table reports the results of **estimated coefficients**. Stock returns are computed from MSCI Index. Equity flows are measured in millions of US dollars. Red: $P<0.05$; Blue: $P<0.10$.*

Table 4-5 International equity flows and *one-month-ahead* stock returns: OLS estimates

Countries	**Coef**	**t stat**	**P value**
Asia			
China	-0.002	-1.151	0.251
India	-0.001	-0.564	0.573
Indonesia	0.004	0.597	0.551
Malaysia	0.005	1.270	0.205
Pakistan	-0.001	-0.033	0.974
Philippines	0.000	0.023	0.982
Thailand	0.002	0.210	0.834
Latin America			
Argentina	-0.003	-0.742	0.459
Brazil	0.000	0.324	0.746
Chile	-0.006	-0.915	0.361
Colombia	-0.012	-1.960	0.051
Mexico	0.002	1.231	0.220
Peru	0.001	0.505	0.614
East EU			
Czech	0.002	0.274	0.784
Hungary	0.018	0.640	0.523
Poland	-0.068	-2.173	0.031
Russia	0.010	0.957	0.339
Others			
Egypt	0.029	1.020	0.309
Morocco	0.124	1.076	0.283
Turkey	-0.012	-1.626	0.105
South Africa	-0.011	-2.012	0.045

Notes: Stock returns are computed from MSCI Index. Equity flows are measured in millions of US dollars. Red: $P<0.05$; Blue: $P<0.10$.

Table 4-6 International equity flows and *one-month-ahead* stock returns: IVX-wald estimates

Countries	**Coef**	**IVX_Wald**	**P value**
Asia			
China	-0.002	0.998	0.318
India	-0.001	0.209	0.648
Indonesia	0.004	0.194	0.660
Malaysia	0.005	0.856	0.355
Pakistan	0.000	0.000	0.999
Philippines	0.003	0.023	0.878
Thailand	0.001	0.005	0.945
Latin America			
Argentina	-0.002	0.207	0.649
Brazil	0.000	0.145	0.703
Chile	-0.006	1.185	0.276
Colombia	-0.012	1.439	0.230
Mexico	0.002	1.032	0.310
Peru	0.002	0.069	0.793
East EU			
Czech	0.002	0.081	0.776
Hungary	0.018	0.478	0.489
Poland	-0.067	4.528	0.033
Russia	0.011	0.678	0.410
Others			
Egypt	0.030	2.189	0.139
Morocco	0.128	1.477	0.224
Turkey	-0.012	2.505	0.113
South Africa	-0.011	4.892	0.027

Notes: Stock returns are computed from MSCI Index. Equity flows are measured in millions of US dollars. Red: P<0.05; Blue: P<0.10.

Table 4-7 International equity flows and *one-month-ahead* stock returns: IVX-QR estimates

Countries/Quantiles	**0.150**	**0.250**	**0.350**	**0.450**	**0.550**	**0.650**	**0.750**	**0.850**
Asia								
China	-0.003	-0.004	-0.002	-0.003	-0.004	0.000	-0.001	-0.003
India	0.006	0.003	0.000	-0.001	-0.003	-0.004	-0.005	-0.004
Indonesia	0.012	0.004	0.009	-0.001	0.007	0.000	0.003	0.001
Malaysia	0.009	0.006	-0.001	0.005	0.000	0.003	0.002	-0.004
Pakistan	0.031	0.008	0.019	0.001	0.016	0.035	0.019	-0.028
Philippines	0.031	0.009	0.015	0.024	0.017	0.002	0.029	0.021
Thailand	-0.006	0.000	-0.003	-0.012	-0.004	0.008	0.011	0.003
Latin America								
Argentina	-0.005	0.001	-0.001	-0.002	-0.004	-0.006	-0.007	0.009
Brazil	0.002	0.001	0.001	0.000	0.000	0.000	0.000	-0.001
Chile	0.000	-0.004	0.000	-0.004	-0.003	0.000	0.004	-0.002
Colombia	-0.011	-0.018	-0.009	-0.008	-0.010	-0.012	0.011	-0.010
Mexico	0.005	0.003	0.002	0.002	0.003	0.002	0.003	0.002
Peru	0.010	0.006	0.004	0.001	0.001	-0.002	-0.004	-0.006
East EU								
Czech	-0.003	-0.005	-0.001	0.002	0.005	0.002	-0.003	0.003
Hungary	0.018	0.011	0.014	0.015	0.046	0.037	0.042	0.026
Poland	-0.068	-0.042	-0.093	-0.081	-0.064	-0.052	-0.055	-0.030
Russia	0.024	0.020	0.002	0.007	0.000	0.007	0.005	0.004
Others								
Egypt	0.029	0.018	0.028	0.014	0.016	-0.009	-0.005	0.004
Morocco	0.133	0.099	-0.006	-0.012	0.038	0.184	0.160	0.162
Turkey	-0.006	-0.007	-0.010	-0.013	-0.017	-0.010	-0.010	-0.014
South Africa	-0.012	-0.015	-0.016	-0.018	-0.019	-0.014	-0.006	-0.006

*Notes: This table reports the results of **estimated coefficients**. Stock returns are computed from MSCI Index. Equity flows are measured in millions of US dollars. Red: P<0.05; Blue: P<0.10.*

Table 4-8 Out-of-sample test results, 2003:12-2014:12

Countries	(1) OS_R2	(2) CW stats
Asia		
China	-15.129	0.575
India	-5.963	0.415
Indonesia	-6.622	-1.192
Malaysia	-0.296	0.786
Pakistan	-1.258	-1.111
Philippines	-0.927	-0.925
Thailand	-10.635	-0.953
Latin America		
Argentina	-0.193	0.052
Brazil	-1.507	-2.499
Chile	-1.663	-0.123
Colombia	-0.598	0.457
Mexico	-0.944	-0.414
Peru	-0.164	-0.359
East EU		
Czech	-0.402	-0.304
Hungary	-5.320	-0.797
Poland	2.448	1.640
Russia	-1.832	-0.161
Others		
Egypt	-8.326	0.440
Morocco	-1.779	-0.266
Turkey	-1.979	0.360
South Africa	-3.725	0.324

Notes: This table reports the out-of-sample R-squared in the first column. The second column shows the test statistics of Clark and West (2007), where the null hypothesis is that the predictive regression cannot outperform the benchmark (prevailing mean) model. Red: P<0.05; Blue: P<0.10.

4.6 Appendix

To check the robustness of our results, we alter the specifications of equity flows into: (1) net flows; (2) gross inflows over domestic GDP. Furthermore, we also perform the unit root tests for equity flows since their persistence is the focus of this chapter.

4.6.1 Net flows

Although net flows are employed by studies such as Sarno et al. (2016) and Yan et al. (2016), they are not our choice in our main analysis because net flows fails to distinguish investments made between foreign and domestic investors (Forbes and Warnock, 2012). Empirical studies based on net flows, therefore, may yield less accurate results and misinformed policy recommendations (Rothenberg and Warnock, 2012). Readers are referred to Chapter 2 for more discussion about the distinction between net flows and gross flows.

<Insert Table 4.9 - 15 here>

To check the validity of such an assumption, we use net equity flows in the same collection of predictive regressions. It appears that the results of contemporaneous predictability are similar with those based on gross inflows (as shown from Tables 4.9 - 11). Nevertheless, we observe even less evidence of one-month-ahead predictability—both in sample and out-of-sample, both through the conditional mean and conditional quantile regressions. Therefore, such results may again justify our choice of gross inflows.

4.6.2 Gross inflows over GDP

Equity flows in our main empirical analysis are measured in United States Dollars (deflated by CPI). However, Curcuru et al. (2011) argue that such a specification may lead to confounding results because of the wealth effect: if financial wealth is growing—which is a reasonable assumption—a dollar today may suggest significantly different value in ten years. To investigate this possibility, we scale equity flows with gross domestic productivity (GDP), which is a standard method from the literature (e.g., Yan et al., 2016). Nevertheless, we refrain from choosing this specification in our main analysis because GDP are typically released quarterly or even annually, which can hardly help us to forecast.

<Insert Table 4.16 – 22 here>

The results are reported from Tables 4.16 to 22. One can observe that the results are similar with those from our main analysis; such findings may imply a relatively small impact of wealth effect on our main analysis.

4.6.3 Unit root test for equity flows

Since this chapter focuses on the persistence of equity flows, it would be informative to present the results of unit root tests on equity flows.

<Insert Table 4.23 here>

The results of Augmented Dickey–Fuller (ADF) tests are presented at Table 4.23. We observe rejections of the null hypothesis for all countries, which may suggest stationarity of equity flows towards all EMEs.

Nevertheless, Lee (2016) points out that "Unit root tests do not provide a firm guidance on discrepancy between I(0), near or exact unit root processes." As discussed in Section 4.2.1, if equity flows belong to the category of near or exact unit root, the following size distortion may be severe and results invalid.

4.6.4 Issue of reversal causality

Regarding the association between equity flows and stock returns, reversal causality could be a concern: more equity flows could drive up the stock prices; higher prices might in turn attract more flows[41]. Therefore, the literature generally employ Vector Autoregression (VAR) to account for such simultaneity[42].

In this study, we fully acknowledge the drawbacks of not employing VAR. Nevertheless, we choose the IVX-filtering predictive regressions instead because of the following reasons: first, IVX-regressions themselves allow for self-generated instruments which could remove endogeneity—readers are referred to Kostakis et al. (2015) for more discussions. Second, one key contribution of this study is to investigate the impact of equity flows' persistence by applying the IVX-regressions, which is novel in the literature of international capital flow. Unfortunately, IVX-instrumentation is currently unavailable to VAR models. Therefore, it is a compromise to choose IVX regressions instead.

[41] See Hau and Ray (2004) for a detailed discussion on this mechanism of portfolio rebalancing.

[42] See Yan (2015) which investigates the same topic using VAR.

Table 4-9 International equity flows (Net) and *contemporaneous* stock returns: OLS estimates

(1) Countries	(2) Coef	(3) T stat	(4) P value
Asia			
China	0.000	-0.269	0.788
India	0.007	4.156	0.000
Indonesia	0.010	1.204	0.230
Malaysia	0.009	3.179	0.002
Pakistan	0.023	0.870	0.385
Philippines	0.056	4.118	0.000
Thailand	0.021	3.075	0.002
Latin America			
Argentina	-0.005	-0.881	0.379
Brazil	0.003	3.140	0.002
Chile	-0.002	-0.992	0.322
Colombia	0.004	0.594	0.553
Mexico	0.000	-0.144	0.886
Peru	0.004	0.944	0.346
East EU			
Czech	0.016	2.172	0.031
Hungary	-0.020	-1.202	0.231
Poland	-0.012	-0.500	0.618
Russia	0.034	3.012	0.003
Others			
Egypt	0.027	1.439	0.152
Morocco	-0.018	-0.507	0.613
Turkey	0.011	1.212	0.227
South Africa	0.012	2.792	0.006

Notes: Stock returns are computed from MSCI Index. Equity flows are measured in millions of US dollars. Red: $P<0.05$; Blue: $P<0.10$.

Table 4-10 International equity flows (Net) and *contemporaneous* stock returns: IVX-Wald Estimates

Countries	**Coef**	**IVX_Wald**	**P value**
Asia			
China	0.000	0.046	0.830
India	0.007	14.019	0.000
Indonesia	0.010	1.101	0.294
Malaysia	0.009	4.241	0.039
Pakistan	0.026	0.515	0.473
Philippines	0.060	15.314	0.000
Thailand	0.020	5.054	0.025
Latin America			
Argentina	-0.005	0.847	0.357
Brazil	0.003	9.531	0.002
Chile	-0.002	0.550	0.458
Colombia	0.003	0.182	0.669
Mexico	0.000	0.003	0.953
Peru	0.005	0.873	0.350
East EU	0.016	3.835	0.050
Czech	-0.017	0.871	0.351
Hungary	-0.011	0.182	0.670
Poland	0.033	6.496	0.011
Russia			
Others			
Egypt	0.028	2.244	0.134
Morocco	-0.015	0.108	0.743
Turkey	0.011	2.183	0.139
South Africa	0.012	8.028	0.005

Notes: Stock returns are computed from MSCI Index. Equity flows are measured in millions of US dollars. Red: P<0.05; Blue: P<0.10.

Table 4-11 International equity flows (Net) and *contemporaneous* stock returns: IVX-QR Estimates

Countries/Quantiles	**0.15**	**0.25**	**0.35**	**0.45**	**0.55**	**0.65**	**0.75**	**0.85**
Asia								
China	0.000	0.002	0.001	-0.001	-0.001	-0.001	-0.001	-0.001
India	0.009	0.009	0.007	0.007	0.008	0.007	0.004	0.004
Indonesia	0.037	0.034	0.026	0.017	0.016	0.003	0.000	0.005
Malaysia	0.011	0.010	0.006	0.006	0.006	0.007	0.004	0.008
Pakistan	0.028	0.011	0.002	0.002	0.005	0.033	0.035	-0.007
Philippines	0.063	0.056	0.042	0.044	0.045	0.048	0.046	0.070
Thailand	0.012	0.021	0.028	0.027	0.027	0.028	0.028	0.021
Latin America								
Argentina	0.004	0.001	-0.001	-0.003	-0.004	0.002	-0.001	-0.008
Brazil	0.003	0.003	0.002	0.002	0.002	0.002	0.005	0.004
Chile	0.002	0.000	-0.001	-0.002	-0.001	0.000	0.003	0.002
Colombia	-0.004	-0.002	0.005	0.005	0.003	0.007	0.006	0.018
Mexico	-0.002	-0.001	0.000	-0.001	0.000	0.001	0.002	0.001
Peru	0.009	0.006	0.003	0.001	0.005	-0.003	0.000	0.006
East EU								
Czech	0.014	0.012	0.014	0.017	0.020	0.023	0.022	0.019
Hungary	-0.043	-0.027	-0.029	-0.029	-0.032	-0.033	0.004	-0.006
Poland	0.033	0.021	-0.014	-0.021	0.000	0.010	-0.021	-0.055
Russia	0.018	0.040	0.041	0.032	0.023	0.026	0.030	0.050
Others								
Egypt	0.068	0.058	0.059	0.056	0.037	0.037	0.019	-0.003
Morocco	-0.027	0.020	-0.031	-0.052	-0.036	-0.014	-0.024	-0.007
Turkey	0.002	0.008	0.010	0.007	0.003	0.006	0.007	0.018
South Africa	0.024	0.007	0.005	0.003	0.004	0.010	0.009	0.014

Notes: This table reports the results of ***estimated coefficients****. Stock returns are computed from MSCI Index. Equity flows are measured in millions of US dollars. Red: P<0.05; Blue: P<0.10.*

Table 4-12 International equity flows (Net) and *one-month-ahead* stock returns: OLS estimates

Countries	**Coef**	**t stat**	**P value**
Asia			
China	-0.002	-1.522	0.129
India	-0.001	-0.545	0.586
Indonesia	0.004	0.626	0.532
Malaysia	0.005	1.613	0.108
Pakistan	0.012	0.340	0.734
Philippines	0.009	0.556	0.579
Thailand	0.001	0.175	0.861
Latin America			
Argentina	0.000	0.092	0.927
Brazil	0.001	0.741	0.459
Chile	0.001	0.571	0.569
Colombia	-0.006	-0.922	0.357
Mexico	0.002	1.256	0.210
Peru	0.005	1.770	0.078
East EU			
Czech	0.002	0.252	0.802
Hungary	-0.006	-0.300	0.765
Poland	-0.041	-1.668	0.097
Russia	0.011	1.041	0.299
Others			
Egypt	0.039	1.557	0.121
Morocco	0.033	1.078	0.282
Turkey	-0.012	-1.602	0.110
South Africa	-0.005	-0.804	0.422

Notes: Stock returns are computed from MSCI Index. Equity flows are measured in millions of US dollars. Red: P<0.05; Blue: P<0.10.

Table 4-13 International equity flows (Net) and *one-month-ahead* stock returns: IVX-wald estimates

Countries	**Coef**	**IVX_Wald**	**P value**
Asia			
China	-0.002	1.602	0.206
India	-0.001	0.194	0.659
Indonesia	0.005	0.212	0.645
Malaysia	0.005	1.166	0.280
Pakistan	0.013	0.126	0.722
Philippines	0.010	0.385	0.535
Thailand	0.000	0.001	0.975
Latin America			
Argentina	0.001	0.013	0.909
Brazil	0.001	0.434	0.510
Chile	0.001	0.420	0.517
Colombia	-0.005	0.472	0.492
Mexico	0.002	1.562	0.211
Peru	0.005	1.049	0.306
East EU			
Czech	0.002	0.063	0.802
Hungary	-0.007	0.139	0.709
Poland	-0.040	2.431	0.119
Russia	0.013	1.012	0.314
Others			
Egypt	0.039	4.418	0.036
Morocco	0.035	0.602	0.438
Turkey	-0.012	2.456	0.117
South Africa	-0.005	1.243	0.265

Notes: Stock returns are computed from MSCI Index. Equity flows are measured in millions of US dollars. Red: P<0.05; Blue: P<0.10.

Table 4-14 International equity flows (Net) and *one-month-ahead* stock returns: IVX-QR estimates

Countries/Quantiles	**0.150**	**0.250**	**0.350**	**0.450**	**0.550**	**0.650**	**0.750**	**0.850**
Asia								
China	-0.003	-0.003	-0.002	-0.003	-0.003	-0.001	-0.001	-0.003
India	0.006	0.001	0.000	-0.002	-0.002	-0.004	-0.004	-0.004
Indonesia	0.012	0.003	0.009	-0.002	0.006	0.000	0.006	0.002
Malaysia	0.008	0.000	0.002	0.003	0.002	0.003	0.000	-0.003
Pakistan	0.035	0.007	0.020	0.006	0.044	0.053	0.026	-0.028
Philippines	0.031	0.009	0.026	0.026	0.021	0.014	0.034	0.023
Thailand	-0.006	0.001	-0.002	0.003	0.002	0.007	0.009	0.000
Latin America								
Argentina	0.004	0.001	-0.001	-0.002	-0.004	-0.006	-0.007	0.009
Brazil	0.002	0.001	0.001	0.001	0.000	0.000	0.000	-0.001
Chile	-0.002	-0.003	0.000	0.002	0.004	0.006	0.006	0.003
Colombia	-0.004	0.000	-0.004	-0.008	-0.005	-0.001	0.008	-0.008
Mexico	0.000	0.002	0.000	0.002	0.000	0.002	0.003	0.003
Peru	0.010	0.009	0.005	0.003	0.001	0.005	0.009	0.003
East EU								
Czech	-0.002	-0.003	0.000	0.002	0.005	0.002	-0.003	0.003
Hungary	0.004	-0.002	0.000	-0.009	-0.018	-0.028	-0.021	-0.005
Poland	-0.038	-0.023	-0.042	-0.043	-0.044	-0.049	-0.051	-0.034
Russia	0.025	0.021	0.002	0.004	0.000	0.001	0.005	0.012
Others								
Egypt	0.040	0.024	0.041	0.026	0.020	-0.008	0.017	0.011
Morocco	-0.040	-0.014	0.006	0.023	0.004	0.019	0.039	0.056
Turkey	-0.005	-0.007	-0.010	-0.013	-0.017	-0.010	-0.009	-0.015
South Africa	-0.006	-0.004	-0.008	0.001	0.000	-0.004	-0.004	-0.004

Notes: This table reports the results of ***estimated coefficients****. Stock returns are computed from MSCI Index. Equity flows are measured in millions of US dollars. Red: P<0.05; Blue: P<0.10.*

Table 4-15 Out-of-sample test results (Net flows), 2003:12-2014:12

	(1)	(2)
Countries	**OS_R2**	**CW stats**
Asia		
China	-6.231	0.643
India	-5.924	0.434
Indonesia	-6.273	-1.178
Malaysia	-2.207	0.929
Pakistan	-1.066	-0.287
Philippines	-0.541	0.117
Thailand	-10.250	-1.099
Latin America		
Argentina	-2.706	-0.508
Brazil	-1.223	-1.105
Chile	-2.601	-0.793
Colombia	-3.412	-0.269
Mexico	-1.516	-0.283
Peru	0.329	1.173
East EU		
Czech	-0.407	-0.426
Hungary	-8.591	-1.497
Poland	0.582	0.889
Russia	-0.787	-0.394
Others		
Egypt	-2.637	1.145
Morocco	-1.249	1.105
Turkey	-2.353	0.154
South Africa	-3.565	-0.353

Notes: This table reports the out-of-sample R-squared in the first column. The second column shows the test statistics of Clark and West (2007), where the null hypothesis is that the predictive regression cannot outperform the benchmark (prevailing mean) model. Red: $P<0.05$; Blue: $P<0.10$.

Table 4-16 International equity flows (Over GDP) and *contemporaneous* stock returns: OLS estimates

(1) Countries	(2) Coef	(3) T stat	(4) P value
Asia			
China	42.624	1.346	0.180
India	63.860	3.378	0.001
Indonesia	33.675	0.997	0.320
Malaysia	17.732	3.203	0.002
Pakistan	7.755	0.403	0.688
Philippines	53.818	3.763	0.000
Thailand	63.148	4.723	0.000
Latin America			
Argentina	1.160	0.103	0.918
Brazil	43.642	3.471	0.001
Chile	-5.563	-0.995	0.321
Colombia	-0.034	-0.002	0.998
Mexico	20.569	1.986	0.048
Peru	4.879	1.223	0.223
East EU			
Czech	10.330	2.512	0.013
Hungary	3.075	0.255	0.799
Poland	62.229	0.961	0.338
Russia	157.611	2.259	0.025
Others			
Egypt	23.905	1.671	0.096
Morocco	119.619	2.256	0.025
Turkey	28.512	1.213	0.226
South Africa	15.892	2.478	0.014

Notes: Stock returns are computed from MSCI Index. Equity flows are measured in millions of US dollars. Red: P<0.05; Blue: P<0.10.

Table 4-17 International equity flows (Over GDP) and *contemporaneous* stock returns: IVX-Wald Estimates

Countries	**Coef**	**IVX_Wald**	**P value**
Asia			
China	40.345	0.761	0.383
India	63.423	12.264	0.000
Indonesia	33.247	1.406	0.236
Malaysia	18.336	10.304	0.001
Pakistan	9.008	0.094	0.760
Philippines	58.167	13.016	0.000
Thailand	61.406	10.588	0.001
Latin America			
Argentina	2.267	0.022	0.883
Brazil	44.969	14.740	0.000
Chile	-5.780	0.927	0.336
Colombia	0.855	0.002	0.960
Mexico	22.968	4.367	0.037
Peru	4.929	1.620	0.203
East EU			
Czech	10.592	3.856	0.050
Hungary	11.152	0.367	0.545
Poland	66.165	0.810	0.368
Russia	155.371	3.976	0.046
Others			
Egypt	24.331	1.971	0.160
Morocco	120.789	6.069	0.014
Turkey	28.694	2.388	0.122
South Africa	15.755	3.660	0.056

Notes: Stock returns are computed from MSCI Index. Equity flows are measured in millions of US dollars. Red: P<0.05; Blue: P<0.10.

Table 4-18 International equity flows (Over GDP) and *contemporaneous* stock returns: IVX-QR Estimates

Countries/Quantiles	**0.15**	**0.25**	**0.35**	**0.45**	**0.55**	**0.65**	**0.75**	**0.85**
Asia								
China	39.808	36.634	19.773	4.498	16.559	6.201	-13.901	8.240
India	63.441	76.869	69.310	56.818	56.396	51.743	14.484	34.122
Indonesia	74.631	68.258	58.782	54.910	45.455	22.133	20.515	17.062
Malaysia	22.143	18.455	16.055	17.187	17.331	17.742	22.103	20.272
Pakistan	16.599	6.267	-4.424	0.745	1.214	2.061	9.300	-31.561
Philippines	69.728	59.270	53.305	46.089	51.789	49.044	47.974	63.444
Thailand	53.590	58.957	70.436	74.609	75.052	75.962	64.050	69.321
Latin America								
Argentina	12.185	1.758	-4.003	-8.836	11.152	7.836	-3.085	-22.036
Brazil	51.203	58.262	41.643	32.235	32.108	32.860	45.781	43.542
Chile	-15.771	-13.575	-0.660	-0.081	-0.745	-1.995	-2.517	-1.409
Colombia	-10.884	-8.976	14.814	13.802	17.805	12.830	4.246	-9.481
Mexico	24.460	17.208	15.204	26.067	25.105	13.994	18.498	6.665
Peru	4.652	2.824	5.257	2.552	5.585	7.604	15.633	17.467
East EU								
Czech	7.251	6.669	7.448	8.955	10.804	12.081	13.882	14.541
Hungary	12.370	4.895	-3.269	-9.455	-16.328	-25.068	4.557	-5.838
Poland	173.184	83.418	85.650	22.399	63.941	77.890	157.506	-27.906
Russia	178.105	78.791	144.023	176.341	183.548	145.018	164.143	189.923
Others								
Egypt	62.761	60.747	49.051	38.111	22.387	14.387	15.091	-2.639
Morocco	86.788	103.050	119.417	86.665	147.194	157.450	167.081	218.442
Turkey	5.530	12.599	17.064	29.905	13.055	12.093	15.370	39.625
South Africa	20.270	13.613	9.343	6.391	5.987	17.803	17.169	18.516

*Notes: This table reports the results of **estimated coefficients**. Stock returns are computed from MSCI Index. Equity flows are measured in millions of US dollars. Red: P<0.05; Blue: P<0.10.*

Table 4-19 International equity flows (Over GDP) and *one-month-ahead* stock returns: OLS estimates

Countries	**Coef**	**t stat**	**P value**
Asia			
China	-6.494	-0.169	0.866
India	-15.941	-0.934	0.351
Indonesia	35.042	1.243	0.215
Malaysia	5.507	1.167	0.244
Pakistan	-1.158	-0.044	0.965
Philippines	-0.451	-0.021	0.983
Thailand	8.563	0.499	0.618
Latin America			
Argentina	-4.924	-0.429	0.668
Brazil	5.191	0.578	0.564
Chile	-7.386	-1.153	0.250
Colombia	-22.081	-2.006	0.046
Mexico	11.582	1.240	0.216
Peru	1.253	0.808	0.420
East EU			
Czech	2.441	0.486	0.627
Hungary	25.099	1.347	0.179
Poland	-119.97	-1.834	0.068
Russia	5.434	0.088	0.930
Others			
Egypt	32.353	1.157	0.248
Morocco	63.473	1.217	0.225
Turkey	-33.496	-1.721	0.086
South Africa	-21.490	-2.357	0.019

Notes: Stock returns are computed from MSCI Index. Equity flows are measured in millions of US dollars. Red: P<0.05; Blue: P<0.10.

Table 4-20 International equity flows (Over GDP) and *one-month-ahead* stock returns: IVX-wald estimates

Countries	**Coef**	**IVX_Wald**	**P value**
Asia			
China	-7.999	0.030	0.863
India	-14.864	0.642	0.423
Indonesia	35.206	1.590	0.207
Malaysia	5.029	0.725	0.394
Pakistan	-0.584	0.000	0.984
Philippines	2.590	0.025	0.875
Thailand	5.469	0.080	0.777
Latin America			
Argentina	-4.333	0.080	0.778
Brazil	7.114	0.346	0.556
Chile	-7.242	1.478	0.224
Colombia	-20.799	1.476	0.224
Mexico	11.149	1.079	0.299
Peru	1.339	0.119	0.730
East EU			
Czech	2.689	0.245	0.620
Hungary	25.496	2.093	0.148
Poland	-117.357	2.566	0.109
Russia	10.519	0.018	0.894
Others			
Egypt	33.286	3.728	0.054
Morocco	64.764	1.715	0.190
Turkey	-33.489	3.281	0.070
South Africa	-21.617	6.967	0.008

Notes: Stock returns are computed from MSCI Index. Equity flows are measured in millions of US dollars. Red: P<0.05; Blue: P<0.10.

Table 4-21 International equity flows (Over GDP) and *one-month-ahead* stock returns: IVX-QR estimates

Countries/Quantiles	**0.150**	**0.250**	**0.350**	**0.450**	**0.550**	**0.650**	**0.750**	**0.850**
Asia								
China	15.401	-17.608	-34.569	-51.810	14.027	7.213	-9.619	-47.569
India	33.945	-23.526	-11.451	-25.977	-24.005	-41.491	-28.057	-27.251
Indonesia	18.132	52.704	55.846	43.215	48.383	13.326	18.400	46.902
Malaysia	10.249	-0.682	-1.591	1.019	0.007	3.377	2.571	-4.322
Pakistan	31.370	8.608	10.696	0.631	-11.305	20.868	7.808	-47.176
Philippines	38.900	29.354	28.184	30.599	17.619	10.205	34.036	18.507
Thailand	13.283	5.613	-4.641	-15.079	-9.231	7.769	25.935	3.708
Latin America								
Argentina	2.100	2.394	-3.360	-7.909	-14.001	-18.828	-3.322	21.389
Brazil	29.605	12.252	10.108	4.872	-3.848	-4.747	1.789	-7.990
Chile	-0.059	-3.120	-1.002	-4.908	-5.610	-3.572	2.903	-2.159
Colombia	-15.142	-25.959	-9.833	-19.752	-24.195	-19.395	10.766	-15.006
Mexico	19.841	17.890	12.782	9.998	20.004	15.607	17.943	13.277
Peru	5.161	3.314	2.213	1.356	0.301	-0.881	3.499	-3.242
East EU								
Czech	-1.644	-2.818	-0.427	0.986	2.768	4.049	5.757	3.825
Hungary	19.005	10.102	36.967	43.854	40.415	56.857	48.954	40.022
Poland	-118.73	-38.397	-145.19	-147.49	-129.42	-16.506	-75.602	-99.483
Russia	110.077	22.371	-4.244	29.815	-2.204	-51.743	-14.818	31.731
Others								
Egypt	24.192	13.256	37.192	18.296	15.645	4.719	14.977	5.969
Morocco	67.808	32.764	-3.580	11.562	14.878	90.668	68.062	84.221
Turkey	-31.236	-19.966	-23.528	-27.944	-36.449	-41.368	-41.782	-43.280
South Africa	-23.010	-28.509	-30.641	-26.981	-22.684	-17.912	-12.671	-10.119

Notes: This table reports the results of ***estimated coefficients****. Stock returns are computed from MSCI Index. Equity flows are measured in millions of US dollars. Red: P<0.05; Blue: P<0.10.*

Table 4-22 Out-of-sample test results (Over GDP), 2003:12-2014:12

	(1)	(2)
Countries	**OS_R2**	**CW stats**
Asia		
China	-9.774	0.372
India	-3.643	0.674
Indonesia	-7.805	-1.047
Malaysia	0.289	0.707
Pakistan	-0.586	-1.533
Philippines	-0.533	-1.181
Thailand	-10.088	-1.065
Latin America		
Argentina	-0.346	-0.198
Brazil	-0.635	-0.825
Chile	-0.487	0.314
Colombia	0.263	0.808
Mexico	-0.706	-0.244
Peru	0.025	0.243
East EU		
Czech	-0.046	-0.093
Hungary	-2.468	-0.682
Poland	1.649	1.658
Russia	-1.944	-0.728
Others		
Egypt	-7.261	0.385
Morocco	-0.809	-0.004
Turkey	-0.647	0.330
South Africa	-1.291	0.508

Notes: This table reports the out-of-sample R-squared in the first column. The second column shows the test statistics of Clark and West (2007), where the null hypothesis is that the predictive regression cannot outperform the benchmark (prevailing mean) model. Red: P<0.05; Blue: P<0.10.

Table 4-23 ADF test for gross equity flows

(1)	(2)	(3)
Countries	**stat**	**P value**
Asia		
China	-5.329	0.010
India	-3.743	0.022
Indonesia	-4.842	0.010
Malaysia	-5.693	0.010
Pakistan	-3.959	0.011
Philippines	-5.266	0.010
Thailand	-4.288	0.010
Latin America		
Argentina	-5.292	0.010
Brazil	-4.788	0.010
Chile	-5.264	0.010
Colombia	-3.843	0.017
Mexico	-5.196	0.010
Peru	-4.855	0.010
East EU		
Czech	-5.845	0.010
Hungary	-5.351	0.010
Poland	-5.546	0.010
Russia	-4.847	0.010
Others		
Egypt	-7.818	0.010
Morocco	-5.315	0.010
Turkey	-5.618	0.010
South Africa	-3.822	0.018

Notes: 0.010 is the lowest P-value that the ADF test from R package "tseries" can report. The actual P value could be below 0.010 where 0.010 is shown.

Chapter 5 Conclusion

This thesis investigates international capital flows and their impact on the emerging financial markets using several state-of-the-art econometric models. The main research topics discussed are as follows: (a) determinants of capital flows towards emerging market economies (EMEs); (b) evidence of rational bubbles in the emerging equity markets and its associations with short-term speculative flows (equity, debt and bank flows); (c) the link between international equity flows and predictability of emerging stock markets' returns.

Chapter 2 characterizes the determinants of cross-border flows towards emerging market economies *conditional on* different episodes of external financing: e.g., surges, tranquil times, and stops. Using a panel of 51 EMEs over 1990-2011, this chapter conducts the empirical analysis with a recent quantile regression model for dynamic panel data with fixed effects. The key findings can be summarized as follows: first, although results from our preliminary analysis of the conditional-mean regressions suggest a general lack of significance among both global ("push") and domestic ("pull") conditions, a new picture emerges as we proceed to conduct our conditional quantile analysis: in the upper quantiles where EMEs typically experience large inflows, global factors dominate—surges in gross inflows are strongly associated with more abundant global liquidity condition, less global risk aversion, higher world growth rate and stronger regional contagion; the pull factors are, in contrast, insignificant in general. However, in the lower quantiles, push factors remain significant, but more interestingly, pull factors start to play an important role. In particular, we find that EMEs with a higher return rate, better macro-fundamentals (higher real growth rate, better institutional quality), more prudent macro policy (lower public debt and less credit expansion) may experience less gross inflow reductions during episodes of relatively low gross inflows. Second, we apply the same quantile regression model to net flows and gross outflows, and find that net flows are relatively more stable and less sensitive to external shocks compared to gross inflows. We further show that such an observation may be a result of the strongly offsetting co-movement between gross inflows and outflows, as suggested by the literature (e.g., Broner et al., 2013; Adler et al., 2016). The contributions of this chapter are threefold: firstly, we introduce to the literature of capital flows a novel quantile regression model of Galvao (2011), which allows for dynamic panel data controlling for fixed effects; secondly, the benefit of applying this method is that its estimation provides a novel answer to the debate on the relative importance between push and pull factors; thirdly, we confirm the importance of choosing gross flows rather than net flows, which has been increasingly recommended by the literature. Specifically, we show that merely investigating net flows—as the early literature did—might overlook the ongoing dynamics of gross flows and misinterpret the empirical results. The results from this chapter may also hold some policy implications: first, as capital flows are strongly sensitive to push factors during episodes of surges, such large inflows may be reversed abruptly if global conditions suddenly change. Policymakers, therefore, need to watch out for the sustainability of their external financing and avoid excessive spending or borrowing during good times. Second, despite the overall importance of global conditions, strong fundamentals and prudent macro policy could make reductions of gross inflows less severe during "capital drought"; policy makers should still aim to build up sound pull conditions, whose role tends to be overlooked by the recent literature.

Chapter 3 examines evidence of rational bubbles in 22 emerging stock markets and its association with international "short-term flows" (portfolio and bank flows). In particular, we adopt the generalized supremum Augmented Dickey-Fuller (*GSADF*) test of Philips et al. (2015), to detect explosive time series behaviours from stock prices, which are considered to be strong indications of rational bubbles (Engested, 2015). Our contributions are twofold: first, we find a strong evidence of financial exuberance across a broad range of EMEs synchronously—there was no precedent of such a global overheating, nor do we have such a sign in real time. Hence, this study together with Pavlidis et al. (2015), which detects a similar timeline of bubbles in the global housing markets (mainly from advanced economies), complete a picture of global financial overheating before the global financial crisis. Second, we also show that the chronology of these bubbles' synchronization was in line with the boom and bust of short-term capital flows towards EMEs. Moreover, we use a pooled probit model to show that among different types of "short-term flows" equity flows appear to process the strongest association with episodes of exuberance. Therefore, such a finding highlights the "portfolio channel" that transmits global financial shocks, as pointed out by the literature (e.g., Puy, 2016). Finally, this chapter also provides some policy recommendations: first, the unusual concurrent bubbles among different risky emerging stock markets were by no means usual; they should have been viewed as an early-warning of financial overheating. Since such an observation may happen again in the future, our study might serve as a way to monitor global financial exuberance and function as an early warning mechanism in real time. Second, the significant association between equity flows and presence of bubbles suggests that policy makers consider tools such as capital control to limit the transmission of exuberance through such "portfolio channel" in due time (e.g., when bubbles are growing).

Chapter 4 investigates the link between international equity flows and predictability of emerging markets' stock returns. We employ the state-of-the-art predictive regressions based on IVX filtering in our empirical analysis. The motivation of employing such models is driven by concerns of equity flows' persistence: international equity flows may be persistent (e.g., Froot and Donohue, 2002; Albuquerque et al., 2007; Ülkü, 2015), such a feature may lead to invalid results (e.g., serve size distortion) if equity flows is employed as a predictor in a standard predictive regression. To that end, we employ a IVX-wald model of Kostakis et al. (2015), which can handle predictor variables with various degrees of persistence. In addition, we employ the IVX-version of quantile regression (IVXQR) of Lee (2016), which enables us to examine the predictability of stock returns over its whole conditional distribution. Based on such techniques, we investigate both in-sample and out-of-sample predictability. The key findings are summarized as follows: we find a significant link between equity flows and *contemporaneous* stock returns among a large number of emerging equity markets (especially the Asian markets). However, there seems to be weak evidence that international equity flows could predict one-month-ahead stock returns (neither in-sample nor out-of-sample). Nevertheless, such findings may suggest possibilities of predictability if data of higher-frequency (e.g., daily or weekly) were employed. Therefore, the contribution of this chapter might be methodological, because it will be interesting to use the same set of IVX-regressions—which are novel in the literature—to investigate this topic again, for daily or weekly equity flows are even more persistent (Ülkü, 2015).

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