Emerging Stock Market Exuberance and International Short-term Flows

ABSTRACT

We investigate bubble-like dynamics in 22 Emerging Market Economies (EMEs). We identify the existence of synchronized stock markets' exuberance across EMEs before the 2000s Global Financial Crisis (GFC). We also investigate whether international short-term capital flows help to predict such episodes of exuberance. We find that all three types of short-term flows are significant, but international equity flows prove the most robust predictor. International capital flows (especially equity flows) partially explain the synchronization of exuberance detected and thus demand close attention when monitoring bubble-like dynamics.

Keywords: Global Financial Crisis; Stock Bubbles; Capital Flows; Emerging Markets

JEL classification: E44; F21; F32; G1.

"Much of the earlier literature focused on the fundamental question of whether contagion actually occurred during major crises . . ., still do not answer the fundamental question of why a negative shock is transmitted internationally and through what channels contagion occurs."

(Forbes, 2013)

1. Introduction

Although Emerging Market Economies (EMEs) own significant growth potential, their financial underdevelopment usually results in a shortage of stores of value, making EMEs fertile ground for the financial bubbles (Caballero and Krishnamurthy, 2006). The boom and bust of emerging equity markets were particularly impressive in the 2000s. Bartram and Bodnar (2009) report that the stock prices in emerging markets increased 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 until around the same level through June 2008. However, at the end of 2008, prices collapsed (down 54.4%), leading 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. Such dramatic fluctuations call for a thorough investigation of bubbles across many EMEs, which has not been empirically conducted by far.

At the same time, international short-term capital flows (i.e., portfolio equity flows, portfolio debt flows and bank flows) were particularly active in the 2000s[1]. For example, Fuertes et al. (2016) find that both portfolio flows and bank credit flows were "flooded" with reversible and temporary components (i.e., hot money) in the 2000s. More importantly, many studies have shown that the rushing in such flows into EMEs gives rise to exuberance/bubbles through different mechanisms. Fuertes et al. (2019) document that equity flows to EMEs chase returns, and Jotikasthira et al. (2012) show that global equity mutual funds' flow-performance chasing behaviour can trigger bubble-like dynamics of the stock prices. On the other hand,

[1] We focus on these short-term flows rather than foreign direct investment (FDI) because short-term flows are more likely to contribute to transmitting financial exuberance (e.g., Fuertes et al., 2016; Tong and Wei, 2011; Yan et al., 2016).

recent literature has also highlighted international bank flows' role in forming the global financial cycle (e.g., Miranda-Agrippino and Rey, 2020) and transmitting financial shocks across borders (e.g., Amiti et al., 2019; Bruno and Shin, 2015; Yan et al., 2016). Specifically, Martínez-García and Grossman (2020) argue that foreign financial spillovers may alter the time-varying discount rate and thus generate explosive behaviour/exuberance in asset prices[2]. To the best of our knowledge, it remains an open question whether these speculative capital flows generate exuberance/bubbles in the emerging market stocks and which channel is more significant.

Taken together, in this paper, we investigate three major research questions: first, was there evidence of exuberance across a large number of emerging stock markets, especially before the global financial crisis in 2008? Secondly, did international short-term flows contribute to such exuberance? Thirdly, which type of short-term flow was significant?

We follow Phillips et al. (2011) and define the stock market exuberance in a time series context as explosive autoregression behaviours, and employ the state-of-art Backward Supremum Augmented Dickey-Fuller (BSADF) proposed by Phillips et al. (2015a, b) and its panel variant proposed by Pavlidis et al. (2016) to detect stock bubbles in EMEs empirically. This test 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 test has significant advantages over other tests[3]. First, it possesses discriminatory power whenever bubbles are periodically collapsing, when standard methods such as unit root

[2] International debt flows can potentially trigger stock prices' exuberance through a similar mechanism: i.e., generating explosiveness behaviours through altering the time-varying discount rate.

[3] See, e.g., Homm and Breitung (2012), Philips and Shi (2018), which compare the properties of several bubble tests and advocate this model for many reasons, especially real-time bubble monitoring. As mentioned in Philips et al. (2015a), "*These measures are not simply ex-post detection techniques but anticipative dating algorithms that use data only up to the point of analysis for ongoing assessment, giving an early warning diagnostic that can assist regulators in market monitoring*".

or co-integration tests suffer from the pitfall of low power (Evans, 1991). Second, it generalizes the earlier version of a sup ADF test (Phillips et al., 2011), thereby detecting multiple bubbles, which is more typical for volatile stock prices. Third, although financial bubbles are of different categories (e.g., Meltzer, 2002), our test accommodates rational bubbles and other bubble-generating mechanisms such as intrinsic bubbles, herd behaviour, and time-varying discount factor fundamentals.

Using this empirical methodology, we identify the synchronized stock bubbles across a broad range of EMEs. There is no precedent for global overheating, nor do we have such a sign in real-time. In particular, our date-stamping strategy based on the Phillips et al. (2015a, b) suggests an interesting timeline: Evidence of exuberance appeared among several Emerging European and 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 EMEs in our database are in a "bubble stage". Such observations could have functioned as a strong warning of global overheating. Almost all explosive prices collapsed simultaneously in 2008. The chronology of this synchronization coincides with the movement of short-term capital flows towards EMEs, especially equity flows.

Based on such an observation, we investigate the possible role of each short-term flow in the formation of stock bubbles in EMEs. Unlike most studies that are based on the standard linear regressions for crisis transmission, we alternatively rely on the binary choice regression method (i.e., our dependent variable is one if a bubble exists and zero otherwise), as it is immune to the complexity of the nonlinear structure, break mechanisms inherent in stock bubbles, and the associated pseudo stationarity problems (e.g., Forbes and Warnock, 2012; Calderon and Kubota, 2013; Ghosh et al., 2014).

Regarding capital flows data, we define foreign inflows as the gross inflows of foreign investors (sometimes also labelled capital inflows) rather than net flows[4] for several reasons. i) The international capital flows by foreign and domestic investors (dubbed gross inflows and outflows, respectively) may move in opposite directions. Hence, gross inflows and outflows should be investigated separately (Calderon and Kubota, 2013). ii) The traditional literature focuses on net flows when net flows roughly mirror gross inflows of foreign investors, as the gross outflows of domestic investors are negligible before the 2000s, which is no longer the case when gross outflows have increased significantly since then (Broner et al., 2013; Milesi Ferretti and Tille, 2011; Forbes and Warnock, 2012). iii) By focusing on gross inflows, the "sudden stop episodes" captured are "true sudden stops" (a sharp decrease in gross capital inflows) without contamination from "sudden flight" (a sharp increase in gross capital outflows) (Rothenberg and Warnock, 2011). Similarly, the "surges" captured are "true surges" (a sharp increase in gross capital inflows) without contamination from "retrenchment" (a sharp decrease in gross capital outflows). iv) This choice aligns with recent studies (Forbes and Warnock, 2012; Alberola et al., 2016; Adler et al., 2016; Byrne and Fiess, 2016).

We find equity flows, rather than other flows, are most significantly associated with the stock bubbles in EMEs, especially during the late 2000s Global Financial Crisis (GFC). The literature has conjectured a strong role for equity flows but has not found enough evidence (e.g., Broner et al., 2006; Rose and Spiegel, 2010, 2011). These results are robust to full sample versus sub-sample analysis, Probit versus Logit model, controlling for domestic variables, year/quarter dummies, as well as multicollinearity tests, unit root tests and long-run memory tests.

[4] “Net flows”, as defined in Forbes and Warnock (2012), is the net of gross inflows and gross outflows. 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.

This paper contributes to three strands of literature. Firstly, it indirectly draws upon studies that seek to explain the worldwide stock crashes in EMEs (e.g., Khwaja and Mian, 2008; Agosin and Huaita, 2011; Broto et al., 2011; Schnabl, 2012; Byrne and Fiess, 2016; Fuertes et al., 2016). While most studies take a centre-periphery perspective and focus on how the crisis transmits from the United States origins to EMEs, we alternatively focus on EMEs and examine whether there are stock bubbles among EMEs before the GFC. Consistent with the literature (e.g., Caballero and Krishnamurthy, 2006), we identify the existence of synchronized stock bubbles among EMEs before the GFC. We suggest that the late 2000s equity crashes in EMEs may be due to stock bubbles already existing.

Secondly, this study complements the prolific literature of international capital flows by associating them with stock markets (e.g., Dahlquist and Robertsson, 2004; Bartram et al., 2015). A classic research question is how international investors propagate financial shocks across borders. The literature has conjectured three tangible financial transmission channels: a) portfolio equity flows (e.g., Broner et al., 2006; Rose and Spiegel, 2010, 2011); b) portfolio debt flows (e.g., Froot and Ramadorai, 2008; Milesi-Ferretti and Tille, 2011); c) bank credit (e.g., Bruno and Shin, 2015; Cetorelli and Goldberg, 2012a, 2012b, 2012c; Lu et al., 2020; Yan et al., 2016) [5]. Unlike most studies based on the standard linear regressions for crisis transmission, this study alternatively relies on the binary choice regression method. It is immune to the complexity of the nonlinear structure and break mechanisms inherent in stock bubbles. Our new methodology enables us to uncover the equity flows channel for the first time, which provides additional support for this channel and echoes recent papers using fund

[5] The international finance literature typically holds international banks as one of the reasons. (e.g., Peek and Rosengren, 1997; Acharya and Schnabl, 2010; Milesi-Ferretti and Tille, 2011; Tong and Wei, 2011; Cetorelli and Goldberg, 2011, 2012a, b, c; Bruno and Shin, 2015; Buch and Goldberg, 2015; Yan et al., 2016). The banking literature documents that the recent bank globalization process has played a major role in the transmission of the GFC (Aiyar, 2012; Cetorelli and Goldberg, 2011, 2012a, b, c; De Haas and Van Horen, 2012, 2013; Giannetti and Laeven, 2012a, b).

data (e.g., Jotikasthira et al., 2012; Raddatz and Schmukler, 2012; Puy, 2016; Hau and Lai, 2017).

Finally, we extend the analysis of financial exuberance from developed markets to EMEs and from housing markets to stock markets. To the best of our knowledge, the Philips et al. (2015a and 2015b) tests have been used in many areas but not yet applied to a large sample of equity markets[6]. Pavlidis et al. (2016) find evidence of housing bubbles in advanced economies with a similar chronology of vitality: The United States housing market boom spread out to other (mainly advanced) countries after 2003. This synchronization collapsed during the GFC. This study finds similar observations in the stock markets of EMEs, which is somehow unexpected, as the literature (e.g., Milesi-Ferretti and Tille, 2011) argues that EMEs' exposure to global financial risk was modest before the GFC. This paper complements Pavlidis et al. (2016) by showing that financial overheating is global—even for EMEs.

The rest of the paper is organized as follows: Section 2 outlines our empirical methodology, and Section 3 describes our sample of data. Section 4 identifies synchronized stock bubbles in EMEs, and Section 5 investigates its association with three types of short-term capital flows. Section 6 concludes. We delegate additional results to Online Appendix.

2. Methodology

We briefly describe our date-stamping strategy based on Phillips et al. (2015a and 2015b) in this section. We start from the standard Augmented Dickey-Fuller (ADF) regression, which is:

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

where y_t represents stock prices in this study, Δ is the difference operator, k is the maximum number of lags in our specification, and ε_t is the error term. Based on this model, Phillips et al.

[6] For instance, Philips and Shi (2018) summarize multiple influential applications and conclude, "*The PSY algorithm has been applied to a wide range of markets, including foreign exchange, real estate, commodities and financial assets, and has attracted attention from policymakers and the financial press*".

(2011) suggest a recursive implementation on a forward expanding sample sequence to detect bubbles when bubbles periodically collapse effectively. 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 1) is of particular interest, and the test statistic is:[7]

$$ADF_{r_1}^{r_2} = \frac{\hat{\beta}_{r_1,r_2}}{s.e.(\hat{\beta}_{r_1,r_2})}. \tag{2}$$

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 the sup value of the corresponding ADF statistic sequence estimated from each subsample. Fixing the starting point r_0 of the sample sequence at 0 and increasing the endpoint r_2 from r_0 (the minimum window size) to 1, the test statistic (namely *SADF* test) is:

$$SADF(r_0) = \sup_{r_2 \in [r_0,1]} ADF_0^{r_2}. \tag{3}$$

The disadvantage of the *SADF* test is its low power to detect multiple bubbles in the sample. To solve this problem, Phillips et al. (2015a, b) propose the Generalized Supremum Augmented Dickey-Fuller (GSADF), which is a *general* version of the Supremum Augmented Dickey-Fuller (*SADF*) test that allows the starting point $r_1$to vary within a feasible range, i.e., $[0, r_2 - r_0]$. The *GSADF* test statistics is the sup value of the *ADF* statistic sequence obtained from this double recursion over all feasible ranges of r_1 and r_2:

$$GSADF(r_0) = \sup_{r_1 \in [0, r_2 - r_1],\ r_2 \in [r_0,1]} ADF_{r_1}^{r_2}. \tag{4}$$

Equation (4) shows that rejecting the null hypothesis (that is, unit root) of the *GSADF* test suggests evidence of explosiveness.

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

As both market participants and policymakers may be more interested in pinning down the start and end of bubbles, Phillips et al. (2015a, b) propose a date-stamping statistic based on Backward Supremum Augmented Dickey-Fuller (BSADF):

$$BSADF_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} BADF_{r_1}^{r_2}, \tag{5}$$

where BADF is the Backward ADF statistic as defined by Phillips et al. (2015a, b), and the endpoint of each subsample is fixed at r_2 and the starting point varies from *0* to $r_2 - r_0$. In this case, the start of a bubble is defined as the first observation where the *BSADF* statistic exceeds its critical value:

$$\widehat{r_e} = \inf_{r_2 \in [r_0, 1]} \{r_2 \colon BSADF_{r_2}(r_0) > scv_{r_2}^{\alpha}\}. \tag{6}$$

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

$$\widehat{r_f} = \inf_{r_2 \in [\widehat{r_e}, 1]} \{r_2 \colon BSADF_{r_2}(r_0) < scv_{r_2}^{\alpha}\}, \tag{7}$$

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

We further employ the panel BSADF statistic below from Pavlidis et al. (2016) to gauge the explosiveness at the country group level:

$$Panel\ BSADF_{r_2}(r_0) = \frac{1}{N}\sum_{i=1}^{N} BSADF_{r_2}(r_0), \tag{8}$$

We follow Philips et al. (2015a, b) and set a minimum duration period (e.g., by $\log(T)$ where T denotes the sample size) to exclude occasional episodes of explosiveness. Moreover, we generate finite-sample critical-values of *SADF*, *BSADF* and *GSADF* test statistics by Monte Carlo simulations. Their limit distributions are non-standard and depend on the minimum window size. In addition, as we use quarterly data, we choose the minimum size, r_0 equal to 36 observations, and we set the autoregressive lag length *k=4* to reduce computational costs[8].

[8] For potential readers interested in this debate, we refer to Philips and Shi (2018) for more details.

Finally, we are aware of some critiques towards Phillips et al. (2015a and 2015b). For instance, Harvey et al. (2016) show that non-stationary volatility could potentially affect size distortion. However, as reiterated in Philips and Shi (2018), the main advantage of the strategy proposed in Phillips et al. (2011, 2015a, b) is real-time monitoring, while the follow-up remedies (such as the ones in Harvey et al., 2016; Philips and Shi, 2018) are primarily designed for *ex-post* analysis[9]. Hence, we focus on Phillips et al. (2015a, b) instead of others in this paper.

3. Data

We collect capital flows' data from Bluedorn et al. (2013) and International Financial Statistics (IFS) and compute each type of flows as the sum of the last four quarters, to make quarterly capital flows less noisy. Subject to data availability, our sample of quarterly foreign flows range from 1998Q3 to 2011Q4. Following the literature (e.g., Ghosh et al., 2014; Yan et al., 2016), we scale capital flows by domestic GDP and express their percentages.

We collect Morgan Stanley Capital International (MSCI) data through Bloomberg, which provides broad coverage of 22 major EMEs and an overall index: the MSCI emerging markets index[10]. Our sample covers the period from January 1995 to December 2015[11]. Like Phillips et al. (2011 and 2015a), we collect monthly stock indices in USD and deflate them using the US Consumer Price Index (CPI) from the Federal Reserve Bank of St. Louis. To match the quarterly frequency of international capital flows in this study, we convert monthly observations of exuberance (identified by the date-stamping strategy we described in the previous section) into quarterly dummies with the value of one (and zero otherwise) if there is

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

[10] We choose as many countries as possible from both the MSCI Emerging and Frontier Markets groups. Nevertheless, many 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 as there is a controversy whether they should be classified as EMEs.

[11] We choose to start from January 1995 due to data availability. Data for countries such as Czech, Hungary and so forth are unavailable before January 1995.

a stock bubble in at least two months within that quarter[12].

We do not consider many variables commonly used in developed markets (e.g., dividends) in the main analysis of this study due to the poor quality of data in EMEs. We suspect that there is a problem of misreporting, for we observed a considerable amount of zero dividends for some countries. For example, Pakistan's dividend data start with January 1995 but show a series of zeros between November 1996 and May 1998—it is unlikely for a whole nation to experience zero dividends for such a long time. In addition, it may be difficult to argue for explosiveness in dividends. First, the literature usually assumes that dividends follow a random walk with drift (e.g., Homm and Breitung, 2012). Second, many empirical studies investigating other markets find no evidence of explosiveness in dividends (e.g., Phillips et al., 2011). Hence, we focus on data of prices in this study.

[Insert Figure 1 around here]

Panel A of Figure 1 displays the time series trajectories of the MSCI emerging market real price index. It shows that the stock prices in EMEs have generally been volatile during the past two decades, and the bubble-like dynamic during the mid-2000s is most outstanding. In particular, the first bubble-like dynamic occurred around 1999, reaching its peak in 2000, in the presence of the U.S. DotCom bubble (Phillips et al., 2011). Moreover, the boom-and-bust that emerged in the early 2000s appeared much more severe: stock prices increased sharply after 2003, but after September 2008, they started to collapse. Although stock prices revived after 2009, their trajectories no longer display such a noticeable bubble-like dynamic as was observed before the crisis. Such an observation motivates our interest to test the presence of bubbles using the approach in Phillips et al. (2015a and 2015b).

[12] Our main results are robust to alternative definitions of stock bubbles—i.e., with the dummy taking the value of 1 if there is a stock bubble in all three months within that quarter, or with the dummy taking the value of 1 if there is a stock bubble in any one of the three months within that quarter.

4. Stock Market Exuberance in Emerging Stock Markets

This section first discusses the stock market exuberance in the emerging market index and then discusses individual EMEs. Before utilizing the BSADF test, we compare SADF and GSADF by applying both tests to real equity prices and dividends in EMEs. The results are presented in Online Appendix A. We find little evidence for bubbles from the fundamental side (e.g., dividends). Still, equity price bubbles appear in almost every EME, especially when we use GSADF, which supports the claim that the GSADF test in Philips et al. (2015a, b) is more powerful than the SADF test in Philips et al. (2011). Since this study is mainly about real-time monitoring, we now focus on one special case of GSADF (i.e., the BSADF test).

4.1. MSCI Emerging Market Composite Index

We start our empirical investigation with the MSCI Emerging market composite index. Panel A and B in Table 1 report the summary statistics and the empirical results of real stock prices based on the Backward Supremum Augmented Dickey-Fuller (BSADF) test of Phillips et al. (2015a, b), respectively. Panel A suggests that our sample has enough variation. The test statistics for the MSCI Emerging Market Composite Index is significant at 1% in Panel B, suggesting that the prices have been explosive in our sample.

[Insert Table 1 around here]

From a policy perspective, it is critical to date-stamp the periods when bubbles are present. We follow the algorithm proposed by Phillips et al. (2015a, b) and identify periods of explosiveness whenever the *BSADF* statistics exceed the 95% *BSADF* critical value sequence in the finite sample. As previously mentioned, we only define a bubble when the length of its explosive regime exceeds three months to exclude occasional explosive observations.

Panel B of Figure 1 displays the estimated *BSADF* statistics and 95% critical values. It shows a uniquely sustained period of explosiveness in 2007, associated with the peak for stock prices shown in Panel A of Figure 1, shaded in orange areas. This period of an explosive regime appeared in April 2007 and lasted until February 2008, implying that the overall EMEs are in a bubble stage during this period. The results in Panel B of Figure 1 suggests that the MSCI composite index has a couple of other explosive regimes (not shaded) when the estimated *BSADF* statistics are above the 95% critical values. The first bubble occurred at the start of the sample but did not last long enough. Episodic explosiveness emerged again in January 2006 but disappeared after April 2006.

In summary, we find evidence of stock bubbles in EMEs overall—we detect explosive behaviours in the MSCI EME composite price index. We date-stamp that bubbles occurred between April 2007 and February 2008. This bubble-like dynamic is unique compared to other occasional explosive regimes that are all short-lived. We investigate each market in the next subsection to have a more granular view of stock bubbles in EMEs.

4.2. Individual EMEs

In what follows, we present our empirical results for the 22 individual EMEs. Panel B of Table 1 shows that the panel *BSADF* statistics for all country groups are much higher than the critical value at the 99% level (2.39). In comparison, the panel *BSADF* statistics of Latin America (3.527) and Emerging Europe (3.579) are substantially higher than the ones of Asia (3.061), the Middle East and Africa (3.171). Interestingly, the panel BSADF statistic for 22 EMEs (3.335) is much higher than the BSADF statistic of the MSCI Emerging market composite index (2.7), which underscores the synchronized explosiveness. At the country level, 17 out of 22 EMEs' *BSADF* statistics are above the critical value at the 99% level (2.39), while the other five are higher than the critical value at the 95% level (1.80). Hence, our empirical results signal widespread explosiveness—a reliable indicator of the presence of bubbles—among these EMEs over the past two decades.

[Insert Figure 2 around here]

Next, we date-stamp the timeline of such bubbles. Figure 2 displays the periods of stock market exuberance for all countries in our sample[13]. Also, through Figures 3 to 6, we display the *BSADF* test statistics sequence against the critical values for each stock market.

[Insert Figure 3 to 6 around here]

As an overall picture, Figure 2 shows a concurrent episode of stock market exuberance — which appeared after 2003 and peaked in 2008—among many EMEs. The majority of these booms collapsed simultaneously before the late 2000s GFC. This finding collaborates with our previous results on the MSCI emerging markets composite index.

We now turn to the chronology of exuberance. Figure 2 shows that explosiveness hardly existed before 2003—only South Africa displayed explosiveness between June 1998 and December 1998. The stunning picture appeared in the middle 2000s: starting from late 2003, evidence of bubbles appeared in different continents—Latin America (e.g., Colombia and Peru), Eastern 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.

Stock market exuberance became pervasive after 2006. Figure 2 shows that more countries displayed explosive dynamics which lasted long enough to be identified as bubbles. We find evidence in Asia (e.g., India and Pakistan), Latin America (e.g., Argentina, Brazil, Chile, and Mexico), Eastern Europe (e.g., Poland and Russia), the Middle East (e.g., Morocco and Turkey), and Africa (e.g., South Africa). All 22 EMEs in our sample are in explosive regimes in the mid-2000s. However, explosiveness in some countries (e.g., India, Brazil, Turkey and South Africa) disappeared after the mid-2000s, leading to a break of overall exuberance (shown in the first line in Figure 2).

Synchronized bubbles across different EMEs peaked in 2007—15 out of 22 countries displayed explosive behaviour. Although the "participation rate" (68%) is the same as the

[13] In unreported results, we combine adjacent periods of exuberance when the length of the gap between them is shorter than *log T*, three months, given our sample size.

synchronization in early 2006, the bubbles are much more severe in 2007. Figure 2 shows significantly fewer gaps of explosive episodes in 2007. This result also agrees with the findings based on the composite index, which suggests an overall bubble EMEs between April 2007 and February 2008. These bubbles collapsed simultaneously during the GFC. The date-stamping technology of Phillips et al. (2015a, b) suggests that the latest collapse happened in Brazil in August 2008, while the Lehman Brothers declared bankruptcy in September 2008. In tabulated results, we formally test this synchronized behaviour—using the panel GSADF proposed by Pavlidis et al. (2016) —and find similar results.

The stock prices among EMEs stayed low during 2008-2009. The recent recovery from the GFC resurrected the stock prices, raising concerns about financial overheating again. However, as shown in Figure 2, our findings suggest that such worries are unnecessary; by the end of 2014, we can detect explosiveness only in Pakistan—this is much weaker evidence of overheating than that of the pre-crisis era.

In summary, our study identifies synchronized bubbles across a large number of EMEs during the mid-2000s. In particular, these synchronized bubbles appeared in a few EMEs in late 2003, became pervasive after 2005, peaked in 2007 and collapsed in late 2008.

5. Are the Stock Bubbles in EMEs Due to Short-term Capital Flows?

The previous section reports an unusual synchronization of bubbles across the EMEs during the mid-2000s, and we find the surges of international capital flows accompany the synchronization. In this section, we empirically investigate the link between bubbles and capital flows. Firstly, we discuss our baseline results without control variables; next, we control for domestic variables and further add robustness after that.

5.1. Baseline Results

The lower panel of Figure 7 presents our sample's annual average short-term capital flows relative to the GDP towards 18 EMEs[14]. 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 7). In the early 2000s, the volume of short-term flows stayed low, and there is little evidence of stock market exuberance in EMEs. Next, short-term flows increased by more than 1% of the GDP in 2003, and then explosiveness emerged in some Latin American and East European countries. Thirdly, short-term flows continued booming until 2007. We observe a sharp increase in stock prices (as shown in the upper panel of Figure 7) and increasingly massive indications of bubbles across the EMEs (as shown in Figure 2). In addition, both short-term flows and the stock market's exuberance collapsed in late 2008. Finally, it seems that the movement of equity flows leads while one of the bond flows and bank credit lags to some extent.

[Insert Figure 7 around here]

Based on such observations, we use the following Probit model to investigate the association between short-term flows and the occurrence of bubbles.

$$\Pr\left(EXU_{i,t} = 1\right) = F\left(STF_{i,t-1}\beta\right), \tag{9}$$

where $EXU_{i,t}$ is a dummy taking the value of 1 if the country is identified as being in an explosive regime, while $STF_{i,t}$ The short-term capital flows (i.e., portfolio equity flows, portfolio debt flows, and bank flows) are measured as the backward moving average of the past four quarters. We lag all regressors by one quarter to avoid endogeneity and reverse causality. We are aware of including more lags in the literature with monthly data (e.g., Yan et al., 2016), but it is not uncommon to include only one lag when dealing with quarterly data on this topic. Our results are robust to include three more lags, but we omit the results here, as it seems difficult to conjecture that short-term capital flows cause the stock bubbles in the EMEs' next

[14] We exclude 4 EMEs (i.e., Argentina, Jordan, Morocco and Pakistan) from this section's analysis due to data availability of international capital flows. As a result, in this section, our sample reduces to 18 EMEs from 1998q3 to 2011q4. Our results do not change quantitatively when we add these 4 EMEs.

quarter before this quarter. Furthermore, the possible impact of long-term capital flows on emerging stock markets is beyond the scope of this paper. We control for country dummy variables and rely on the Huber-White sandwich (robust) standard errors.

[Insert Table 2 around here]

Panel A of Table 2 shows the results from the Probit model above regarding the association between stock market exuberance and the short-term capital flows in EMEs. Firstly, portfolio equity flows have consistently shown significance. For example, Column 1 indicates that a 1% rise in equity flows relative to the 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 from 4.9% to 4.0%, its significance remains at a level of 1%. Moreover, Column 7 reports our results on the subsample of bubble-like periods, which start from the 2nd Quarter of 2003 (when synchronized stock bubbles began to emerge from our sample) [15]and end in the 2nd Quarter of 2009 [16]. During the bubble-like period, equity flows' marginal effect goes up from 4.0% to 7.8% and the Pseudo R2 increases from 17% to 25%, implying a larger impact in the presence of synchronized stock bubbles.

With a smaller economic magnitude, debt and bank flows are also statistically significant both on their own (as shown in Column 2 and 3) and in the full specification shown in Column 6. When bank flows are the single regressor (as shown in Column 3), a 1% rise in the average bank flows over the past four quarters (relative to domestic GDP) is associated with a 2.1% higher likelihood of a bubble's presence. Column 6 (with a model of the full specification) confirms a significant result, and its magnitude remains at 2.2%. However, according to Column 7, the marginal effect of bank credit (to some smaller extent debt flows)

[15] Interestingly, there are some other studies, which also hold the mid-2000s as the start of the surges of international capital flows before the late 2000s GFC, see, e.g., Milesi-Ferretti and Tille (2011), Bluedorn et al. (2013); Ghosh et al. (2014).

[16] Many studies hold either the 1st quarter or the 2nd quarter of 2009 as the end of the late 2000s GFC, see, e.g., Milesi-Ferretti and Tille (2011), Brière et al. (2012), Frankel and Saravelos (2012), Fratzscher, M. (2012), Raddatz and Schmukler (2012); Bekaert et al. (2014), etc.

becomes insignificant in the subsample. In other words, equity flows affect the stock markets in EMEs more than bond flows and bank credit, especially during bubble-like periods.

In summary, our results from the Probit model suggest a strong association between portfolio equity flows and episodes of stock market exuberance. This link is even more prominent during the bubble-like period from the 2^{nd} Quarter of 2003 to the 2^{nd} Quarter of 2009 when bubbles are pervasive across different EMEs. In stark contrast, the evidence for portfolio bond flows and bank credit is much weaker.

5.2. Incorporating Domestic Variables

To check the robustness of our results, we control for two sets of domestic variables proposed by other studies in this subsection. The first set of domestic variables strikes a balance among the pairwise correlations with stock market exuberance and international capital flows. In contrast, the second set of domestic variables mainly affects stock market exuberance. For both domestic variables, we include indicators measuring business cycle: productivity (as measured by real GDP growth rate) and inflation (as measured by the percentage change of the CPI index). The rationale is that a boom or expansion of the business cycle might predict a sudden appreciation of asset prices and potentially the presence of bubbles (Pavlidis et al., 2016). We choose the inflation rate as a proxy of the soundness of the monetary policy, as high inflation can be a result of erratic and distortionary monetary condition (Broto et al., 2011).

Except for the real GDP growth rate and inflation, we also include institutional quality index, exchange rate regime, trade, and financial openness for the first domestic variables. Countries with worse institutional quality or higher political risk would depress capital inflows (Gozgor, 2018). Thus, we collect data from the International Country Risk Guide (ICRG) and calculate the institutional quality index as the average value of all components in the table of political risk (Ghosh et al., 2014). Third, as the EMEs with rigid exchange rate regimes are more susceptible to speculative attacks (Ghosh et al., 2014; Obstfeld, 1996), we further control for the de facto exchange rate flexibility index proposed by Ilzetzki et al. (2019), which ranges from 1 to 15 with a higher value implying less exchange rate rigidity[17]. Finally, we control trade and financial openness. A higher possibility of bubbles in EMEs is associated with higher external exposures—both in trade and financial terms—to the global market (Gozgor, 2014). The data for *de jure* financial openness is collected from Chinn and Ito (2008), where a higher index value implies less capital control. The degree of trade openness is measured by the ratio of total trade to GDP—a higher value suggests greater trade openness (Broto et al., 2011) [18].

[Insert Table 3 around here]

Panel A of Table 3 shows the robustness of our results for equity flows. As for domestic control variables, EMEs with a higher GDP growth rate, a lower inflation rate, and a flexible exchange rate regime are more likely to be associated with explosive episodes. More importantly, equity flows remain significant throughout different specifications (Columns 1 to 4). Interestingly, in the bubble-like period from the 2nd quarter of 2003 to the 2nd quarter of 2009, we find an even stronger association between equity flows and episodes of stock market exuberance—the magnitude of the marginal effect doubles (from 4.4% to 9.8%).

Debt flows are only significant at 10% in the full specification (Column 3 in Panel B of Table 3). Although in the sub-sample analysis (Column 4 in Panel B of Table 3) its significance goes up to 5%, the magnitude of its marginal effect is 3.1% and is less than one-third of that of equity flows.

[17] As another robustness check, we alternatively use the exchange rate classification of Shambaugh (2004), a dummy variable taking the value of 1 if the exchange rate stays within a +/- of 2% band in a year and zero otherwise. The results are qualitatively similar and omitted here for brevity.

[18] As another robustness check, we follow Yan et al. (2016) and further control for the VIX, the TED spread, and the U.S. 10-year interest rate as push factors and the results are qualitatively similar. However, due to the strong collinearity brought by these global variables, we take caution when interpreting them and deliberately omit them here for brevity. We follow Dong and Yoon (2019) to omit regional factors.

In stark contrast, bond flows and bank credit have a much smaller impact: Panel C of Table 3 suggests a lack of significance for bank flows across different specifications. Bank flows play a less prominent role in transmitting stock market exuberance across EMEs.

For the second set of domestic variables, we follow Martínez-García and Grossman (2020) and replace institutional quality index, exchange rate regime, trade and financial openness with the real domestic interest rate, domestic credit expansion and domestic unemployment rate. The rationale is as follows: financial spillovers from the alternate domestic financial markets. In the theoretical model of Martínez-García and Grossman (2020), such domestic financial variables can lead to explosive asset prices (e.g., stock prices) by affecting the risk-premia and, ultimately, the discount rate. Specifically, we follow Martínez-García and Grossman (2020) and control for real domestic interest rate, which indicates the opportunity cost of purchasing in the stock markets. Moreover, we also control domestic private credit expansion—which captures the deviation of the domestic credit-to-GDP ratio from its long-term trend—that can fuel stock prices and boom-and-bust cycles. The unemployment rate measures both the state of the domestic business cycle and the boom-and-bust cycle of the stock market[19]. We re-estimate our empirical models using the second set of domestic variables for Table 3, 4, 5, 6, 7 and report the results in Online Appendix B, C, D, E, and F, respectively. The results using the second set of domestic variables are qualitatively similar to those using the first set, and our main conclusions remain robust.

Overall, equity flows seem to be the most robust type of short-term flows in transmitting explosive regimes. This finding contrasts with most studies using capital flows data but echoes recent papers using fund data (e.g., Jotikasthira et al., 2012; Raddatz and Schmukler, 2012; Puy, 2016; Hau and Lai, 2017).

[19] Regarding the source of such domestic variables, we collect data for real interest rates from International Financial Statistics, International Monetary Fund. The data for both private credit and unemployment rate are from World Development Indicators, World bank.

5.3. Further Robustness Checks

To add robustness to the association between short-term flows and bubbles, we conduct further robustness checks. Specifically, we 1) re-estimate our model using the Logit model with Fixed effects; 2) add domestic variables to our Logit model with Fixed effects; 3) include year (or quarter) dummies; 4) and check possible multicollinearity among domestic factors via the Variation Inflation Factor (VIF) Test. Finally, we check the stationarity and long-run memory of our capital flow variables. The results for the tests above are presented in Panel B of Table 2, Table 4, Table 5 (6), and Table 7, respectively.

[Insert Table 4 around here]

We use a logit model with fixed effects as a robustness check for the following reasons. Firstly, following the literature (e.g., Forbes and Warnock, 2012; Martínez-García and Grossman, 2020), we would like to see whether our results are subject to the choice of binary outcome models (i.e., probit, logit, etc.). Secondly, we control for fixed effects to see whether the episodes of exuberance are subject to country-specific (and yet unobserved) factors—i.e., whether some emerging markets are more likely to be the fertile grounds of bubbles/exuberance because of their characteristics, which are fixed over time. Thirdly, it is well-known that a Probit model with panel data cannot control for fixed effects due to the potential incidental parameters problem (Arellano and Hahn, 2005, 2016; Fernández-Val, 2009; Greene et al., 2002). As a result, we use the Logit model with fixed effects to add robustness to our results. Panel B of Table 2 presents the results when we re-estimate our models using a Logit model. Table 4 presents the results when we add domestic variables into the Logit model. Both results suggest that equity flows remain statistically significant, while bond flows and bank credit become insignificant. For instance, the exponentiated coefficient (or odds ratio as each exponentiated coefficient is the ratio of two odds) in Table 4 for equity flows is 1.896, which suggests that when the backward moving average equity flows (over GDP) is 1% higher, it is almost two times more likely to enter an explosive (bubble) regime.

This evidence may not be enough without further controlling for time dummies. Consequently, we add a year dummy variable for the following motivation: from Figure 2, we observe that most exuberance happens during 2002-2007. Therefore, we would like to see whether our results are robust—e.g., equity flows still display a significant coefficient—after controlling for these years. Empirically, we generate a dummy variable for each year and add them to our baseline regressions. We control for 13-year dummies (i.e., 1999-2011) since we have 14 years in total in our sample to avoid multi-co-linearity.

Similarly, we alternatively control 53 quarter dummies (as we have 54 quarters in total in our sample) and find qualitatively similar results. Since the estimated coefficients of the time dummies are of little economic meaning, we do not report them for brevity. Specifically, we add year dummies in both Probit and Logit models and present the results in Table 5. The equity flows remain a robust predictor of bubbles with a positive and statistically significant coefficient of 1.867 and 0.056, respectively. In contrast, bond flows and bank credit are no longer statistically significant at any level. Importantly, the Pseudo R2 in our Logit (Probit) model increases to about 50% (40%) after adding year dummies, with the largest Pseudo R2 coming from our Logit model with equity flows. As reported in Table 6, our results qualitatively remain the same when we replace year dummies with quarter dummies.

[Insert Table 5 around here]

[Insert Table 6 around here]

To account for the possibility of multicollinearity among the domestic factors in regressions, we present the results of the VIF test in Table 7. Our results suggest that both the average and individual VIF scores are far below 10, regarded as the tolerance VIF score. Therefore, multicollinearity is not an issue in our pooled analysis.

[Insert Table 7 around here]

Suppose a substantial portion of the capital flows is non-stationary. In that case, we need to use the non-stationary binary choice model from Park and Phillips (2000) instead of the standard binary choice model. Although Panel B of Figure 7 suggests few stochastic trending behaviours for international capital flows, we further check the feature of our capital flows data via standard unit roots and long memory tests.

We compute the standard Augmented Dickey-Fuller test statistic (ADF stat) for the null hypothesis of unit root (non-stationary) behaviour versus stationarity. Specifically, we use a regression including a constant and the augmentation lag order is selected with the Modified Akaike Information Criterion (MAIC) in Ng and Perron (2001). The maximum number of lags is 12. We find a unit root in no more than three markets for each type of capital flow. Using the rescaled range (R/S, 'range over standard deviation') test in Lo (1991), we further test the null hypothesis of long-range independence versus long-range dependence (LRD), finding that the null can be rejected at no more than two markets at the conventional 5% statistical level for each type of capital flow. Overall, the long-range dependence statistics collaborate with the ADF statistics and justify our model choice. These untabulated statistics are available from the authors upon request.

6. Concluding Remarks

We empirically investigate the presence of stock bubbles in 22 EMEs before the GFC and their association with international (short-term) capital flows. We employ a state-of-art BSADF test proposed by Phillips et al. (2015a, b) and its panel variant proposed by Pavlidis et al. (2016), which allow us to provide a comprehensive and robust answer to our questions regarding the possible existence of stock bubbles and whether these bubbles are synchronized. So far, this sophisticated and flexible test has been mainly used in the housing and U.S. stock markets to detect bubbles, and we are the first to apply it to detect stock bubbles in EMEs comprehensively.

Such an application yields several new insights—e.g., there are pervasive stock bubbles across different EMEs before the GFC, and they are synchronized. We provide fresh evidence that this method can be viewed as an early warning to monitoring stock market exuberance, which may benefit market participants and regulators.

Specifically, we identified a bubble in MSCI emerging markets composite index in 2007. Furthermore, we extend our investigation to 22 individual EMEs, and the empirical results confirm a synchronization of bubbles among a considerable amount of EMEs in the early-to-mid 2000s. However, these bubbles simultaneously collapsed during the late 2000s GFC.

The timeline of bubbles coincides with the movement of short-term flows (portfolio equity flows, portfolio debt flows and bank flows) towards EMEs. Based on such an observation, we investigate the possible role of each short-term flow in the formation of stock bubbles in EMEs. Unlike most studies, based on the standard linear regressions for crisis transmission, we alternatively rely on the binary choice regression method (dependent variable equals to 1 if a bubble exists and zero otherwise) as it is immune to the complexity of the nonlinear structure and break mechanisms inherent in stock bubbles.

This new methodology enables us to uncover the equity flows channel for the first time. Among three kinds of flow, equity flows are most significantly associated with the occurrences of stock bubbles. Our results are robust to full sample versus sub-sample analysis, Probit versus Logit model, controlling for domestic variables, year/quarter dummies, as well as multicollinearity tests, unit root tests and long-run memory tests.

Although it is tempting to conclude that our study is incompatible with the extant studies that emphasise global banks' crisis transmission role, our study can also be viewed as complementary to these studies as we focus on different aspects of crisis transmission. Bank credit may affect the magnitude of bubbles more than other flows, while equity flows may be more important in determining the occurrences of bubbles during the GFC.

Regarding policy lessons, our findings endorse the efforts of policymakers and international organizations to implement better surveillance on international capital flows, especially equity flows.

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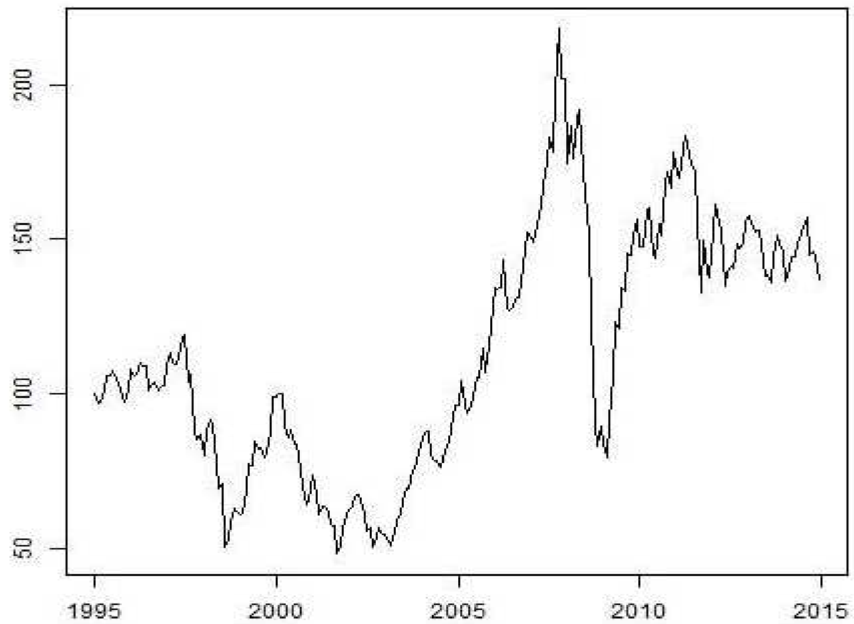
Panel A. MSCI Emerging Market Index (Real Prices)



Panel B. Estimated BSADF statistics and 95% critical values

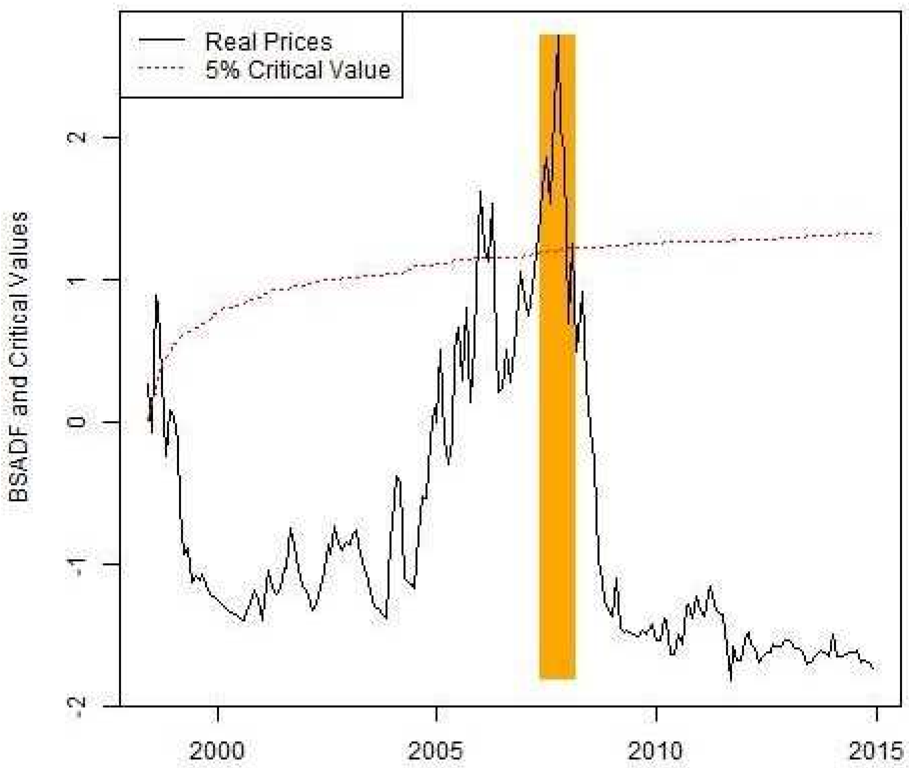


Figure 1. MSCI Emerging Market Index. Panel A plots the MSCI Emerging Market Index in USD deflated by U.S. Consumer Price Index (CPI), taking the real price in January 1995 as 100. Panel B plots the estimated BSADF statistics and 95% critical values based on the MSCI Emerging Markets Overall index. Shaded areas indicate periods of exuberance detected by the BSADF test. Our sample covers the period from January 1995 to December 2015.

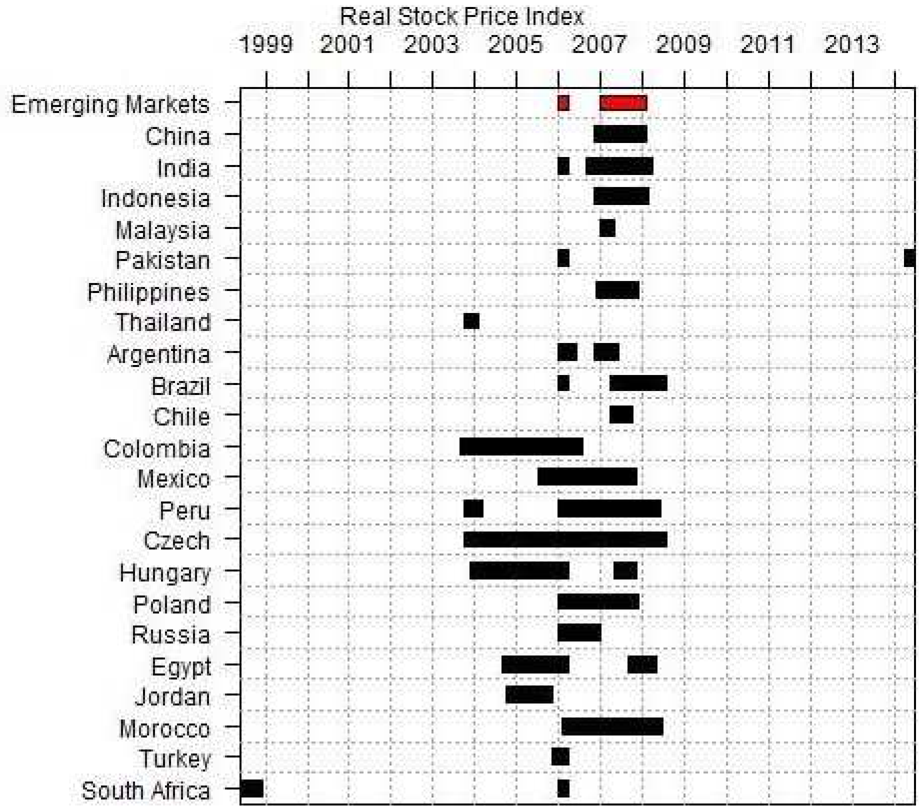


Figure 2. Date Stamping of Equity Exuberance for Individual EMEs. This diagram shows episodes of exuberance detected in real stock prices. The first line shows the bubble episode detected from the composite index. Length of exuberance exceeds the threshold, logT (T denotes sample size) identified as bubbles. Our sample covers the period from January 1995 to December 2015.

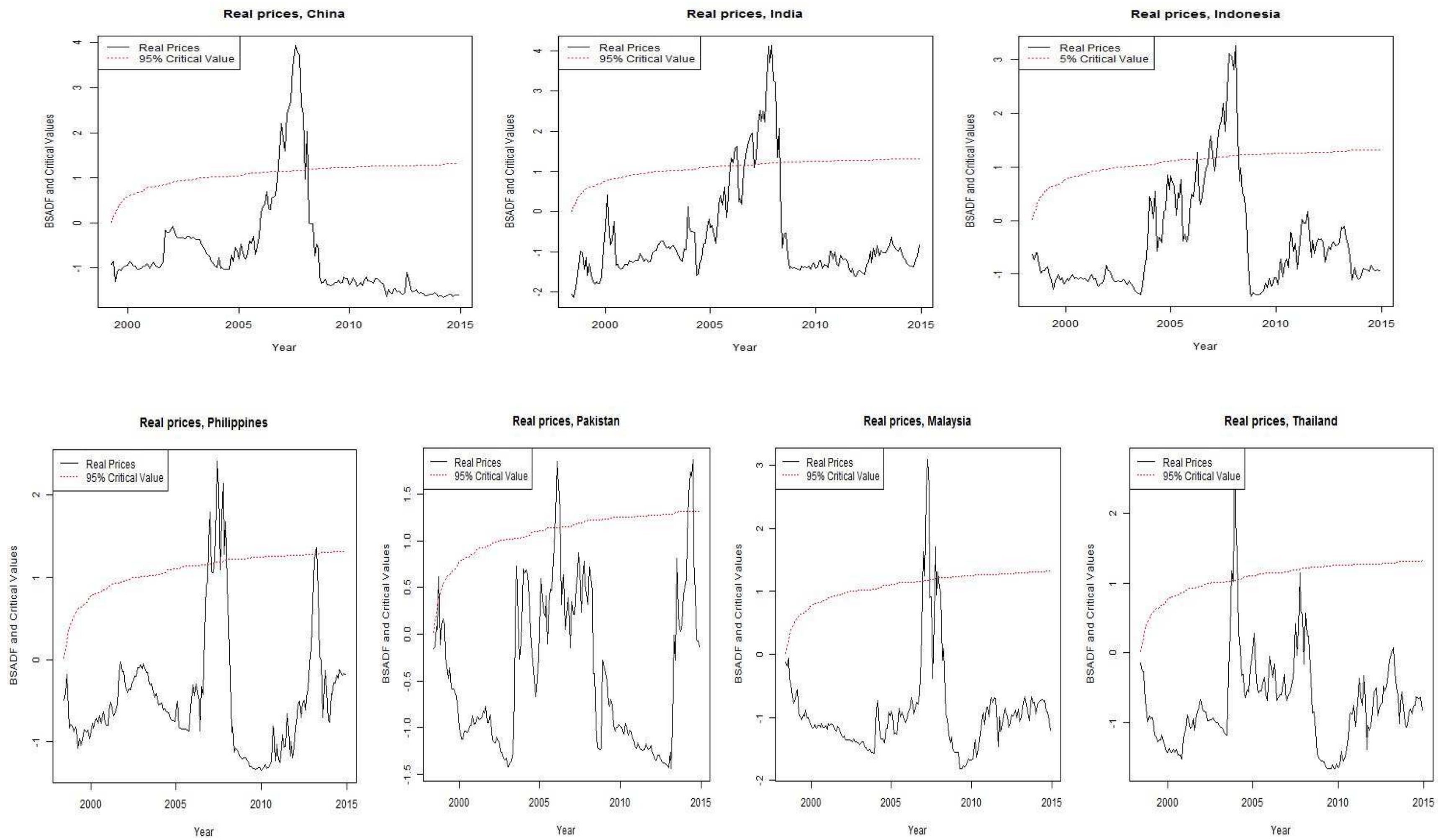


Figure 3. Equity Exuberance in Emerging Asia. This table displays the Backward Supremum Augmented Dickey-Fuller (*BSADF)* test statistics sequence against each stock market's critical values in Emerging Asia. Our sample covers the period from January 1995 to December 2015.

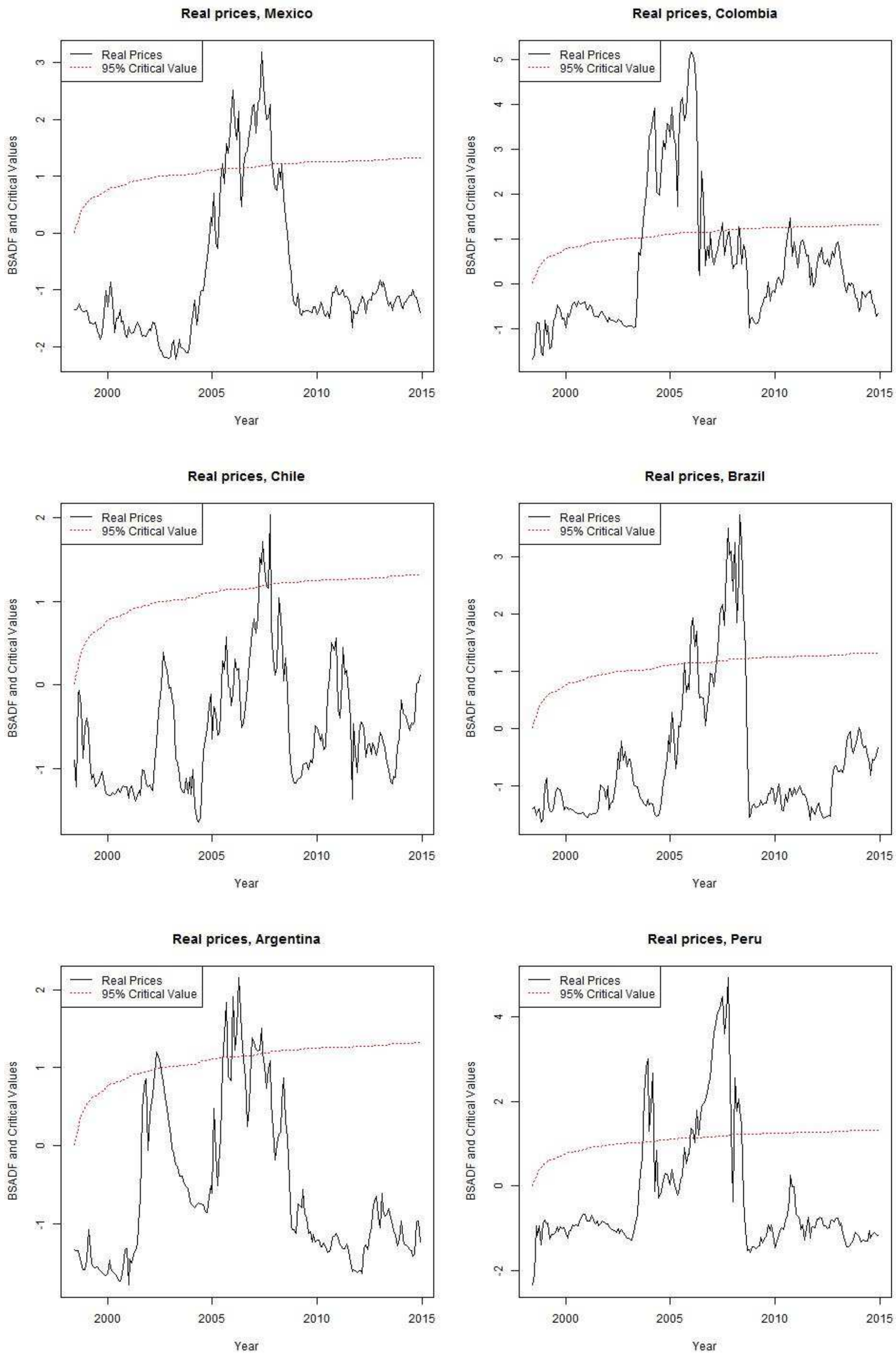


Figure 4. Equity Exuberance in Emerging Latin America. This table displays the Backward Supremum Augmented Dickey-Fuller (*BSADF)* test statistics sequence against the critical values for each stock market in Emerging Latin America. Our sample covers the period from January 1995 to December 2015.

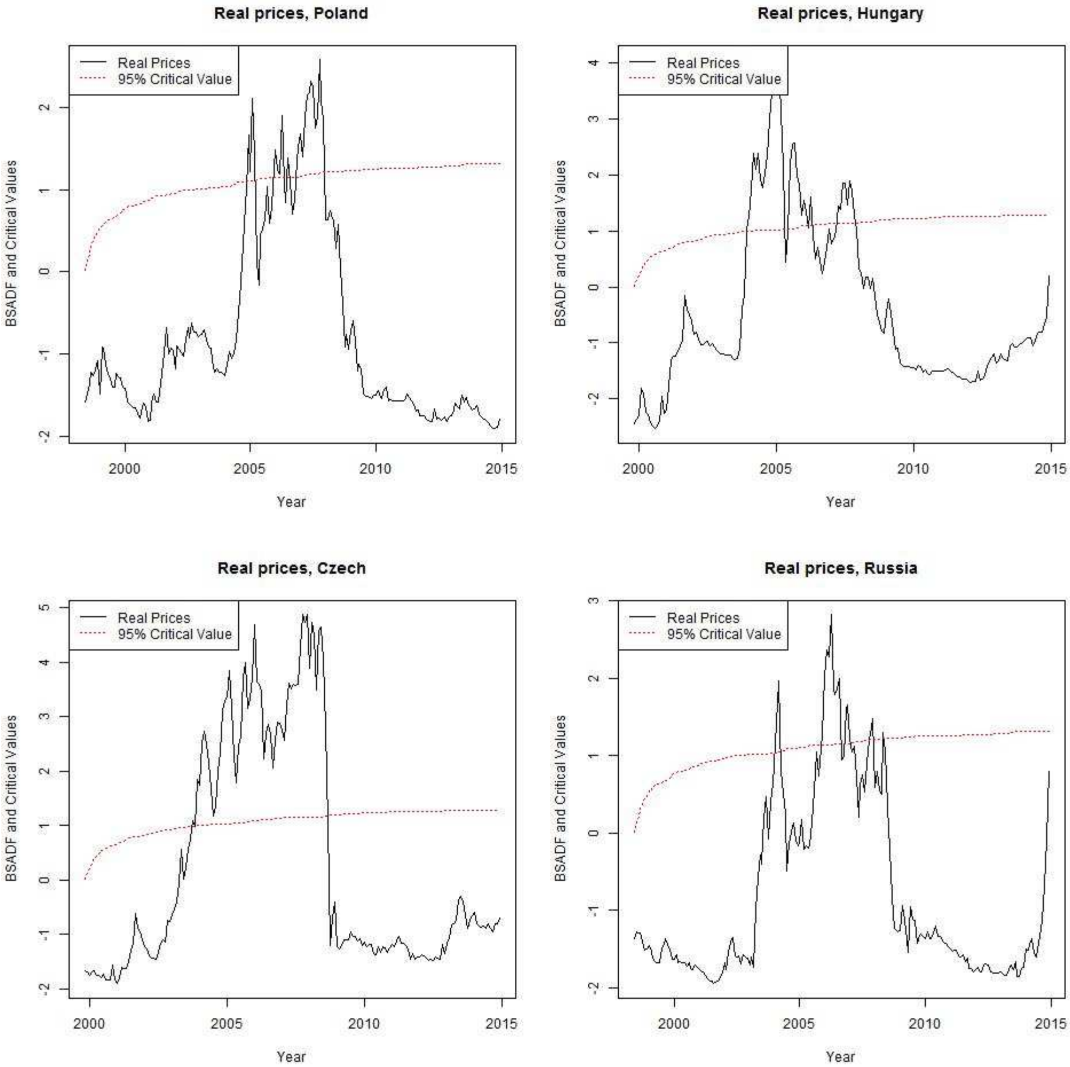


Figure 5. Equity Exuberance in Emerging Europe. This table displays the Backward Supremum Augmented Dickey-Fuller (*BSADF)* test statistics sequence against the critical values for each stock market in Emerging Europe. Our sample covers the period from January 1995 to December 2015.

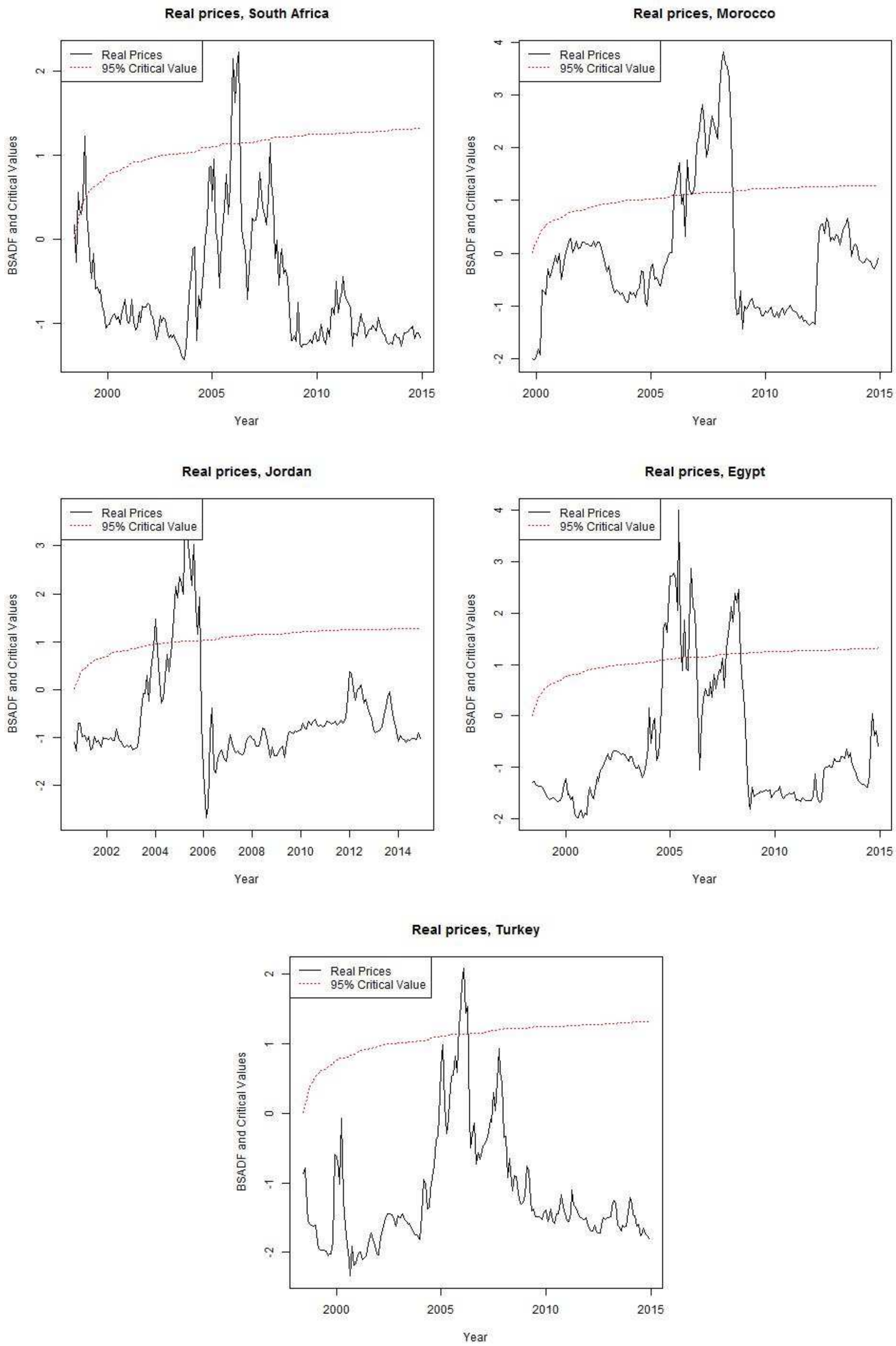


Figure 6. Equity Exuberance in Other EMEs. This table displays the Backward Supremum Augmented Dickey-Fuller (*BSADF)* test statistics sequence against the critical values for each stock market in other emerging market economies. Our sample covers the period from January 1995 to December 2015.

(a) Annual Real Prices of MSCI Emerging Market Index

(b) Annual Short-term Flows to EMEs

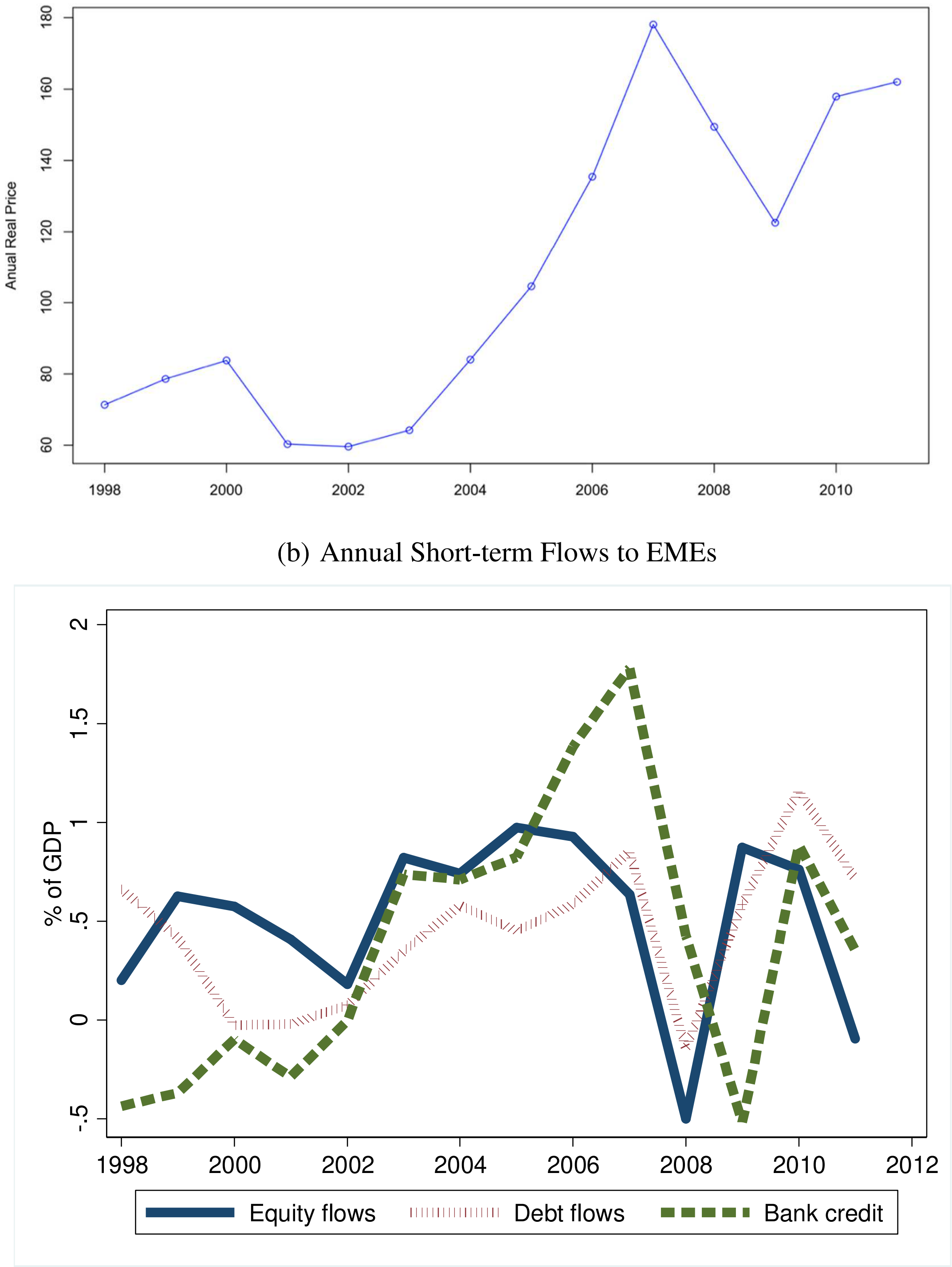


Figure 7. Annual Stock Prices and Short-term Gross Capital Inflow. Panel A and B present annual real prices for the MSCI Emerging Market Index and the annual average short-term capital flows relative to GDP towards the EMEs in our sample, respectively. Our sample covers the period from 1998 to 2011.

Table 1. Summary Statistics and BSADF Statistics for MSCI Indices in EMEs. Panel A and B report the summary statistics and the empirical results of real stock prices based on the generalized Backward Supremum Augmented Dickey-Fuller (BSADF) test of Phillips et al. (2015a, b), respectively. The five columns in panel A report the number of observations (Obs), the mean value (Mean), Standard Deviation (Std.Dev.), The minimum value (Min), Maximum value (Max) for the 18 EMEs from 1998q3 to 2011q4, respectively. Panel B reports the BSADF (panel BSADF) statistics for 22 EMEs (4 country groups) and from 1995 to 2015 with an autoregressive lag length of k=4, while *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

Panel A: Summary statistics

Variable	Obs	Mean	Std.Dev	Min	Max
Bubble dummy variable	972	0.10	0.30	0.00	1.00
Equity flows to GDP (in %)	880	0.44	1.19	-7.21	6.68
Debt flows to GDP (in %)	880	0.88	1.73	-9.22	9.35
Bank flows to GDP (in %)	827	0.30	1.91	-11.02	8.93
Real domestic growth rate (in %)	972	4.21	3.72	-13.13	14.16
Domestic inflation rate (in %)	972	7.79	11.58	-1.41	85.74
ICRG institutional quality index (*10)	972	5.58	0.73	3.65	7.22
De facto exchange rate regime	972	9.39	2.92	2.00	15.00
Trade openness (in %)	972	63.23	40.63	13.25	192.12
Chinn-Ito de jure financial openness	972	0.25	1.31	-1.86	2.44
Real domestic interest rate (in %)	972	3.42	7.72	-63.01	36.53
Domestic credit expansion (in %)	972	-5.20	19.74	-54.57	48.44
Domestic unemployment rate (in %)	884	8.52	6.18	0.62	33.29

Panel B:BSADF test results (95% Critical Value: 1.80; 99% Critical Value: 2.39)

Emerging markets (Overall)	**2.700** ***		
Asia		**Latin America**	
China	3.927 ***	Argentina	2.147 **
India	4.123 ***	Brazil	3.721 ***
Indonesia	3.257 ***	Chile	2.031 **
Malaysia	3.085 ***	Colombia	5.159 ***
Pakistan	1.864 **	Mexico	3.176 ***
Philippines	2.407 ***	Peru	4.929 ***
Thailand	2.763 ***		
		Middle East and Africa	
Emerging Europe		Egypt	3.997 ***
Czech	4.865 ***	Jordan	3.737 ***
Hungary	4.056 ***	Morocco	3.812 ***
Poland	2.577 ***	Turkey	2.082 **
Russia	2.819 ***	South Africa	2.226 **

Table 2. Regression of Bubble Episodes on "Short-term Flows". This table reports the marginal effects from the Probit model and the exponentiated coefficients (or odds ratio as each exponentiated coefficient is the ratio of two odds) from the Logit model, respectively. Dependent variable: Dummy variables equal to 1 if the country is in a bubble stage, zero otherwise. Robust standard errors are in parentheses. All three capital flows are measured as the backward moving average of the past four quarters. All regressors are lagged by one quarter to avoid endogeneity and reverse causality. The full sample period is from 1998q3 to 2011q4, while the sub-sample period is from 2003q2 to 2009q2. Country dummies are included in the regressions, while *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Equity flows	Debt flows	Bank flows	Equity + debt flows	Equity + bank flows	Full sample	Sub-sample
Panel A: Probit model							
Equity flows to	0.049 ***			0.044 ***	0.044 ***	0.040 ***	0.078 ***
GDP (in %)	(0.014)			(0.013)	(0.013)	(0.012)	(0.025)
Debt flows to		0. 022 ***		0.020 ***		0.017 **	0.029 *
GDP (in %)		(0.069)		(0.007)		(0.006)	(0.016)
Bank Flows to			0.021 ***		0.024 ***	0.022 ***	-0.007
GDP (in %)			(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
Panel B: Fixed-effect Logit model							
Equity flows to	0.557 *			0.523 *	0.520 *	0.482 *	0.654 ***
GDP (in %)	(0.169)			(0.170)	(0.171)	(0.171)	(0.245)
Debt flows to		0.259 *		0.250 *		0.212 *	0.240 *
GDP (in %)		(0.086)		(0.090)		(0.089)	(0.130)
Bank Flows to			0.246 *		0.282 *	0.263 *	-0.034
GDP (in %)			(0.082)		(0.087)	(0.091)	(0.138)
Pseudo R2	0.0275	0.0219	0.0231	0.0460	0.0483	0.0629	0.0651
Observations	814	814	759	814	759	759	375

Table 3. Probit Regression of Bubble Episodes on "Short-Term Flows" with Domestic Variables (Marginal Effect). Dependent dummy variables equal one if the country is in a bubble stage and zero otherwise. Robust standard errors are in parentheses. Capital flows are the backward moving average of the past four quarters. All regressors are lagged by one quarter to avoid endogeneity and reverse causality. The full sample is from 1998q3 to 2011q4, while the sub-sample is from 2003q2 to 2009q2. Country dummies are included in the regressions, while *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

	Panel A: Equity flows				Panel B: Debt flows				Panel C: Bank flows			
	Full sample	Full sample	Full sample	Sub-sample	Full sample	Full sample	Full sample	Sub-sample	Full sample	Full sample	Full sample	Sub-sample
Equity flows to GDP (in %)	0.032 ***	0.043 ***	0.044 ***	0.098 ***								
	(0.012)	(0.013)	(0.013)	(0.029)								
Debt flows to GDP (in %)					0.017 **	0.010 *	0.010 *	0.031 **				
					(0.007)	(0.006)	(0.006)	(0.016)				
Bank flows to GDP (in %)									0.006	-0.001	-0.002	-0.036 *
									(0.008)	(0.008)	(0.008)	(0.020)
ICRG institutional quality index (*10)	0.057 *	0.037	0.035	0.158* *	0.081 **	0.061 *	0.059 *	0.143	0.076 **	0.062 *	0.057 *	0.138
	(0.034)	(0.034)	(0.034)	(0.095)	(0.034)	(0.032)	(0.032)	(0.095)	(0.032)	(0.033)	(0.033)	(0.097)
Real domestic growth rate (in %)	0.037 ***	0.031 ***	0.030 ***	0.033 **	0.037 ***	0.033 ***	0.031 ***	0.040 ***	0.036 ***\	0.034 ***	0.033 ***	0.045 ***
	(0.005)	(0.004)	(0.004)	(0.014)	(0.005)	(0.004)	(0.004)	(0.013)	(0.005)	(0.005)	(0.005)	(0.014)
Domestic inflation rate (in %)		-0.015 ***	-0.014 ***	-0.011		-0.013 ***	-0.012 ***	-0.010		-0.013 ***	-0.011 ***	-0.008
		(0.004)	(0.004)	(0.011)		(0.004)	(0.004)	(0.011)		(0.004)	(0.004)	(0.010)
De facto exchange rate regime		0.027 ***	0.023 ***	0.039 **		0.023 ***	0.021 ***	0.035 *		0.023 ***	0.018 ***	0.031
		(0.007)	(0.007)	(0.018)		(0.006)	(0.006)	(0.018)		(0.006)	(0.007)	(0.027)
Trade openness (in %)			0.001	0.003			0.001	0.002			0.000	0.003
			(0.001)	(0.003)			(0.001)	(0.003)			(0.001)	(0.003)
Chinn-Ito de jure financial openness			0.026	-0.069			0.017	-0.071			0.028	-0.056
			(0.019)	(0.065)			(0.018)	(0.064)			(0.019)	(0.068)
Pseudo R2	0.27	0.32	0.32	0.36	0.27	0.30	0.31	0.26	0.29	0.29	0.29	0.25
Observations	814	814	814	400	814	814	814	400	759	759	759	375

Table 4. Results Based on the Logit Model with Domestic Variables. This table reports the exponentiated coefficients (or odds ratio as each exponentiated coefficient is the ratio of two odds) from the Logit model with fixed effects and domestic variables. Dependent variable: Dummy variables equal one if the country is in a bubble stage and zero otherwise. All three capital flows are measured as the backward moving average of the past four quarters. All regressors are lagged by one quarter to avoid endogeneity and reverse causality. The full sample period is from 1998q3 to 2011q4, while the sub-sample period is from 2003q2 to 2009q2. Country dummies are included in the regressions. There are robust standard errors in parentheses, while *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

	(1) Equity flows	(2) Debt flows	(3) Bank flows	(4) Equity + debt flows	(5) Equity + bank flows	(6) Full sample	(7) Sub-sample
Equity flows to GDP (in %)	1.896 ***			1.832 ***	1.728 ***	1.639 **	1.807 **
	(0.401)			(0.392)	(0.355)	(0.344)	(0.471)
Debt flows to GDP (in %)		1.144		1.083		1.117	1.220
		(0.108)		(0.108)		(0.114)	(0.168)
Bank flows to GDP (in %)			0.942		0.955	0.936	0.780
			(0.098)		(0.104)	(0.105)	(0.135)
ICRG institutional quality index (*10)	1.495	2.201	2.065	1.521	1.488	1.555	3.631
	(0.985)	(1.415)	(1.346)	(1.002)	(0.988)	(1.036)	(3.845)
Real domestic growth rate (in %)	1.512 ***	1.535 ***	1.572 ***	1.508 ***	1.545 ***	1.549 ***	1.333 **
	(0.118)	(0.119)	(0.132)	(0.118)	(0.131)	(0.132)	(0.170)
Domestic inflation rate (in %)	0.821 ***	0.838 ***	0.851 **	0.829 ***	0.854 **	0.866 **	0.948
	(0.055)	(0.057)	(0.058)	(0.057)	(0.058)	(0.060)	(0.095)
De facto exchange rate regime	1.360 **	1.326 **	1.260	1.355 **	1.361 *	1.356 *	1.323
	(0.172)	(0.154)	(0.186)	(0.170)	(0.239)	(0.237)	(0.525)
Trade openness (in %)	1.005	1.002	0.995	1.005	0.995	0.996	1.033
	(0.021)	(0.020)	(0.020)	(0.021)	(0.021)	(0.021)	(0.038)
Chinn-Ito de jure financial openness	1.439	1.223	1.447	1.385	1.615	1.542	0.549
	(0.529)	(0.430)	(0.507)	(0.513)	(0.598)	(0.574)	(0.347)
Pseudo R2	0.25	0.23	0.20	0.25	0.22	0.23	0.12
Observations	814	814	759	814	759	759	375

Table 5. Adding Year Dummies. This table reports the exponentiated coefficients (or odds ratio as each exponentiated coefficient is the ratio of two odds) for the Logit model with year dummies and marginal effects for the Probit model with year dummies. Dependent variable: Dummy variables equal one if the country is in a bubble stage and zero otherwise. Robust standard errors are in parentheses. All three capital flows are measured as the backward moving average of the past four quarters. All regressors are lagged by one quarter to avoid endogeneity and reverse causality. Country dummies are included. The drop of observation in the Probit model is due to multicollinearity among year dummies. The estimated coefficients of year dummies are omitted for brevity, while *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Logit	Probit	Logit	Probit	Logit	Probit	Logit	Probit
Equity flows to	1.867 **	0.056 **					1.593 *	0.045 *
GDP (in %)	(0.533)	(0.025)					(0.454)	(0.025)
Debt flows to			1.255	0.011			1.205	0.01
GDP (in %)			(0.194)	(0.015)			(0.203)	(0.015)
Bank flows to					0.923	0.003	0.986	0.007
GDP (in %)					(0.178)	(0.020)	(0.198)	(0.020)
ICRG institutional	1.890	0.099	2.245	0.081	1.307	0.041	1.582	0.062
quality index (*10)	(2.367)	(0.098)	(2.800)	(0.098)	(1.555)	(0.092)	(1.997)	(0.098)
Real domestic	1.265	0.016	1.363 *	0.019	1.258	0.016	1.235	0.014
growth rate (in %)	(0.217)	(0.015)	(0.238)	(0.014)	(0.216)	(0.015)	(0.225)	(0.016)
Domestic inflation	1.036	-0.002	1.047	-0.001	1.074	0.004	1.068	0.002
rate (in %)	(0.116)	(0.010)	(0.113)	(0.010)	(0.102)	(0.008)	(0.114)	(0.009)
De facto exchange	1.306	0.031 **	1.263	0.028 **	0.777	-0.012	0.709	-0.015
rate regime	(0.228)	(0.014)	(0.211)	(0.014)	(0.340)	(0.040)	(0.331)	(0.043)
Trade openness	0.971	-0.001	0.945	-0.003	0.956	-0.004	0.970	-0.002
(in %)	(0.042)	(0.004)	(0.037)	(0.004)	(0.042)	(0.003)	(0.048)	(0.004)
Chinn-Ito de jure	0.176 *	-0.148 *	0.162 *	-0.148 **	0.246	-0.114 *	0.211	-0.124 *
financial openness	(0.171)	(0.079)	(0.151)	(0.074)	(0.224)	(0.067)	(0.203)	(0.070)
Pseudo R2	0.51	0.41	0.50	0.40	0.48	0.39	0.49	0.40
Observations	814	461	814	461	759	433	759	433

Table 6. Replacing Year Dummies with Quarter Dummies. This table reports the exponentiated coefficients (or odds ratio as each exponentiated coefficient is the ratio of two odds) for the Logit model with quarter dummies and marginal effects for the Probit model with quarter dummies. Dependent variable: Dummy variables equal one if the country is in a bubble stage and zero otherwise. Robust standard errors are in parentheses. All three capital flows are measured as the backward moving average of the past four quarters. All regressors are lagged by one quarter to avoid endogeneity and reverse causality. Country dummies are included. The drop of observation in the Probit model is due to multicollinearity among quarter dummies. The estimated coefficients of quarter dummies are omitted for brevity, while *, **, and *** indicate statistical significance at 15%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Logit	Probit	Logit	Probit	Logit	Probit	Logit	Probit
Equity flows to GDP (in %)	1.817 **	0.069 ***					1.554 *	0.059 **
	(0.551)	(0.027)					(0.474)	(0.028)
Debt flows to GDP (in %)			1.220	0.010			1.122	0.001
			(0.206)	(0.018)			(0.214)	(0.019)
Bank flows to GDP (in %)					0.794	-0.012	0.863	-0.011
					(0.183)	(0.026)	(0.209)	(0.025)
ICRG institutional quality index (*10)	2.154	0.105	2.611	0.091	1.595	0.053	1.678	0.067
	(2.782)	(0.117)	(3.388)	(0.115)	(2.006)	(0.113)	(2.242)	(0.118)
Real domestic growth rate (in %)	1.291	0.022	1.40 *	0.026	1.306	0.022	1.243	0.017
	(0.242)	(0.020)	(0.258)	(0.020)	(0.240)	(0.020)	(0.246)	(0.021)
Domestic inflation rate (in %)	1.041	0.002	1.052	0.003	1.070	0.007	1.060	0.005
	(0.119)	(0.011)	(0.116)	(0.010)	(0.108)	(0.008)	(0.119)	(0.010)
De facto exchange rate regime	1.338	0.038 **	1.314	0.04 **	0.778	-0.014	0.682	-0.022
	(0.250)	(0.017)	(0.237)	(0.017)	(0.361)	(0.048)	(0.339)	(0.051)
Trade openness (in %)	0.974	-0.001	0.946	-0.004	0.962	-0.004	0.982	-0.001
	(0.046)	(0.005)	(0.040)	(0.004)	(0.046)	(0.004)	(0.053)	(0.005)
Chinn-Ito de jure financial openness	0.163 *	-0.191 **	0.14 **	-0.20 **	0.218	-0.16 **	0.205	-0.162 *
	(0.163)	(0.090)	(0.139)	(0.087)	(0.209)	(0.082)	(0.208)	(0.084)
Pseudo R2	0.59	0.42	0.58	0.40	0.57	0.39	0.58	0.41
Observations	814	336	814	336	759	315	759	315

Table 7. Variation Inflation Factor (VIF) Test for Multicollinearity. This table reports the Variation Inflation Factor (VIF) for the main variables in our regressions.

Variable Names	VIF Score	VIF Score	VIF Score
Equity flows to GDP (in %)	1.14		
Debt flows to GDP (in %)		1.12	
Bank flows to GDP (in %)			1.22
ICRG institutional quality index (*10)	1.58	1.60	1.60
Real domestic growth rate (in %)	1.24	1.16	1.26
Domestic inflation rate (in %)	1.53	1.30	1.29
De facto exchange rate regime	1.20	1.17	1.17
Trade openness (in %)	1.65	1.45	1.48
Chinn-Ito de jure financial openness	1.34	1.25	1.21
Mean VIF	1.42	1.29	1.32