Does the relative importance of the push and pull factors of foreign capital flows vary across quantiles?

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ABSTRACT

We empirically gauge the relative importance of the various push and pull factors for the magnitude of foreign flows to 51 emerging markets (EMs) across quantiles. We propose a quantile regression dynamic panel model with fixed effects and reveal several new findings: a) Global risk aversion and regional contagion are generally significant across most quantiles. b) Foreign short-term flows retreat less from EMs with stronger fundamentals during stress episodes. c) EMs that previously experienced larger portfolio debt and bank inflows tend to suffer more during stress episodes. Hence, we provide novel evidence supporting the global financial cycle hypothesis, investor differentiation hypothesis, and the "more-in-more-out" hypothesis.

Keywords: Foreign flows; Emerging market; Surge; Sudden stop; Global financial cycle

JEL classification: E44; F21; F32; G1.

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1. Introduction

The determinants of foreign flows have been of long-standing interest to both policy-makers and researchers in international economics and international finance. Volatile foreign inflows are problematic, particularly to emerging markets (EMs)[1]; during financial stress episodes, sharp reductions in capital flows (i.e., sudden stops) can cut off EMs from international capital markets. Even when external financing is abundant, surges in capital flows are worrisome due to associated problems, such as financial overheating, loss of competitiveness because of real currency appreciation, and increased vulnerability to financial crises. Given the policy challenges posed by frequent euphoria and drought in external financing flows, unearthing their characteristics and determinants can help EMs design appropriate policies.

When empirically investigating the determinants of capital flows, the "*push-pull*"[2] framework has been prominent since the seminal work of Calvo et al. (1993) and Fernandez-Arias (1996). Push factors refer to external/supply-side conditions (e.g., global interest rates, global risk aversion), which "*push*" or encourage foreign inflows toward EMs. In contrast, pull factors (e.g., domestic interest rate, growth rate) are domestic/demand-side factors that "*pull*" or attract foreign capital toward EMs (Koepke, 2019). The distinction between push and pull factors is vital. For instance, push factors are exogenous from the viewpoint of EMs. If capital flows to EMs are driven merely by push factors, EM policy-makers may have to insulate their economies from a global shock at the expense of some globalization benefits. In contrast, if the determinants are mostly "pull factors", then policy-makers in EMs have more policy tools available to respond (Cerutti et al., 2019).

[1] We choose to focus on the EMs in this paper, as they are still segregated from the developed markets, albeit the dramatic globalization over the past decades (e.g., Bekaert and Harvey, 2017).

[2] We are aware that the terms, such as push factors and pull factors, are used in a different way in the literature sometimes. Following the mainstream literature (e.g., Griffin et al., 2004; Forbes and Warnock, 2012; Fratzscher, 2012; Ghosh et al., 2014; Fuertes et al., 2016; Sarno et al., 2016), the present paper uses push factors to describe global factors and pull factors to associate with country-specific determinants. Less than often, a few papers describe push factors as these in countries that experience capital outflows and pull factors these in countries having capital inflows. Similar cases happen to other terminologies later in the paper and we follow the mainstream literature by using the standard definition rather than the alternatives.

The relative importance of push/pull factors remains an ongoing debate[3]. This issue becomes more complex in extreme episodes (e.g., sudden stops, surges) when capital flows behave differently and have different determinants. The extant literature has investigated (a) the determinants of capital flows using a standard panel data approach (e.g., Ahmed and Zlate, 2014); (b) the factors that explain the occurrence of episodes of extreme capital flows vs. the magnitude of capital flows during extreme episodes (e.g., Forbes and Warnock, 2012; Ghosh et al., 2014; Calderón and Kubota, 2019) using binary outcome panel models; and (c) the determinants of investor differentiation[4] across EMs during financial stress episodes (Eichengreen and Gupta, 2015; Aizenman et al. 2016; Ahmed et al., 2017; Mishra et al., 2018) using cross-sectional models.

An empirical approach that nests the above approaches would be very useful. Such a model can enable us to reconcile some of the seemingly contradictory results. Quantile regression (QR), initially proposed by Koenker and Bassett (1978), provides a promising framework. Compared with conventional statistical methods investigating the effects of the independent variables on the conditional mean of the dependent variable, QR models seek to investigate the potential heterogeneous effects across different conditional quantiles of the distribution of the dependent variable. Such heterogeneous effects are particularly of interest in the context of international capital flows. Specifically, different locations of the distribution of capital flows suggest different episodes of the movements of capital flows: the lower quantiles potentially represent episodes of relatively low capital flows (even sudden stops in the very left tail), median quantiles relatively tranquil or smooth foreign flows, and upper quantiles abundant external financing. Such heterogeneous effects motivate us to investigate the determinants of capital flows during both "*normal*" times and "*extreme episodes*." To this end, we employ a novel quantile regression dynamic panel model with fixed effects from Galvao (2011), as investigating capital flows in a dynamic panel context is relevant since capital flows are

[3] See Hannan (2018) Koepke (2019) for recent surveys of the literature on this topic.
[4] The investor differentiation hypothesis suggests that international capital flows retreat less (more) from Ems with stronger (weaker) fundamentals during stress episodes.

persistent, especially during episodes of surges[5]. Moreover, we compare the extent to which our lower/upper quantiles are equivalent to the episodes of stops/surges in Forbes and Warnock (2012) or Ghosh et al. (2014), as well as the stress episodes defined by Ahmed et al. (2017). Such comparisons are novel to the literature.

We use annual data from 51 EMs over 1990–2017 and start with a conditional-mean regression by employing a standard dynamic panel data approach (Arellano and Bond, 1991). We find that capital flows are persistent, but few push/pull factors are consistently and statistically significant at the conventional level (i.e., 5%): two exceptions are global risk aversion and regional contagion. Such a finding supports the hypothesis that the global financial cycle (GFCy) drives capital flows (e.g., Passari and Rey, 2015; Rey, 2018; Miranda-Agrippino and Rey, 2020).

Next, we proceed to our main empirical analysis using a quantile regression dynamic panel model with fixed effects (Galvao, 2011), providing us with much richer information regarding the relative importance of push/pull factors. Among the push factors, global risk aversion and regional contagion are generally significant across almost all quantiles, which provides fresh evidence supporting the GFCy hypothesis. Nevertheless, in the 90th quantile, all push factors are insignificant, and the fluctuations in capital flows are explained by pull factors alone, which supports the view that conditional on the occurrences of surges, the magnitude of capital flows is largely explained by pull factors (Ghosh et al., 2014). Moreover, there are more significant push factors in the median quantiles (where capital flows are relatively stable) than in other quantiles. Regarding the pull factors, we find stronger evidence for the investor differentiation hypothesis in the lower quantiles (Ahmed et al., 2017). Indeed, foreign investors retreat less from EMs with stronger fundamentals during stress episodes of relatively low capital flows.

Moreover, we analyze disaggregated capital flows, and the empirical results complement our

[5] We control for lagged capital flows, as Bond (2002) argues that "*even when coefficients on lagged dependent variables are not of direct interest, allowing for dynamics in the underlying process may be crucial for recovering consistent estimates of other parameters*".

findings focusing on gross inflows in several ways. First, global risk aversion, proxied by the VIX index, is significant for *all* types of disaggregated flows. VIX even affects FDI, which is typically considered a long-term flow and thus least affected by global cyclical developments (Koepke, 2019). Second, the evidence for the investor differentiation hypothesis is stronger in the lower quantiles of short-term flows (i.e., equity, debt, and bank flows). Third, during stress episodes, pull factors are heterogeneously associated with different short-term flows, e.g., public indebtedness (domestic credit expansion) is significant in the lower quantiles of portfolio debt (bank) flows. Finally, there is stronger evidence in portfolio debt and bank flows supporting the "*more-in-more-out*" hypothesis, i.e., EMs that previously experienced larger inflows tend to suffer more during periods of stress (Eichengreen and Gupta, 2015).

Altogether, our results contribute to the literature in the following respects. First, among the literature on international capital flows, our research is the first study that systematically compares the quantile regression approach with alternative methods. Taking the low-flow episodes as an example, we find that whenever an external financial drought is persistent (e.g., lasting a few years), Forbes and Warnock (2012; 2021) tend to only flag the beginning of episodes of extremely low flows; the latter part of such episodes will be included in our lower quantiles. Moreover, compared with studies, such as Ahmed et al. (2017), our lower quantiles do a better job of including "stop" episodes local to a particular EM due to its domestic crisis—e.g., Turkey in 2001, Egypt in 2011—and thus disqualified to be identified as emerging market-wide stress episodes. Overall, our lower quantiles represent episodes of external financial drought that are persistent (e.g., lasting even a few years) and severe (e.g., even at historically low levels) and thereby provide a focused view in our analysis of the determinants of capital flows during stress episodes[6].

Second, our QR estimates provide a framework that nests the literature modeling extreme episodes (e.g., stops/surges) of capital flows. Moreover, our conditional quantile estimates in the

[6] Since we define the upper quantiles systematically, a similar conclusion can be applied to the upper quantiles.

upper/lower quantiles relate to the magnitude of surges/stops conditional on their occurrences[7]. In this case, the literature implies a significant role for pull factors. For instance, Ghosh et al. (2014) suggest that conditional on the occurrence of a surge in a particular EM, the magnitude of that surge depends largely on pull factors. Our results in the 90th quantile provide additional support for this view. Regarding the *magnitude* of stops, our findings in the lower quantiles suggest an even stronger role of pull factors. Such evidence is novel.

Third, our results in the lower quantiles reconcile the findings in the literature regarding the investor differentiation hypothesis (Ahmed et al. 2017). Conditional on episodes of low capital flows, we find that EMs with stronger domestic fundamentals (i.e., higher real GDP growth rate, larger reserve accumulation, better institutional quality, smaller private credit expansion, real exchange rate depreciation, and less public indebtedness) suffer less reduction in foreign flows. Such findings disagree with Eichengreen and Gupta (2015) and Aizenman et al. (2016) but support the findings of Ahmed et al. (2017) and Mishra et al. (2018). Such differences are due to differences in data frequency, dependent variable, definitions of stress episodes, and methodology. More importantly, our results add and even reconcile some of the seemingly contradictory results of such literature by suggesting that investor differentials among EMs during stress episodes could be more evident in a longer time window (e.g., a few years).

Fourth, our findings underscore the importance of the GFCy (e.g., Passari and Rey, 2015; Rey, 2018; Miranda-Agrippino and Rey, 2020). Using the VIX as a proxy, we find that GFCy has been consistently significant across both our conditional-mean and quantile regressions, almost all quantiles of the conditional distribution of gross inflows, and all types of disaggregated capital flows. Therefore, we contribute to this strand of literature by suggesting that GFCy affects international capital flows both routinely (across various episodes) and pervasively (across all types of disaggregated flows).

The remainder of the paper is organized as follows. Section 2 discusses the related global push

[7] Section 4.3 presents details on how our conditional quantile estimates relate to the magnitude of surges/stops.

and domestic pull factors as well as their data sources. Section 3 introduces our empirical strategy. The results from a preliminary analysis are presented in Section 4. The main empirical results are discussed in Section 5, while Section 6 selectively discusses a battery of robustness checks. Section 7 concludes the paper, and the details of the results from our robustness tests are shown in the online appendix.

2. Push and pull factors and their data sources

Our capital flow data for 51 EMs over 1990–2017 are taken from the database of Bluedorn et al. (2013) and the latest updates from the international financial statistics (IFS) database. Data from Bluedorn et al. (2013) fill the missing observations in the IFS from other possible sources (e.g., Haver Analytics, CEIC, and EMED databases). Following a common practice in the literature (e.g., Yan et al., 2016), we scale capital flows by domestic GDP and express them in percentages. As there are different types of capital flows, we focus on private capital flows that exclude flows to official sectors.[8] Furthermore, we focus on foreign inflows, or the gross inflows of foreign investors (sometimes also labeled capital inflows), rather than net flows[9]. We focus on foreign inflows due to the reports in recent studies suggesting that the same determinant may drive international capital flows by foreign and domestic investors (dubbed gross inflows and outflows, respectively) in opposite directions[10] and confound the response of net flows. In addition, we analyze both aggregated gross inflows and their components—i.e., foreign direct investments (FDIs), portfolio equity flows, portfolio debt flows, and bank flows. Finally, we focus on the *level* rather than the first difference in capital flows, as the first difference may neglect the dynamics of capital flows.[11] In Table A1 of our appendix, we report additional information

[8] See Section II of Bluedorn et al. (2013) for details of their definition of private capital flows. Roughly speaking, they exclude changes in recorded reserves, IMF lending, and other flows where the official sector (central bank or monetary authority and general government) are recorded as a counterparty.

[9] 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 inflows. Similarly, gross outflows "*is the net of domestic residents' purchases of foreign assets and domestic residents' sales of foreign assets*". A positive value for the gross outflows represents domestic capital outflows. Finally, "net flows", as defined in Forbes and Warnock (2012), is the net of gross inflows and gross outflows.

[10] See for example, Forbes and Warnock (2012), Alberola et al. (2016), Adler et al. (2016), Byrne and Fiess (2016).

[11] For example, as capital flows are 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 the measurement based on first difference would neglect the dramatic persistence of booms.

(e.g., countries used to obtain our benchmark results, the time window for which data are available for each country, etc.) for our sample.

We model the magnitude of capital flows to country i at time t, $K_{i,t}$, as a function of vectors of global push factors, g_t', and domestic pull factors, $d_{i,t}'$.

$$K_{i,t} = K_{i,t-1}\alpha_0 + g_t'\beta_1 + d_{i,t}'\beta_2 + \varepsilon_{i,t} \tag{1}$$

2.1. Push factors

"*Push factors*" are the determinants that affect the supply conditions from creditor countries (Ghosh et al. 2014). In our empirical investigation, we choose a few factors of high relevance according to the recent literature. First, we include the real-world interest rate, measured as U.S. 3-month treasury-bill rate deflated by U.S. inflation. Second, a rise in uncertainty in global economic conditions can trigger a "*flight to safety*", encouraging capital flowing out of EMs toward countries perceived to be safe havens—typically advanced economies, such as the United States. To measure this global risk aversion or global risk appetite, we choose the VIX index from the Chicago Board Options Exchange[12]. Global productivity shocks, which can result in variations in global growth rates, may lead to lending booms and bursts and thus result in variations in cross-border capital flows (Aguiar and Gopinath, 2007; Forbes and Warnock, 2012). We capture foreign trade shocks as the real U.S. growth rate (Broto et al., 2011). Finally, as recent literature also highlights the increasingly important role of regional contagion[13], we capture this effect by following Ghosh et al. (2014) and measure contagion as the average net capital flows (in percentages of GDP) to other countries in the region.

2.2. Pull factors

Pull factors are the demand-side conditions that reflect the characteristics of each recipient country.

[12] This index is the implied volatility of S&P 500 options prices. The larger the VIX index, the higher expected near-term risk in financial assets and thus a lower risk aversion among investors (Forbes and Warnock, 2012). Rey (2018) argues that the presence of GFCy drives international capital flows and comoves with VIX. While there are several measurements of GFCy, Cerutti et al. (2019) argue that "*VIX is widely considered the favorable direct measure, most closely related to GFCy*".

[13] See, for example, Bekeat et al. (2014), Puy (2016) and Apergis et al. (2019).

We choose our pull factors based on the suggestions of the literature.

First, according to neoclassical theory, international capital flows to EMs with higher domestic returns. To capture this effect, we choose the average value of available domestic interest rates (money market rate, treasury-bill rate, etc.) deflated by inflation as a proxy.

Second, EMs with stronger domestic fundamentals are more attractive to foreign investors. For example, foreign investors may be attracted by improving economic performance, which is measured by the real GDP growth rate. Furthermore, better institutional qualities, or low political risks, encourage foreign inflows. We collect data about "*law and order"* from the International Country Risk Guide (ICRG) as our institutional quality index. Moreover, large exchange rate deprecation during stops and appreciation during surges can discourage foreign inflows–we measure such movements in exchange rates as the log difference of the current real effective exchange rate and its long-term trend (Calderón and Kubota, 2019). We also control for the prudence of domestic policies—both in monetary and fiscal terms. Excessive private credit expansion is a sign of the frangibility of domestic financial systems, which suggests international investors leaving this country. We measure this as the credit-to-GDP gap to capture the deviation of the credit-to-GDP ratio from its long-term trend[14]. As the expansionary fiscal policy is usually associated with increased public spending, we include public debt to GDP from a global debt database (Mbaye et al., 2018). Additionally, as larger international reserves enable EMs to stabilize capital flows, especially during episodes of financial stress, Scheubel and Stracca (2019) list international reserves as a crucial component of the global financial safety net (GFSN). Finally, we also control for the ratio of international reserves to domestic GDP. Moreover, to control for the current account balance, we control for the current account deficit/surplus over GDP[15].

Furthermore, we investigate the impacts of the domestic market structures of EMs, especially

[14] In contrast, measurements, such as "credit-to-GDP ratio", may speak for more about "financial depth" rather than "credit expansion".

[15] Regarding the impact of current account deficit on capital flows, the literature present mixed results. On one hand, a higher current account surplus signals improved creditworthiness, thus potentially attracting more capital flows. On the other hand, a smaller current account deficit suggests a reduced external financial need, thus potentially reducing foreign capital flows. The literature presents more evidence of the later effect, according to a recent survey of Koepke (2019).

their openness in financial and trade terms. In particular, we seek to examine whether EMs with larger financial (trade) exposure to the world will suffer more from the reduction in capital flows during difficult times: 1) the data for financial openness are collected from the updated database of Chinn and Ito (2008), where a higher value of the index represents less capital control; and 2) the degree of trade openness is measured by the ratio of total trade to GDP, whereas higher value would suggest greater trade openness (Broto et al., 2011).

[Insert Table 1 around here]

Table 1 presents the summary statistics, the data sources for all these variables, and the results of our diagnostic test for multicollinearity—i.e., the variation inflation factor (VIF) test. There are enough variations for all variables in our sample, and the characteristics are reasonable. The VIF statistics for all the estimated coefficients are significantly below 10, which is generally regarded as the tolerance VIF. In other words, we did not find severe multicollinearity for the chosen factors. We provide the details of our sample (e.g., countries used to obtain our benchmark results, the time window for which data are available for each country, etc.) in Section A1 of our online appendix.

3. Methodology

3.1. Dynamic panel data (DPD) approach

Although we are particularly interested in the determinants of capital flows *conditional at different episodes* through quantile regression, it is, nevertheless, reasonable to start with *conditional-mean regression* as a benchmark model. We employ the dynamic panel data approach proposed by Arellano and Bond (1991). In particular, we utilize the system GMM proposed by Blundell and Bond (1998) to simultaneously explore extra moment conditions, with standard errors that are robust to heteroscedasticity and autocorrelation within panels. Regarding the potential endogeneity of the push and pull factors, we follow Forbes and Warnock (2012) and employ a one-period lag for all pull factors. Overall, following the specification in Eq. (1), our model is estimated as follows:

$$K_{i,t} = K_{i,t-1}\alpha_0 + g_t'\beta_1 + d_{i,t-1}'\beta_2 + \eta_i + \varepsilon_{i,t}, \tag{2}$$

where η_i captures the fixed effects in country i.

Our data have relatively small cross-sectional units (*N*=51 in total) relative to time observations per unit (T =17 on average), and the traditional DPD approach may result in a large instrument collection, overfitting of endogenous variables, and yield invalid results. To avoid this issue, we utilize the "*collapsed instruments"* method of Roodman (2009).

3.2. Quantile regression dynamic model with fixed effects

Our empirical investigation primarily relies on the quantile regression dynamic panel model with fixed effects proposed by Galvao (2011). Quantile regression, as introduced by Koenker and Bassett (1978), estimates "models in which quantiles of the conditional distribution of the response variable are expressed as functions of observed covariates" (Koenker and Hallock, 2001). Therefore, when setting capital flows as the response variable, QR models are valuable tools to unearth the relationship between capital flows and their determinants are conditional on different locations of capital flow distribution—i.e., different episodes of capital flow movements, such as surges or stops. The quantile regression version of the model specification in Equation (1) can be rewritten as follows:

$$Q_{K_{i,t}}\left(\tau \middle| K_{i,t-1}, g'_t, d'_{i,t-1}\right) = \eta(\tau)_i + \alpha(\tau)K_{i,t-1} + \beta_1(\tau)g'_t + \beta_2(\tau)d'_{i,t-1} + \varepsilon_{i,t}, \tag{3}$$

where τ is the quantile index such that $\tau \in (0, 1)$ and η represents the individual effect. In the context of a dynamic panel, compared with traditional quantile regression models, our methodology has advantages, such as accounting for individual effects and smaller bias due to the presence of the lagged dependent variable $K_{i,t-1}$. Readers can refer to Appendix A for more technical details of this model.

Based on this model, the quantiles of gross inflows are defined relative to the entire panel rather than relative to the time series of each country. Therefore, some of the results might be country-specific—for instance, if a country is relatively close to gross inflows, it appears mostly in the low-inflow quantiles[16]. This finding could be a potential concern, but we consider our approach sound in

[16] We thank one anonymous referee for pointing this out.

our context. We provide a more detailed discussion in Appendix A.

4. Preliminary analysis

4.1. Quantiles of gross inflows

[Insert Figure 1 around here]

Figure 1 plots the quantiles of gross inflows into all EMs in our dataset[17]. The median value of gross inflows is 4.56% (over domestic GDP), which suggests that foreign investors have invested heavily in EMs from 1990 to 2017.

[Insert Figure 2 around here]

Figure 2 displays the quantiles of gross inflows for a few representative EMs. Taking China as an example, we observe generally large gross inflows toward this country over the past two decades. The largest observations of annual gross inflows to China occurred from 2005 to 2007, before the onset of the global financial crisis—they were 7.72%, 7.66%, and 7.62% in 2005, 2006, and 2007, respectively. Such large observations are approximately equivalent to the 70th quantile of the full sample, which includes 51 EMs (as shown in Figure 1). Moreover, the minimum observation of annual gross inflows is -0.89%, which happens in 2015—a period associated with financial market stress in China, as defined by Ahemed et al. (2017). As Figure 1 shows, the lower quantiles of our full sample incorporate such an observation.

For Turkey, the gross inflows reached their peak at 11.82% over GDP in 2006, before the outbreak of the global financial crisis. Since 11.82% is above the 75th quantile of gross inflows (see Figure 1) of EMs, it would be listed among the upper quantiles and is thus considered a surge. In contrast, Turkey experienced the lowest gross inflows (-5.87%) in 2001, when Turkey faced a severe domestic economic crisis. Such a stress episode of external financial drought would be included in the lower quantiles of the full sample.

[17] We have trimmed the observations below the 1st and beyond the 99th quantile of the distribution of gross inflows.

4.2. The equivalence of the upper/lower quantiles to "stress episodes"

In this section, we compare our econometric method with those of the extant literature, since such a discussion functions as a base to reconcile our results and/or explain differences with results found in the existing literature. Specifically, we aim to demonstrate to what extent our upper/lower quantiles of gross inflows are equivalent to the stress episodes defined in the literature. Below, we report both similarities and differences from three influential studies.

4.2.1. Comparison to "*surges/stops*" in Forbes and Warnock (2012)

The criterion introduced in Forbes and Warnock (2012, FW hereafter)[18] has been followed by several subsequent studies on international capital flows.[19] This criterion defines episodes of extreme capital movements in the following way. First, it calculates the 4-quarter moving sum of gross capital inflows (denoted as C_t) and computes its annual year-over-year change in C_t:

$$C_t = \sum_{i=0}^{3} Gross\ inflows_{t-i}, \text{ with t = 1, 2, …, N and} \tag{4}$$

$$\Delta C_t = C_t - C_{t-4}, \text{ with t = 5, 6, …, N.} \tag{5}$$

Next, it computes the rolling means (RM) and rolling standard deviations (RSD) of ΔC_t over the last 5 years. A stop episode is defined starting from the first-month *t* that ΔC_t decreases more than one standard deviation below its rolling mean, provided that it reaches two standard deviations below at some point. Such a stop episode ends once gross inflows are no longer at least one standard deviation below their mean. A surge episode can be defined using a symmetric approach.

We provide a systematic comparison of the start/end dates of our low quantile events (particularly the lower 20th quantiles) with the start/end dates of the stop episodes in FW. For brevity, we focus on "stops", as FW defines "surges" using a symmetric approach and thus would yield similar discussions. Moreover, since our study differs from Forbes and Warnock (2012) in several aspects (e.g., data frequency, country coverage, time window, etc.), we make the following adjustments in this

[18] In what follows, we refer it as the FW criterion for brevity.
[19] See, for example, Calderón and Kubota (2019), Scheubel et al. (2019), and Forbes and Warnock (2021).

exercise: first, we rely on the updated list of extreme episodes from Forbes and Warnock (2021), which updates and builds on the dataset and methodology introduced in Forbes and Warnock (2012). Such an updated list would cover our sample period, 1990–2017. Second, we only report those EMs included in the common sample of both studies. Third, since the data frequency in Forbes and Warnock (2021) is quarterly while we use annual data, we define a year as a stop year if only that year has at least 3 quarters, which Forbes and Warnock (2021) identify as stops. Based on such adjustments, we present our results in Table 2 as follows:

[Insert Table 2 around here]

Regarding the similarities, Table 2 shows some of the "stop" episodes according to the FW criterion map in our lower quantiles. Specifically, Column (1) lists a considerable number of episodes that both studies identify as "stops", e.g., Argentina in 1990, 2001, 2009; Czech Republic in 2009, Estonia in 2009, etc.

However, as shown in Column (3), there are some episodes that the FW approach uniquely identifies as "stops"—e.g., Argentina in 1999, 2008; Brazil in 1993, 2008, and 2009; etc. In Column (4), we display the average gross inflows during such episodes, which suggests that the mean value of the gross inflows across all such "stop" episodes is 6.01%. Such a result implies that the FW approach can capture those "stops" episodes in which gross inflows remain relatively high after the drop of capital flows; our lower quantiles tend to exclude such circumstances.

On the other hand, Column (5) displays the "stop" episodes that the FW criterion misses but our lower quantiles successfully capture, which implies that the FW approach tends to only flag the beginning of some "stop" episodes. For instance, both FW and our study identify Argentina in 2001, Indonesia in 1998, Russia in 2014, and Sri Lanka in 2001 as stops (as shown in Column (1)). Nevertheless, only our lower quantiles consider the subsequent years as stops—i.e., Argentina during 2002–2005, Indonesia during 1999–2003, Russia during 2015–2017, and Sri Lanka during 2002–2003 (as shown in Column (6)). Moreover, both studies identify 2009 as a "stop year" in Estonia, Hungary, Latvia, Lithuania, and South Korea, as shown in Column (1). Such identifications potentially occurred due to the impact of the global financial crisis in 2008. However, Forbes and Warnock (2021) do not consider the subsequent years (i.e., Estonia during 2010–2011, Hungary during 2010–2013, Latvia during 2010–2011, Lithuania in 2010, and South Korea during 2010–2011) as stops, even though the gross inflows to these EMs remain low and even negative in our dataset —as shown by their average gross inflows during such periods in Column (6).

To understand how such discrepancies happen, we examine the methodology of the FW approach. Specifically, based on Eq. (4) and (5), FW flags the beginning of a stop episode if

$$\Delta C_t - RM < -RSD. \tag{6}$$

provided that at some point (during the "stop" episode)

$$\Delta C_t - RM < -2RSD. \tag{7}$$

If we define a variable called the *Threshold* that flags the start of a stop episode, Equation (6) is equivalent to

$$Threshold = \Delta C_t - RM + RSD < 0 \tag{8}$$

Similarly, we define another variable called Threshold2 showing whether ΔC_t decreases more than two standard deviations below its rolling mean. In this case, Equation (7) is equivalent to

$$Threshold2 = \Delta C_t - RM + 2RSD < 0 \tag{9}$$

According to Equation (8) above, FW would cease to identify a stop episode when $Threshold > 0$, which would happen if

a) ΔC_t becomes sufficiently large, or

b) RM becomes sufficiently low, or

c) RSD becomes sufficiently large.

To illustrate with concrete examples and avoid excessive reporting of numbers, we consider two case studies of Argentina and Sri Lanka—both EMs are typical examples showing that FW tends to flag only the beginning of a stop episode (e.g., Argentina in 2001; Sri Lanka in 2001), but our quantile regression approach considers the subsequent years as stops (e.g., Argentina during 2002–2005; Sri Lanka during 2002–2003). Table 3 shows the gross inflow data and the values of C_t, ΔC_t RM, RSD, and Threshold.

[Insert Table 3 here]

Regarding Sri Lanka, FW mark 2001q2–2002q1 as stops. According to Equations (5) and (6), $Threshold$ is negative during 2001q2–2002q1, suggesting that ΔC_t decreases more than one standard deviation below its rolling mean during this period. Moreover, $Threshold2$ is negative at 2001q4, implying that ΔC_t decreases more than two standard deviations (below its rolling mean) at this time. Therefore, the FW approach classifies 2001q2–2002q1 as a stop.

However, although gross inflows to Sri Lanka remain mostly negative until the end of 2003 (as shown by the data in Column 2), FW does not consider them to be stops, which occurs for two reasons: first, the persistently low and negative gross inflows drag down the rolling mean (as shown in Column 5). For instance, RM reaches -0.14 at 2002q1—such a magnitude is more than 4 times larger than -0.03 at 2001q2. Second, ΔC_t keeps increasing from 2001q4 to 2003q3, implying that although gross inflows stay at low levels, they are on an upward trend. These factors eventually make the Threshold value positive so that FW no longer classifies the episodes starting from 2002q2 as stops.

Similarly, for Argentina, FW flag 2000q4–2002q2 as stops. However, as Column (2) demonstrates, Argentina experienced negative gross inflows until the end of 2004. Foreign investors continued to massively withdraw during 2003–2004; for instance, gross inflows were -3.29% within one single quarter at 2002q4. Nevertheless, FW do not consider 2002q3–2004q4 as stops. Based on Equation (4), the components of our variable *Threshold* (i.e., ΔC_t, RM, and RSD, as reported from Column (4) to (6)) can help explain their discrepancy: first, ΔC_t becomes sufficiently large by the start of 2003. For instance, gross inflows increase from -3.29% over GDP at 2002q2 to -2.68% at 2002q3, making ΔC increase from -10.9 to 0.22. Second, the rolling mean, RM, is kept low by the persistent entries of negative flows. For instance, RM reaches -8.82 at 2003q2, compared with -0.38 at 2004q4.

Third, the dramatic decrease in gross inflows during the stop episodes makes capital flows volatile, such that the rolling standard deviations increase from 7.78 at 2000q4 to 11.33 at 2002q2. As illustrated by Equation (4), all these factors eventually contribute to the positive entry of $Threshold$, implying the end of stop episodes[20].

To summarize, from the analysis above, some of the "stop" episodes according to the FW criterion map into our lower quantiles. Nevertheless, if gross inflows decrease from surges but remain at a decent level (i.e., 5% over GDP), our lower quantiles may fail to capture such observations while the FW approach would not. On the other hand, whenever an episode of external financing drought is persistent (e.g., Argentina and Sri Lanka in the 2000s), the FW criterion tends to flag the beginning of the stop episodes. In contrast, the later episodes would also be considered part of the "stop" episodes by our lower quantiles approach[21].

4.2.2. Comparison to "surges" in Ghosh et al. (2014)

Ghosh et al. (2014) begin their empirical investigation focusing on surges of net flows (rather than gross flows), where they define a surge "if it lies both in the top 30th quantile of the country's own distribution of net capital flows (expressed in percent of GDP) and in the top 30th quantile the entire sample's distribution of net flows (in percent of GDP)." Moreover, a surge is defined as a liability-driven surge (that is, driven mainly by foreign investors) when the change in liability flows is greater than the change in asset flows.

[20] One should also bear in mind that our different definitions of capital flows might also contribute to the discrepancies reported above. Specifically, this paper focuses on private gross inflows, excluding capital flows from the official sectors (e.g., those under "other investment" flows of the Balance of Payment Statistics of IMF) if feasible. However, this consideration is not explicitly mentioned by Forbes and Warnock (2012; 2021). This might explain some contradictions in our datasets. For instance, according to our data, Lithuania experiences negative gross inflows in 2010. Thus, such a negative entry is included in our lower 20th quantiles and thus considered as a stop. However, Forbes and Warnock (2021) report positive gross inflows to Lithuania in 2010, which is not considered as a stop.

[21] Regarding "surges", FW criterion defines them in a symmetric approach. Therefore, a similar conclusion applies if we compare their "surges" to our upper quantiles—FW criterion may tend to flag the start of surge episodes whenever they are persistent (i.e., lasting for a few years), which is evident in the early 2000s among Ems pervasively.

Our upper quantiles are unlikely to be identical to such "surges" since our method differs from Ghosh et al. (2014) in the selection of EMs in terms of the sample, time intervals, and type of capital flows under major investigation (i.e., net flows versus gross flows). Nevertheless, if other factors were equal, their "surges" were likely to be nested (as a subset) in our upper quantiles. First, our upper quantiles refer to the top 30th quantiles of the entire panel, while "surges", as defined by Ghosh et al. (2014), relating to the top 30th quantiles of the entire panel and the country's own distribution. Second, a large observation of net flows may relate to an even larger level of gross flows. By definition, net flows are the net of gross inflows (dominated by foreign investors) and gross outflows (dominated by domestic investors). Moreover, studies, such as Broner et al. (2013), report a strong correlation between gross inflows and outflows—in particular, during expansions, foreign investors invest more dramatically (i.e., a surge in gross inflows) and domestic agents invest more abroad (i.e., an increase in gross outflows). Since net flows are the net of both inflows and outflows, whenever net flows are large, such a correlation during expansion means even larger gross inflows. Therefore, our upper quantiles would nest the "surges" defined in Ghosh et al. (2014).

4.2.3. Comparison to the "stress episodes" in Ahmed et al. (2017)

Ahemed et al. (2017) assess the importance of economic fundamentals during eight severe emerging market-wide financial stress episodes starting in the mid-1980s. We compare the levels of gross inflows during such financial stress episodes with those in our lower quantiles. [22]

[Insert Table 4 around here]

Following Ahemed et al. (2017), we use annual data instead of monthly data and report the summary statistics of gross inflows during such stress episodes of the contemporary year in Table 4. The detailed list of countries that belong to the low quantiles during each crisis episode is shown in Table A2 of our appendix.

[22] One major caveat of such a comparison arises from the difference in time frequencies—Ahmed et al. (2017) uses monthly data. Their stress episodes typically last only for a few months, while our dataset is annual.

Regarding the similarities, our lower quantiles should nest the sufficiently low (especially the minimum) values of gross inflows across all stress episodes. In particular, the minimum values across all "stress episodes" are below -4%; they should be all included in the lower 10th quantiles in our sample.

For the differences, first, our lower quantiles seem to provide a more focused view on the EMs experiencing severely low foreign inflows. According to Table 4, not every EM experiences drought in foreign inflows during each stress episode. For instance, the mean value of gross inflows in 1998 (when the Asian and Russian crisis happens) is 4.25% over GDP, which is not dramatically low. One potential reason is that the effects of such stress episodes may be local or regional. To illustrate this point, in Panel B, we first classify the EMs in our sample into 4 regions: LA (Latin America), EEU (Eastern Europe), Asia (excluding EMs from the Middle East), and Other (Middle East and Africa). Next, we report the number of EMs within the region during the stress year according to Ahmed et al. (2017) included in the lower 20th quantiles of gross inflows. From Panel B, we observe that in 1998, only 8 out of 51 EMs (in our sample) experience gross inflows below the 20th quantile. Among them, 7 out of 8 are from Asia, highlighting that the effects of stress episodes (e.g., such as the Asian Financial Crisis) on gross inflows toward EMs may be local or regional. Since not every EM experiences drought in external financing during such stress episodes, the empirical approach of Ahmed et al. (2017) may contain many EMs that do not experience sudden stops. In contrast, our lower quantiles provide a more focused view on the EMs that experience severely low foreign inflows.

Second, Ahmed et al. (2017) exclude those "stop" episodes local to a particular EM due to its domestic crisis and thereby are disqualified to be identified as emerging market-wide stress episodes—e.g., Turkey in 2001 and Egypt in 2011. To be more specific, we report the summary statistics of gross inflows during noncrisis years in Column (11), where we observe that the minimum value during the noncrisis years is -49.25. This value is lower than the minimum values during 9 out of the 10 years when EM-wide financial stresses happen. Such a result suggests that a country-specific (rather than EM-wide) crisis could also trigger extremely low gross inflows; such episodes would be ignored by Ahmed et al. (2017) but are incorporated in our low-flow quantiles.

Moreover, the comparison based on Table 4 also displays a potential disadvantage of our quantile regression approach. For example, the mean value of gross flows in 2009 (i.e., after the outbreak of the global financial crisis) is 4.03% over GDP, which is not a dramatically lower level. Although gross inflows drop significantly because of the global financial crisis, such a relatively high mean value can be the result of the previously high and persistent inflows. Taking Peru as an example, its gross inflows were 13.63% in 2007 but dropped by almost half to 7.78% in 2008 (still at a decent level). Such observations satisfy the definition of sudden stops from Edward (2004) —i.e., "an abrupt and major reduction in capital inflows to a country that has been receiving large volumes of foreign capital." However, our lower quantiles may fail to incorporate such observations due to their relatively high levels—this is one of the disadvantages of the quantile regression approach.

4.2.4. Summary

To summarize these comparisons, our lower/upper quantiles are expected to nest some of the "extreme episodes" of these three studies, thus laying the foundation for future comparisons of our empirical results.

We are aware of the differences, and thus the strengths and limitations, of our conditional quantile approach. Regarding the disadvantages, if gross inflows decrease from surges but remain at a decent level (i.e., 5% over GDP), our lower quantiles may fail to capture such observations. However, methods, such as the FW criterion, that focus on deviations from the rolling historical mean better define them as "stops". In other circumstances, our conditional quantile approach has some advantages. First, as our discussion in Section 4.2.1 shows, whenever an external financial drought is persistent (e.g., lasting a few years), methods, such as the FW criterion, tend to only flag the beginning of episodes of extremely low flows, while the latter part of such episodes will be included in our lower quantiles. Second, as our discussion regarding Ahmed et al. (2017) shows, not every EM experiences foreign financial drought during stress episodes. In this sense, our lower quantiles do a reasonable job at including EMs that truly experience severely low gross inflows. Furthermore, our lower quantiles even include “stop” episodes local to a particular EM due to its domestic crisis—e.g., Turkey in 2001 and Egypt in 2011—which would not be included as emerging market-wide stress episodes, as defined by Ahmed et al. (2017). Overall, our lower (upper) quantiles represent episodes of severe external financial drought (exuberance) where gross inflows are at historically low (high) levels and provide a focused view in our analysis of the determinants of capital flows during stress episodes.

4.3. The relationship between conditional quantile estimates and capital flows

Our conditional quantile estimates speak more for the intensive margin than for the intensive margin. Specifically, within the literature addressing the extreme movements of capital flows, there is a difference between the “extensive margin” and “intensive margin”. For instance, in the context of “surges,” an extensive margin suggests the likelihood of the occurrence of a surge event; an intensive margin refers to the magnitude of capital flows conditional on the occurrence of a surge event. In our context, for example, we suppose the real domestic GDP growth rate displays a significant coefficient of 0.4 in the 10th quantile of the distribution of gross inflows, where the level of capital flows should be low enough to be classified as a “stop”. Conditional on the occurrence (extensive margin) of a “stop” episode, a 1% higher real domestic growth rate is associated with a 0.4% (over domestic GDP) lower reduction in the magnitude of gross inflows. Therefore, such an estimated coefficient is more relevant to the conditional intensive margin.

5. Empirical results

5.1. Results from the conditional-mean regression

In what follows, we report our empirical results, starting with our benchmark conditional-mean regressions estimated by dynamic panel data (DPD), as reported in Table 5. The first row shows that gross inflows are persistent, as their AR (1) coefficients consistently display positive and strongly significant estimates from Column (1) to (4).

[Insert Table 5 around here]

Among push factors, global risk aversion (as measured by VIX) is consistently significant, and a one-point rise in this index is associated with a 0.178% reduction in gross inflows relative to domestic GDP. In addition, the contagion factor is consistently significant through all specifications. In the results for the full model shown in Column (4), a 1% increase in the average gross flows in neighboring countries within the same region may yield 0.614% of the increase in gross inflows over GDP. In contrast, the real-world growth rate and interest rate are generally insignificant.

Regarding the pull factors, in the final specification (as shown in Column (4)), only two pull factors appear significant. The current account balance displays a negatively significant coefficient. A 1% (over domestic GDP) larger current account deficit reduces 0.256% more gross inflows over GDP. In addition, the stock of international reserves is also significant. International reserves that are higher by 1% over GDP are associated with 0.105% higher gross inflows.

Finally, the results of diagnostic tests in the bottom rows are favorable—all regressions passed the Arellano–Bond tests for AR (2) and Hansen's overidentification tests. According to Roodman (2009), the instrument count should be below the number of panel units. The number of instruments is reasonable because of employing the "collapsed instruments" method from Roodman (2009).

In summary, the consistent significance of global risk aversion supports the GFCy hypothesis that the VIX significantly drives capital flows. In particular, Rey (2018) suggests the presence of GFCy in capital flows, and such a cycle comoves with the VIX. Moreover, the consistent significance of regional contagion suggests that such a financial cycle is present not only globally but also regionally among EMs. Regarding pull factors, few of them are consistently significant (such as global risk aversion and regional contagion). No clear evidence of foreign investor differential according to real interest differentials[23] or different domestic fundamentals (e.g., real domestic growth rate, institutional quality, etc.).

Nevertheless, such results based on conditional-mean regressions potentially neglect that capital flows may behave differently in extreme episodes when their determinants are different. For example, pull factors that signal stronger domestic fundamentals can be more significant during episodes of financial stress and low foreign inflows. We leave such questions to our conditional quantile estimates in the next subsection.

5.2. Results from the conditional quantile regression

In what follows, we present our empirical results based on the dynamic quantile regression model with fixed effects (Galvao, 2011). We first present our results based on gross inflows and follow with disaggregated flows.

5.2.1. Episodes of bursts in the lower quantiles

We start with the lower quantiles where gross inflows are low. For simplicity, we display the results from a selection of lower quantiles (τ = 10th, 20th, 30th) through Column (1) to (3) in Table 6.

[Insert Table 6 around here]

First, in the 10th quantile, the estimated coefficient for the lagged capital flows is negative. Such a sign confirms the "*more-in-more-out*" hypothesis—that is, EMs that previously experienced larger inflows tend to suffer from the reduction in larger capital flows during periods of stress (Eichengreen and Gupta, 2015). Nevertheless, its coefficient is statistically insignificant, disagreeing with the finding of Ahmed et al. (2017). Such inconsistency may arise from our different sample frequencies—the data frequency in Ahmed et al. (2017) is monthly, while we use annual data. Therefore, the "*more-in-more-out*" phenomenon may be more likely to hold in a shorter time-series sample. In addition, this hypothesis appears to be more evident in short-term flows rather than gross flows (including more

[23] That is, gross inflows toward an EM should be higher whenever its real domestic interest rate is higher, or world interest rate is lower.

long-term and less volatile FDI). We leave this examination for our analysis on disaggregated flows in Section 5.5.

Second, regarding the push factors, both VIX and regional contagion remain highly significant, which is in line with our conditional-mean estimates shown in Section 5.1. In particular, in the 10th quantile, VIX displays a coefficient of -0.126. On average, at the 10th quantile of the distribution of gross inflows—where the observations of capital flows are likely to be associated with the occurrences of "sudden stops"—a one-point rise in VIX leads to a reduction in the magnitude of gross inflows over GDP of approximately 0.126%. Moreover, the real-world interest rate and growth rate appear insignificant in the lower quantiles.

Third, regarding the estimated coefficients for pull factors in the lower quantiles, we find strong evidence of foreign investor differentiation across EMs according to their fundamentals (Ahmed et al., 2017)[24]. During stress episodes of relatively low flows, foreign investors will retreat less from EMs with stronger fundamentals—e.g., higher real GDP growth rate, larger reserve accumulation, better institutional quality, smaller private credit expansion, real exchange rate depreciation, and less public indebtedness. International reserves display significantly positive estimates in the lower quantiles, which is particularly relevant to recent discussions about the global financial safety net (GFSN), of which international reserves are a crucial component (Scheubel and Stracca, 2019; Scheubel et al., 2019). In low quantiles, countries with larger current account deficits and higher trade openness suffer a larger reduction in foreign flows. Interestingly, compared with the results in the other two selected lower quantiles, the magnitude (absolute value) of all estimated coefficients for such pull factors is the largest in the 10th quantile. The more severe the capital drought is, the more evident foreign investor differentiation according to the fundamentals of EMs.

[24] We are aware of our differences from previous literature. Typically, prior studies examine how stronger fundamentals in Ems mitigate the pressures of exchange rate depreciation, reduce asset prices, increase bond yields, and so on—which are the consequences of foreign investors withdrawing their capital from Ems. Our results in the lower quantiles provide an alternative measurement of "investor differentiation" based on the magnitude of reductions in foreign flows themselves (rather than their consequences).

Therefore, such results for pull factors in the lower quantiles disagree with Eichengreen and Gupta (2015) and Aizenman et al. (2016) but support Ahmed et al. (2017) and Mishra et al. (2018). More specifically, Eichengreen and Gupta (2015) do not find strong evidence that countries with better macroeconomic fundamentals—e.g., smaller budget deficits, lower debts, more reserves, and stronger growth rates—suffered fewer deteriorations of their domestic financial conditionals after the "tapering talk" of the Federal Reserves in May 2013. Similarly, the findings of Aizenman et al. (2016) do not suggest that EMs with stronger fundamentals are less adversely exposed to the tapering news of the Federal Reserves in the short-run (24 hours following the announcement). In contrast, Ahmed et al. (2017) find strong evidence of investor differentiation across EMs during all EM-wide financial stress after the GFC of 2008. Moreover, Mishra et al. (2018) report that countries with better macroeconomic fundamentals (e.g., improved current account, fiscal balances, and GDP growth) experienced a smaller increase in yields around the episode of Taper Tantrum, indicating that markets differentiated countries based on their macroeconomic fundamentals.

Three possible reasons can potentially reconcile such differences. First, data frequency may matter—our data are annual, while the data of Eichengreen and Gupta (2015) and Aizenman et al. (2016) are monthly/daily. Therefore, it is likely that foreign investor differentiation would be more evident over a longer time window (Aizenman et al., 2016).

Second, the choice of the dependent variable is different. Most studies in this body of literature investigate the changes in domestic financial conditions (e.g., exchange rate, stock prices, bond yields, etc.) because of capital flows moving out of the EMs. However, we look directly at capital flows (particularly gross inflows), as challenges posed by large fluctuations in capital flows are often at the forefront for policy-makers (Dahlhaus and Vasishtha, 2020).

Third, we define stress episodes differently compared with this body of literature: the lower conditional quantiles of capital flows differ from a subsample of capital flows in EMs during a particular stress episode, such as Taper Tantrum—the latter is employed by this strand of literature. As shown in Section 4.2.3, our lower quantiles include episodes of severe external financial drought (where gross inflows are at historically low levels), and these are caused by a domestic crisis and their domestic impacts (e.g., Turkey in 2001, Egypt in 2011). Such episodes may be neglected by Ahmed et al. (2017). Therefore, our lower-quantile estimates suggest that "foreign investor differentiation" exists in the broader spectrum of "stress episodes", even those whose impacts are domestic. Therefore, it is likely that our strong evidence supporting "investor differentiation during stress times" is due to our different measurements based on the lower quantiles of capital flows.

5.2.2. Episodes of tranquility in the median quantiles

Next, we turn to the results in the median quantiles (τ = 40th, 50th, 60th) where gross inflows are relatively tranquil or smooth. These results are reported in Column (4) - (6), Table 6.

There are more significant push factors in the median quantiles than in the lower quantiles. First, both global risk aversion and regional contagion remain highly significant (even at the 1% level). Second, the other two push factors are also significant—the real U.S. S interest rate possesses negative coefficients in the 50th and 60th quantiles, where a higher real U.S. growth rate is associated with higher gross inflows.

In contrast, there are fewer significant pull factors compared with the lower quantiles, with a few exceptions of institutional quality index and current account balances. Such a pattern is similar to our findings based on the conditional-mean regression (in Section 5.1).

5.2.3. Episodes of booms in the upper quantiles

In Column (7)-(9), we present our results from the upper quantiles (τ = 70th, 80th, 90th) associated with episodes of booming inflows into EMs.

Regarding the push factors, in the 70th and 80th quantiles, both risk aversion and regional contagion remain highly significant (at the 1% level). These two push factors play important roles across most parts of the conditional distribution of gross inflows. In addition, in the 70th and 80th quantiles, the effect of the real-world growth rate retains its significance.

Interestingly, in the 90th quantile, all push factors become insignificant. In contrast, the magnitudes of gross inflows are largely explained by pull factors. EMs with less overvalued currencies (as measured by REER deviation from trend), larger current account surpluses, and higher trade openness are associated with large gross inflows in magnitude. This pattern (between push and pull factors) confirms Ghosh et al. (2014), arguing that push factors act as "gatekeepers" determining the occurrences of surges. Specifically, Ghosh et al. (2014) argue that if a surge occurs, its magnitude depends largely on pull factors—this finding is similar to our case in the 90th quantile. Such an association with Ghosh et al. (2014) is reasonable—in Section 4.2.2, we argue that our upper quantiles are likely to nest their "surges."[25]

Last, the results from the 90th quantile (as shown in Column (9), Table 6) show unexpected signs for a few estimated coefficients of pull factors. For example, the impact of real domestic GDP on gross flows is negative, while that of public indebtedness is positive. In our analysis of disaggregated flows, we show that such unexpected estimates may arise from sovereign-to-sovereign transactions (which IFS data fail to distinguish from market transactions) in bond flows.

5.3. Goodness-of-fit

Thus far, we interpret our empirical results based on the estimated coefficients. However, Cerutti et al. (2019) underscore the need to examine the goodness-of-fit to see what proportion of the variations in capital flows is explained by push or pull factors. Based on this idea, we first follow Koenker and Machado (1999) to compute the pseudo R-squared (or R1) values—a measurement of goodness-of-fit in a quantile regression context. Additionally, we also compute the contribution of push/pull factors to goodness-of-fit based on variance decomposition of linear models.

[25] Nevertheless, we are aware that such results are not identical with Ghosh et al. (2014), which report these significant pull factors to be external financial need, capital account openness and exchange rate regime. Such differences may stem from different datasets, definitions of surges, and econometric estimations.

5.3.1. Pseudo R-squared values

For brevity, we present the details of these tests in our online appendix. The key results are summarized below.

First, neither push nor pull factors display large R1 values. Across all quantiles, push factors typically show R1 values less than 0.05; pull factors are typically less than 0.10. Such results suggest that although push/pull factors display statistically significant coefficients in many circumstances, neither push nor pull factors can substantially explain the variations in capital flows. Nevertheless, although the low R1 values are somehow disappointing, the results are in line with the literature. Readers are referred to Cerutti et al. (2019) and the references therein for further information.

Second, we observe varying R1 values (and thus different quantitative importance) across different quantiles. For instance, pull factors display an R1 value of 0.085 in the 10th conditional quantile, compared with 0.018 in the 50th quantile. Such a result suggests that pull factors are more important, not only in terms of the statistical significance of estimated coefficients but also the goodness-of-fit in the left tail (compared with the median). It reaffirms the foreign investor differentiation hypothesis during periods of stress, i.e., they retreat less from EMs with stronger fundamentals during stress episodes, which is not evident during "normal" periods.

Finally, such results are not subject to the number of push/pull factors. In our empirical analysis, we have more pull than push factors. Therefore, the higher R1 values for the pull factors in the lower quantiles may be driven by their larger numbers. To address this issue, we examine the adjusted R1 values (despite adjusted R-squared values), confirming that our results do not depend on the number of variables.

5.3.2. Variance decomposition

Apart from the R1 values, another approach would be to perform variance decompositions (based on linear models, such as OLS) and compare the estimated shares of the variance attributed to push and pull factors. Moreover, in Section 5.1, we also tested push/pull factor importance through linear models (specifically, dynamic panel data). Therefore, we also perform this exercise to gain more insights from the goodness-of-fit; the detailed results are reported in our online appendix. The key results are summarized in the following paragraphs.

First, push factors seem to explain a insignificant portion of the variation in capital flows. In particular, they generally account for less than 10% of the overall R-squared values—such an observation is even more evident in the lower 10th quantiles. Therefore, such results seem to once again back up the findings from Cerutti et al. (2019) and the references therein, which report that although push factors display significant coefficients, they show limited explanatory power.

Second, pull factors account for more than half of the variations in the lower quantiles. In particular, they contribute to 66.96% (62.68%) of the R-squared values based on our subsample of the lower 10^{th} (20^{th}) quantiles. Nevertheless, their contributions to the R-squared statistics drop more than half in the upper 20^{th}/10^{th} quantiles. Therefore, such results confirm our finding that pull factors play an important role during stress episodes when capital flows are relatively low, providing evidence of foreign investor differentiation across EMs according to their fundamentals (Ahmed et al., 2017).

5.4. Summary of the quantile regression results based on gross inflows

Overall, we find a different pattern between push/pull factors across the conditional distribution of gross inflows. Such results nest and go beyond the findings of the extant literature.

Global risk aversion and regional contagion are the most consistently significant push factors, as both are not only consistently significant in our conditional-mean regressions (as shown in Table 5) but also in almost all conditional quantile estimates (as shown in Table 6). Since VIX is considered a proxy of the GFCy (Cerutti et al. 2019), such a finding contributes to the recent literature (e.g., Passari and Rey, 2015; Rey, 2018; Miranda-Agrippino and Rey, 2020) that GFCy matters routinely, not just in any single episode, such as acute retrenchment. As regional contagion has also been consistently significant, such a financial cycle is present not only globally but also regionally.

Pull factors are more significant in the tails of the distribution of gross inflows compared with the median quantiles. In the very right tail (i.e., 90th quantile), pull factors are more significant than push factors. This finding is consistent with the argument from Ghosh et al. (2014) that pull factors largely explain the magnitude of a surge. In the lower quantiles, pull factors play a crucial role. During stress episodes, foreign investors retreat less from EMs with stronger fundamentals (i.e., higher real GDP growth rate, larger reserve accumulation, better institutional quality, smaller private credit expansion, real exchange rate depreciation, and public indebtedness). Such a finding supports the hypothesis of Ahmed et al. (2017) that highlights the importance of domestic fundamentals, according to which foreign investors differentiate during stress episodes.

Finally, our findings imply that investor differentials during stress episodes could be more evident in a longer time horizon, such as a few years, compared with time windows of a few days or months. Specifically, as our analysis in Section 4.2 shows, compared with the FW criterion, our quantile regression approach has the advantage of identifying the entire duration of a stop episode rather than just flagging the onset. Moreover, since our data frequency is annual, the entire duration of a stop (captured by our lower quantiles) could mean a few years—for instance, as shown by Table 2, Argentina during 2001–2005, Brazil during 1990–1991, Hungary during 2010–2013, etc. Moreover, our empirical results report strong evidence of investor differential during stress episodes (i.e., in the lower quantiles). Altogether, such results suggest that investor differentials are evident when we consider a long time horizon of stops (e.g., a few years). Such a finding can potentially reconcile some of the seemingly contradictory results of the literature on investor differentials that use an alternative methodology and high-frequency data[26].

[26] See, for instance, Eichengreen and Gupta (2015), Aizenman et al. (2016), Ahmed et al. (2017), and Mishra et al. (2018).

5.5. Results based on the disaggregated flows

The empirical literature has documented that different components of international capital flows (FDI, portfolio equity, portfolio debt, and other investment) may have different properties and determinants. Therefore, we conduct the same quantile regression analysis on all types of disaggregated flows. The empirical results are reported in Tables 6 and 7. The key results are summarized as follows.

First, we find stronger evidence supporting the "*more-in-more-out*" hypothesis in two volatile short-term flows—portfolio bond flows and bank flows. From their results in the 10th quantile, lagged capital flows display negative and significant coefficients. The magnitude of lagged bank flows is -0.84, whose absolute value is more than double that of bond flows. Conditional on a stress episode, an EM with 1% higher bank flows over domestic GDP in the previous year will experience an 0.84% larger reduction in bank inflows. Such a result supports that of the literature highlighting the volatile nature of bank flows (e.g., Fuertes et al., 2016 and Yan et al. 2016). In contrast, there is little evidence for investor differentiation in FDI, whose lagged flows display positive coefficients in the lower quantiles (albeit statistically insignificant). Such an observation is in line with the view that FDI involves long-term investments and is less volatile (e.g., Fuertes et al., 2016).

Second, VIX—which potentially measures GFCy—shows significant coefficients in all types of disaggregated flows. Such significant estimates are present in not only short-term flows (i.e., portfolio equity, portfolio debt, and bank flows) but also long-term flows (i.e., FDI), even though the latter should be the least affected by global cyclical developments (Koepke, 2019). Therefore, our results suggest that GFCy matters to international flows not only routinely (i.e., across various quantiles of gross inflows) but also pervasively (i.e., across various types of disaggregated capital flows).

Third, as shown in the 10th and 20th conditional quantiles of all disaggregated flows (in both Tables 6 and 7), the evidence for the investor differentiation hypothesis is stronger in the short-term flows (equity, bond, and bank flows) compared with FDI, since all short-term flows have more significant pull factors in the lower quantiles. Such a difference can arise from the long-term nature of

FDI and thus its lower responsiveness to domestic conditions during periods of stress. On the other hand, the stronger link between short-term flows and pull factors in the lower quantiles agrees with findings from recent literature. For instance, Amiti et al. (2019) report that during times of crisis, bank flows are more affected by country-specific factors compared with noncrisis years.

In addition, during stress episodes, there is a heterogeneous association between disaggregated capital flows and pull factors. For instance, Column (6) and (7) of Table 7 show that private credit expansion is most associated with the lower quantiles of bank flows. During episodes of low bank flows, EMs with larger private credit expansion will suffer large drops in bank inflows. Moreover, in our previous analysis focusing on gross inflows, public indebtedness only displays a marginally significant coefficient in the 30th quantile. Nevertheless, as displayed in Column (6) and (7) of Table 8, public indebtedness is more significant in the lower quantiles of bond flows. Such a result indicates that during stressful periods of low bond flows, EMs with higher public indebtedness experience a large reduction in bond flows. Such associations between private credit expansion (public indebtedness) and bank (portfolio debt) flows make intuitive sense.

Finally, our analysis on disaggregated flows also helps reconcile some of the counterintuitive results from the estimates of gross inflows. For example, in the 90th conditional quantile of gross inflows (as shown in Column (9) of Table 6), real domestic GDP growth is negatively associated with gross inflows. Table 8 shows that such an association is mainly from bond flows[27]. Alfano et al. (2014) also find such a negative correlation between debt flows and the real GDP growth rate. They show that such a negative correlation is mainly driven by sovereign-to-sovereign borrowing and lending rather than private or market-driven transactions. Therefore, such counterintuitive results in bond flows potentially/can result from the data quality of portfolio bond flows. As reported by Alfano et al. (2014), "the IFS database covers both private and public issuers and holders of debt securities. However, it is

[27] In addition, in the upper quantiles of bond flows, there are some other counterintuitive results, such as a positive correlation between global risk aversion and bond flows.

difficult to divide the available data by private-public creditor and debtor". This issue, however, is not problematic in the other types of disaggregated flows. First, FDI and equity flows can be assigned to private-to-private transactions (Alfano et al., 2014). Second, Bluedorn et al. (2013) report that there is more information in IFS data to distinguish public and private transactions in other investment flows (i.e., bank flows) compared with portfolio bond flows.

6. Robustness checks

We perform several robustness checks by altering the specifications of the determinants of capital flows (such as real-world interest rate, international reserves, and institutional quality index), including additional regressors (e.g., exchange rate regime and real global commodity price index), and alternating sample specifications (e.g., dropping two large economies, China and India, from the sample and dropping more regressors from our models). To avoid generating excessive tables, we focus on gross inflows for robustness checks. For brevity, we present the detailed results in our online appendix. The following text is a summary of the results.

First, the pattern between push and pull factors emerging from our core empirical results remains. VIX and regional contagion consistently display significant estimates across the whole conditional distribution. Moreover, there is robust evidence of foreign investor differentiation during stress times, as pull factors are more significant in the lower quantiles compared with the median.

Second, both international reserves and institutional quality index are consistently significant in the lower quantiles even after altering their specifications. In contrast, the real-world interest rate does not become more significant even when we use expected interest rates from forecasts of a professional survey.

Third, altering our sample specifications would not greatly affect our main empirical results, as shown in Table 6.

7. Concluding remarks

The relative importance of push/pull factors remains an ongoing debate (Hannan, 2018). This issue becomes more complex in extreme episodes (e.g., sudden stops and surges), in which capital flows behave differently and have different determinants. We propose an empirical approach that nests the various approaches in the literature discussed above and allows us to interpret or even potentially reconcile some of the seemingly contradictory results. Specifically, using a large panel of 51 EMs over 1990–2017, we investigate the determinants for foreign flows across quantiles using a novel quantile regression model for dynamic panel data with fixed effects.

As a preliminary analysis, we find that capital flows are largely driven by global risk aversion (VIX) and regional contagion when we use the total volumes of foreign flows via the dynamic panel model with fixed effects, which focuses on the conditional mean of foreign flows. This finding supports the hypothesis of GFCy (e.g., Rey, 2018). We find little evidence that other push/pull factors drive the movements of foreign flows.

The quantile regression dynamic panel model with fixed effects provides more information regarding the relative importance between push/pull factors and nests the findings of several extant studies. In particular, VIX and regional contagion are significant across almost all quantiles. Moreover, there are more significant push factors in the median quantiles (where capital flows are relatively stable) than in other quantiles, while we observe more significant pull factors in the tails. In the lower quantiles (where gross inflows are relatively low), foreign investors retreat less from EMs with stronger fundamentals. Thus, we provide fresh evidence and additional support for the investor differentiation hypothesis.

Next, we analyze disaggregated capital flows (i.e., FDI, equity, debt, and bank flows), complementing our findings based on gross inflows. First, the statistical significance of these estimated coefficients confirms the importance of VIX and thus potentially the presence of GFCy. VIX is significant for all types of disaggregated flows, even the long-term flow—FDI. Second, there is stronger evidence supporting the "*more-in-more-out*" hypothesis in the lower quantiles of short-term flows. Third, during stress episodes, there is a heterogeneous association between disaggregated capital flows and pull factors.

Our results draw the attention of policy-makers to a couple of issues. First, given the strong evidence for the investor differentiation hypothesis, policy-makers in EMs should build up stronger domestic fundamentals to buffer the drought of external financing. Second, given the strong evidence in portfolio debt and bank flows supporting the "*more-in-more-out*" hypothesis, policy-makers should monitor the sustainability of capital flows, especially when there are abundant debt and bank flows. Third, push factors (especially VIX) are significant across most episodes for gross inflows. Therefore, policy-makers should pay close attention to factors signaling GFCy, as a sharp rise in global risk aversion leads to a sudden drop in gross inflows, even during episodes of abundant foreign financing.

There are some caveats to our investigation. First, although both push and pull factors display a decent number of significant coefficients, neither can explain much regarding the variations of capital flows in terms of goodness-of-fit. Such a problem has also been reported by other studies (such as Cerutti et al., (2019) and the references therein), which underlines the difficulty of empirically modeling capital flows within the "push-pull" framework. Second, if we reduce the number of EMs, we can consider alternative data sources in the literature, such as daily data (as in Griffin et al., 2004; Richards, 2005; Ülkü and Weber, 2014; Ülkü, 2015; and Fuertes et al., 2019), monthly TIC data sources (as in Fuertes et al., 2016; Sarno et al., 2016; Yan et al., 2016), and quarterly international financial statistics (IFS) data sources. Data with higher frequency may provide a better fit for short-term flows. Moreover, there are also many alternative measures of capital flows. For instance, many papers on extreme episodes use raw flow data without scaling, while many other papers scale capital flows by CPI or stock market capitalization (Griffin et al., 2004; Richards, 2005; Fuertes et al., 2016; Yan et al., 2016; Fuertes et al., 2017). Although we have tried standard disaggregated measures of capital flows, there are also alternative ways to disaggregate capital flows. For example, Forbes and Warnock (2014) usefully split flows into equity (i.e., portfolio equity and FDI) and debt (bonds and banking). In this paper, we choose to focus on annual data over 1990–2017, as it offers the largest cross-sectional sample (51 EMs) to the best of our knowledge, recognizing that most other databases can only offer up to 30 or fewer EMs. We suspect alternative data sources, measures, and frequencies can affect the analysis. However, the variety and poor quality of international capital flows for EMs, in general, hinder our further investigation. These issues are open for future research.

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Figures

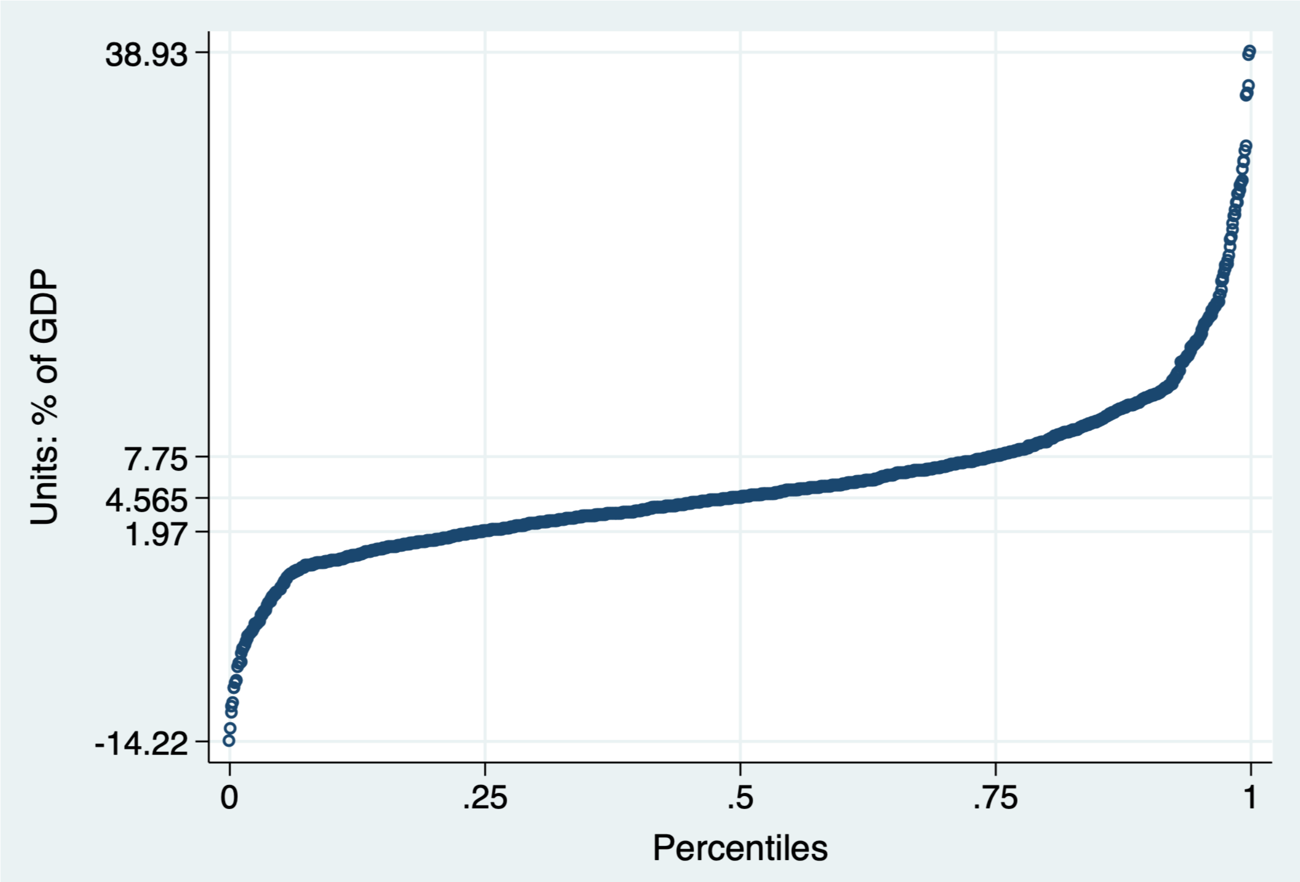

Figure 1. Quantiles of gross inflows to EMs, 1990-2017. This figure plots the quantiles of average gross inflows towards EMs during 1990-2017. The vertical axis is the percentage of GDP while the horizontal axis displays the quantiles of gross inflows. Data source: Bluedorn et al. (2013) and IFS.

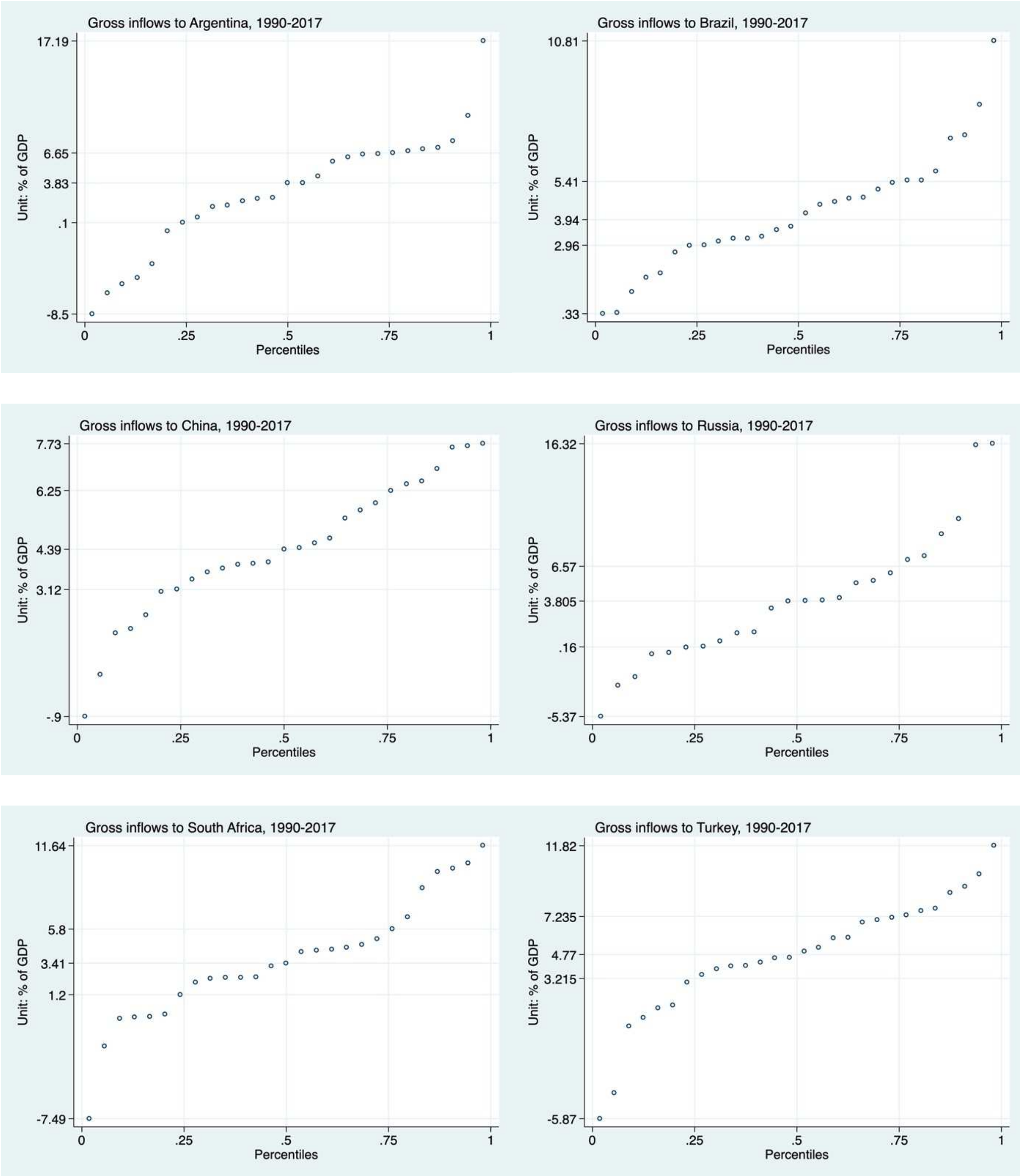

Figure 2. Gross inflows to some representative EMs, 1990-2017. The selected EMs (from left panels to right panels, from up panels to down panels) are Argentina, Brazil, China, Russia, South Africa, and Turkey, respectively. The vertical axis is the percentage of GDP while the horizontal axis displays the quantiles of gross inflows. Data source: Bluedorn et al. (2013) and IFS.

Tables

Table 1. Summary statistics.

	Unit	Observations	mean	S.D.	min	max	VIF	Source
Gross inflows	% of GDP	1056	6.03	11.08	-125.3	124		Bluedorn et al. (2013) and IFS
FDI flows	% of GDP	1045	3.52	4.53	-29.22	54.95		Bluedorn et al. (2013) and IFS
Portfolio equity flows	% of GDP	753	0.27	0.99	-9.80	6.75		Bluedorn et al. (2013) and IFS
Portfolio bond flows	% of GDP	865	1.06	2.58	-10.82	33.90		Bluedorn et al. (2013) and IFS
Bank flows	% of GDP	968	1.05	8.60	-117.61	122.28		Bluedorn et al. (2013) and IFS
Real world interest rate	In %	1056	0.21	1.74	-3.1	3	1.41	Federal Reserve Economic Data, St. Louis Fed
Global risk aversion		1056	20.17	6.07	11.1	33	1.43	Federal Reserve Economic Data, St. Louis Fed
Real world growth rate	In %	1056	2.43	1.73	-2.7	5	1.74	Federal Reserve Economic Data, St. Louis Fed
Regional contagion		1056	2.42	3.83	-19.2	19	1.18	Authors' calculation
Real domestic interest rate	In %	1056	2.59	8.32	-29.8	75	1.12	IFS
Real domestic growth rate	In %	1056	4.22	4.09	-17.7	23	1.16	IFS
Institutional quality index		1056	3.66	1.12	0.0	6	1.21	International Country Risk Guide (ICRG)
REER deviation from trend		1056	-1.75	12.61	-77.4	38	1.34	https://www.bruegel.org/
Public indebtedness	% of GDP	1056	44.34	30.01	1.2	220	1.21	Global debt database, IMF
Private credit expansion		1056	-4.32	24.43	-146.7	160	1.21	Global financial development database, World Bank
International reserves	% of GDP	1056	17.25	13.77	1.2	165	1.41	World development indicators, World Bank
Current account balance	% of GDP	1056	-0.60	7.93	-29.0	45	1.23	IFS
Trade openness		1056	68.43	36.95	12.1	196	1.32	Authors' calculation (based on data from IFS)
Financial openness		1056	0.29	1.47	-1.9	2	1.14	Updated data from Ito and Chinn (2008)

Table 2. Comparison between the stop episodes identified by Forbes and Warnock (2021) and the lower 20th quantiles of this study

	Stop episodes identified by both studies		By FW criterion only		By the lower 20th quantiles of this study	
Country	**Episodes**	**Gross inflows**	**Episodes**	**Gross inflows**	**Episodes**	**Gross inflows**
	(1)	(2)	(3)	(4)	(5)	(6)
Argentina	1990,2001,2009	-3.39	1999,2008	4.30	2002-2005,2014	-3.88
Brazil	None		1993,2008,2009	3.81	1990,1991,2002	0.61
Chile	None		2000,2009	7.49	1991	-0.25
Colombia	None		2015,2016	7.53	1991,2003	-0.50
Costa Rica	None		2009,2014,2015	7.13	None	
Croatia	None		2005,2010	5.29	None	
Czech	2009	0.62	2003,2006	6.30	None	
Estonia	2009	-3.60	1999,2008,2015	13.14	2010,2011	-2.00
Guatemala	2009		1995,2000,2001		1999	
Hungary	2009	-5.57	None		1990, 2010-2013,2015,2017	-9.42
India	1990,1991,	0.78	2009,2015,2016	5.35	1995	1.01
Indonesia	1998	-14.45	2009	3.26	1997,1999-2003	-3.15
South Korea	1997,1998,2008,2009	-4.54	None		2001,2010,2011,2015,2016	-0.50
Latvia	2009,2015	-7.49	None		2010,2011	-2.51
Lithuania	2009	-5.97	1999,2001	8.72	1993,2010,2012,2013,2015	-1.87
Malaysia	None		2006	4.52	2001,2005,2008,2015	-2.55
Mexico	1995	-0.44	2009,2015	3.79	None	
Panama	None		2009	9.61	1998,2000,2002,2003	-7.21
Peru	None		1999,2009,2014	4.57	1990,1991,2000	0.56
Philippines	1998,2008	-1.61	None		1992,2001,2003,2004,2009,2015	0.75
Poland	None		2002,2009	5.41	1991,2013	0.60
Russia	2009,2014	-1.27	None		1994,1999,2000,2015-2017	-1.28
Slovak	1999	-2.05	2012	6.46	2001,2009,2015	-3.61
Slovenia	None		2009	2.04	2012,2015,2016,2017	-3.70
South Africa	None		None		1990,1991,1993,2002,2015,2016	-1.87
Sri Lanka	2001	-0.57	2015	2.63	1995,1998 ,2002,2003	0.32
Thailand	1997,2008	-0.86	1992,2012	8.16	1998-2003,2011,2014-2016	-4.14
Turkey	1994,2001,2009	-3.32	2008	6.87	1991	0.69
All		-3.35		6.01		-1.90

Notes: Gross inflows are based on our dataset, defined as the average levels over domestic GDPs during the stop episodes listed. Data source: Bluedorn et al. (2013), Forbes and Warnock (2021) and IFS.

Table 3. Discussing the method of FW

(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
Time	***Gross inflows***	C_t	ΔC_t	***Rolling mean (RM)***	***Rolling s.d. (RSD)***	***Threshold***	***Threshhold2***	***Stop?***
	Example 1: Sri Lanka							
2001q1	*-0.14*	*0.30*	*-0.21*	*-0.01*	*0.33*	*0.13*	*0.46*	*No*
2001q2	*0.06*	*0.17*	*-0.51*	*-0.03*	*0.35*	***-0.14***	*0.21*	***Yes***
2001q3	*-0.18*	*-0.01*	*-0.74*	*-0.06*	*0.38*	***-0.30***	*0.08*	***Yes***
2001q4	*-0.08*	*-0.34*	*-1.01*	*-0.10*	*0.44*	***-0.48***	***-0.04***	***Yes***
2002q1	*-0.09*	*-0.29*	*-0.59*	*-0.13*	*0.45*	***-0.01***	*0.44*	***Yes***
2002q2	*-0.06*	*-0.40*	*-0.57*	*-0.14*	*0.46*	*0.04*	*0.50*	*No*
2002q3	*-0.25*	*-0.47*	*-0.45*	*-0.17*	*0.46*	*0.18*	*0.64*	*No*
2002q4	*0.02*	*-0.37*	*-0.02*	*-0.19*	*0.45*	*0.61*	*1.06*	*No*
2003q1	*-0.06*	*-0.34*	*-0.05*	*-0.20*	*0.44*	*0.59*	*1.03*	*No*
2003q2	*-0.01*	*-0.29*	*0.11*	*-0.20*	*0.44*	*0.75*	*1.19*	*No*
2003q3	*-0.05*	*-0.09*	*0.37*	*-0.15*	*0.45*	*0.97*	*1.42*	*No*
2003q4	*-0.12*	*-0.24*	*0.12*	*-0.12*	*0.44*	*0.68*	*1.13*	*No*
	Example 2: Argentina							
2000q4	*-0.18*	*11.37*	*-9.67*	*-0.38*	*7.78*	***-1.50***	*7.83*	***Yes***
2001q1	*-0.14*	*8.38*	*-9.11*	*-1.00*	*7.97*	***-0.14***	*7.47*	***Yes***
2001q2	*-2.01*	*3.85*	*-10.52*	*-1.51*	*8.24*	***-0.77***	***-1.79***	***Yes***
2001q3	*-3.68*	*-6.00*	*-23.59*	*-2.97*	*9.42*	***-11.21***	*0.76*	***Yes***
2001q4	*-7.30*	*-13.12*	*-24.49*	*-4.33*	*10.46*	***-9.70***	*3.43*	***Yes***
2002q1	*-3.40*	*-16.38*	*-24.76*	*-5.75*	*11.22*	***-7.79***	*8.11*	***Yes***
2002q2	*-3.52*	*-17.90*	*-21.75*	*-7.20*	*11.33*	***-3.22***	*18.78*	***Yes***
2002q3	*-2.68*	*-16.91*	*-10.90*	*-8.14*	*10.77*	*8.01*	*29.17*	*No*
2002q4	*-3.29*	*-12.89*	*0.22*	*-8.59*	*10.18*	*18.99*	*34.07*	*No*
2003q1	*-1.32*	*-10.81*	*5.57*	*-8.78*	*9.86*	*24.21*	*36.00*	*No*
2003q2	*-3.00*	*-10.29*	*7.61*	*-8.82*	*9.79*	*26.21*	*36.14*	*No*
2003q3	*-2.07*	*-9.67*	*7.23*	*-8.52*	*10.19*	*25.95*	*31.32*	*No*
2003q4	*-4.21*	*-10.59*	*2.30*	*-8.07*	*10.47*	*20.85*	*7.83*	*No*

Notes: Column (2) shows the level of gross inflows relative to the domestic GDP from Forbes and Warnock (2021). Column (5) and (6) refer to the rolling means and standard deviations of ΔC_t over the last 5 years. Column (7) and (8) show whether such an episode is qualified as a stop according to Forbes and Warnock (2012, 2021). Data source: Forbes and Warnock (2021).

Table 4. Summary statistics for gross inflows during the "*stress episodes*" as defined by Ahmed et al. (2017)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Stress episodes	Mexican crisis		Asian crisis	Russian crisis	Argentine crisis	Global financial crisis		European sovereign debt crisis	Taper tantrum	Financial stress in China	non-crisis years
Time	September 1994 to March 1995		July 1997 to January 1998	August to November 1998	April to October 2002	September 2008 to February 2009		July to December of 2011	May to August of 2013	July to September of 2015	All others (AO)
Year	1994	1995	1997	1998	2002	2008	2009	2011	2013	2015	AO
Panel A: Summary statistics of gross inflows of the contemporary year (unit: % over GDP)											
Mean	6.44	5.36	7.94	4.25	3.29	9.70	4.03	3.59	1.96	2.16	6.16
S.D.	10.45	6.04	6.58	5.17	8.68	19.20	17.37	5.81	20.93	5.04	8.94
Min	-4.20	-1.21	-2.78	-14.45	-33.69	-14.21	-18.04	-24.86	-125.32	-17.92	-49.25
Panel B: Number of EMs within the region during the stress year included in the lower 20th quantiles											
LA (13)	1	2	0	1	5	1	5	1	0	0	
EEU (16)	1	1	0	0	0	0	9	4	4	9	
Asia (10)	0	2	4	7	4	4	3	3	1	6	
Other(12)	3	6	2	0	6	0	3	1	1	1	
Total (51)	5	11	6	8	15	5	20	9	6	16	

Notes: LA=Latin America; EEU= Eastern Europe; Asia=Asia (ex. EMs from the Middle East); Other= Middle East and Africa. The number in the bracket after the name abbreviation of each region denotes the number of EMs within this region in the whole sample. Data source: Bluedorn et al. (2013) and IFS.

Table 5. Dynamic panel data approach estimates. The dependent variable is gross private capital flow relative to GDP. *Robust standard errors are in the parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. The data source for all variables are described in Table 1.*

	(1)	(2)	(3)	(4)
Lagged gross inflows	0.470***	0.479***	0.471***	0.415***
	(0.104)	(0.105)	(0.105)	(0.099)
Real world interest rate	-0.093	-0.041	-0.071	0.114
	(0.077)	(0.093)	(0.094)	(0.163)
VIX	-0.182***	-0.188***	-0.198***	-0.178***
	(0.033)	(0.036)	(0.041)	(0.051)
Real world growth rate	0.038	-0.052	-0.067	-0.084
	(0.170)	(0.174)	(0.199)	(0.193)
Regional contagion	0.306***	0.347***	0.408***	0.614***
	(0.099)	(0.093)	(0.094)	(0.133)
Real domestic interest rate		0.033	0.022	0.052
		(0.034)	(0.050)	(0.050)
Real domestic growth rate		0.039	0.167**	0.124
		(0.065)	(0.072)	(0.089)
Institutional quality index		-0.350	-0.300	0.448
		(1.190)	(1.008)	(1.259)
REER deviation from trend		-0.022	-0.020	-0.043
		(0.030)	(0.034)	(0.036)
Public indebtedness			0.027	0.044
			(0.030)	(0.035)
Private credit expansion			0.030**	0.024
			(0.014)	(0.020)
International reserves				0.105**
				(0.041)
Current account balance				-0.256**
				(0.118)
Trade openness				0.038
				(0.062)
Financial openness				1.240
				(0.844)
Hansen P-value	0.298	0.141	0.305	0.264
AR(2) P-value	0.385	0.310	0.269	0.257
Observations	1250	1113	1066	1054
No. of countries	51	51	51	51
No. of instruments	10	22	28	40

Table 6. Determinants of gross capital inflows. *The dependent variable is the gross private capital flow relative to domestic GDP. * p < 0.10, ** p < 0.05, *** p < 0.01. The data source for all variables are described in Table 1.*

	Quantiles	10th	20th	30th	40th	50th	60th	70th	80th	90th
	Lagged gross inflows	-0.44	0.055	0.295**	0.555***	0.700***	0.735***	0.855***	0.975***	1.55***
		(0.403)	(0.118)	(0.127)	(0.025)	(0.134)	(0.142)	(0.122)	(0.175)	(0.045)
Push factors	Real world interest rate	-0.384	-0.211	-0.161	-0.126	-0.14**	-0.124*	-0.069	-0.038	0.006
		(0.244)	(0.15)	(0.116)	(0.083)	(0.066)	(0.079)	(0.087)	(0.117)	(0.21)
	VIX	-0.126**	-0.076***	-0.075***	-0.089***	-0.088***	-0.077***	-0.071***	-0.095***	-0.052
		(0.048)	(0.025)	(0.021)	(0.02)	(0.018)	(0.021)	(0.022)	(0.033)	(0.046)
	Real world growth rate	-0.164	0.014	0.119	0.103	0.194***	0.248***	0.222**	0.278**	0.06
		(0.203)	(0.099)	(0.075)	(0.068)	(0.071)	(0.072)	(0.1)	(0.125)	(0.256)
	Regional contagion	0.398**	0.318***	0.266***	0.273***	0.229***	0.215***	0.201***	0.218***	0.149
		(0.173)	(0.094)	(0.076)	(0.064)	(0.052)	(0.06)	(0.069)	(0.074)	(0.112)
Pull factors	Real domestic interest rate	-0.046	0.001	0.009	0.012	0.013	0.013	0.004	0.016	0.025
		(0.054)	(0.02)	(0.022)	(0.02)	(0.017)	(0.02)	(0.025)	(0.03)	(0.037)
	Real domestic growth rate	0.438***	0.251***	0.139***	0.049	0.027	0.03	-0.045	-0.101	-0.431***
		(0.081)	(0.038)	(0.039)	(0.033)	(0.031)	(0.043)	(0.057)	(0.064)	(0.095)
	Institutional quality index	0.804*	0.628***	0.607***	0.515***	0.405***	0.365***	0.409***	0.241	0.146
		(0.428)	(0.178)	(0.162)	(0.13)	(0.108)	(0.115)	(0.153)	(0.206)	(0.307)
	REER deviation from trend	0.066**	0.021	0.005	0.005	-0.006	-0.017	-0.027**	-0.025	-0.088***
		(0.031)	(0.014)	(0.012)	(0.01)	(0.011)	(0.011)	(0.013)	(0.017)	(0.033)
	Public indebtedness	-0.023	-0.011	-0.013*	-0.006	-0.003	-0.001	0.01	0.026**	0.067***
		(0.02)	(0.008)	(0.007)	(0.006)	(0.005)	(0.005)	(0.008)	(0.013)	(0.025)
	Private credit expansion	-0.061***	-0.033***	-0.022***	-0.013*	-0.008	-0.003	-0.004	-0.001	0.027
		(0.014)	(0.009)	(0.007)	(0.008)	(0.008)	(0.009)	(0.01)	(0.01)	(0.021)
	International reserves	0.096**	0.058**	0.034**	0.018	0.018	0.01	-0.001	0.005	-0.076**
		(0.04)	(0.025)	(0.015)	(0.015)	(0.012)	(0.014)	(0.018)	(0.026)	(0.034)
	Current account balance	-0.545***	-0.252***	-0.159***	-0.062**	-0.05***	-0.033	0.006	0.061	0.333***
		(0.145)	(0.061)	(0.043)	(0.028)	(0.019)	(0.027)	(0.029)	(0.043)	(0.114)
	Trade openness	-0.032*	-0.02***	-0.01**	-0.005	0.005	0.01	0.014*	0.023**	0.056***
		(0.017)	(0.007)	(0.004)	(0.005)	(0.004)	(0.006)	(0.008)	(0.01)	(0.017)
	Financial openness	-0.054	0.051	0.098	0.074	0.059	0.18	0.19	0.404*	0.354
		(0.28)	(0.154)	(0.13)	(0.118)	(0.103)	(0.147)	(0.182)	(0.221)	(0.414)
	R1 explained by push factors	0.043	0.031	0.028	0.029	0.031	0.031	0.026	0.027	0.025

	R1 explained by push factors	0.085	0.051	0.036	0.025	0.018	0.021	0.023	0.031	0.044

Table 7. Determinants of FDI and bank flows. *The dependent variable is the gross Foreign Direct Investments (FDI) or bank credit inflows relative to domestic GDP. All pull factors are lagged by 1 period. Robust standard errors are in the parentheses. (* p < 0.10, ** p < 0.05, *** p < 0.01). The data source for all variables are described in Table 1.*

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		FDI					**Bank flows**				
		Lower quantiles		Median	Upper quantiles		Lower quantiles		Median	Upper quantiles	
	Quantiles	10th	20th	50th	80th	90th	10th	20th	50th	80th	90th
Push factors	Lagged inflows	0.315	0.59	0.845**	1.145***	1.465***	-0.84***	-0.545	-0.04	0.8**	0.78*
		(0.393)	(0.396)	(0.328)	(0.234)	(0.184)	(0.031)	(0.38)	(0.086)	(0.353)	(0.417)
	Real world interest rate	-0.068*	-0.049	-0.058*	-0.003	-0.026	0.169	0.042	-0.01	-0.068	-0.106
		(0.035)	(0.033)	(0.032)	(0.055)	(0.113)	(0.192)	(0.083)	(0.035)	(0.054)	(0.098)
	VIX	-0.004	-0.01	-0.016***	-0.023**	-0.04**	-0.087**	-0.041***	-0.04***	-0.022	-0.075**
		(0.013)	(0.008)	(0.006)	(0.01)	(0.02)	(0.035)	(0.015)	(0.011)	(0.018)	(0.033)
	Real world growth rate	-0.051	0.007	0.016	0.042	0.083	-0.176	-0.099*	-0.065*	0.04	-0.084
		(0.042)	(0.033)	(0.027)	(0.06)	(0.104)	(0.127)	(0.057)	(0.035)	(0.065)	(0.112)
	Regional contagion	0.051**	0.033*	0.057***	0.042	-0.008	0.093	0.078*	0.098**	0.051	0.134*
		(0.021)	(0.019)	(0.018)	(0.03)	(0.039)	(0.085)	(0.045)	(0.04)	(0.043)	(0.073)
Pull factors	Real domestic interest rate	0.007	0.014*	0.011**	0.008	0.012	-0.023	-0.008	0.001	0.005	0.033
		(0.01)	(0.008)	(0.005)	(0.007)	(0.014)	(0.026)	(0.009)	(0.007)	(0.009)	(0.024)
	Real domestic growth rate	0.035***	0.032***	0.008	-0.007	0.032	0.343***	0.215***	0.082***	-0.017	-0.017
		(0.012)	(0.011)	(0.01)	(0.033)	(0.045)	(0.072)	(0.05)	(0.025)	(0.036)	(0.058)
	Institutional quality index	0.075	0.065	0.08**	0.133	0.037	-0.462	-0.11	0.091	0.123	0.485**
		(0.08)	(0.063)	(0.037)	(0.11)	(0.194)	(0.29)	(0.119)	(0.058)	(0.128)	(0.241)
	REER deviation from trend	-0.004	-0.004	0.001	-0.005	0.001	0.024	0.014	0.004	-0.006	-0.01
		(0.007)	(0.005)	(0.004)	(0.008)	(0.013)	(0.023)	(0.009)	(0.005)	(0.008)	(0.015)
	Public indebtedness	-0.004	-0.002	0.002	0.007	0.011	-0.008	-0.004	0.001	-0.001	0.004
		(0.003)	(0.002)	(0.001)	(0.005)	(0.012)	(0.011)	(0.006)	(0.003)	(0.006)	(0.016)
	Private credit expansion	-0.003	-0.002	0.001	0.005	0.011	-0.031***	-0.019***	-0.006*	-0.001	0.001
		(0.003)	(0.002)	(0.003)	(0.005)	(0.008)	(0.012)	(0.007)	(0.003)	(0.004)	(0.007)
	International reserves	0.012	0.004	0.006	-0.004	-0.02	0.044*	0.021	0.016	0.023*	0.011
		(0.008)	(0.005)	(0.004)	(0.008)	(0.015)	(0.025)	(0.016)	(0.012)	(0.013)	(0.022)
	Current account balance	-0.023	-0.009	-0.008	0.009	0.044	-0.105*	-0.053	-0.038**	-0.011	-0.02
		(0.017)	(0.008)	(0.014)	(0.024)	(0.035)	(0.056)	(0.035)	(0.015)	(0.028)	(0.035)
	Trade openness	-0.007	-0.004	0.001	0.01*	0.028**	-0.018*	-0.016***	-0.004	0.005	0.011
		(0.005)	(0.004)	(0.001)	(0.005)	(0.012)	(0.01)	(0.005)	(0.004)	(0.005)	(0.009)
	Financial openness	0.034	-0.049	-0.005	0.062	0.044	-0.382	-0.062	0.086	0.344*	0.595*
		(0.095)	(0.057)	(0.032)	(0.069)	(0.137)	(0.248)	(0.11)	(0.061)	(0.178)	(0.31)

Table 8. Determinants of Portfolio equity and debt flows. *The dependent variable is gross portfolio equity or bond inflows relative to domestic GDP. All pull factors are lagged by 1 period. Robust standard errors are in the parentheses. (* p < 0.10, ** p < 0.05, *** p < 0.01). The data source for all variables are described in Table 1.*

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Portfolio equity flows					Portfolio debt flows				
		Lower quantiles		Median	Upper quantiles		Lower quantiles		Median	Upper quantiles	
	Quantiles	10th	20th	50th	80th	90th	10th	20th	50th	80th	90th
Push factors	Lagged inflows	-0.150	0.070	0.675***	1.845***	0.31***	-0.375***	-0.11	0.785***	1.295***	1.79***
		(0.287)	(0.186)	(0.014)	(0.057)	(0.026)	(0.106)	(0.197)	(0.121)	(0.079)	(0.042)
	Real world interest rate	-0.014	-0.019	0.009	0.043	0.065	-0.098*	-0.09**	-0.06**	0.042	0.151
		(0.024)	(0.013)	(0.008)	(0.032)	(0.054)	(0.056)	(0.038)	(0.024)	(0.064)	(0.119)
	VIX	-0.015***	-0.006**	0.001	0.008	0.016	-0.024	-0.015**	-0.003	0.024	0.06**
		(0.004)	(0.003)	(0.002)	(0.008)	(0.015)	(0.016)	(0.007)	(0.005)	(0.016)	(0.025)
	Real world growth rate	0.058**	0.04**	0.037***	0.02	0.127**	0.181***	0.147***	0.04*	-0.005	-0.071
		(0.026)	(0.016)	(0.012)	(0.031)	(0.063)	(0.046)	(0.039)	(0.024)	(0.067)	(0.128)
	Regional contagion	-0.002	-0.002	-0.004	-0.014	-0.001	-0.006	-0.002	-0.01	-0.023	-0.071
		(0.008)	(0.005)	(0.003)	(0.01)	(0.018)	(0.031)	(0.027)	(0.013)	(0.025)	(0.048)
Pull factors	Real domestic interest rate	0.007	0.001	0.001	-0.005	0.015	0.019*	0.002	0.007	-0.016	-0.042
		(0.004)	(0.002)	(0.001)	(0.007)	(0.014)	(0.011)	(0.006)	(0.004)	(0.015)	(0.033)
	Real domestic growth rate	0.010	-0.001	0.004	0.013	0.027	0.026	0.009	-0.004	-0.094***	-0.169***
		(0.01)	(0.005)	(0.004)	(0.011)	(0.017)	(0.035)	(0.017)	(0.012)	(0.034)	(0.055)
	Institutional quality index	0.093**	0.048*	-0.006	-0.007	-0.024	0.078	0.112*	0.031	0.085	0.269
		(0.038)	(0.026)	(0.017)	(0.056)	(0.114)	(0.136)	(0.066)	(0.037)	(0.113)	(0.237)
	REER deviation from trend	-0.005	-0.004*	-0.004**	-0.001	-0.012*	0.02**	0.006	-0.007	-0.019*	-0.052***
		(0.004)	(0.002)	(0.001)	(0.004)	(0.007)	(0.01)	(0.007)	(0.005)	(0.01)	(0.019)
	Public indebtedness	-0.003	-0.002	-0.001*	0.002	-0.005	-0.017**	-0.009***	-0.002	0.009	0.026**
		(0.003)	(0.001)	(0.001)	(0.003)	(0.004)	(0.007)	(0.003)	(0.002)	(0.007)	(0.012)
	Private credit expansion	-0.004*	-0.001	0.001	0.003**	0.004	0.002	0.005*	0.001	-0.003	0.001
		(0.002)	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)	(0.003)	(0.002)	(0.004)	(0.008)
	International reserves	-0.01*	-0.004	0.002	0.006	0.022**	0.001	-0.01	-0.002	-0.007	-0.04
		(0.006)	(0.003)	(0.001)	(0.007)	(0.011)	(0.014)	(0.007)	(0.005)	(0.013)	(0.027)
	Current account balance	-0.006	-0.005	0.001	0.017	-0.007	-0.016	-0.011	-0.005	-0.009	0.04
		(0.006)	(0.004)	(0.002)	(0.011)	(0.013)	(0.015)	(0.009)	(0.008)	(0.022)	(0.037)
	Trade openness	-0.003**	-0.001	0.001	0.002	0.002	-0.012***	-0.005**	0.001	0.009**	0.019**
		(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.005)	(0.002)	(0.002)	(0.004)	(0.009)
	Financial openness	-0.009	-0.017	-0.012	0.052	-0.117	0.056	0.086	0.038	0.168**	0.297**
		(0.031)	(0.015)	(0.009)	(0.036)	(0.087)	(0.094)	(0.056)	(0.03)	(0.081)	(0.136)

Appendix A. Further information on the methodology

A1. Technical details about the methodology

Our primary empirical tool is the quantile regression dynamic panel model with fixed effects, as proposed by Galvao (2011)[28], which has several advantages over traditional quantile regression (QR) models.

First, this model accounts for individual effects, which are not straightforward in QR estimates. Traditional panel data methods (e.g., first difference and demean) cannot remove the individual effects in quantile regression models because of their nonlinearity. Moreover, the introduction of cross-section dummy variables in traditional panel data methods as a compromise is invalid when the number of groups in the panel data is large, as the inclusion of numerous dummies may inflate the variability of the estimated coefficients of other regressors. Based on these considerations, Koenker (2004) proposes a penalty method that shrinks the individual effects toward a common value, which can be expressed as follows:

$$\left(\hat{\eta}, \hat{\alpha}, \hat{\beta}\right) = \min_{\eta,\alpha,\beta} \sum_{i=1}^{N} \sum_{t=1}^{T} \rho_\eta \times (K_{i,t} - \eta(\tau)_i - \alpha(\tau)K_{i,t-1} - \beta_1(\tau)g_t' - \beta_2(\tau)d_{i,t-1}'),$$

$$\beta = (\beta_1, \beta_2), \tag{1}$$

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 address fixed effects in his model.

Second, the model from Galvao (2011) works for dynamic panel data, which is novel among QR models. Typically, in using dynamic panel techniques via quantile regression, the presence of the lagged dependent variable ($K_{i,t-1}$) leads to the same bias as in the case of ordinary least squares (OLS). Galvao (2011) provides a solution, following the literature on instrumental variable quantile regression (e.g., Chernozhukov and Hanson, 2006; 2008). Using

[28] We are grateful to the author of Galvao (2011) who shared the codes with us.

this model, we first assume for clarity and simplicity $K_{i,t-1}$ as the only endogenous variable in our regression. In addition, following Galvao (2011), we employ $K_{i,t-2}$ as the instrumental variable (IV), namely, $W_{i,t}$.[29] In Equation (1), the coefficient for the lagged dependent, α, can be estimated as follows:

$$\hat{\alpha} = \min_{\alpha} ||\hat{\gamma}(\alpha)||_A, \tag{2}$$

where

$$\left(\hat{\eta}(\alpha), \hat{\beta}(\alpha), \hat{\gamma}(\alpha)\right) = \min_{\eta,\alpha,\gamma} \sum_{i=1}^{N} \sum_{t=1}^{T} \rho_\eta \times \left(K_{i,t} - \eta(\tau)_i - \alpha(\tau)K_{i,t-1} - \beta_1(\tau)g_t' - \beta_2(\tau)d_{i,t-1}' - W_{i,t}'\gamma(\tau)\right), \tag{3}$$

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

$$\hat{\theta}(\tau) \equiv \left(\hat{\beta}(\tau), \hat{\alpha}(\tau)\right) \equiv \left(\hat{\beta}(\hat{\alpha}(\tau), \tau), \hat{\alpha}(\tau)\right). \tag{4}$$

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 in (4) finds parameter values for α and β through the inverse step (2) such that the value of the coefficient $\gamma(\alpha, \tau)$ on the instrument in the ordinary quantile regression step (3) is driven as close to zero as possible. Hence, by minimizing the IV coefficient, the estimator of α can be recovered (Galvao, 2011).

A2. A potential concern of the methodology

Based on Galvao (2011), the quantiles of gross inflows are defined relative to the entire panel rather than relative to the time series for each country. This definition could lead to a potential concern: some of the results might be country-specific—for instance, if a country that is relatively closed (open) to gross inflows appears mostly in the low-inflow (high-inflow)

[29] 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 an 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 available upon request.

quantiles. If such observations dominate the lower/higher quantiles, some results could be country-specific rather than specific to the episodes of high/low gross inflows.[30]

Despite this concern, we argue that our empirical model is sound for the following reasons:

[Insert Table A3 here]

First, our low-inflow/high-inflow quantiles cover the majority of countries in the full sample, and they are not dominated by a few individual countries. Specifically, we report in Table A3 the number of countries included in the lower/upper 20th quantiles, as well as the summary statistics of the observations per country included in such low-inflow/high-flow quantiles. From Panel A, we observe that our lower quantiles cover 49 EMs out of 51 in the full sample. Such a number indicates that 96% of EMs in our full sample are covered in the low-inflow quantiles. In contrast, our upper 20th quantiles cover relatively fewer EMs, as shown in Column (2). However, they still include 40 out of 51 EMs, suggesting a coverage ratio of 78%.

Second, our empirical results are likely to be country-specific if a considerable number of EMs display many *observations per country*. To that end, we examine the statistics of *observations per country* in the lower/upper 20th quantiles. First, Column (1) of Panel B displays the statistics in the low-flow quantiles, where we observe the mean value as 5.30. This value is the same as the mean of 5.30 (i.e., 260/49) if the number per country is evenly distributed in the lower 20th quantiles, given the number of total observations 260 and the number of countries included 49. Such a result suggests that EMs in the lower quantiles are close to evenly distributed. Second, the standard deviation is 3.28 (as shown in the final row of Column 1). According to the Empirical Rule in Statistics, 95% of the distribution is expected to lie within two standard deviations. This finding would suggest that in the lower quantiles of gross inflows, 95% of the EM observations are expected to lie between 0 and 11.86. Therefore, such statistics suggest that the low-flow quantiles are not dominated by a few specific EMs by having large observations per

[30] We thank one anonymous referee for pointing this out.

country. We can apply a similar exercise to the upper 20^{th} quantiles and obtain a similar conclusion.

Third, a further discussion of Section 4.2.3 of our main paper, where we compare our quantile regression approach with the "stress episodes" in Ahmed et al. (2017), shows that our lower quantiles capture the time-series variation in gross inflows for each country. Therefore, our results in the lower/higher quantiles are not country-specific. In particular, in Panel B of Table 4, we observe that the statistics of the number of EMs within each region (included in our lower 20^{th} quantiles) vary across different financial stress episodes, as defined by Ahmed et al. (2017). Specifically, in Panel B of Table 4, we first classify the EMs in our sample into 4 regions: LA (Latin America), EEU (Eastern Europe), Asia (excluding EMs from the Middle East), and others (Middle East and Africa). We observe that, for instance, our lower 20^{th} quantiles capture few EMs from EEU during all the stress episodes before the GFC during 2008–2009. However, our lower quantiles include 9 out of 16 EEU countries (in our sample) during the GFC in 2009 and 9 during the Chinese financial stress episode in 2015. Moreover, EMs in Asia (excluding those in the Middle East) were largely included in our lower quantiles in 1998 when the Asian and Russian crises occurred. In particular, 7 out of 10 Asian EMs (in our sample) were included in our lower 20^{th} quantiles in 1998. However, our low gross inflow quantiles do not include any Asian EMs in 1994, when the Mexican financial crisis occurred. Such results suggest that our lower quantiles indeed capture the time-series variation in the gross inflows for each country—despite the potential concern of country-specific factors, our econometric method could still be sound.

Finally, our empirical model, Galvao (2011), incorporates fixed effects. Hence, even if country-specific factors might be a matter of concern, they have already been controlled for by our empirical model in all conditional quantiles.

Table A1. Countries and their sample intervals.

Latin America (LA)		Eastern Europe (EEU)		Asia (ex. EMs from the Middle East)		Other (Middle East and Africa)	
Country	Sample interval	Country	Sample interval	Country	Sample interval	Country	Sample interval
Argentina	1995-2015	Belarus	1999-2017	China	1996-2016	Angola	1999-2016
Brazil	1995-2017	Bulgaria	1995-2017	India	1990-2010	Egypt	1990-2010
Chile	1990-2016	Czech	1991-2017	Indonesia	1990-2016	Jordan	1991-2016
Costa Rica	1990-2016	Croatia	2000-2015	Kazakhstan	2000-2016	Kuwait	1995-2016
Colombia	1991-2011	Cyprus	1990-2014	Malaysia	1990-2016	Libya	2001-2010
Dominican Republic	2001-2017	Ecuador	1991-2010	Pakistan	1990-2016	Morocco	1995-2013
El Salvador	1995-2010	Estonia	2000-2011	Philippines	1990-2016	Saudi Arab	2000-2011
Guatemala	1990-2011	Hungary	1992-2017	South Korea	1990-2016	Syria	1990-2008
Mexico	1994-2016	Latvia	2000-2017	Sri Lanka	1990-2010	Tunisia	1993-2010
Panama	1990-2010	Lithuania	2000-2017	Thailand	1990-2017	Turkey	1990-2016
Peru	2000-2013	Poland	1996-2017			South Africa	1990-2016
Trinidad and Tobago	1990-2009	Romania	1997-2017				
Uruguay	1991-2016	Russia	1997-2017				
		Slovak Rep	1997-2017				
		Slovenia	2000-2017				
		Ukraine	1999-2016				

Table A2. The list of countries belonging to the lower 20th quantiles for each crisis episode. *Flows = Gross inflows (unit: % over GDP). T & T = Trinidad and Tobago. Data source: Bluedorn et al. (2013) and IFS.*

	(1)				(2)		(3)		(4)	
Stress episodes	Mexican crisis				Asian crisis		Russian crisis		Argentine crisis	
Time	September 1994 to March 1995				July 1997 to January 1998		August to November 1998		April to October 2002	
	1994	***Flows***	***1995***	***Flows***	***1997***	***Flows***	***1998***	***Flows***	***2002***	***Flows***
Country	El Salvador	1.17	Bulgaria	-0.45	Indonesia	-0.07	Indonesia	-14.46	Argentina	-8.50
	Libya	-0.21	Egypt	0.74	Korea, Rep	0.42	Korea, Rep	-4.48	Brazil	0.36
	Russia	0.62	India	1.02	Libya	-0.39	Libya	-0.41	Colombia	0.07
	Saudi Arabia	0.63	Kuwait	-0.25	Pakistan	0.82	Pakistan	0.58	Egypt	1.14
	Turkey	-4.21	Libya	-0.55	Syria	0.44	Panama	-0.19	Indonesia	-0.54
			Mexico	-0.45	Thailand	-2.78	Philippines	0.88	Libya	0.08
			Morocco	0.77			Sri Lanka	-0.26	Oman	-2.60
			Oman	0.24			Thailand	-10.19	Pakistan	-1.19
			Saudi Arabia	-1.22					Panama	-25.34
			Sri Lanka	0.92					Saudi Arabia	-2.68
			T & T	-0.61					South Africa	-0.18
									Sri Lanka	0.27
									Syria	-5.20
									Thailand	-4.94
									Uruguay	-33.70

Table A2. (continued)

	(5)				(6)		(7)		(8)	
Stress episodes	Global financial crisis				European sovereign debt crisis		Taper tantrum		Financial stress in China	
Time	September 2008 to February 2009				July to December of 2011		May to August of 2013		July to September of 2015	
Year	***2008***	***Flows***	***2009***	***Flows***	***2011***	***Flows***	***2013***	***Flows***	***2015***	***Flows***
Country	Korea, Rep	-12.05	Oman	1.01	Bulgaria	-0.67	Angola	0.03	Belarus	0.88
	Malaysia	-8.27	Pakistan	1.07	Cyprus	-24.86	Cyprus	-125.33	Bulgaria	0.39
	Philippines	-4.11	Philippines	0.49	Ecuador	0.73	Hungary	-7.09	China	-0.90
	Thailand	1.05	Romania	0.21	Egypt	-4.58	Lithuania	-9.56	Hungary	-17.92
	T & T	-14.22	Russia	-0.30	Estonia	-3.50	Pakistan	-0.01	Korea, Rep	-0.93
	2009	***Flows***	Slovak rep	-9.79	Korea, Rep	-1.67	Poland	0.35	Kazakhstan	1.18
	Argentina	-0.71	Turkey	0.11	Latvia	-0.49			Kuwait	0.98
	Czech	0.63	T & T	-11.29	Pakistan	0.74			Lithuania	-2.72
	Ecuador	-5.20	Ukraine	-1.85	Thailand	-1.11			Malaysia	-0.71
	El Salvador	-1.18							Philippines	0.93
	Estonia	-3.61							Romania	1.18
	Guatemala	-0.89							Russia	-5.37
	Hungary	-5.58							Slovak rep	-1.06
	Korea, Rep	-2.07							Slovenia	-3.31
	Kuwait	-10.12							South Africa	-2.41
	Latvia	-18.05							Thailand	-2.91
	Lithuania	-5.98							Ukraine	-4.28

Table A3. Summary statistics of number of countries and observations per countries in the lower/upper quantiles. *Data source: Bluedorn et al. (2013) and IFS.*

	(1)	**(2)**
	Lower 20th quantiles	**Upper 20th quantiles**
Number of observations	260	260
Panel A: statistics of country coverage		
Number of countries included (NCI)	49	40
Number of countries in the full sample (NCF)	51	51
Coverage ratio (NCI/NCF)	96%	78%
Panel B: statistics of observations per country （included in the lower/upper 20th conditional quantiles)		
Mean	5.30	6.47
Standard deviation	3.28	4.80