EUROPEAN CENTRAL BANK

EUROSYSTEM

Working Paper Series

Fernando Eguren-Martin, Cian O'Neill,
Andrej Sokol, Lukas von dem Berge

Capital flows-at-risk: push, pull and the role of policy

No 2538 / April 2021

Abstract

We characterise the probability distributions of various categories of gross capital flows conditional on information contained in financial asset prices in a panel of emerging market economies, with a focus on 'tail' events. Our framework, based on the quantile regression methodology, allows for a separate role of push- and pull-type factors, and because it is based on high-frequency data, can quantify the likelihood of different outturns before official capital flows data are released. We find that both push and pull factors have heterogeneous effects across the distributions of gross capital flows, which are most marked in the left tails. We also explore the role of various policies, and find that macroprudential and capital flows management measures are stabilising, leading to lower chances of either large portfolio inflows or outflows.

Keywords: capital flows, sudden stops, capital flight, retrenchment, capital flow surges, push versus pull, capital controls, macroprudential policy, financial conditions indices, quantile regression.

JEL Codes: F32, F34, G15.

Non-Technical Summary

This paper presents a novel empirical approach to study capital flows to emerging market economies. We use panel quantile regression to characterise the probability distributions of capital flows conditional on information contained in financial asset prices, also exploring the implications of macroprudential and capital flows management measures.

By modelling the full conditional distributions, we improve upon conventional approaches in three ways. First, we are able to assess the informational content of 'push' and 'pull'-type factors across different parts of those distributions. Second, we avoid the usual reliance on arbitrary thresholds for defining extreme events (such as 'sudden stops' or 'bonanzas'), and instead offer a direct mapping from risk factors to different parts of the distributions of capital flows, including the tails. Finally, our framework yields conditional distributions of capital flows based on financial information observed at high frequency, and thus provides a quantification of the probability of different capital flows realisations before official data are released (at lower frequency and with delays), opening the door to 'nowcasting'-like exercises.

As a first step, we develop measures of push- and pull-type factors based on traded asset prices. We then establish that push-type "shocks" have a significant effect on the distribution of non-resident capital flows to emerging markets, and that these effects are heterogeneous across different types of flows. Interestingly, not only the *locations*, but also the *shapes* of the distributions of flows change, highlighting the benefits of using a quantile-based approach. Typically it is the left tail of the distribution (i.e. the probability of large capital outflows) that reacts most strongly. The reaction to pull-type shocks is qualitatively similar. We also investigate the term structure of these effects on the left tails of distributions and show that while the impact of push shocks decays quickly, becoming statistically insignificant after a few quarters, that of pull-type shocks is more persistent for both portfolio and banking flows.

Finally, we assess the informational content of capital flows management measures and macroprudential policy actions for the conditional distributions of capital flows to emerging markets. We find that capital controls targeting portfolio outflows are not associated with changes in that distribution, but controls limiting inflows are associated with a 'narrower' distribution, that is, a lower probability of either large capital outflows or inflows. As for macroprudential policy, we find that tighter policy is also associated with narrower conditional distributions. Furthermore, tighter macroprudential policy is associated with a smaller impact of push factors on capital flows-at-risk. This is consistent with the idea that macroprudential policy instruments improve a country's financial resilience, providing some insurance against shocks.

1 Introduction

This paper presents a novel empirical approach to study capital flows to emerging market economies. We use panel quantile regression to characterise the probability distributions of gross capital flows to emerging market economies conditional on information contained in financial asset prices. We also explore the implications for those distributions of macroprudential and capital flows management measures.

By modelling the full conditional distributions, we improve upon conventional approaches in three ways. First, we go 'beyond the mean', and are able to assess the informational content of 'push' and 'pull'-type factors across different parts of those distributions. Second, we avoid the usual reliance on arbitrary thresholds for defining extreme events (such as 'sudden stops' or 'bonanzas'), and instead offer a direct mapping from risk factors to different parts of the distribution of capital flows, including the tails. This is important to the extent that capital flows monitoring and management usually involves a balancing act between encouraging inflows and limiting the scope for disruptively large outflows. Finally, our framework yields conditional distributions of capital flows based on financial information observed at high frequency, and thus provides a quantification of the probability of different capital flows realisations before official data are released (at lower frequency and with delays).

As a first step, we develop measures of push- and pull-type factors based on traded asset prices. Using these measures, we establish that push-type 'shocks' have a significant effect on the distribution of non-resident capital flows to emerging markets, and that these effects are heterogeneous across different types of flows.[1] While foreign direct investment (FDI) flows are largely unaffected by push shocks, portfolio and banking flows react significantly.[2] Interestingly, it is not only the *location*, but also the *shape* of the distribution of portfolio and banking flows that changes, highlighting the benefits of using a quantile-based approach. In both cases, it is the left tail of the distribution (i.e. the probability of large capital outflows) that reacts most strongly, and this effect is more marked for portfolio flows.[3] The reaction to pull-type shocks is more homogeneous across capital flow types, with both the medians and

[1]As will become clear in Section 2, 'shocks' should not be interpreted as structural drivers of capital flows, even when exogeneity can be plausibly defended, and hence our results should not be read in an causal manner, but rather as establishing useful reduced-form relationships.

[2]The lack of an effect on FDI is in line with previous literature. See, for example, Montiel and Reinhart (1999), Gupta and Ratha (1999), Hernndez et al. (2001), Albuquerque et al. (2005), De Vita and Kyaw (2008), Broner et al. (2013).

[3]Strictly speaking, the left tail of the distribution is not necessarily associated with capital outflows, or more precisely 'negative gross inflows', but we will stick to this characterisation throughout the paper given its relevance for the sample considered.

left tails of the respective distributions moving to the left in response to negative shocks, and the right tails remaining largely unaffected.[4] The negative tail effect is strongest for banking flows in this case. We also investigate the term structure of these effects on the left tails of distributions and show that while the impact of push shocks decays quickly, becoming statistically insignificant after a few quarters, that of pull-type shocks is more persistent for portfolio and banking flows.

Our framework can also be used for 'nowcasting'-like exercises, as it relies on high frequency financial information to compute conditional distributions for capital flow realisations which are observed at lower frequency and with delays. We take the case of portfolio flows into Brazil as a case study, and show how conditioning on financial information available at the time would have increased the likelihood of the outflows observed during the Brazilian crisis of 2002 from around 10% to approximately 40%, making the tail event still sizeable, but much less unexpected.

Finally, we consider the information content of two types of policy, namely capital flows management measures and macroprudential policy actions, for the conditional distributions of capital flows to emerging markets.[5] We find that capital controls targeting portfolio outflows are not associated with changes in that distribution, but controls limiting inflows are associated with a 'narrower' distribution, that is, with a lower probability of either large capital outflows or inflows. As for macroprudential policy, we find that tighter policy is also associated with narrower conditional distributions. Furthermore, tighter macroprudential policy is associated with a smaller impact of push factors on capital flows-at-risk[6]. This is consistent with the idea that macroprudential policy instruments improve a country's financial resilience, providing some insurance against shocks.

The rest of the paper is structured as follows. Section 1.1 reviews the existing literature studying the determinants of capital flows to emerging markets, and places our contribution within that context. Section 2 describes the approach behind the construction of our asset price-based proxies for push and pull factors. Section 3 presents our main results in terms of the effect of push and pull factors on the distributions of different types of capital flows to emerging markets, and showcases how the resulting distributions can be used as a policy tool. In Section 4 we provide a series of robustness checks to our main results, including by considering additional control variables and dropping specific crisis episodes from our sample.

[4] This is not statistically significant in the case of FDI and portfolio flows.

[5] See Rebucci and Ma (2019) for a review of the recent literature on capital flows management measures, including similarities and differences with macroprudential policy.

[6] For our purposes, this will be the 5th percentile of the corresponding conditional distribution.

Section 5 analyses the effects of capital flows management measures and macroprudential policy, and Section 6 concludes.

1.1 Related literature

International capital flows are at the heart of the global economy. While they bring a range of benefits to recipient countries, their fickleness also creates risks. As Obstfeld (2012) and Mendoza (2010) show, capital flows play an important role for financial stability in emerging markets, and sudden stops in capital flows are associated with large output losses. A large empirical literature, starting with the seminal contributions of Calvo et al. (1993) and Fernandez-Arias (1996), introduced the distinction between global 'push' and domestic 'pull' risk factors. Koepke (2019) provides a thorough literature review. Our paper speaks directly to two strands of this literature.

First, there is a long tradition of papers, such as Calvo et al. (2004), Ghosh et al. (2016) and Forbes and Warnock (2012), among many, which study extreme episodes in capital flows, typically labelled 'sudden stops' (in the case of extreme outflows) and 'surges' (in the case of extreme inflows). These papers usually resort to defining some – inevitably arbitrary – cut-off points for the magnitude of flows, which are then used to identify discrete episodes (be it sudden stops or surges). In a second stage they then run probit-type prediction models to single out risk factors associated with the occurrence of such episodes. Our paper proposes a new and improved tool that can be used to study such episodes by modelling the entire (conditional) distribution of capital flows, in parallel fashion to recent work by Adrian et al. (2018) and Adrian et al. (2019) on "GDP-at-Risk". By modelling the entire conditional distribution of capital flows, one can assess the effects of a range of risk factors across different parts of that distribution (and at different horizons), avoiding the need to take a stance on what constitutes a sudden stop and what does not, and allowing heterogeneous effects across quantiles to be considered. In addition, this conditioning approach can yield a quantification of the likelihood of capital flows realisations in 'real time', that is, after observing high frequency financial variables, but before official capital flows data are released (at lower frequency and with delays).

Second, many papers, including for example Montiel and Reinhart (1999) and Forbes et al. (2016), have evaluated the effectiveness of various policy actions such as capital controls or macroprudential measures in reducing the incidence of extreme episodes such as sudden stops.[7] We contribute to this literature by embedding a quantification of capital flows management and macroprudential measures into our framework, which again allows to assess their impact across different parts of the distribution of capital flows and at different horizons. In contrast to most of the literature on capital controls, e.g. Forbes and Warnock (2012) and Gelos et al. (2019), we find tentative evidence that certain types of capital flows management measures can help reduce capital flows-at-risk. We also find some evidence that macroprudential policies are associated with a reduction in capital flows-at-risk. This extends findings in the literature that focus on the effect of policies on mean capital flows (e.g. Hoggarth et al. (2016) and Beirne and Friedrich (2017)). However, it is in contrast to Gelos et al. (2019), who find little evidence on the effectiveness of such policies on the tail of the capital flows distribution.

Finally, Gelos et al. (2019), who also develop an empirical 'capital flows-at-risk' model based on panel quantile regression, is most closely related to our paper in both substance and methodology. Nevertheless, our papers differ along several dimensions. While Gelos et al. (2019) focus on non-resident portfolio flows, our paper provides results for all types of non-resident flows, including portfolio flows but also banking and FDI flows. We also differ in our construction of proxies for push and pull factors. While we propose measures of risks based on traded asset prices, Gelos et al. (2019) follow the more conventional approach of using a narrow set of observed measures, including US variables such as BBB corporate spreads as proxies for push factors, and a range of domestic variables (e.g. GDP growth) as a proxy for pull-type factors. In contrast, we construct a truly 'global' measure for our push-type proxy, and clean our pull proxy from the portion of its variation that is actually attributable to push factors. We show that these proxies contain more robust information for characterising the distribution of capital flows in comparison to 'standard' factors used in the literature. Importantly, we also provide insights into the term-structure effects of push and pull factors across different horizons, and quantify the exposures of different types of flows to push and pull-type shocks using relative entropy measures. In terms of assessing the impact of policy measures, while Gelos et al. (2019) attempt to estimate the effect of policy 'shocks' on capital flows-at-risk, our paper follows the more conventional approach of establishing robust reduced-form relationships using better-targeted 'raw' policy measures.[8]

[7] In the context of GDP-at-risk, Aikman et al. (2019) study the effect of macroprudential policy in a panel quantile regression setting.

[8] For example, our quantification of capital flows management measures only considers those that apply to the type of flows under consideration (i.e. portfolio flows from non-residents), while Gelos et al. (2019) rely on coarser indices.

2 Proxying for push and pull factors using asset price information

Capital flows can be thought of as determined, at least partially, by the risk-adjusted macroeconomic outlook, to the extent that this affects the rate of return on investment. Therefore, any attempt to characterise the distribution of capital flows needs a quantification of these determinants.

Taking these concepts to the data is not an easy task. Measuring the set of risks facing an economy is problematic in general given the myriad sources which could play a role, and this problem is particularly acute when the degrees of freedom at the disposal of the econometrician are rather limited, as in our case. Faced with this issue, we rely on two levels of aggregation to measure a set of risks affecting capital flows to emerging markets. First, we use asset prices, which are themselves forward-looking and a function of the risk-adjusted outlook too, as information aggregation devices that can provide high-frequency insights into the forces affecting capital flows. Note, however, that to the extent that changes in asset prices will be driven, to a large extent, by the same series of underlying structural shocks driving capital flows, it is important to consider them as devices to help characterise the distribution of capital flows without giving any causal interpretation to the relations uncovered.

The decision to use asset prices as a proxy for macroeconomic risk sources affecting capital flows is not exempt from its own related issues, most importantly the question of which assets to look at. This is where our second level of aggregation comes into play. To the extent that we are interested in using these assets to extract information about the underlying risk-adjusted macroeconomic outlook, which should affect all of them (arguably to varying degrees), one option is to avoid focusing on one particular asset and instead try to measure common variation across a wide set of them. We follow this approach and construct country-specific indices summarising common movement across a set of asset prices.

In the context of capital flows, it is customary and useful to distinguish between global ('push') and local ('pull') factors (Calvo et al., 1993), which have been shown to have heterogeneous effects. In this paper, we decompose the indices described above into their global and local components, which we then use as inputs in our characterisation of the distributions of capital flows. The approach to come up with these proxies for push and pull factors is explained in more detail in what follows.

2.1 Methodology

We construct country-level Financial conditions indices (FCIs) in the spirit of Arregui et al. (2018) and Eguren-Martin and Sokol (2019), using data for 43 advanced and emerging market economies between April 1995 and December 2018. The financial series included are as follows: term, sovereign, interbank and corporate spreads, long-term interest rates, equity returns and volatility and relative market capitalisation of the financial sector.[9] We rely on principal component analysis to extract country-specific summary measures of financial conditions (which correspond to the first principal component of the series considered).[10]

In order to decompose our country-specific FCIs into global and local components we proceed in two steps. First, we extract a global component out of our 43 country-specific indices by combining them using GDP-PPP weights, and treat this as our proxy for global financial conditions, reflecting developments across advanced and emerging market economies.[11] Figure 1 shows the evolution of this measure over the last 30 years. There is a significant co-movement between financial conditions indices, as captured by our global component, but material cross-country dispersion remains, as shown by the gray ranges. This residual heterogeneity is important as it can serve as a proxy for pull factors. We regress the country-specific indices on this global component one-by-one, and take the residual of that regression to be our country-idiosyncratic measure of financial conditions.[12]

Armed with our measure of global financial conditions and a set of country-specific (EM) domestic (or 'local') financial conditions, we set out to explore their informational content in helping characterise the distributions of capital flows to our panel of emerging market economies.

In Section 4 we show that these indices contain more robust information for the characterisa-

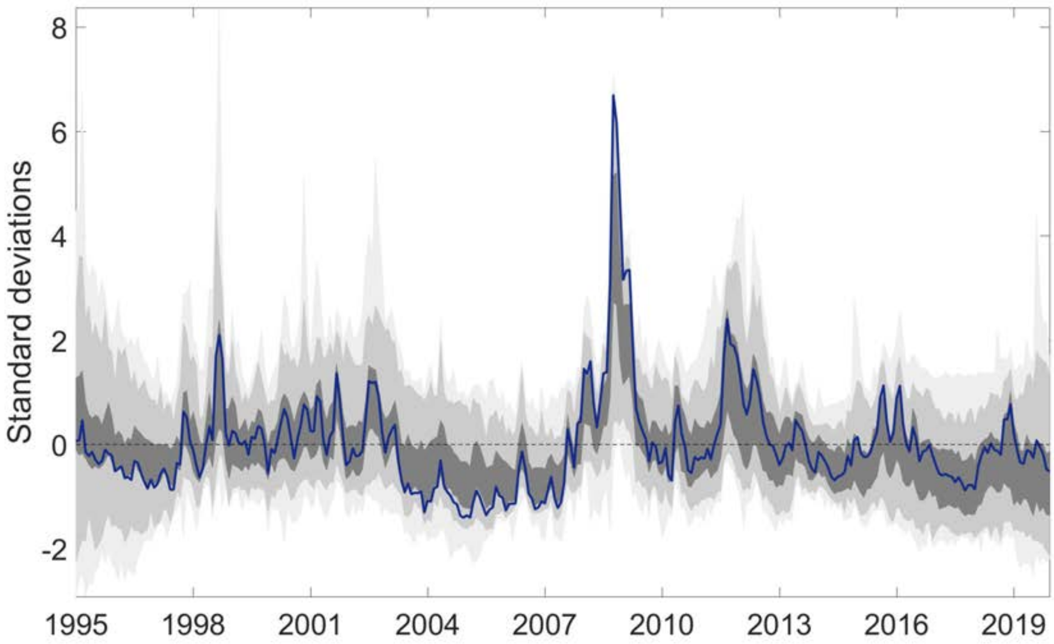
[9] A detailed description of the variables used and corresponding data sources can be found in Appendix A.

[10] Note that the resulting first principal component of the series considered is very similar to the common factor obtained when following Arregui et al. (2018) and relying on the method of Koop and Korobilis (2014) which allows for time variation in the parameters and attempt to 'clean' financial conditions from changes that reflect a response to macroeconomic news (proxied by industrial production and CPI inflation). This can be interpreted the result of relative stability in the parameters and the fact that asset prices tend to react to news about *expected* rather than realised macroeconomic aggregates.

[11] Extracting a global factor out of our country-specific indices using Principal Component Analysis yields very similar results.

[12] Note that this procedure guarantees orthogonality between global and domestic components over the whole sample, but clearly does not rule out some degree of co-movement within subsamples, which is important to bear in mind in order to understand the joint behaviour of push and pull factors in a quantile regression framework, as opposed to standard regression analysis.

Figure 1 Global Financial Conditions Index, 1995-2019.



Note: Index in deviations from its historical mean. Higher values signal tighter financial conditions. The blue line is the global FCI, the dark gray swathe the inter-quartile range of the 43 country FCI. The mid-gray swathe covers 90 percent of country FCIs, while the light gray swathe shows the min-max range.

tion of the distribution of capital flows into emerging market economies than more standard factors typically used in the literature, such as the VIX index or domestic GDP growth.

3 Capital Flows-at-Risk: push and pull factors

The main aim of our paper is to characterise the *entire distribution* of capital flows to emerging market economies, putting special emphasis on tail outcomes and distinguishing between the role of push- and pull-type factors. In this section we lay out our approach for doing so, which is based on the quantile regression methodology and uses the Financial conditions indices estimated in Section 2 as main inputs.

Characterising distributions is particularly useful in the context of capital flows because it *goes beyond the mean*, which has been the object of study of a large part of the literature, while avoiding the reliance on arbitrary thresholds to define extreme events (sudden stops and surges), a prevalent feature in previous attempts to study tail events.[13]

3.1 Push and pull factors across types of non-resident flows

In order to characterise the distribution of capital flows we rely on quantile regression (Koenker and Bassett, 1978). In contrast to standard regression, which provides an estimate of the conditional mean of a variable of interest given a set of explanatory variables, quantile regression allows to model, quantile by quantile, the entire conditional distribution of a dependent variable given a set of covariates. This allows to capture features that are lost when only focusing on average responses.

We specify a linear model for the conditional quantiles of capital flows as follows:

$$Q_{KF_{i,t+h}}(\tau|X_{i,t}) = \alpha_h(\tau) + \beta_{1,h}(\tau)GFCI_t + \beta_{2,h}(\tau)DFCI_{i,t} + \epsilon_i \tag{1}$$

where $KF_{i,t+h}$ is the sum of capital inflows into country i in the three quarters starting at $t+h$, $GFCI_t$ and $DFCI_{i,t}$ are our global and domestic Financial conditions indices, and ϵ_i is a country-specific quantile-invariant fixed effect that is estimated following the two-step procedure of Canay (2011). Function Q computes quantiles τ of the distribution of $KF_{i,t+h}$ given a set of covariates $X_{i,t}$. Appendix D provide technical details about estimation and inference.

Given our sample size and focus on 'tail' events, we aim to keep equation (1) as parsimonious as possible. Nevertheless, in Section 4 we show that our main results are robust to including a battery of additional controls as independent variables, including more 'standard' variables typically used in the literature to characterise capital flow dynamics.

We estimate equation (1) on a panel of 15 emerging market economies from 1996Q1 to 2019Q4.[14] We focus on gross capital inflows (net flows from non-residents), and estimate the distributions of portfolio, foreign direct investment and 'other' (mostly banking) flows separately. Table 1 provides descriptive statistics for our sample.[15]

[13]See, for example, Calvo et al. (2004).

[14]The countries considered are Argentina, Brazil, Chile, Colombia, Hungary, India, Indonesia, Korea, Mexico, Peru, Philippines, Russia, South Africa, Thailand and Turkey. This sample is determined by the availability, from 1996 onward, of quarterly gross capital flows data, split into FDI, portfolio and other flows, as well as reliable high frequency financial data to estimate FCIs. Our estimation drops Hungary when looking at FDI due to unreliable patterns in the data.

[15] See Appendix A for definitions and data sources.

Table 1 Descriptive Statistics for panel covering 15 EMEs, 1996:Q1 - 2019:Q4

	Gross inflows (Percent of GDP)				Gross outflows (Percent of GDP)			
	Total	Portfolio	Banking	FDI	Total	Portfolio	Banking	FDI
Mean	4.4	1.3	0.6	2.6	2.8	0.9	1.0	1.0
Median	4.4	1.1	0.5	2.1	2.1	0.4	0.7	0.6
Min	-27.7	-16.4	-28.7	-8.0	-15.9	-9.3	-12.7	-16.9
Max	34.1	27.7	21.1	29.4	36.0	18.9	21.0	17.2

Note: Quarterly gross capital flows data are from the IMF's international financial statistics, and expressed as percentages of quarterly GDP.

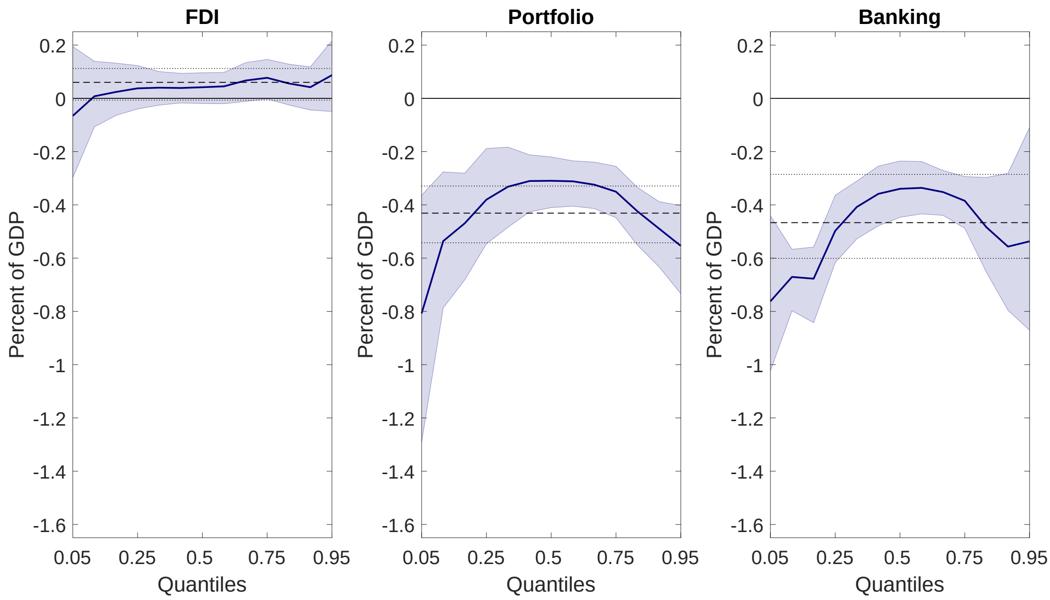
As described in Section 2, we rely on global and domestic financial conditions indices as summary measures of the risk-adjusted economic outlook facing an economy. The distinction between domestic and global factors is particularly useful to place our findings within the vast literature analysing the determinants of capital flows to emerging markets. Beginning with Calvo et al. (1993), many studies have uncovered differential roles for 'push' (external) and 'pull' (domestic) factors in affecting flows. Our approach can be understood in those terms too.

Note that there is a certain asymmetry between our push and pull factors. To the extent that our indices are extracted from financial asset prices, which will at least in part reflect a set of structural shocks that are also driving capital flows, they cannot themselves be regarded as 'true' shocks, and their effects should thus not be interpreted in a causal sense. Having said that, all emerging markets we consider are small enough for the usual 'small open economy' assumption to be plausible, which means that at least our push factor can still be plausibly regarded as exogenous (if driven by a combination of underlying 'true' structural shocks). More generally, one can think of our exercise as simply extracting information from asset prices that is useful for characterising the distribution of capital flows. This exercise is insightful even in the absence of a clear causal link, not least because of the timeliness with which we observe asset prices compared to official flows statistics. That is, the framework presented can be used to effectively 'nowcast' capital flows distributions. We explore this avenue in more detail in Section 3.4.

Following Forbes and Warnock (2012), we focus on non-resident flows (often referred to as 'gross inflows') in our analysis, splitting these into FDI, portfolio and 'other' (mostly banking flows). Figures 2 and 3 report the results of taking equation (1) to the data. More specifically, they report near term (that is, in the current quarter and following two quarters) sensitivities across quantiles of the three different types of inflows to push and pull factors, respectively.

Coefficients are also reported in more detail in Tables C.1, C.2 and C.3 in Appendix C.1. Both plots reveal differences in coefficients across quantiles, which are typically starkest in the tails. The fact that tail-coefficients differ, in many cases, from OLS coefficients shows that simple mean-based models miss important features of the effects of push and pull factors on the distributions of capital flows. Specifying a model for the conditional mean as well as the variance would also provide an incomplete picture, given the heterogeneous effects on the left and right tails of the distributions. As discussed in section 1.1, a number of papers have effectively focused on the left tail only by specifying models that predict sudden stop events, but they rely on arbitrary cut-off rules and speak only to the likelihood of observing a sudden stop, without quantifying its likely severity.

Figure 2 Effects of global financial conditions on gross inflows

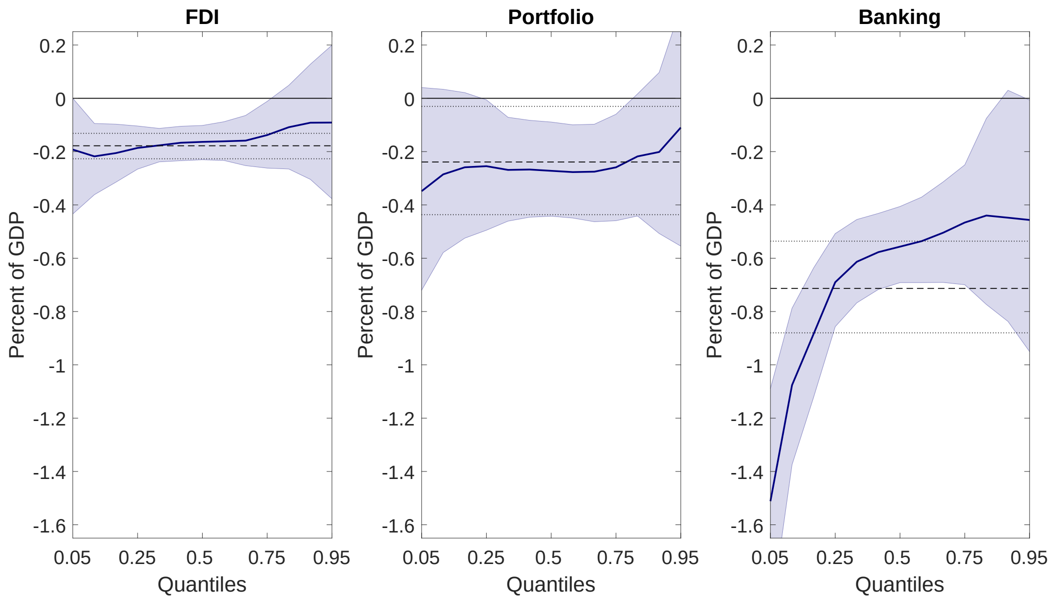


Note: The chart shows the estimated effect of a one standard deviation tightening in global financial conditions on the three different types of capital inflows across quantiles. The one standard deviation confidence intervals are based on block bootstrap methods following Fitzenberger (1998). Dashed lines show the OLS estimates and dotted lines the associated one standard deviation confidence bands.

Focusing on push factors first, Figure 2 shows the near-term effects across quantiles of tighter global financial conditions on foreign direct investment, portfolio and banking inflows. In line with the existing literature (see Koepke (2019)), we find no significant response of foreign direct investment to our global factor, whereas both portfolio and banking inflows slow down significantly when global financial conditions tighten. Interestingly, the effect of a tightening in global financial conditions for the latter two types is very heterogeneous across different parts of the distributions. Portfolio flows and banking flows are significantly more responsive in the tails relative to the centre of the distribution, in line with the findings in previous papers that push factors play an important role in driving sudden stops as well as surges (Ghosh et al. (2016), Forbes and Warnock (2012), Byrne and Fiess (2016)).

Turning to local financial conditions, which are our proxy for pull factors (Figure 3), we find a small negative effect on the median of the distribution of foreign direct investment in the near term, with effects in both tails statistically insignificant. Portfolio flows similarly show a small negative response to a tightening in local financial conditions at the median, with insignificant effects in both tails. Banking flows, meanwhile, respond much more strongly in the left tail than in the right tail. This suggests that tighter local financial conditions are associated with a significantly higher probability of large negative banking inflows, raising the probability of a sudden stop in banking flows. At the same time, a loosening in local financial conditions appears to have a much smaller effect on the probability of large positive banking inflows, not raising the probability of a surge significantly.

Figure 3 Effects of local financial conditions on gross inflows



Note: The chart shows the estimated effect of a one standard deviation tightening in local financial conditions on the three different types of capital inflows across quantiles. The one standard deviation confidence intervals are based on block bootstrap methods following Fitzenberger (1998). Dashed lines show the OLS estimates and dotted lines the associated one standard deviation confidence bands.

Overall, we find that global and local financial conditions contain useful information to characterise the left tail of portfolio and banking flows. But there is a difference in relative magnitudes within each type of flow, with portfolio flows more sensitive to global conditions and banking flows more sensitive to local conditions. This finding is in line with the existing literature on the drivers of sudden stops.[16] Meanwhile, we find that country-specific financial conditions do not have useful information for characterising surges, while global conditions do have information that help characterise surges in portfolio flows and banking flows. For a more thorough assessment of the relative sensitivity to local and global conditions across types of flows, see Section 3.3.

While results in this section focus on the informational content of financial conditions for characterising the distribution of capital flows in the short term (the contemporaneous quarter and the subsequent two quarters), there is also merit in exploring the informational content in terms of flows further into the future. In results reported in Appendix C.2 we do so by using a panel quantile version of the local projection method in Jorda (2005).[17] Given the large interest in sudden stops in capital flows, we report results displaying effects on the very left tail of our distribution (i.e. its 5th percentile, our measure of capital flows-at-risk).[18] For both portfolio and banking flows, the effect of global financial conditions on capital flows-at-risk is strongest in the near term and fades almost fully within a year. Local financial conditions, in contrast, have a more persistent effect. There are no effects on FDI flows from either global or local financial conditions across the term structure, in line with contemporaneous results.

3.2 The conditional distribution of capital flows

The estimates reported so far speak to the partial effects on the conditional quantiles of capital flows arising from changes in our push and pull factors. It is instructive to also visualise the resulting empirical distributions (which give a clearer view of the overall magnitudes involved), and the shifts arising from changes in these factors. Our quantile regressions from equation (1) provide us with an estimate of the conditional quantile function, that is, the inverse of the corresponding cumulative distribution function. Following the approach in Adrian et al. (2019), we map that estimate into a parametric distribution function by fitting the skewed t-distribution developed by Azzalini and Capitanio (2003):

[16] See Koepke (2019). A key argument in Carney (2019) is based on this finding. Given the relatively larger sensitivity of portfolio flows to push factors, a shift away from banking and towards market-based finance could raise emerging economies' exposure to the global financial cycle.

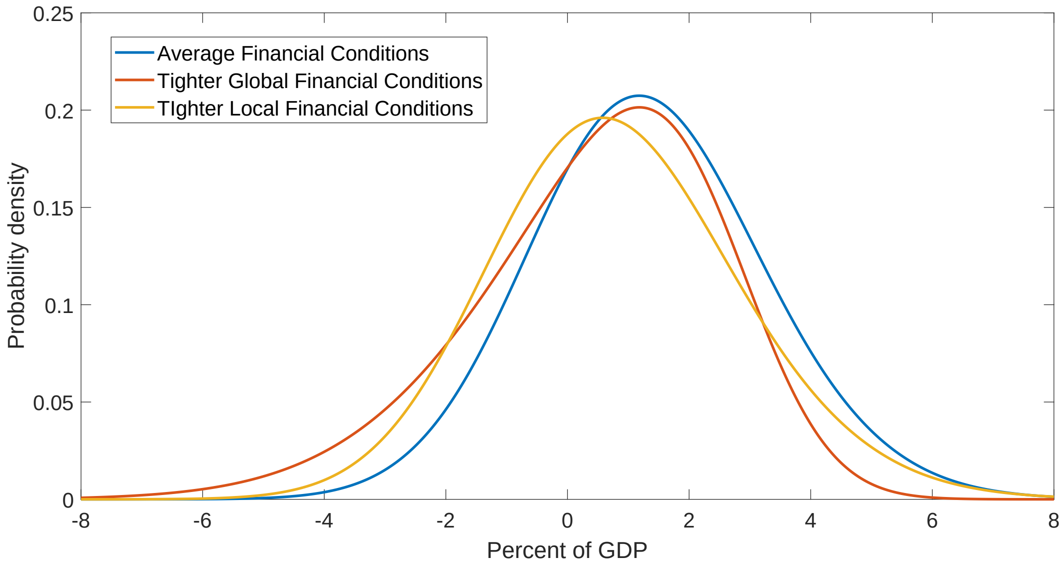
[17] See Adrian et al. (2018) for an application to GDP growth.

[18] While not reported here, the simple OLS estimator exhibits a very similar term structure, suggesting that the term structure of both push and pull effects is not quantile-specific. In line with this, our estimates for the term structure of other quantiles look similar to the fifth percentile reported here.

$$f\left(y;\mu,\sigma,\alpha,\nu\right)=\frac{2}{\sigma}t\left(\frac{y-\mu}{\sigma};\nu\right)T\left(\alpha\frac{y-\mu}{\sigma}\sqrt{\frac{\nu+1}{\nu+\left(\frac{y-\mu}{\sigma}\right)^2}};\nu+1\right), \tag{2}$$

where $t(\cdot)$ and $T(\cdot)$ denote the probability density function and the cumulative density function,respectively, of the Student t distribution. The distribution's parameters determine its location μ, scale σ, fatness ν, and shape α.[19] An advantage of using the skewed-t distribution is its flexibility in accomodating fat tails or skewness, which are both relevant features when modelling capital flows.

Figure 4 Conditional distributions of portfolio flows



Note: The chart shows fitted skewed-t distributions of portfolio inflows in the near term (current quarter plus following two), given average financial conditions (blue), local financial conditions two standard deviations tighter than average (yellow) and global financial conditions two standard deviations tighter than average (red).

The blue line in Figure 4 shows our estimated conditional distribution of gross portfolio inflows to the 'average' emerging market in our panel when both global and local financial conditions are at their historic averages. In Section 3.1, we find the effect of local financial conditions to be largest in the left tail and around zero in the right tail. As a consequence, the right tail of the fitted distribution for portfolio flows in Figure 4 does not move markedly when local financial conditions tighten, whereas the left tail does shift further to the left (yellow line). As Figure 2 shows, we find that tighter global financial conditions impact negatively

[19] The well-known t-distribution is a special case of this skewed-t distribution with $\alpha = 0$, as is the normal distribution with mean μ and standard deviation σ when $\alpha = 0$ and $\nu = \infty$.

both the lower and upper quantiles of the distribution of portfolio inflows, while the effect on the centre of the distribution is more moderate. As a consequence, when global financial conditions tighten, the main effect on the distribution is that it becomes more skewed to the left (orange line). In other words, tighter global and tighter local financial conditions both increase the chances of sudden stops in portfolio flows (left tail events), but only tighter global financial conditions also reduce the likelihood of surges or 'bonanzas'.

Figure 4 neatly illustrates some of the benefits of our approach. By estimating quantile-specific effects, we can capture changes in the shape of the distribution of capital flows that go beyond changes in the conditional mean or variance. In addition, and in contrast to traditional sudden stop prediction models, our methodology can quantify, at any given time, how bad sudden stops could be rather than just how likely a sudden stop event is to occur.

3.3 Measuring relative exposures to push and pull factors

While the results in Section 3.1 speak to the relative effects of push and pull factors across different parts of the distribution of particular types of flows, we cannot use them to directly compare effects across flow types because of the different magnitude of these flows. In this section we exploit relative entropy measures to quantify the divergence in the conditional distributions of capital flows facing different levels of push and pull factors.[20] Intuitively, for each type of flow, we measure how much more probability mass is assigned to the lower tail of the distribution when global or local financial conditions tighten. Unlike our earlier results, such measures can be compared across different types of flows and 'shocks'.

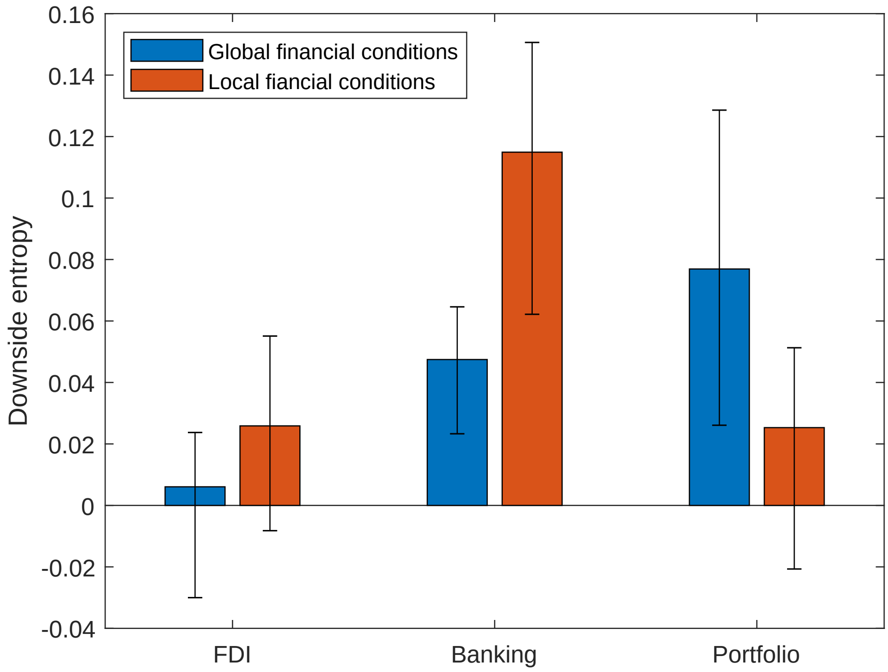
We begin by fitting distributions similar to those shown in Figure 4 (that is, conditional on average global and local financial conditions, and on one standard deviation tighter global and local conditions in turn) to portfolio, banking and FDI flows. In a second step, and for each type of flow and 'shock', we measure the divergence between the left tails of the distributions conditional on average and tighter financial conditions, respectively. The exact definitions of our relative entropy measures are provided in Appendix D.4.[21]

Figure 5 shows the resulting 'downside entropies'. It can be seen that portfolio and banking flows experience most divergence, whereas the downside entropies of FDI flows are statistically and economically insignificant when facing a tightening in either global and local conditions.

[20] See Adrian et al. (2019) for an application of this approach to GDP growth and Eguren-Martin and Sokol (2019) for an application to exchange rate returns.

[21] By left 'tail' we refer to the mass to the left of the 5th percentile of the distribution

Figure 5 Exposure of capital outflows to push and pull factors



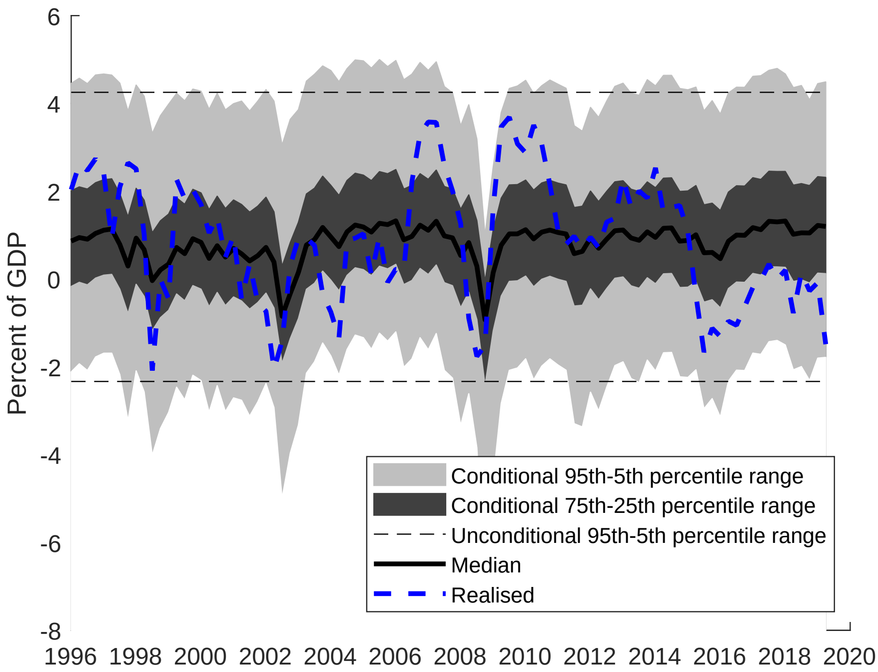
Note: The chart shows the downside relative entropy (defined as the percent divergence in the probability mass left of the 5th percentile) between the distribution of a particular type of gross capital flow (as labeled on the x-axis) conditional on average financial conditions and the one resulting (i) from tighter global conditions (and average local conditions) in blue and (ii) from tighter local conditions (and average global conditions) in red. The bars show point estimates, while lines indicate 68% bootstrapped confidence intervals.

Following a tightening in global conditions, there is a significant additional mass assigned to the left tail of the distribution of both portfolio and banking flows. Although point estimates are higher for portfolio flows, the difference between the two is not statistically significant. In contrast, when facing an increase in local financial conditions, downside entropy measures tell us that both types of flows see an increased probability of sharp outflows, but that the reaction of banking flows is markedly stronger than that of portfolio flows.

3.4 Conditional distributions as a policy tool

The possibility to compute time-varying distributions of capital flows for specific countries is one of the main advantages of our approach with respect to the existing literature. This feature is especially useful to the extent that our conditioning variables are observed at

Figure 6 Conditional distributions of non-resident portfolio flows into Brazil and realisations



Note: The chart shows ranges inferred from both (i) an unconditional distribution over the entire sample (dashed lines) and (ii) a distribution conditional on global and local financial conditions (solid black line and grey areas) based on our estimates from Section 3.1. Overlaid we show the realisations of non-resident portfolio flows into Brazil (dashed blue line). Capital flows are smoothed using the current and next two quarters, as in our regressions.

high frequency because they are based on asset prices, while official capital flows data are typically released at low frequency and with delays. This means that 'nowcasting'-type exercises can convey useful information about upcoming capital flows data releases.[22] While this dimension could be explored further in a truly real-time setting going forward, in this section we showcase, for illustrative purposes, some in-sample applications focusing on past episodes.[23]

One way in which conditional distributions are useful is to analyse the past time-series behaviour of capital flows into and out of a particular country. While existing approaches

[22]The term 'nowcasting' refers to the prediction of the present, the very near future, and the very recent past. See Banbura et al. (2011) or Banbura et al. (2013) for an overview of the concept.

[23]The main difference between our illustrative applications and a truly real-time exercise lies in the computation of the financial conditions indices: in a real-time setting, these would need to be computed based only on information available up to the time of the nowcast only, whereas we simply use the FCIs, computed from the whole sample, up to the time of the nowcast. This entails a different standardisation, and therefore potentially a different reading of financial conditions relative to past experience.

typically categorise extreme episodes according to pre-defined thresholds (see, for example, Forbes and Warnock, 2012), our framework allows to assess the degree to which flows were extreme in a more nuanced fashion. Figure 6 shows the time series of non-resident portfolio flows into Brazil, benchmarked against both (i) an unconditional distribution and (ii) a time-varying conditional distribution following our framework.[24] It can be seen that it is not always the case that large outflows are unexpected given the prevailing push and pull factors, and, conversely, that sometimes smaller outflows appear unwarranted.

Another way in which our framework can provide further insights is by focusing on a particular episode and disentangling the role of push and pull factors. Figure 7 focuses on an episode of sharp portfolio outflows from Brazil in 2002. In panel (A) we can see that, once we condition on global and local financial conditions, the probability of observing an outflow of the scale observed goes up to around 40%, from around 10% if financial conditions were set at their historical averages. At the same time, panel (B) shows that the increase in the probability of such an event happening was driven predominantly by a deterioration in domestic financial conditions (our proxy for pull-type factors).[25]

4 Robustness

In this section we show that our baseline results are robust to a battery of robustness checks, in terms of both explanatory variables considered (Section 4.1) and the relevance of particular crisis periods (Section 4.2).

4.1 Additional regressors

Quantile regression can place high demands on the data, especially when modelling extreme quantiles. Because of this, we aim to keep our preferred specification as parsimonious as

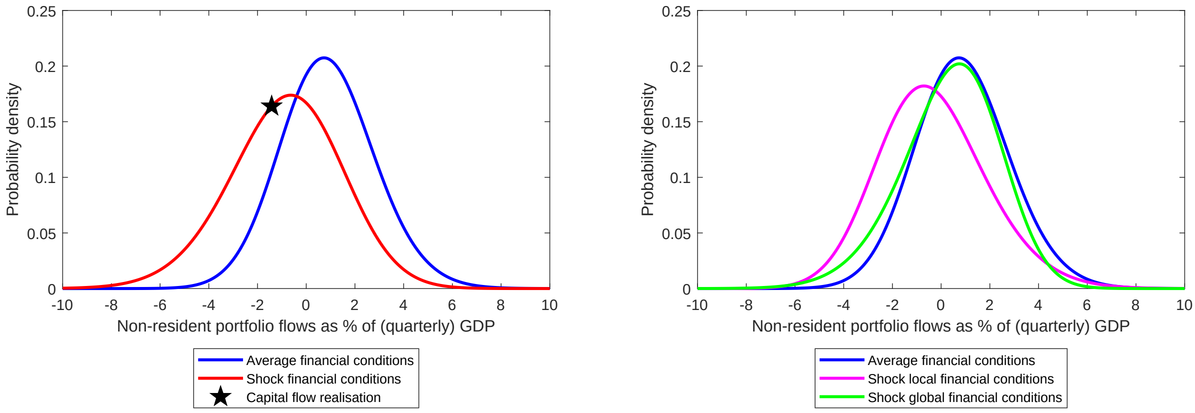
[24] Conditional distributions in this section are based on the panel coefficients reported in Figures 2 and 3, and Table C.1. Due to the uncertainty inherent to estimating tail dynamics from a single country's data, we generally prefer the use of panel coefficients. That said, single-country quantile regressions for Brazil, reported in Appendix C.3, show that results are broadly in line with the panel, with the sensitivity to pull factors slightly higher.

[25] In panel (B) of Figure 7 we alternatively set the value of global and local financial conditions to their realisation in Q3 2002, while keeping the other one fixed at its historical average (which is 0 by construction). These two exercises, similar to the ones carried out in Figure 4, aim to quantify the 'contribution' of individual regressors to the shape of the conditional distribution. The resulting distributions should however not be confused with the marginal distributions that would result by integrating out the other regressor, or, in the case of the blue line, with the unconditional distribution of the dependent variable.

Figure 7 Probability distributions of non-resident portfolio flows into Brazil in Q3 2002 and realisation

(A) Conditional distribution and realisation

(B) Conditional distribution drivers



NOTE. Panel A: The red line shows the conditional probability density of non-resident portfolio flows into Brazil, accounting for information on global and local financial conditions, with the outturn overlaid (black star). The blue line shows the distribution that would have resulted had global and local financial conditions been at their historical averages (of zero). Panel B: The blue line shows the same distribution as in Panel A. The magenta line shows the incremental effect of setting local financial conditions to their 2002Q3 value, while keeping global financial conditions at 0. The green line shows the incremental effect of setting global financial conditions to their 2002Q3 value, while keeping local financial conditions at 0. Capital flows are smoothed by averaging current quarter and next two quarters in both panels.

possible. Nevertheless, this section documents that our core results are qualitatively robust to including various controls that are standard in the empirical literature on capital flow dynamics.

Table B.1 in Appendix B reports coefficients corresponding to the left tail (5th percentile) and the median of portfolio flows distributions resulting from a number of specifications that include other standard push (US GDP growth, US monetary policy, the VIX index) and pull proxies (domestic GDP growth and equity returns) in addition to our global and local financial conditions indices. In all cases, our global financial conditions index remains the most robust driver of the left tail and the median of the distribution of non-resident portfolio flows into EMEs. Also, our domestic financial conditions index retains its relevance for explaining median outcomes (and increases its relevance for the left tail) once further ‘pull’-type variables are added to the specification.

4.2 Excluding particular crisis episodes

Modelling the entire probability distribution of a variable of interest, including its tails, naturally also draws information from extreme observations, which are rare by definition. Thus, excluding even a small number of such events from the estimation sample could lead to changes in the results. Against this background, it is notable to see (in Figures B.1 and B.2 in Appendix B) that our baseline results are not materially affected by the exclusion of the global financial crisis (GFC) and euro area crisis (EA crisis) from our sample period. The same figures also show that our main results are broadly consistent to using exclusively data before the GFC, which effectively halves the number of data points considered.[26]

5 The role of policy

In this section, we study the information content of capital flows management measures and macroprudential policies for characterising the distributions of capital flows in emerging markets. For this purpose, we rely on widely used policy indices which proxy for the stance of policy (along the relevant dimension) in a given country at a given point in time.[27] We focus on portfolio flows as our object of study.

Although these indices are described in more detail in the subsequent sections, it is worth emphasising that none of these measures constitutes 'policy shocks'; that is, they measure the overall stance of policy, including those policy moves which constitute a reaction to other underlying forces. This means that our results should not be interpreted as the causal effect of a particular type of policy action on the distribution of capital flows, but rather as the quantification of potentially useful reduced-form relationships.[28]

5.1 Capital flows management measures

We first quantify the impact of the overall stance of capital flows management (CFM) measures on the distribution of portfolio capital flows.

[26] For this exercise, we re-estimate financial conditions indices with data up to 2007 only.

[27] The indices either measure the breadth of policies in place at a given point in time for a particular country (capital flows management), or the accumulation of past actions (macroprudential), so neither constitutes a precise measure of the absolute policy stance.

[28] For a very recent attempt to quantify the impact of macroprudential policy shocks on a different variable, namely GDP growth at risk, see Franta and Gambacorta (2020).

For this purpose we rely on data from Fernandez et al. (2016), who measure capital controls for ten asset categories over 1995-2016 for a large set of countries (including the 15 EMs in our sample). A clear advantage of these data, in contrast to other popular datasets, is that their granularity allow us to focus on measures that most directly affect the flows we are interested in, namely portfolio flows from non-residents, and to split between measures targeting inflows and outflows. On the negative side, the data only report the presence or absence of controls across a series of categories, but not their intensity. This means that a higher value of the CFM index represents a broader set of controls in place, but does not necessarily speak to the strength of these controls.[29]

We extend our baseline model specification (1) with measures of controls on inflows and outflows for each country-time observation, lagged by four quarters to reduce endogeneity concerns. Our analysis focuses on the coefficients associated with those variables (β_3 and β_4 in equation (3)). It is important to introduce controls on inflows and outflows separately and jointly because of their typically positive correlation (and potential heterogeneous effects), which could otherwise yield misleading results. We also include interaction terms between our global financial conditions index and both CFM measures as additional explanatory variables.

$$
\begin{aligned}
Q_{KF_{i,t+h}}(\tau|X_{i,t}) = \alpha_h(\tau)+\beta_{1,h}(\tau)GFCI_t+\beta_{2,h}(\tau)DFCI_{i,t}+\beta_{3,h}(\tau)KAO_{i,t-4}+\beta_{4,h}(\tau)KAI_{i,t-4} \\
+ \beta_{5,h}(\tau)KAO_{i,t-4} * GFCI_t + \beta_{6,h}(\tau)KAI_{i,t-4} * GFCI_t + \epsilon_i \quad (3)
\end{aligned}
$$

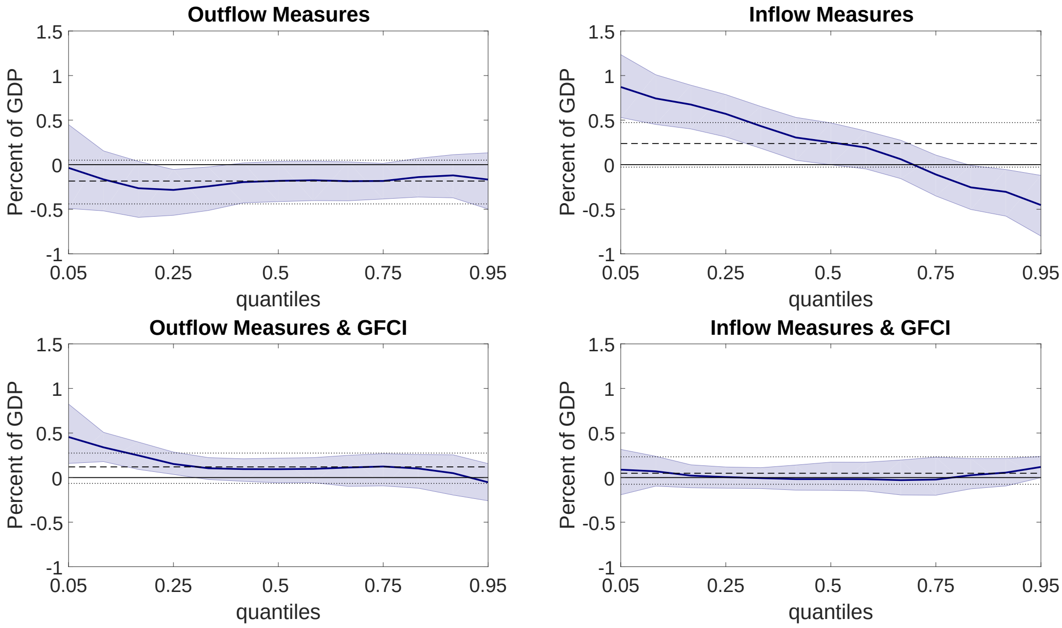
where $KAO_{i,t}$ and $KAI_{i,t}$ represent controls on non-resident outflows and controls on non-resident inflows, respectively, and the rest of the variables coincide with those in equation (1).

Both the country fixed-effects and the lagging of policy indices partially reduce concerns about potential endogeneity, but our results should still not be read in a causal way, as we do not have a measure of policy shocks and actions could still be taken in response to changes in the outlook (which would also affect capital flows).

Figure 8 shows the effects of a one standard deviation increase in our indices for controls on non-resident portfolio outflows and inflows on the distribution of non-resident portfolio flows. More controls on outflows have a negative but only marginally statistically significant effect on the distribution of capital flows to our set of EMs, and the effect is similar across the distribution. That is, the entire distribution of flows shifts marginally to the left, hence going against the intended effect of the measure, as outflows become marginally more likely.

[29] Episodes of tightening of previously existing controls are also lost on this account.

Figure 8 Effects of capital flows management measures



Note: The chart shows the effects of a one standard deviation tightening in the indices of capital flows measures applied to outflows and inflows from non-residents, as well as in these two measures interacted with the GFCI, to the distribution of portfolio capital flows from non-residents. The one standard deviation confidence intervals are based on block bootstrap methods following Fitzenberger (1998). Dashed lines show the OLS estimates and dotted lines the associated one standard deviation confidence band.

In contrast, controls on inflows significantly change the shape of the distribution of portfolio flows, with larger effects in the tails: the left tail moves sharply to the right, while the right tail moves to the left; that is, controls on inflows are associated with a ‘narrower’ distribution in which large outflow and large inflow episodes are less likely. This does not seem to come at the cost of smaller median flows.

Although there is some tentative evidence of controls on outflows (negatively) affecting the probability of large outflows if global financial conditions also tighten, the coefficients for both interaction terms are small and generally insignificant. This suggests that stronger capital flow management measures are not particularly helpful when global financial conditions tighten.

Relating these results to the existing literature is not straightforward given the different nature of past exercises. The closest paper to ours is Gelos et al. (2019), as they also focus on the effect of capital flows management measures on capital flows distributions. However, and in contrast to our approach, they consider CFM measures as an aggregate, without splitting them into those affecting inflows and outflows, and without focusing on those affecting non-residents in particular (in order to match the type of flows modelled). They also attempt to extract a 'shock' component out of their changes by relying on probit-type regressions. We have tested a further extension of (1) which includes a coarse measure of aggregate CFMs that does not distinguish residency nor direction of flows, and find that this measure does not seem to be have a significant effect on the distribution of non-resident portfolio flows, similar to the very small effects reported by Gelos et al. (2019) (See Appendix C.4).[30] The contrast with the more nuanced results displayed in Figure 8 speaks to the importance of using granular CFM measures in this type of analysis.

Forbes and Warnock (2012) do split between measures affecting inflows and outflows in one of their exercises, but focus on predicting discrete 'stops' and 'surges', and typically find no effect of capital control measures, in contrast to our results. Finally, Forbes et al. (2016) look at a small number of measures for Brazil over 2006-2013, and assess their impact on portfolio allocations of (a subset of) mutual funds (which are themselves a subset of the overall portfolio flows considered here). Discussions about the external validity of their results aside, their findings are also in contrast to ours because they find that tighter controls on inflows lead to a reallocation in portfolio shares away from the country implementing those measures.

5.2 Macroprudential policy

We also quantify the impact of macroprudential policy measures on the distribution of portfolio capital flows. Since the financial crisis, many countries have seen an acceleration in the set-up of institutional frameworks tasked with the specific responsibility of monitoring systemic risks, making the understanding of their effects on capital flows a pressing issue.[31] [32]

In order to quantify macroprudential measures we rely on the dataset of Cerutti et al. (2017), which captures the use of macroprudential tools in a large dataset of countries, including the 15 EMs in our sample, over the period 2000-2014. The dataset focuses on the introduction

[30] Gelos et al. (2019) do not report marginal impacts for CFM measures alone, but only their effect interacted with global financial conditions, where they find that tighter controls have a very small but positive effect on the likelihood of large outflows.

[31] Edge and Liang (2019) state that policy committees have been formed in 47 countries with this purpose in mind, many of which are EMEs.

[32] Policies with macroprudential aims were also used before the financial crisis, and in our sample of EMEs the level of activism is relatively stable pre and post-crisis (Cerutti et al. (2017)).

of new measures considering twelve different instruments, and does not attempt to capture the intensity of the measures or how the intensity changes over time.[33] In each quarter, the use of an additional measure across the instruments considered adds a unit to the index for that country, and the removal of a measure subtracts one unit.[34] We cumulate measures introduced over time in each country given that these policies may have a lasting effect. For example, building a larger capital requirement should make the banking system more resilient not just when it is introduced, but in all periods while it is in place. Before estimation, the indices are standardised using data across the entire sample.

As with the CFM measures in Section 5.1, we extend our baseline specification (1) with measures of macroprudential policy for each country-time observation, lagged by four quarters to reduce endogeneity concerns. Our analysis focuses on the coefficients associated with those variables. Also as in the case of CFM measures, we consider both macroprudential policy measures alone and interacted with our index of global financial conditions. The specification is hence analogous to that in Equation (3).

Figure 9 shows the impact of a one standard deviation increase in the macroprudential index across the distribution of portfolio capital flows. We can see in the first panel that there is a clear difference in the impact of macroprudential policy across different quantiles - the coefficients are significantly positive in the left tail and significantly negative in the right tail, but are generally insignificant in the centre of the distribution.[35] This suggests that introducing macroprudential policy measures is associated with a narrower distribution of capital flows; that is, with a lower likelihood of both large outflows and large inflows. Thus, these results provide tentative evidence that the introduction of macroprudential policies is associated with less fickle capital flows.

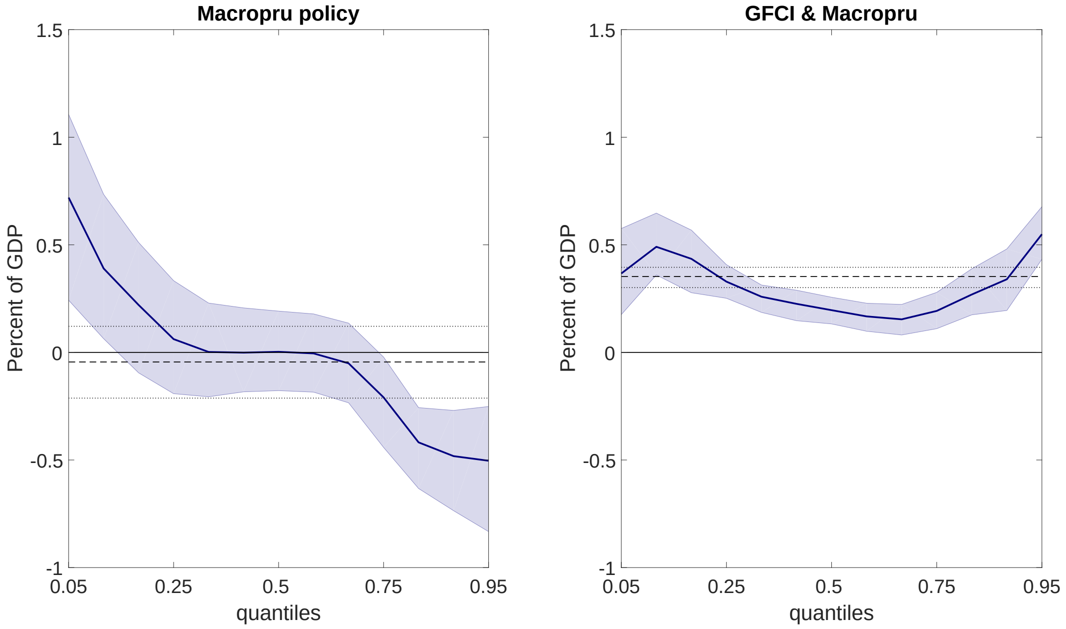
Figure 9 also shows the coefficient on the interaction term, which suggests that the negative effect of a tightening in global financial conditions is reduced across the distribution when a tighter macroprudential policy is in place. This could be interpreted as being consistent with

[33]The instruments considered are: General Countercyclical Capital Buffer/Requirement; Leverage Ratio for banks; Time-Varying/Dynamic Loan-Loss Provisioning; Loan-to-Value Ratio; Debt-to-Income Ratio; Limits on Domestic Currency Loans; Limits on Foreign Currency Loans; Reserve Requirement Ratios; and Levy/Tax on Financial Institutions; Capital Surcharges on SIFIs; Limits on Interbank Exposures; and Concentration Limits

[34]The lack of intensity measurement means it is difficult to interpret this series as a macroprudential stance - it simply measures the number of macroprudential policies put in place since the beginning of the sample. However, this is not a problem for our econometric specification given the use of country fixed effects.

[35]This result is similar to Figure 8 showing the effect of capital flows measures on inflows. Both results are robust to a specification which includes the macroprudential policy index as well as the index of capital flows measures.

Figure 9 Effects of macroprudential policy actions



Note: The chart shows the effect of a one standard deviation increase in the macroprudential policy index on the the distribution of portfolio capital flows from non-residents, alone and interacted with global financial conditions. The confidence intervals are based on block bootstrap methods following Fitzenberger (1998). Dashed lines show the OLS estimates and dotted lines the associated one standard deviation confidence band.

the notion that strong institutional frameworks are a factor that investors consider when allocating capital.[36]

There are not many studies that examine the effect of macroprudential policies on capital flows, especially in a quantile regression setting focusing on the tails of the distribution. Gelos et al. (2019) rely on a similar approach to ours (but use a different database and only look at interaction terms), and find no effect of macroprudential policy on the distribution of non-resident portfolio flows.

In terms of studies focusing on mean outcomes, Hoggarth et al. (2016) show that a tightening of prudential policy reduces the sensitivity of banking flows to global volatility. The authors also find that prudential policies, when not interacted with volatility, are insignificant. Relatedly, Coman and Lloyd (2019) find that emerging market economies' macroprudential policy can reduce the impact of US monetary policy (typically considered a 'push'-type factor) on

[36] We have also tested a specification including an interaction with local financial conditions, but this is generally insignificant.

capital flows to these economies. These findings are in line with our results in Figure 9, which shows the interaction term is significant in the middle part of the capital flows distribution, where one would expect the mean to lie (right panel), while policy without the interaction term is not (left panel). We extend this finding by showing that both variables are significant in the tails of the capital flows distribution. In a similar study, Beirne and Friedrich (2017) find that macroprudential policies do not have an effect on international banking flows. However, they do find that an interaction term between a measure of the 'regulatory environment' and macroprudential policy does have a significant effect. This result implies that when regulatory quality is high, macoprudential policies have a mitigating effect on international banking flows. In contrast, we find that macroprudential policy has an effect on the tails of capital flows even without including an interaction term.

6 Conclusion

We provide a characterisation of the conditional distributions of a range of capital inflows categories to a panel of emerging market economies, focusing on the tails of such distributions. We find that both push and pull factors contain useful information for characterising capital flows, and that their importance varies across the type of flow, portion of the distribution and horizon considered. We showcase a potential policy use of our framework, in which high frequency financial information can be used to 'nowcast' lower-frequency capital flow releases. We also explore the information content of various policy measures and find that capital flows to countries with (i) broader controls on inflows and (ii) a tighter macroprudential stance display a 'narrower' distribution; that is, a lower likelihood of experiencing sharp outflow or sharp inflow episodes.

References

Adrian, T., N. Boyarchenko, and D. Giannone (2019): “Vulnerable Growth,” *American Economic Review*, 109, 1263–1289.

Adrian, T., F. Grinberg, N. Liang, and S. Malik (2018): “The Term Structure of Growth-at-Risk,” IMF Working Papers 18/180, International Monetary Fund.

Aikman, D., J. Bridges, S. Hacioglu Hoke, C. ONeill, and A. Raja (2019): “Credit, capital and crises: a GDP-at-Risk approach,” Bank of England working papers 824, Bank of England.

Albuquerque, R., N. Loayza, and L. Servn (2005): “World market integration through the lens of foreign direct investors,” *Journal of International Economics*, 66, 267–295.

Arregui, N., S. Elekdag, R. G. Gelos, R. Lafarguette, and D. Seneviratne (2018): “Can Countries Manage Their Financial Conditions Amid Globalization?” IMF Working Papers 18/15, International Monetary Fund.

Azzalini, A. and A. Capitanio (2003): “Distributions generated by perturbation of symmetry with emphasis on a multivariate skew tdistribution,” *Journal of the Royal Statistical Society Series B*, 65, 367–389.

Banbura, M., D. Giannone, M. Modugno, and L. Reichlin (2013): “Now-Casting and the Real-Time Data Flow,” in *Handbook of Economic Forecasting*, ed. by G. Elliott and A. Timmermann, Elsevier, vol. 2, 195–237.

Banbura, M., D. Giannone, and L. Reichlin (2011): “Nowcasting,” in *The Oxford Handbook of Economic Forecasting*, ed. by M. P. Clements and D. F. Hendry, Oxford University Press, 193–224.

Beirne, J. and C. Friedrich (2017): “Macroprudential policies, capital flows, and the structure of the banking sector,” *Journal of International Money and Finance*, 75, 47–68.

Broner, F., T. Didier, A. Erce, and S. L. Schmukler (2013): “Gross capital flows: Dynamics and crises,” *Journal of Monetary Economics*, 60, 113–133.

Byrne, J. P. and N. Fiess (2016): “International capital flows to emerging markets: National and global determinants,” *Journal of International Money and Finance*, 61, 82–100.

Calvo, G. A., A. Izquierdo, and L.-F. Mejia (2004): "On the Empirics of Sudden Stops: The Relevance of Balance-Sheet Effects," NBER Working Papers 10520, National Bureau of Economic Research, Inc.

Calvo, G. A., L. Leiderman, and C. M. Reinhart (1993): "Capital Inflows and Real Exchange Rate Appreciation in Latin America: The Role of External Factors," *IMF Staff Papers*, 40, 108–151.

Canay, I. A. (2011): "A simple approach to quantile regression for panel data," *Econometrics Journal*, 14, 368–386.

Carney, M. (2019): "Pull, push, pipes: sustainable capital flows for a new world order," Bank of England, Speech given at the June 2019 Institute of International Finance Spring Membership Meeting, Tokyo.

Cerutti, E., S. Claessens, and L. Laeven (2017): "The use and effectiveness of macroprudential policies: New evidence," *Journal of Financial Stability*, 28, 203–224.

Coman, A. and S. Lloyd (2019): "In the face of spillovers: prudential policies in emerging economies," Bank of England working papers 828, Bank of England.

De Vita, G. and K. S. Kyaw (2008): "Determinants of capital flows to developing countries: a structural VAR analysis," *Journal of Economic Studies*, 35, 304–322.

Edge, R. M. and J. N. Liang (2019): "New Financial Stability Governance Structures and Central Banks," Finance and Economics Discussion Series 2019-019, Board of Governors of the Federal Reserve System (U.S.).

Eguren-Martin, F. and A. Sokol (2019): "Attention to the tail(s): global financial conditions and exchange rate risks," Bank of England working papers 822, Bank of England.

Fernandez, A., M. W. Klein, A. Rebucci, M. Schindler, and M. Uribe (2016): "Capital Control Measures: A New Dataset," *IMF Economic Review*, 64, 548–574.

Fernandez-Arias, E. (1996): "The new wave of private capital inflows: Push or pull?" *Journal of Development Economics*, 48, 389–418.

Fitzenberger, B. (1998): "The moving blocks bootstrap and robust inference for linear least squares and quantile regressions," *Journal of Econometrics*, 82, 235 – 287.

Forbes, K., M. Fratzscher, T. Kostka, and R. Straub (2016): “Bubble thy neighbour: Portfolio effects and externalities from capital controls,” *Journal of International Economics*, 99, 85–104.

Forbes, K. J. and F. E. Warnock (2012): “Capital flow waves: Surges, stops, flight, and retrenchment,” *Journal of International Economics*, 88, 235–251.

Franta, M. and L. Gambacorta (2020): “On the effects of macroprudential policies on Growth-at-Risk,” *Economics Letters*, 196.

Gelos, R. G., L. Gornicka, R. Koepke, R. Sahay, and S. Sgherri (2019): “Capital Flows at Risk: Taming the Ebbs and Flows,” IMF Working Papers 19/279, International Monetary Fund.

Ghosh, A. R., J. D. Ostry, and M. S. Qureshi (2016): “When Do Capital Inflow Surges End in Tears?” *American Economic Review*, 106, 581–585.

Gonalves, S. (2011): “The Moving Blocks Bootstrap for Panel Linear Regression Models with Individual Fixed Effects,” *Econometric Theory*, 27, 10481082.

Gupta, D. and D. Ratha (1999): *What Factors Appear to Drive Private Capital Flows to Developing Countries? And How Does Official Lending Respond?*, The World Bank.

Hernndez, L., P. Mellado, and R. Valds (2001): “Determinants of Private Capital Flows in the 1970s and 1990s: Is There Evidence of Contagion?” .

Hoggarth, G., C. Jung, and D. Reinhardt (2016): “Capital inflows the good, the bad and the bubbly,” Bank of England Financial Stability Papers 40, Bank of England.

Jorda, O. (2005): “Estimation and Inference of Impulse Responses by Local Projections,” *American Economic Review*, 95, 161–182.

Koenker, R. (2005): *Quantile Regression*, Econometric Society Monographs, Cambridge University Press.

Koenker, R. and G. Bassett (1978): “Regression Quantiles,” *Econometrica*, 46, 33–50.

Koepke, R. (2019): “What Drives Capital Flows To Emerging Markets? A Survey Of The Empirical Literature,” *Journal of Economic Surveys*, 33, 516–540.

Koop, G. and D. Korobilis (2014): “A new index of financial conditions,” *European Economic Review*, 71, 101–116.

Mendoza, E. G. (2010): "Sudden Stops, Financial Crises, and Leverage," *American Economic Review*, 100, 1941–1966.

Mohammadi, S. (2009): "QUANTILEREG: MATLAB function to estimate quantile regression," Statistical Software Components, Boston College Department of Economics.

Montiel, P. and C. M. Reinhart (1999): "Do capital controls and macroeconomic policies influence the volume and composition of capital flows? Evidence from the 1990s," *Journal of International Money and Finance*, 18, 619–635.

Obstfeld, M. (2012): "Financial flows, financial crises, and global imbalances," *Journal of International Money and Finance*, 31, 469–480.

Rebucci, A. and C. Ma (2019): "Capital Controls: A Survey of the New Literature," NBER Working Papers 26558, National Bureau of Economic Research, Inc.

Xiao, Z. (2012): "9 - Time Series Quantile Regressions," in *Time Series Analysis: Methods and Applications*, ed. by T. S. Rao, S. S. Rao, and C. Rao, Elsevier, vol. 30 of *Handbook of Statistics*, 213 – 257.

Zhou, Z. and X. Shao (2013): "Inference for linear models with dependent errors," *Journal of the Royal Statistical Society Series B*, 75, 323–343.

A Data

A.1 Capital flows

Our exercise is based on capital flows data for 15 emerging markets (Argentina, Brazil, Chile, Colombia, Hungary, India, Indonesia, Korea, Mexico, Peru, Philippines, Russia, South Africa, Thailand and Turkey) between 1996 and 2019. We obtain quarterly data on gross capital inflows (net flows from non-residents), split by the type of flow (foreign direct investment, portfolio flows and "other" which mainly consists of banking flows), from the International Monetary Fund's International Financial Statistics. All capital flows data in this paper are expressed as a share of GDP. We obtain data on nominal GDP for all countries in our sample from the IMF's World Economic Outlook database. The sample selection is determined by the availability of quarterly capital flows data from 1996:Q1 onward, as well as by the availability of sufficient reliable high-frequency financial series to estimate financial conditions indices.

A.2 Financial conditions indices

We construct financial conditions indices ('FCIs') for 43 advanced and emerging economies (Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Malaysia, Mexico, Netherlands, New Zealand, Norway, Peru, Philippines, Poland, Portugal, Russia, South Africa, Spain, Sweden, Switzerland, Thailand, Turkey, United Kingdom, United States, Vietnam) as described in section 2. The FCIs are based on term spreads, sovereign spreads, inter-bank spreads, corporate spreads, long-term sovereign yields, equity returns, equity volatility and the relative market capitalisation of the financial sector. All data are sourced via Refinitiv Eikon. Due to data availability, there are small differences in the precise nature of the financial series considered. But generally speaking, the series are defined as follows:

- Term spreads are the difference between a 10-year sovereign yield and a short-term, typically 3-month, sovereign yield.
- Corporate spreads are the difference between broad indices of typically investment-grade corporate bond yields and, as far as possible, sovereign yields of similar maturity.

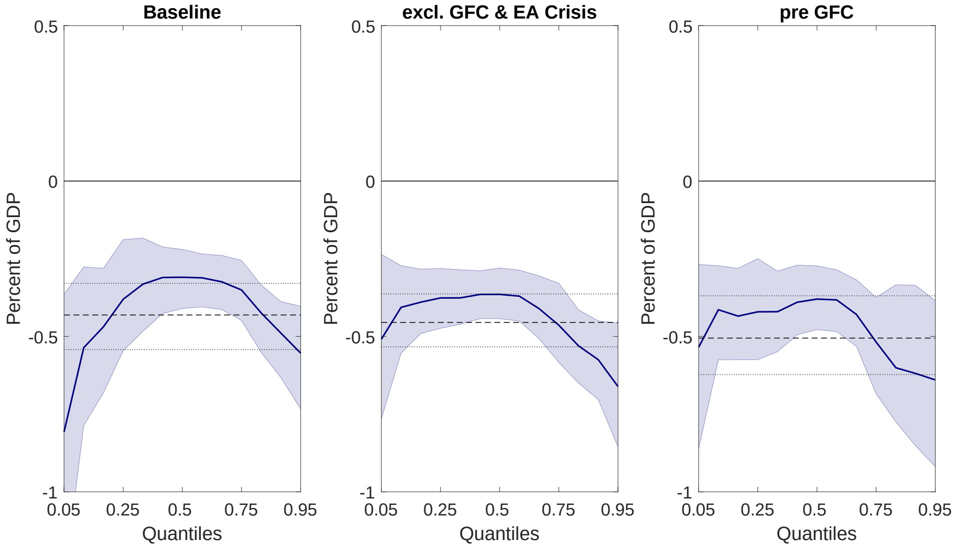
- Inter-bank spreads are the difference between short-term, typically 3-month, inter-bank rates and sovereign yields of the same maturity.
- Where available, we use JP Morgan's stripped sovereign spreads. For other countries, we use the spread between the 10-year sovereign yield and the reference country's 10-year sovereign yield. For most countries, we use the US as the reference. European spreads are reported relative to Germany, advanced East Asian spreads relative to Japan. We use no sovereign spread for the UK.
- Long-term yields are for 10-year sovereign bonds.
- Equity prices enter as log returns on broad stock market indices. For instance, we use the S&P 500 for the US, the FTSE 100 for the UK, and the DAX 30 for Germany.
- Equity volatility is the realised monthly volatility on these broad stock market indices.
- The relative capitalisation of financials is calculated as the ratio of total market capitalisation of financial firms divided by total market capitalisation based on MSCI indices.

We calculate the global FCI as the PPP-weighted average of all 43 country FCIs, restandardising it to have a standard deviation of one. GDP PPP weights are from the IMF's World Economic Outlook database.

B Robustness

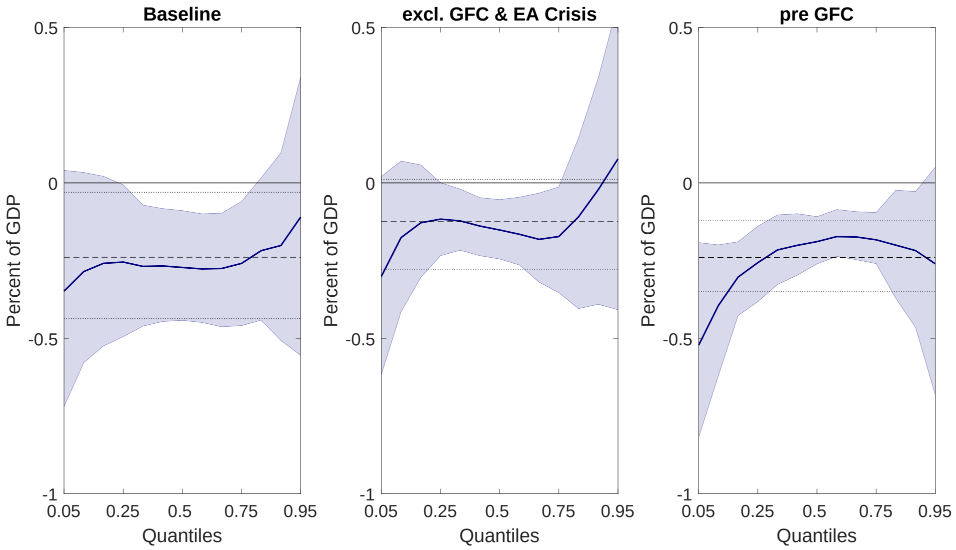
This appendix reports results for the various robustness checks discussed in Section 4.

Figure B.1 Effects of global financial conditions on gross portfolio inflows excluding crises



Note: See Figure 2. Sample period excludes 2008:Q1 to 2012:Q4 for the middle panel and ends in 2007:Q4 for the right panel.

Figure B.2 Effects of local financial conditions on gross portfolio inflows excluding crises



Note: See Figure B.1.

Table B.1 Regression coefficients for our baseline specification and additional regressors

	Baseline (1)		2		3		4	
	Left tail	**Median**	**Left tail**	**Median**	**Left tail**	**Median**	**Left tail**	**Median**
Global FCI	-0.81***	-0.31**	-0.97***	-0.35***	-1.08***	-0.37***	-1.18***	-0.47***
	(-1.29,-0.36)	(-0.41,-0.22)	(-1.55, -0.44)	(-0.51, -0.21)	(-1.66, -0.55)	(-0.52, -0.22)	(-1.81, -0.56)	(-0.66, -0.3)
Country FCI	-0.35	-0.27*	-0.28	-0.25*	-0.26	-0.2*	-0.30	-0.21**
	(-0.72,0.04)	(-0.44,-0.09)	(-0.72, 0.13)	(-0.41, -0.1)	(-0.71, 0.21)	(-0.33, -0.06)	(-0.69, 0.09)	(-0.32, -0.1)
US GDP			-0.23	-0.08	-0.26	-0.07	-0.29	-0.11*
			(-0.52, 0.07)	(-0.18, 0.01)	(-0.57, 0.07)	(-0.17, 0.03)	(-0.58, 0)	(-0.22, -0.03)
US Policy					-0.46*	-0.26*	-0.41*	-0.25*
					(-0.85, -0.09)	(-0.46, -0.11)	(-0.8, -0.01)	(-0.42, -0.1)
VIX							0.06	0.11
							(-0.36, 0.49)	(-0.02, 0.24)
	5		**6**		**7**		**8**	
	Left tail	**Median**	**Left tail**	**Median**	**Left tail**	**Median**	**Left tail**	**Median**
Global FCI	-0.83***	-0.3***	-0.97**	-0.25**	-1.07***	-0.41***	-1.18**	-0.32***
	(-1.26, -0.4)	(-0.36, -0.23)	(-1.52, -0.41)	(-0.34, -0.18)	(-1.54, -0.56)	(-0.56, -0.28)	(-1.93, -0.54)	(-0.47, -0.17)
Country FCI	-0.55*	-0.31***	-0.55*	-0.28***	-0.47*	-0.22***	-0.47	-0.19***
	(-0.97, -0.16)	(-0.45, -0.19)	(-1.06, -0.07)	(-0.41, -0.15)	(-0.88, -0.06)	(-0.33, -0.11)	(-0.99, 0.05)	(-0.29, -0.08)
US GDP					-0.26*	-0.1*	-0.33	-0.15*
					(-0.54, 0)	(-0.19, 0)	(-0.66, 0.04)	(-0.26, -0.06)
US Policy					-0.63*	-0.34*	-0.68*	-0.35*
					(-1.05, -0.24)	(-0.52, -0.22)	(-1.1, -0.24)	(-0.54, -0.2)
VIX					-0.12	0.03	-0.15	-0.07
					(-0.51, 0.2)	(-0.09, 0.16)	(-0.56, 0.22)	(-0.23, 0.08)
Local GDP	-0.24*	0.17***	-0.19	0.24***	-0.20	0.18***	-0.09	0.25***
	(-0.42, -0.08)	(0.1, 0.23)	(-0.5, 0.07)	(0.18, 0.32)	(-0.52, 0.07)	(0.1, 0.26)	(-0.48, 0.23)	(0.18, 0.32)
Local equity returns			0.00	0.2***			0.06	0.23***
			(-0.28, 0.25)	(0.11, 0.28)			(-0.29, 0.41)	(0.17, 0.29)

Note: The left-hand side variable for all regressions reported in this table is non-resident portfolio flows. 'Left tail' refers to the 5th percentile of the distribution. 'Global FCI' and 'Country FCI' refer to our global and country-specific financial condition indices. 'US GDP' stands for the annual growth in US real GDP. 'US Policy' is measured by the Federal Funds Rate. 'Local GDP' is annual growth in real GDP of each country in our sample. 'Local equity returns' is quarterly change in each country's broad stock market index. Block-bootstrapped one standard deviation confidence intervals in brackets. *** 95% confidence interval does not cover zero, ** 90% confidence interval does not cover zero, * 68% confidence interval does not cover zero.

C Additional results

C.1 Baseline regression results

Table C.1 Regression coefficients for the near-term effect of global and local financial conditions on portfolio inflows across quantiles

Dependent variable: Average gross portfolio inflows (% of GDP) in quarters 0-2 ahead

	Percentile						
Variable	5	10	25	50	75	90	95
Global FCI	-0.81***	-0.54**	-0.38**	-0.31**	-0.35**	-0.49***	-0.55***
	(-1.29,-0.36)	(-0.79,-0.28)	(-0.55,-0.19)	(-0.41,-0.22)	(-0.45,-0.26)	(-0.63,-0.39)	(-0.73,-0.40)
Country FCI	-0.35	-0.29	-0.25*	-0.27*	-0.26*	-0.2	-0.11
	(-0.72,0.04)	(-0.58,0.03)	(-0.49,-0.01)	(-0.44,-0.09)	(-0.46,-0.06)	(-0.51,0.10)	(-0.55,0.34)
Number of Observations	1440	1440	1440	1440	1440	1440	1440

Note: Block-bootstrapped one standard deviation confidence intervals in brackets. *** 95% confidence interval does not cover zero, ** 90% confidence interval does not cover zero, * 68% confidence interval does not cover zero.

Table C.2 Regression coefficients for the near-term effect of global and local financial conditions on banking inflows across quantiles

Dependent variable: Average gross banking inflows (% of GDP) in quarters 0-2 ahead

	Percentile						
Variable	5	10	25	50	75	90	95
Global FCI	-0.76**	-0.67***	-0.50***	-0.34***	-0.38***	-0.56*	-0.54*
	(-1.02,-0.44)	(-0.80,-0.57)	(-0.62,-0.36)	(-0.45,-0.24)	(-0.49,-0.29)	(-0.80,-0.28)	(-0.87,-0.11)
Country FCI	-1.51***	-1.08***	-0.69***	-0.56***	-0.47**	-0.45	-0.46*
	(-1.95,-1.09)	(-1.37,-0.79)	(-0.86,-0.51)	(-0.69,-0.41)	(-0.70,-0.25)	(-0.84,0.03)	(-0.95,-0.01)
Number of Observations	1440	1440	1440	1440	1440	1440	1440

Note: See Table C.1.

Table C.3 Regression coefficients for the near-term effect of global and local financial conditions on FDI inflows across quantiles

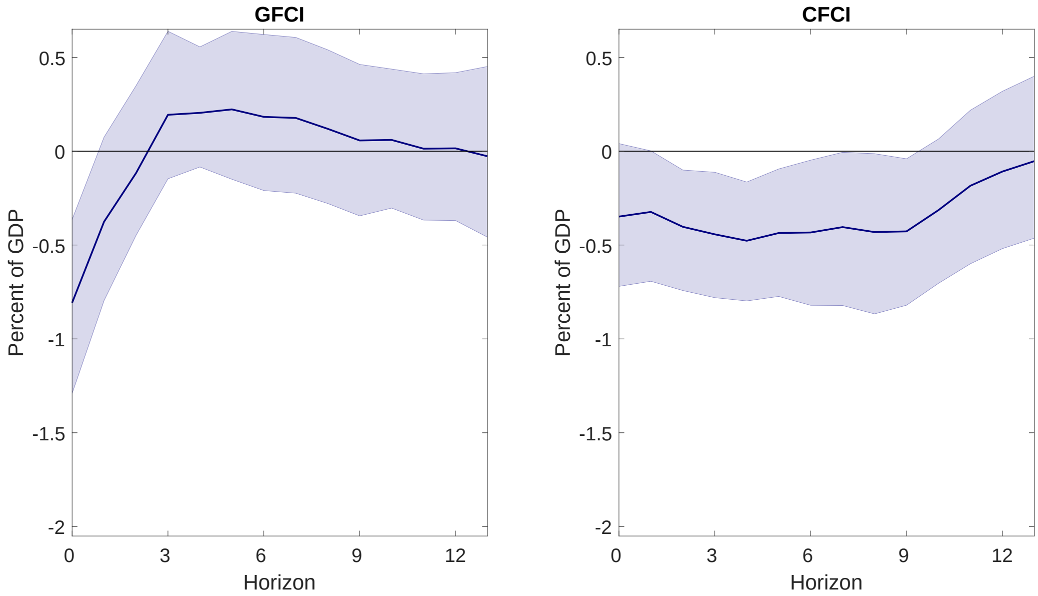
Dependent variable: Average gross FDI inflows (% of GDP) in quarters 0-2 ahead

	Percentile						
Variable	5	10	25	50	75	90	95
Global FCI	-0.07	0.01	0.04	0.04	0.08	0.04	0.09
	(-0.30,0.19)	(-0.11,0.14)	(-0.04,0.12)	(-0.02,0.10)	(0.00,0.15)	(-0.04,0.12)	(-0.05,0.22)
Country FCI	-0.19*	-0.22**	-0.19***	-0.16***	-0.14*	-0.09	-0.09
	(-0.43,0.00)	(-0.36,-0.09)	(-0.27,-0.10)	(-0.23,-0.10)	(-0.26,-0.01)	(-0.30,0.13)	(-0.38,0.20)
Number of Observations	1344	1344	1344	1344	1344	1344	1344

Note: See Table C.1.

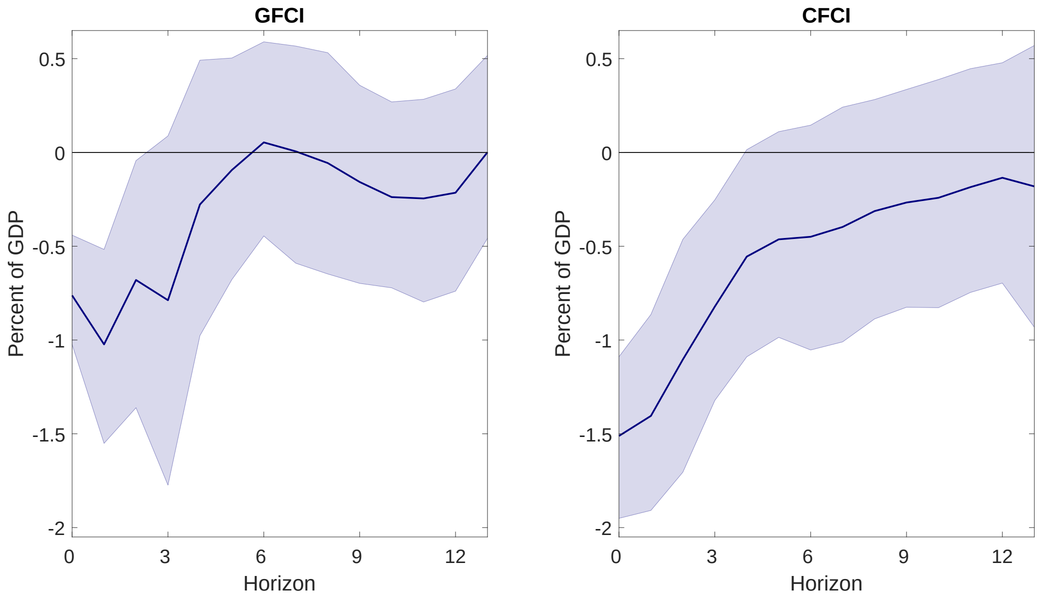
C.2 Term structure effects of global and country-specific financial conditions across capital flow types

Figure C.1 Term structure of effects on gross portfolio inflows



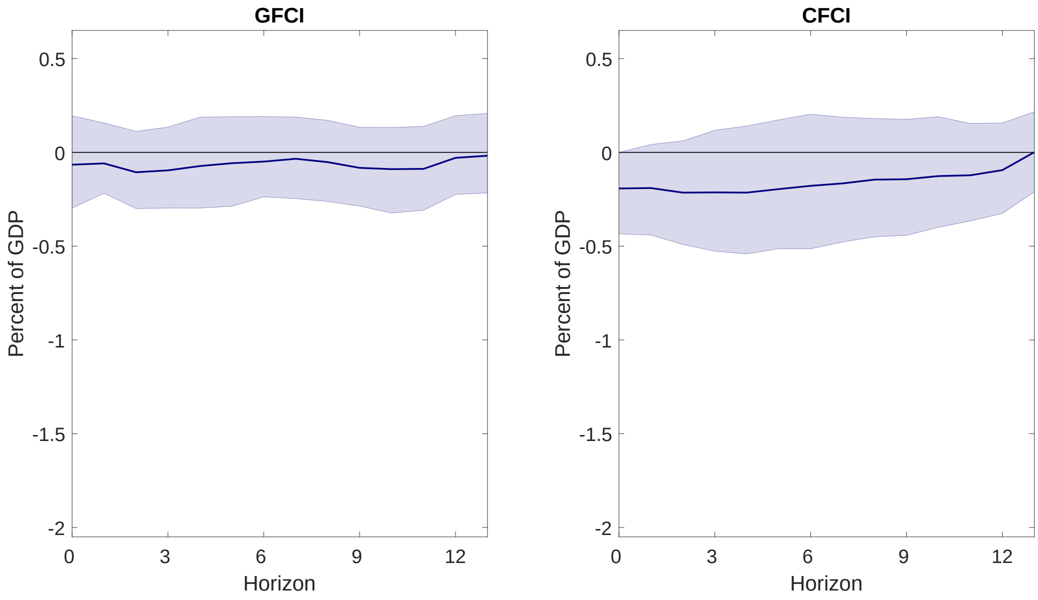
Note: The chart shows the effect of a one standard deviation tightening in global / local financial conditions on the fifth percentile ("Portfolio flows-at-risk") of the forecast distribution of portfolio flows across horizons. The one standard deviation confidence intervals are based on block bootstrap methods following Fitzenberger (1998).

Figure C.2 Term structure of the effect of global and local financial conditions on the fifth percentile of banking flows



Note: See Figure C.1.

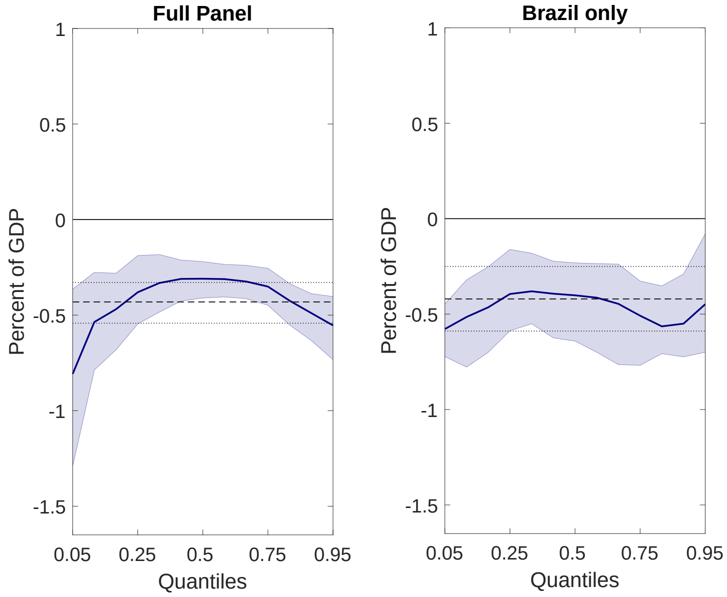
Figure C.3 Term structure of the effect of global and local financial conditions on the fifth percentile of FDI



Note: See Figure C.1.

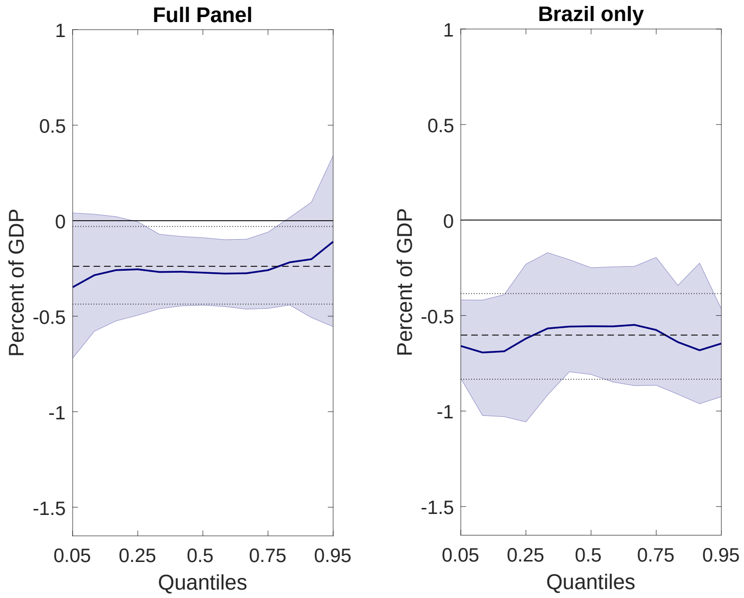
C.3 Portfolio flows to Brazil

Figure C.4 Effects of global financial conditions on portfolio inflows



Note: See Figure 2.

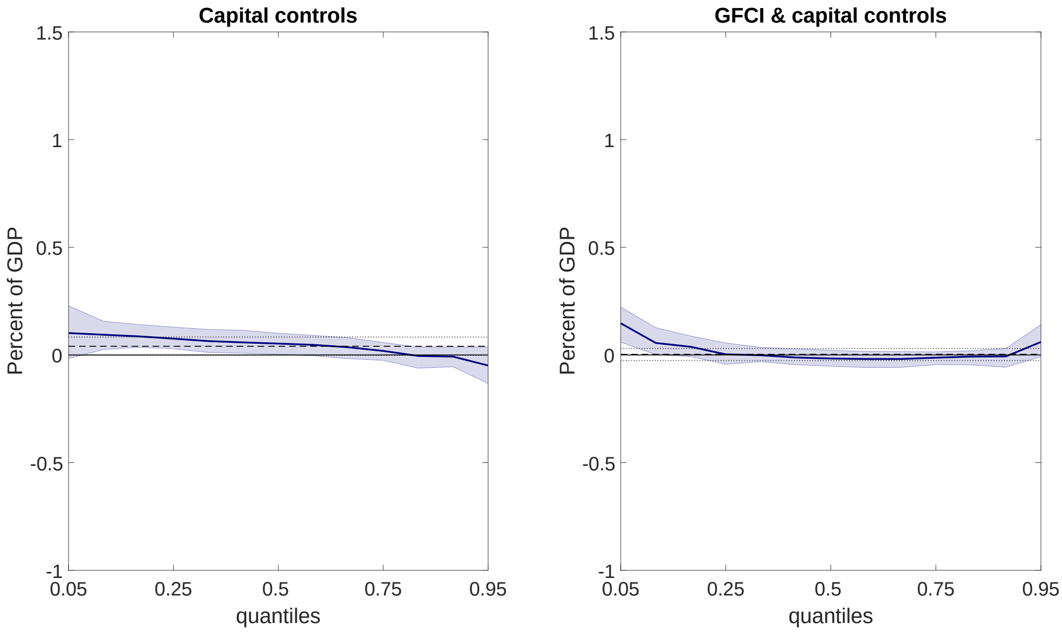
Figure C.5 Effects of local financial conditions on portfolio inflows



Note: See Figure 2.

C.4 Aggregate Capital Flows management measures

Figure C.6 Effects of capital flows management measures



Note: The chart shows the effect of a one standard deviation tightening in our index of aggregate capital flow management measures applied to all flows from residents and non-residents, as well as this measure interacted with our GFCI, to the distribution of portfolio capital flows from non-residents. The one standard deviation confidence intervals are based on block bootstrap methods following Fitzenberger (1998). Dashed lines show the OLS estimates and dotted lines the associated one standard deviation confidence band.

D Estimation and reporting statistics

D.1 Quantile regression

Given a linear model for the conditional quantile function

$$Q_y(\tau|X) = x\beta(\tau) \tag{D.1}$$

the quantile regression estimate $\hat{\beta}(\tau)$ is the minimiser of

$$\hat{V}(\tau) = \min_{\beta\in\mathbb{R}^p} \sum \rho_\tau \left(y_t - x_t'\beta\right) \tag{D.2}$$

where $\rho_\tau(u) = u[\tau - I(u < 0)]$ is the so-called check function.

As discussed in Koenker (2005), the solution of problem D.2 is amenable to linear programming techniques. However, in our MATLAB implementation, we have found it computationally more efficient to approximate the exact solution via an iteratively-reweighted-least-squares (IRLS) algorithm. This is motivated by the close relationship of D.2 to the problem of finding the least-absolute-deviations (LAD) estimator (which obtains for $\tau = 0.5$), and more generally of solving L^p-norm linear regression problems. Building on Mohammadi (2009), we proceed as follows: we start from an initial OLS estimate,

$$\hat{\beta}^{(0)}(\tau) = \left(x'x\right)^{-1} x'y.$$

We then take the residuals $\hat{u}_t{}^{(0)}(\tau) = y_t - x_t\hat{\beta}^{(0)}(\tau)$ and construct a diagonal matrix of weights $w^{(s)}, s > 0$, whose diagonal elements are given by

$$w_{tt}^{(s)}(\tau) = \frac{1}{\rho_{1-\tau}\left(u_i^{(s-1)}(\tau)\right)}$$

We then obtain an updated estimate $\hat{\beta}^{(s)}(\tau)$, residuals $\hat{u}^{(s)}(\tau)$ and weights $w^{(s+1)}(\tau)$ from

$$\hat{\beta}^{(s)}(\tau) = \left(x'w^{(s)}(\tau)'\,x\right)^{-1} x'w^{(s)}(\tau)'\,y$$

and iterate until convergence. Essentially, the procedure approximates D.2 by a convergent sequence of weighted sums of square residuals, where the weights are chosen so as to approximate the check function ρ_τ with a quadratic one.

D.2 Fixed effects

To deal with the quantile-invariant country fixed effects ϵ_i in Equation (1), we follow the two-step procedure proposed by Canay (2011). This consists in first estimating the fixed effects in a standard regression framework (in particular, we use a classic within estimator), and then estimating a standard quantile regression on the pooled data, but 'purged' of the fixed effects. Starting from a model for the conditional *mean* of the data

$$y_{it} = x'_{it}\beta_\mu + \epsilon_i + u_{it} \qquad \mathbb{E}\left(u_{it}|x_{it}, \epsilon_i\right) = 0, \tag{D.3}$$

one can obtain a $\sqrt{T}$-consistent estimator of ϵ_i given an $\sqrt{nT}$-consistent estimator of β_μ (where n denotes the number of cross-sectional units), such as a classic within estimator, which we denote by $\hat{\beta}_\mu$. Then, having recovered $\hat{\epsilon}_i$ from

$$\hat{\epsilon}_i = T^{-1}\sum_{t=1}^{T}\left(y_{it} - x'_{it}\hat{\beta}_\mu\right), \tag{D.4}$$

one can run a standard (pooled) quantile regression, as described in the previous Section, on the 'purged' data $\hat{y}_{it}$, obtained by cleaning the dependent variable from the country fixed effects:

$$\hat{y}_{it} = y_{it} - \hat{\epsilon}_i \tag{D.5}$$

D.3 Bootstrapping

While there are several results available for inference in quantile regression with time-series data (see for example Xiao (2012), Zhou and Shao (2013)), we take a shortcut and deal with potential autocorrelation in the errors from D.2 by bootstrapping confidence intervals for all quantities of interest. Fitzenberger (1998) shows that a moving (or overlapping) block bootstrap procedure provides heteroskedasticity- and autocorrelation-consistent (HAC) standard errors for quantile regression coefficient estimators. As in Adrian et al. (2018), in our panel dataset we only bootstrap along the time dimension, and abstract from the cross-sectional one. To our knowledge there are no specific results for quantile regression, but Gonalves (2011) finds that in OLS panels with individual fixed effects, the moving block bootstrap along the time dimension is robust to cross-sectional dependence of unknown form.

The procedure works as follows: letting $z_t = [y_t, x_t]$ denote the original data (with observations for individual countries suitably stacked), T the sample size and b a suitably chosen block length, a resample z^*_{jt} of length $T^* = b * round(T/b)$ is obtained by joining $round(T/b)$ draws (with replacement) of b consecutive elements of z_t (blocks), where the blocks are allowed to overlap. Each resample z^*_{jt} yields an estimate of the fixed effects $\hat{\epsilon}_j i$ quantile regression coefficients $\hat{\beta}^*_j(\tau)$ and can be used to compute all other statistics of interest. Confidence intervals at level γ for $\hat{\beta}(\tau)$ and other quantities of interest are computed as

$$\left(2\hat{\beta}(\tau) - \hat{\beta}^*_{\frac{1-\gamma}{2}}(\tau), 2\hat{\beta}(\tau) - \hat{\beta}^*_{\frac{\gamma}{2}}(\tau)\right) \tag{D.6}$$

where $\hat{\beta}^*_p(\tau)$ denotes the $p-$th percentile of the bootstrapped draws $\hat{\beta}^*_j(\tau)$

D.4 Relative entropy measures

To quantify and compare heterogeneous tail behaviour across types of flows facing changes in global and local financial conditions we compute measures of distribution divergence. In particular, we use a version of the Kullback-Leibler divergence, also known as relative entropy, to quantify the 'shifts' induced in the tail regions by a tightening of global or local financial conditions. Given a fitted distribution $\hat{g}(x)$ conditional on average global and local financial conditions and another, $\hat{f}(x)$, conditional on a 1 standard deviation tightening in, say, global financial conditions, we compute downside and upside (relative) entropy as

$$\mathcal{L}^D = \int_{-\infty}^{\hat{G}^{-1}(0.05)} \log\left(\frac{\hat{f}(x)}{\hat{g}(x)}\right)\hat{f}(x)dx \tag{D.7}$$

$$\mathcal{L}^U = \int_{\hat{G}^{-1}(0.95)}^{\infty} \log\left(\frac{\hat{f}(x)}{\hat{g}(x)}\right)\hat{f}(x)dx. \tag{D.8}$$

Intuitively, downside and upside entropy measure the additional probability mass assigned to tail events when there is a tightening of global financial conditions. In our capital flows context this quantifies the additional probability of large capital outflows (downside entropy, which we would expect to be positive) and of large capital inflows (upside entropy, which we would expect to be negative).

Acknowledgements

We would like to thank Ambrogio Cesa Bianchi, Nathan Converse, Glenn Hoggarth and seminar participants at the Bank of England, Bank of Italy, the European Economic Association Congress and the IMF for useful comments and suggestions. Work on this paper started while developing the framework presented in Carney (2019). The views expressed in this paper are solely those of the authors and should not be taken to represent those of the Bank of England or the European Central Bank.

Fernando Eguren-Martin
Bank of England, London, United Kingdom; email: fernando.egurenmartin@bankofengland.co.uk

Cian O'Neill
Bank of England, London, United Kingdom; email: cian.o'neill@bankofengland.co.uk

Andrej Sokol
European Central Bank, Frankfurt am Main, Germany; Bank of England, London, United Kingdom; CfM;
email: andrej.sokol@ecb.europa.eu

Lukas von dem Berge
Bank of England, London, United Kingdom; email: lukas.vondemberge@bankofengland.co.uk

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

This paper can be downloaded without charge from www.ecb.europa.eu, from the Social Science Research Network electronic library or from RePEc: Research Papers in Economics. Information on all of the papers published in the ECB Working Paper Series can be found on the ECB's website.

PDF ISBN 978-92-899-4538-7 ISSN 1725-2806 doi:10.2866/897820 QB-AR-21-029-EN-N