BANK OF ENGLAND

Staff Working Paper No. 881

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August 2020

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

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Abstract

We characterise the probability distribution of capital flows for a panel of emerging market economies conditional on information contained in financial asset prices, 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 offers insights into the term-structure of these effects. We find that both push and pull factors have heterogeneous effects across the distribution of capital flows, with the strongest reactions in the left tail. Also, the effect of changes in pull factors is more persistent than that of push factors. Finally, we explore the role of policy, and find that macroprudential and capital flow management measures are associated with changes in the distribution of capital flows.

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

JEL classification: F32, F34, G15.

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The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England nor the European Central Bank, or any of its committees. We are grateful to Ambrogio Cesa Bianchi, Mark Carney, Nathan Converse, Glenn Hoggarth and seminar participants at the Bank of England and the IMF for useful comments and suggestions. Work for this paper started in the context of preparation of the framework presented in Carney (2019).

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ISSN 1749-9135 (on-line)

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 *entire* probability distribution of capital flows to emerging market economies conditional on information contained in financial asset prices. We also explore the implications for that distribution of a series of policy actions, namely macroprudential and capital flow management measures.

By modelling the entire conditional distribution of capital flows, we improve upon conventional approaches in two 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 that distribution. 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 a full characterisation of different parts of the distribution of capital flows, including its tails. This is important to the extent that capital flow monitoring and managing usually involves a balancing act between encouraging inflows and limiting the scope for disruptive large outflows. Our approach offers insights into both the likelihood and the magnitude of potential outcomes.

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 left tails of the respective distributions moving to the left in response to negative shocks, and

[1]As will become clear in Section 2, what we refer to as "shocks" are not truly shocks in the sense of being exogenous to other drivers of capital flows, and hence our results should not be read in a causal manner.

[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.

the right tails remaining largely unaffected.[4]

Focusing on portfolio flows, we provide a detailed analysis of the term structure of the effects of push and pull-type shocks on the left tail of the distribution, with the 5th percentile as our measure of 'capital flows-at-risk'. We show that while the effect of push shocks quickly decays, becoming statistically insignificant after a few quarters, that of pull-type shocks is markedly more persistent, and remains significant for more than two years.

Finally, we consider the informational content of two types of policy, namely capital flow management measures and macroprudential policy actions for the conditional distribution of capital flows to emerging markets.[5] We find that capital controls targeting portfolio outflows are not associated with changes in the distribution, but controls limiting inflows are associated with a 'narrower' distribution; that is, a lower probability of large capital outflows or inflows. As for macroprudential policy, we find that tighter policy is also associated with a narrower conditional distribution. 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.

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 in that context. Section 2 describes the approach behind the construction of our asset price-based proxies for push and pull-type factors. Section 3 presents our core results in terms of the effect of push and pull-type factors on the distribution of different types of capital flows to emerging markets, both contemporaneously and the term-structure of their effects across horizons. Section 4 analyses the effect of capital flow management measures and macroprudential policy on the distribution of capital flows, and Section 5 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. Because

[4] This is still not statistically significant in the case of FDI.

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

of this, a large empirical literature has developed, starting with the seminal contributions of Calvo et al. (1993) and Fernandez-Arias (1996), which introduced the distinction between global "push" and domestic "pull" risk factors. Koepke (2019) provides a very thorough literature review. Our papers 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 distribution of capital flows, in parallel fashion to recent work by Adrian et al. (2018) and Adrian et al. (2019) on "GDP-at-Risk"[6]. By modelling the entire conditional distribution of capital flows, one can assess the effect of a range of risk factors across different parts of the distribution (and at different horizons), avoiding to take a stance on what constitutes a sudden stop and what does not, and allowing heterogeneous effects across quantiles to be considered.

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 flow management and macroprudential measures into our framework, which 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 flow 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 capital flows.

[6] In turn based on the seminal contribution of Koenker and Bassett (1978).

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

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 many types of resident and 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 variance that is actually attributable to push factors. Importantly, we also provide a more detailed account of the term-structure effect 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 correlations using better-targeted 'raw' policy measures.[8]

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 in quantile regression analysis, in which the degrees of freedom the econometrician can rely on are very limited. Faced with this issue, we rely on two levels of aggregation to measure a set of risks affecting capital flows to emerging markets. First,

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

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. Specifically, we are interested in analysing the informational content of asset prices in terms of helping us characterise the entire distribution of capital flows to emerging markets. To the extent that changes in asset prices will be driven, largely, 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 macro 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 macro outlook, which should affect all of them (arguably to varying degrees), one option is to avoid focusing on particular assets 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 distribution of capital flows. The approach to come up with these proxies for push and pull factors is explained in more detail next.

2.1 Methodology

We construct country-level Financial Condition 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 on the series above to extract country-specific summary measures of financial conditions (which correspond to the first principal component of the

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

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 condition 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 for global financial conditions and a set of country-specific (EM) domestic financial conditions we set out to explore their informational content in helping characterise the entire distribution of capital flows to our panel of emerging market economies.

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 quantile regression methodology and uses the Financial Condition Indices estimated in Section 2 as main inputs.

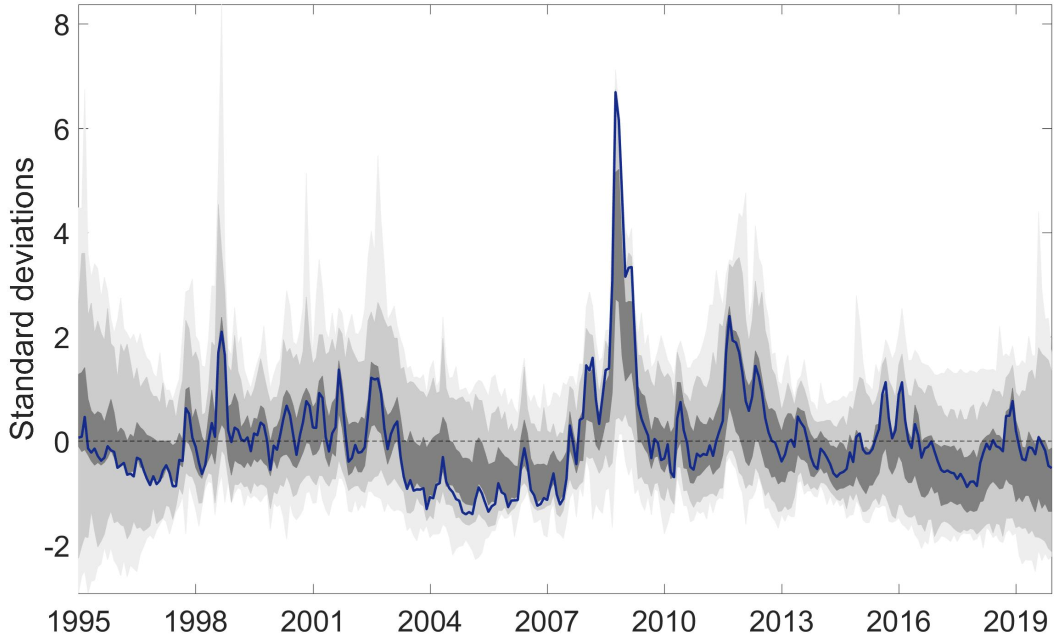
Characterising distributions is particularly useful in the context of capital flows because it *goes beyond the mean*, which has been the object of study of a large part of the literature,

[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 mean 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. Also, orthogonality at the mean does not guarantee orthogonality across the entire distribution.

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.

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 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:

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

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

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 Condition Indices, and ϵ_i is a country-specific quantile-invariant fixed effect as in Canay (2011). Function Q computes quantiles τ of the distribution of $KF_{i,t+h}$ given a set of covariates $X_{i,t}$.

Quantile regressions place high demands on the data, which is why we keep equation (1) as parsimonious as possible. Nevertheless, in Appendix B we show that results are qualitatively robust to including lags of the dependent variable or GDP growth as independent variables. Appendix D discusses technical details of quantile regression and the bootstrap method used for constructing confidence intervals.

We estimate equation (1) on a panel of 13 emerging market economies from 1996Q1 to 2018Q4.[14] We focus on gross capital inflows (net flows from non-residents), and estimate the distribution of portfolio, foreign direct investment and 'other' (mostly banking) flows separately.[15] See Appendix A for definitions and data sources.

As described in Section 2, we rely on global and domestic financial condition indices as summary measures of the risk-adjusted economic outlook facing an economy, which then become inputs into our quantile regressions. The distinction between domestic and global factors is particularly useful to place our findings in terms of the vast literature analysing 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.

There is a certain asymmetry between our push and pull factors. To the extent that they are estimated out of financial asset prices, which will in part react to a set of structural shocks which are common to capital flows, they cannot be regarded as truly exogenous, and changes should not be interpreted as 'shocks' with causal effects. Having said that, all emerging markets considered are small enough for the usual 'small open economy' assumption to be plausible, which means that our push factor can indeed be regarded as exogenous with a certain degree of confidence. More generally, one can think of our exercise as extracting information from asset prices which is useful to characterise 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 could be used as a basis for the 'nowcasting' of capital flow

[14]The countries considered are Argentina, Brazil, Chile, Colombia, Hungary, India, Indonesia, Mexico, Peru, Philippines, Russia, South Africa, and Turkey.

[15]Appendix C also reports results for resident flows, as well as a split of portfolio flows into debt and equity.

distributions.

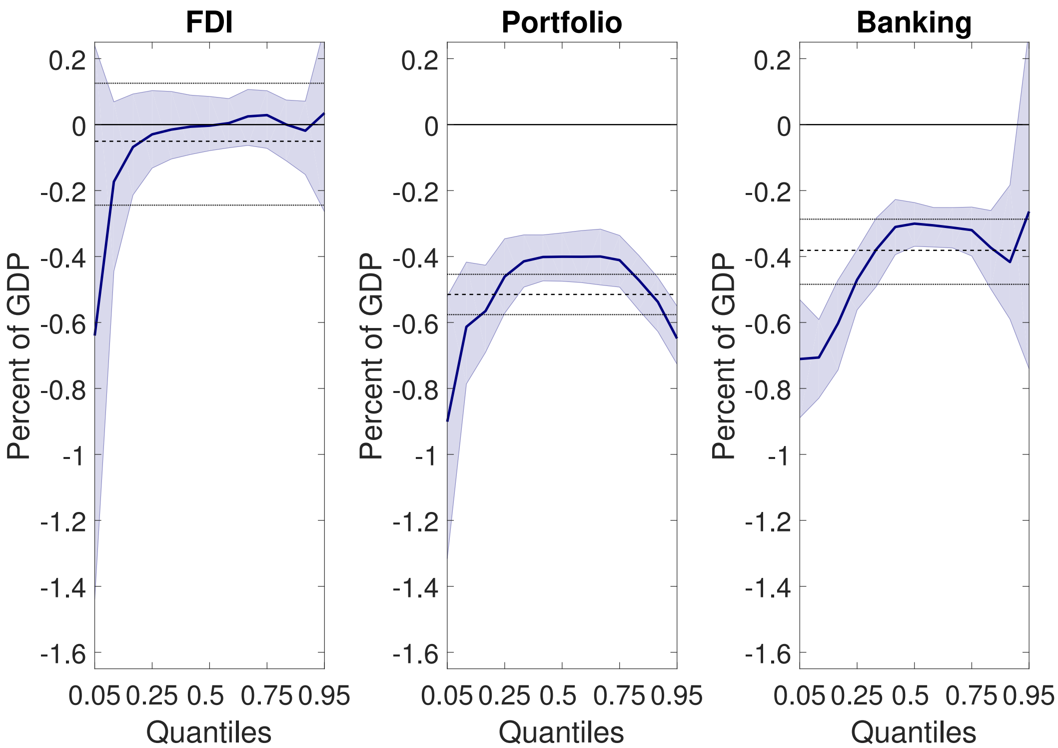
Following Forbes and Warnock (2012), we focus on non-resident flows (often referred to as 'gross inflows') in our analysis, splitting these into FDI, portfolio and 'other' (mostly banking flows).[16] Figures 2 and 3 report the sensitivities across quantiles of the three different types of inflows, in the near term (that is, in the current quarter and following two quarters), to push and pull factors, respectively. 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 effect of push and pull factors on the distribution of capital flows. Specifying a model for the conditional mean as well as the variance would also provide an incomplete picture, given heterogeneous effects on left and right tails of the distribution. 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.

Focusing on push factors first, Figure 2 shows the near-term effect 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, which highlights the usefulness of our quantile regression approach. Portfolio flows in particular 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 show a negative response to a tightening in local financial conditions, which is strongest in the left tail and becomes small and insignificant in the right tail. Banking flows, meanwhile, respond much more strongly in the left tail than in the right tail, suggesting that tighter local financial conditions are associated with a significantly higher probability of negative banking inflows (i.e. outflows from non-residents), but do not significantly alter the probability of large

[16] Results for resident flows ('gross outflows') can be found in Appendix C.2.

Figure 2 Effect of global financial conditions on gross inflows



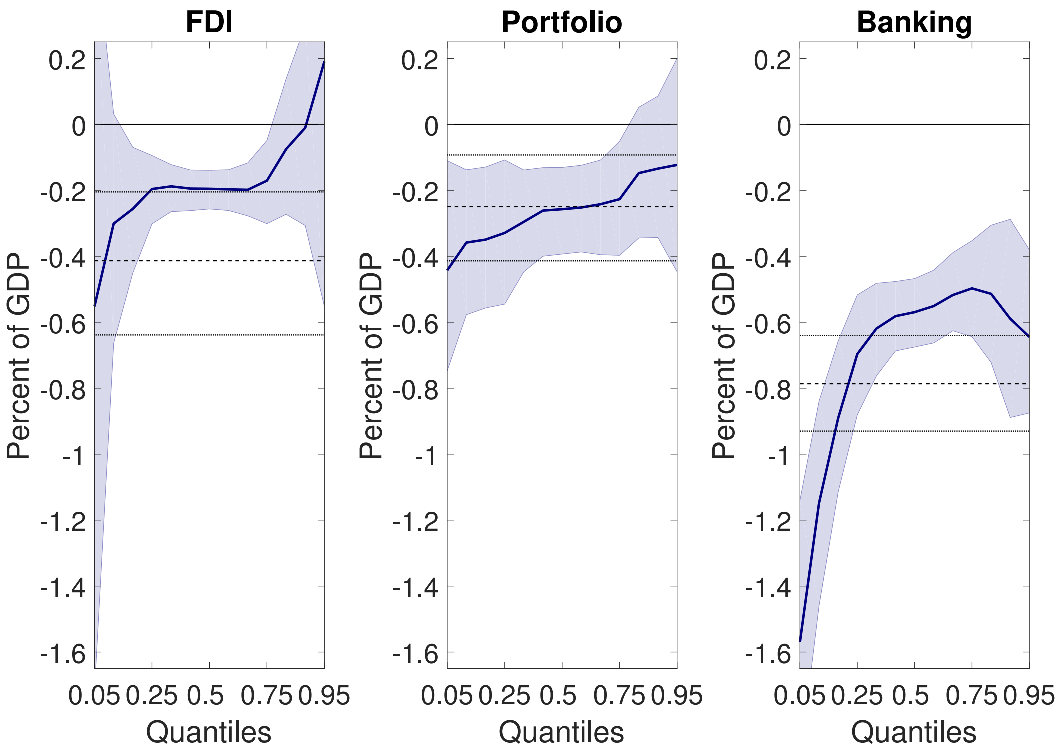
Note: The chart shows the estimated effect of a one standard deviation tightening in global financial conditions on the three different types of capital inflows across quantiles. The one standard deviation confidence intervals are based on block bootstrap methods following Fitzenberger (1998). Dashed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

positive banking inflows.

Overall, we find that the left tail of the distributions of portfolio and banking flows in the near term is affected by both global and local financial conditions. But there is a difference in relative magnitudes within 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.[17] 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, but not in banking flows. For an assessment of relative sensitivity to local and global conditions across types of flows, see Section 3.3

[17] 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.

Figure 3 Effect 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.

While our finding that push factors play an important role for risks of sudden stop episodes in gross inflows is in line with the existing literature, our result on the importance of pull factors for risks to both portfolio and banking flows seems to contrast somewhat with Forbes and Warnock (2012), who find no significant effect of pull factors. A possible explanation is that our local financial condition indices are orthogonalised with respect to global financial conditions. This might offer a cleaner identification of true 'pull' conditions than Forbes and Warnock (2012)'s use of untreated variables such as local GDP growth, which should be driven in part by global macroeconomic conditions. Moreover, our result on the importance of pull factors for banking flows is strongest in the far left tail, suggesting that pull factors may have a role in particularly severe sudden stop episodes. Traditional sudden stop prediction models, which effectively 'count' sudden stops without quantifying their severity, could miss this dimension.[18]

[18] An alternative explanation is that we do not control for spillovers between emerging market economies.

A further split of portfolio flows into those debt and equity-based (reported in Appendix C.3) highlights further heterogeneity in the effect of push and pull factors. While a tightening in the push-type factor leads to an increased risk of sharp outflows for both debt and equity flows, a tightening in the pull-type factor only has a significant effect on the left tail of the distribution of portfolio debt flows, but no significant effect on equity flows.

3.2 The conditional distribution of capital flows

The estimates reported so far speak to the partial effect on the conditional quantiles of the distribution arising from changes in our push and pull factors. One could also look at the resulting fitted distributions (which would give a more clear view of the overall magnitudes involved), and the resulting shifts arising from changes in these factors. Our quantile regressions from equation (1) provide us with estimates of the conditional quantile function, which is an inverse cumulative distribution function. Following the approach in Adrian et al. (2019), we map these estimates into a conditional probability distribution function by fitting the skewed t-distribution developed by Azzalini and Capitanio (2003):

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

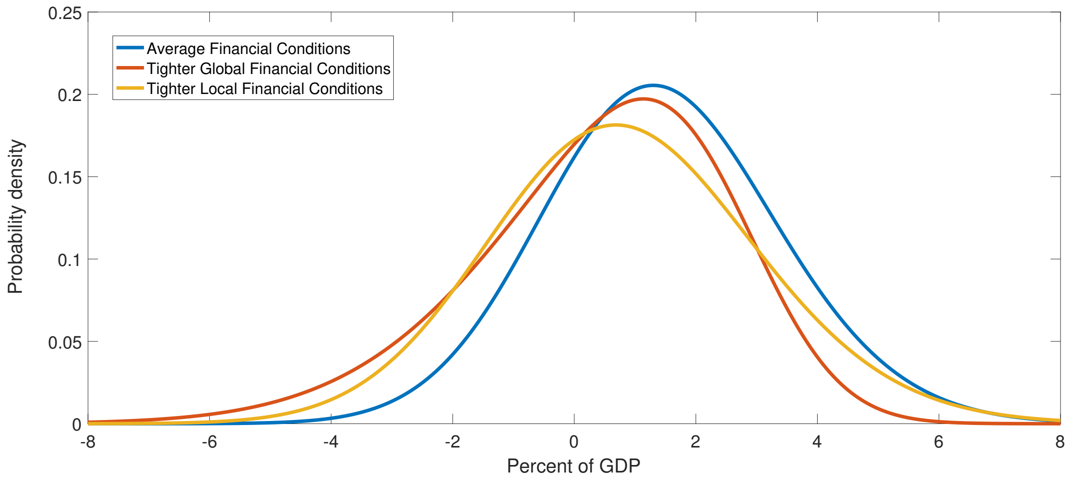
where t($\cdot$) and T($\cdot$) respectively denote the probability density function and the cumulative density function of the Student t distribution. The distribution's parameters determine its location μ, scale σ, fatness ν, and shape α.[19] An advantage of using the flexible skewed -t distribution is that it requires only limited parametric assumptions. For instance, if capital flows were normally distributed, we should expect to fit a normal distribution. But should the distribution of capital flows exhibit fat tails or skews, our estimation procedure is well-suited to model this as well.

The blue line in Figure 4 shows our estimated conditional distribution for gross portfolio inflows to an average emerging market in our panel when both global and local financial conditions are around their historic average. 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,

If, for example, local financial conditions in Brazil affect local conditions in Argentina above and beyond their respective co-movement with global conditions, our model could assign to pull factors what Forbes and Warnock (2012) would explicitly count as spillovers.

[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 $\nu = \infty$.

Figure 4 Conditional distributions of portfolio flows



Note: This chart shows fitted skewed t-distributions for portfolio inflows in the near term (current quarter plus next 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 right tail of the fitted distribution for portfolio flows in Figure 4 does not move 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 reduce both the lower quantiles and the upper quantiles of the distribution of portfolio inflows significantly, while the effect on the centre of the distribution is more moderate. Consequently, when global financial conditions tighten, both the right and the left tail of the distribution of portfolio inflows in Figure 4 shift to the left by more than the centre of the distribution (orange line). In other words, tighter global and tighter local financial conditions both increase the chance of sudden stops in portfolio flows (left tail events), but only tighter global financial conditions also reduce the likelihood of surges or 'bonanzas' in portfolio flows.

Figure 4 speaks to the benefits of the quantile regression methodology. By estimating quantile-specific effects, we can capture changes in the shape of the distribution of capital flows that go beyond changes in conditional mean or variance. Additionally, 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 exposure to push and pull factors

While results in Section 3.1 speak to the relative effect 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 size of these flows. However, one can think of alternative approaches to inform such comparisons. In this section we rely on relative entropy measures to quantify the divergence in the conditional distribution 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 a particular tail of the distribution when, say, global financial conditions tighten from their average level (the additional mass on the left tail of the orange distribution compared to the blue distribution in Figure 4). These measures can indeed 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 separately. In a second step, and for each type of flow and 'shock' separately, we measure the divergence between a particular tail of the distribution conditional on average financial conditions and that of the distribution conditional on tighter financial conditions. For each type of flow, we do this separately for global and local financial conditions, and for left and right tails. In order to quantify the divergence between distributions we make use of relative entropy measures, which are described in detail in Appendix D.3.[21]

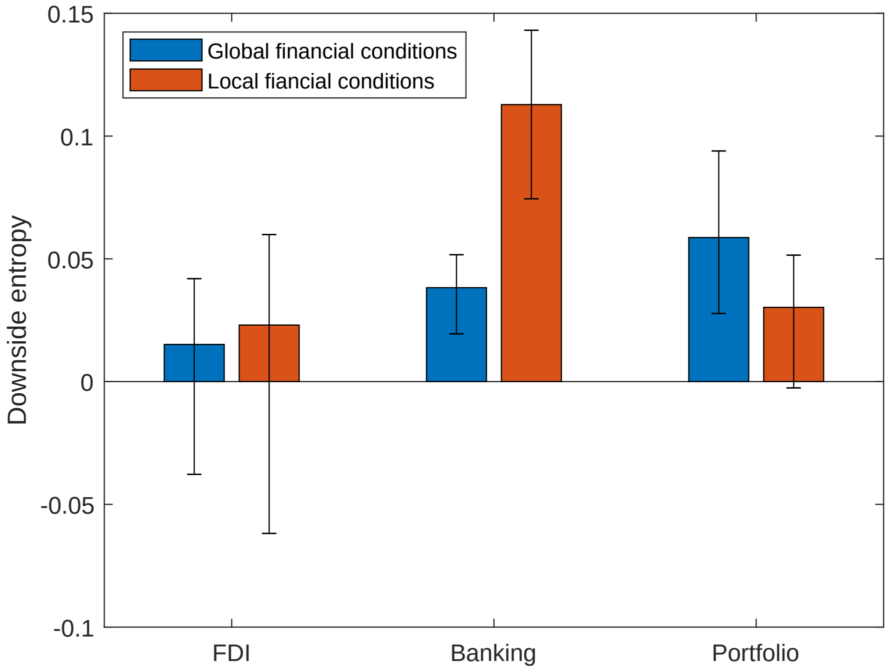
Figure 5 shows the results for the left tail of such distributions (typically called 'downside entropy'); that is, the additional probability mass assigned to the event of large capital outflows, quantified by the bars.[22] It can be seen that portfolio and banking flows concentrate most of the action, as the downside entropy of FDI flows is insignificant facing a tightening in both global and local conditions. In the face of 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 across these two is not statistically significant. In contrast, facing an increase in local financial conditions, downside entropy measures tell us that both types of flows faced an increase probability of sharp outflows, but that the reaction of banking flows is significantly stronger

[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, and by 'right tail' to the mass to the right of the 95th percentile.

[22]Upside entropy results can be found in Appendix C.4.

Figure 5 Exposure of capital outflows to push and pull factors



Note: This chart shows the downside relative entropy (divergence in mass to left of 5th percentile) between a distribution of a particular type of gross capital flow (as labeled in x-axis) conditioning on average financial conditions and (i) one with tighter global conditions (and average local conditions) in blue and (ii) one with tighter local conditions (and average global conditions) in orange. Bars correspond to point estimates, while lines indicate 68% confidence intervals.

than that of portfolio flows.

3.4 The term structure of push and pull factors

While results in Section 3.1 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 merit in exploring the informational content in terms of flows further into the future. In this section we do so by changing the starting point over which capital flows on the left-hand side of equation (1) are measured, leaving the right-hand side unchanged. For this purpose, we use a panel quantile version of the local projection method in Jorda (2005).[23] For simplicity we focus on portfolio flows here.

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

Appendix C.1 reports term structure results for banking flows and FDI. We do not find significant differences in the term structure of push and pull effects between portfolio flows and banking flows.

In order to keep the exposition clear, we need to lose one dimension when adding another. Hence, when introducing different horizons for the effect of push and pull factors on capital flows, we need to stop reporting results for the entire distribution but focus on a particular quantile instead. 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 fifth percentile, our measure of capital flows-at-risk).

As Figure 6 shows, the effect of global financial conditions on capital flows-at-risk is strongest in the near term and fades entirely within a year. Local financial conditions, in contrast, have a more persistent effect and only start to fade after two years.[24] This result reinforces our finding that, despite the strong and potentially growing role of push factors, local conditions remain an important determinant of capital flows.

Neither global nor local conditions exhibit a clear sign reversal at longer horizons, which Adrian et al. (2018) do find in the case of GDP-at-risk. 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. It is worth noting that the relatively short sample considered could play a role in making it difficult to unveil longer-term dynamics with a high degree of precision.

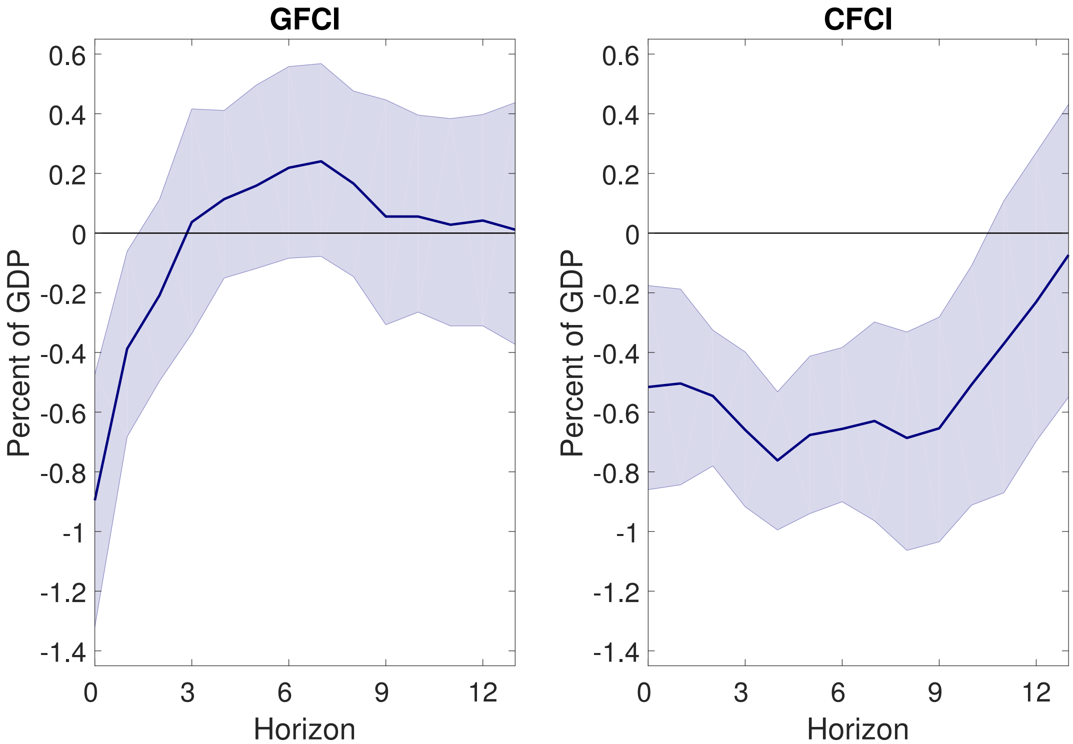
To summarise, changes in global as well as local financial conditions can change the shape of the distribution of capital flows, because different quantiles are affected in different ways. But the effects on all quantiles appear to fade at similar rates.

4 The Role of Policy

In this section, we analyse the informational content of capital flow management measures and macroprudential policies to characterise different quantiles of the distribution 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

[24] These results are robust to the inclusion of a lagged dependent variable as a regressor.

Figure 6 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 interval is based on block bootstrap methods following Fitzenberger (1998).

point in time.[25] 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 constitute '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 results should not be interpreted as the causal effect of a particular type of policy action on the distribution of capital flows, but instead as reporting potentially useful conditional correlations.

[25] The referred indices either measure the breadth of policies in place at a given point in time for a particular country (capital flow management), or the accumulation of past actions (macroprudential), so none constitutes a precise measure of the absolute policy stance.

4.1 Capital flow management measures

In this section we measure the conditional correlation of the overall stance of capital flow management (CFM) measures with the distribution of portfolio capital flows.

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 wide set of countries (including the 13 EMs which are the object of study of this paper). A clear advantage of these data, in contrast to other popular datasets, is that their granularity allow us to focus on measures that 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 report presence or not of controls across a series of categories, but not their magnitude. This means that a higher value of the CFM index represents a wider breadth of controls in place but does not necessarily speak to the strength of these controls.[26]

We extend our baseline model specification (1) with measures of controls on inflows and outflows for each country-time observation, lagged four quarters to reduce endogeneity concerns. Our analysis will focus on the coefficients associated with those variables (β_3 and β_4 in equation (3)); that is, their effect on the quantiles of the distribution of capital flows being modelled. 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 lead to misleading results otherwise. We also include interaction terms between our global financial conditions index and both CFM measures as additional explanatory variables.

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

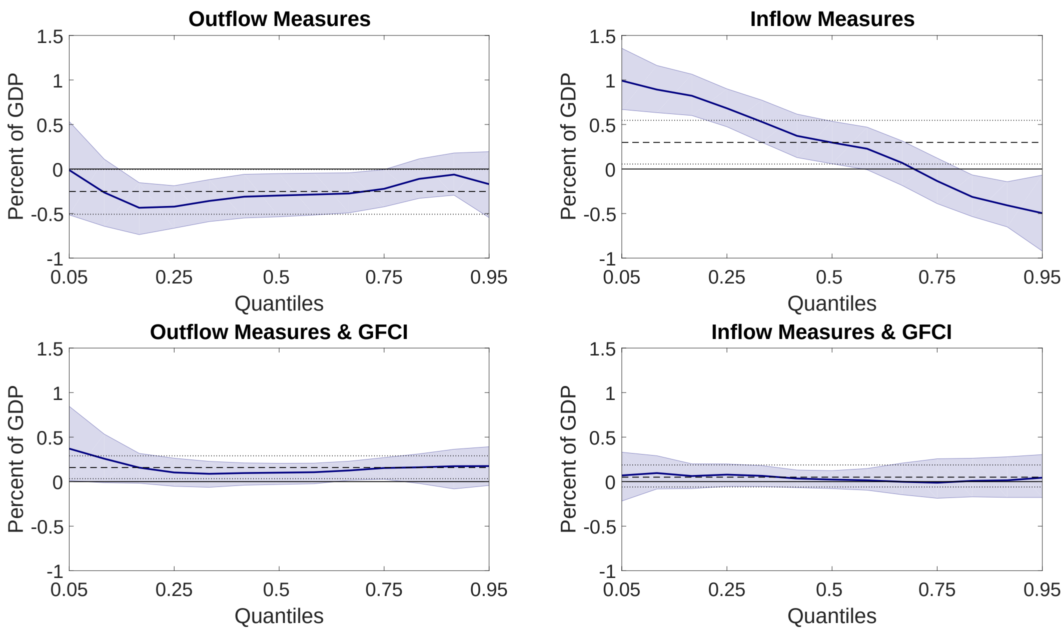
where $KAO_{i,t}$ and $KAI_{i,t}$ represent controls on non-resident outflows and controls on non-resident inflows, respectively, and the rest of the variables coincide with those in equation (1).

Both the country fixed-effects and the lagging of the policy variables partially reduce concerns about potential endogeneity, but results should still not be read in a causal way, as we do

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

not have a measure of 'true shocks' and actions could still be taken in response to changes in the outlook (which would also affect capital flows).

Figure 7 Effect of capital flow management measures



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

Figure 7 shows the effect 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. Higher 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. In contrast, controls on inflows significantly change the shape of the distribution of portfolio flows, with the larger effects focusing on the tails. In the face of tighter inflow controls, 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. The effect on the tails with a virtually unchanged median suggest an instance in which the benefits of quantile regression over mean-based approaches become clear.

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 previous literature is not straightforward given a difference in the nature of past exercises. The closest paper to ours in spirit is Gelos et al. (2019), as they also focus on the effect of capital flow management measures on capital flow 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 (similarly to the very small effects reported by Gelos et al. (2019), described below).[27] The contrast with the more nuanced results displayed in Figure 7 speaks to the importance of using granular CFM measures in this type of analysis.

More specifically, Gelos et al. (2019) do not report unconditional results for CFM measures but only their effect in the face of tighter global financial conditions, when they find that tighter controls have a very small but positive effect on the likelihood of large outflows. In terms of the rest of the literature, 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 to the extent that they find that tighter controls on inflows lead to a reallocation in portfolio shares away from the country implementing those measures.

[27] See Appendix C.5 for results.

4.2 Macroprudential policy

In this section we measure the conditional correlation of macroprudential policy measures with 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 particularly timely.[28] [29]

In order to quantify macroprudential activity we rely on the dataset of Cerutti et al. (2017), which measures the use of macroprudential policies in a large dataset of countries, including the 13 EMs under consideration in this study, over the period 2000-2014. The dataset focuses on the introduction 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.[30] In each quarter, the use of an additional measure across the instruments considered adds 1 to the index for that country, and the removal of a measure subtracts 1.[31] 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 indices are standardised using data across the entire sample.

As it is the case with CFM measures in Section 4.1, we extend our baseline specification (1) with measures of macroprudential policy for each country-time observation, lagged four quarters to reduce endogeneity concerns. Our analysis will focus on the coefficients associated with those variables; that is, their effect on the quantiles of the distribution of capital flows being modelled. 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 8 shows the impact of a one standard deviation increase in the macroprudential index

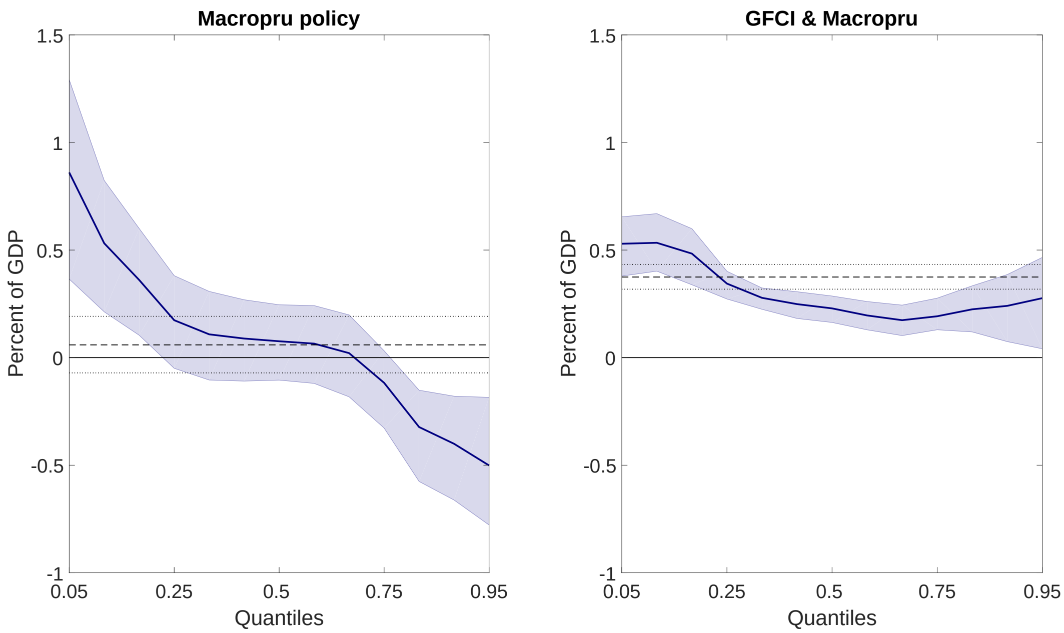
[28]Edge and Liang (2019) state that policy committees have been formed in 47 countries with this purpose in mind, many of which are EMEs.

[29]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)).

[30]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

[31]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.

Figure 8 The effect of macroprudential policy across quantiles



Note: The chart shows the effect of a one standard deviation increase in our index of macroprudential policy on the the distribution of portfolio capital flows from non-residents. The confidence interval is based on block bootstrap methods following Fitzenberger (1998). Dashed lines show the OLS estimates and dotted lines the associated one standard deviation confidence band.

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 at the left tail and significantly negative at the right tail, but are generally insignificant at the centre of the distribution.[32] 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. Once more, these results highlight the benefits of relying on a quantile-based approach in opposition to OLS, as well as providing tentative evidence supporting policymakers goals of increased stability.

The panel also shows the coefficient on the interaction term, which shows 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 consistent with

[32]This result is similar to Figure 7 showing the effect of capital flow measures on inflows. Both of these results are robust to a specification which includes the macroprudential policy index as well as the index of capital flow measures.

the theory that strong institutional frameworks are a factor that investors consider when allocating capital.[33]

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 prudential policy tightening reduces the sensitivity of mean banking flows to global volatility, through an interaction term of volatility and policy actions. 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 capital flows to these economies. These findings align with our results in Figure 8, which shows the interaction term is significant at the centre of the capital flows distribution (right panel), while policy without the interaction term is not (left panel). We extend this finding by showing that both variables are significant at 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 mean international banking flows in a simple specification. 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 bank flows. In contrast, we find that macroprudential policy has an effect on the tail of capital flows even without including an interaction term.

5 Conclusion

In this paper we provide a characterisation of the entire conditional distribution of a range of capital flow 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 also explore the informational content of

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

policy measures and uncover that capital flows to countries with (i) broader controls on inflows and (ii) tighter macroprudential stances display a 'narrower' distribution; that is, a lower likelihood of experiencing sharp outflow or sharp inflow episodes.

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A Appendix: Data

A.1 Capital flows

Our exercise is based on capital flows data for 13 emerging markets (Argentina, Brazil, Chile, Colombia, Hungary, India, Indonesia, Mexico, Peru, Philippines, Russia, South Africa and Turkey) between 1996 and 2018. We obtain quarterly data on gross capital inflows (net flows from non-residents) and gross capital outflows (net flows from 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 International Monetary Fund's World Economic Outlook database.

A.2 Financial condition indices

We construct financial condition 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.

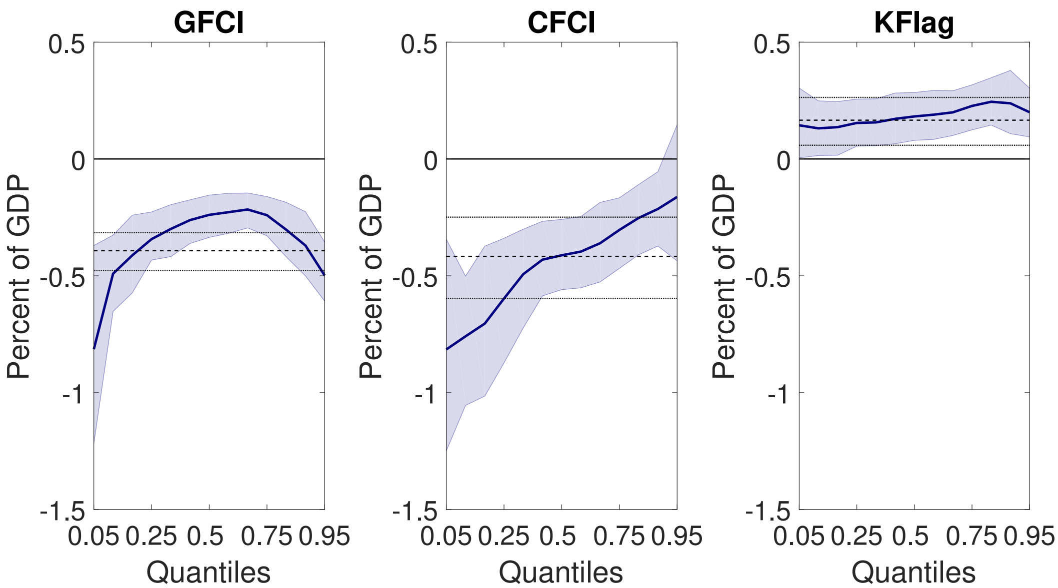
- Where available, we use JP Morgan's stripped sovereign spreads. For other countries, we use the spread between the 10-year sovereign yield and the reference country's 10-year sovereign yield. For most countries, we use the US as the reference. European spreads are reported relative to Germany, advanced 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. PPP weights are from the International Monetary Fund's World Economic Outlook database.

B Appendix: Robustness

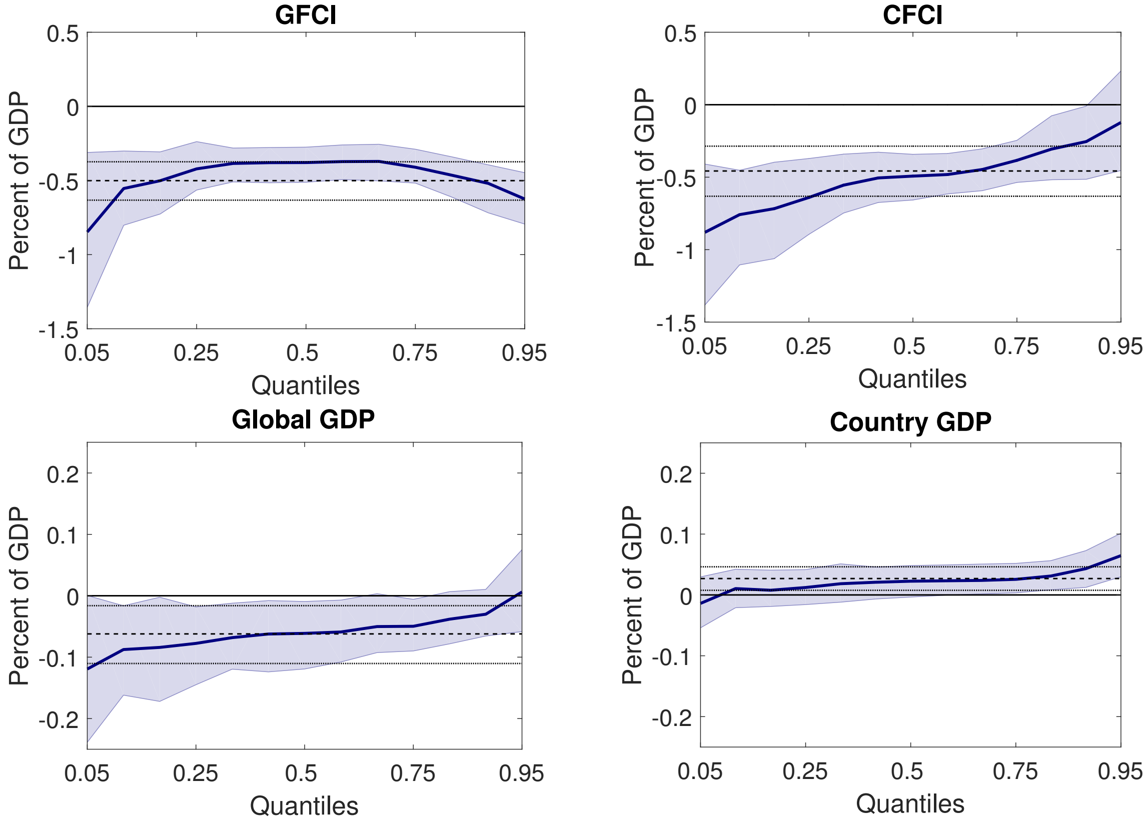
Quantile regressions place high demands on the data, which is why we keep the number of regressors as low as possible in our preferred specification. Nevertheless, this section documents that our core results are qualitatively robust to including lags of the dependent variable or GDP growth as independent variables.

Figure B.1 The effect of global and local financial conditions on portfolio flows, controlling for the first lag of portfolio flows



Note: The chart shows the estimated effect of a one standard deviation tightening in global and local financial conditions on portfolio flows. The one standard deviation confidence interval is based on block bootstrap methods following Fitzenberger (1998). Dashed lines show the OLS estimates and dotted lines the associated one standard deviation confidence bands.

Figure B.2 The effect of global and local financial conditions on portfolio flows, controlling for GDP growth

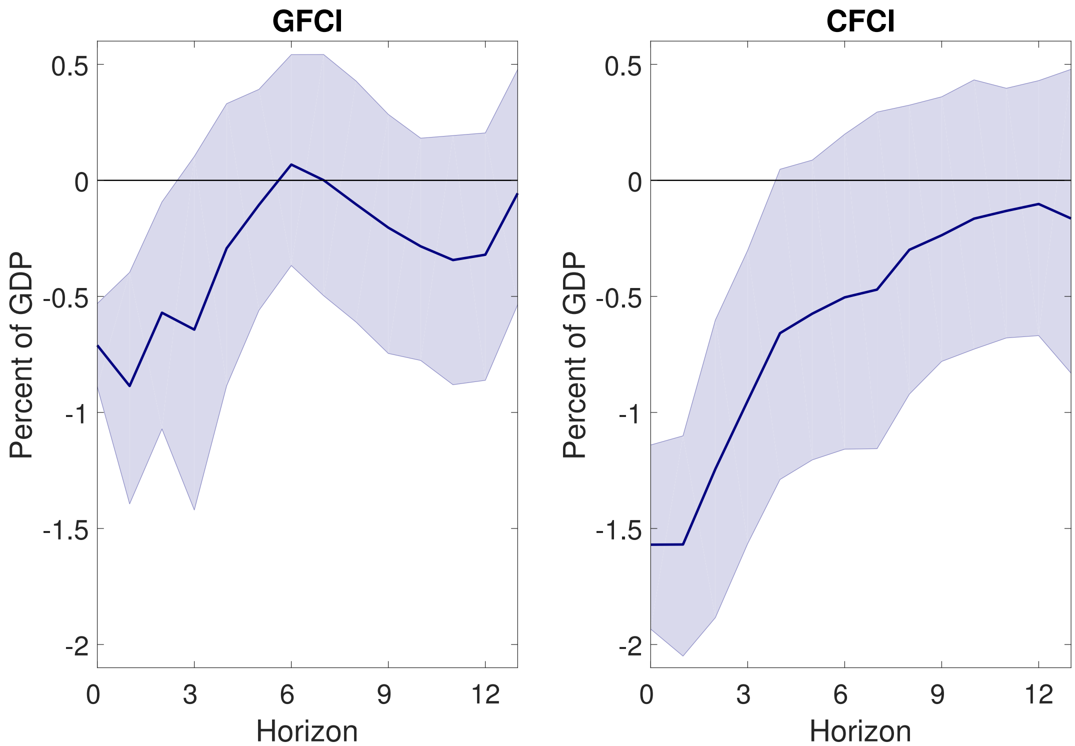


Note: The chart shows the estimated effect of a one standard deviation tightening in global and local financial conditions on portfolio flows. The one standard deviation confidence interval is based on block bootstrap methods following Fitzenberger (1998). Dashed lines show the OLS estimates and dotted lines the associated one standard deviation confidence bands.

C Appendix: Additional results

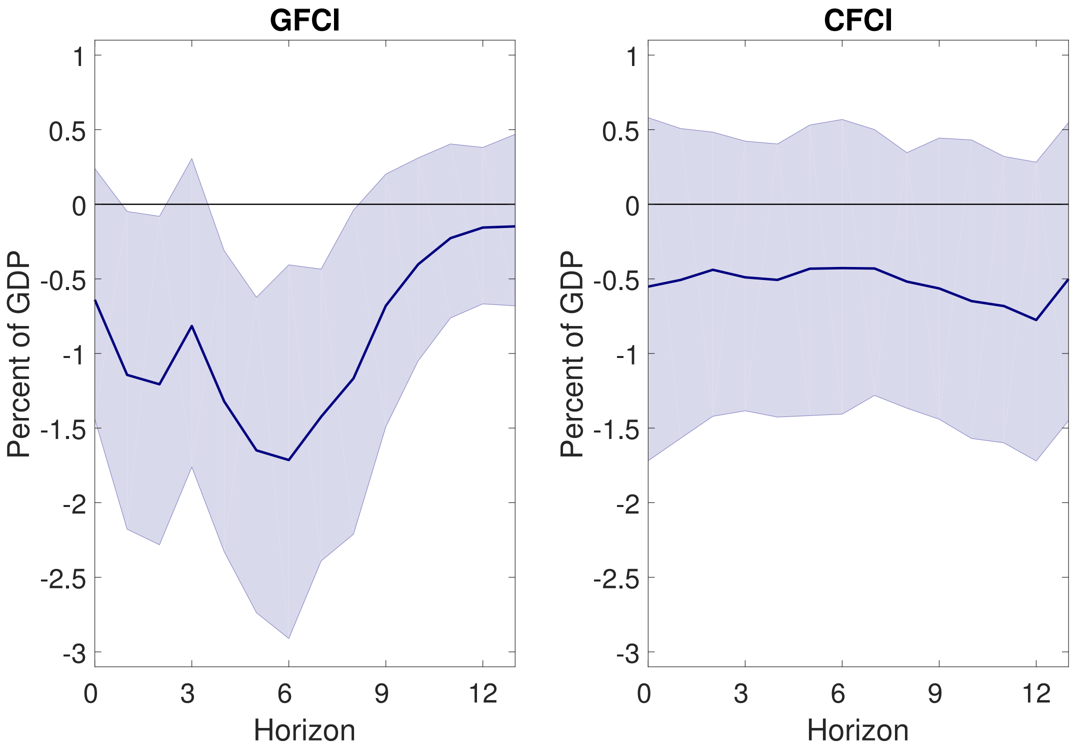
C.1 Term structure of banking and FDI flows

Figure C.1 Term structure of the effect of global and local financial conditions on the fifth percentile of banking flows



Note: The chart shows the estimated effect of a one standard deviation tightening in global and local financial conditions on the fifth percentile of banking flows across horizons. The one standard deviation confidence interval is based on block bootstrap methods following Fitzenberger (1998).

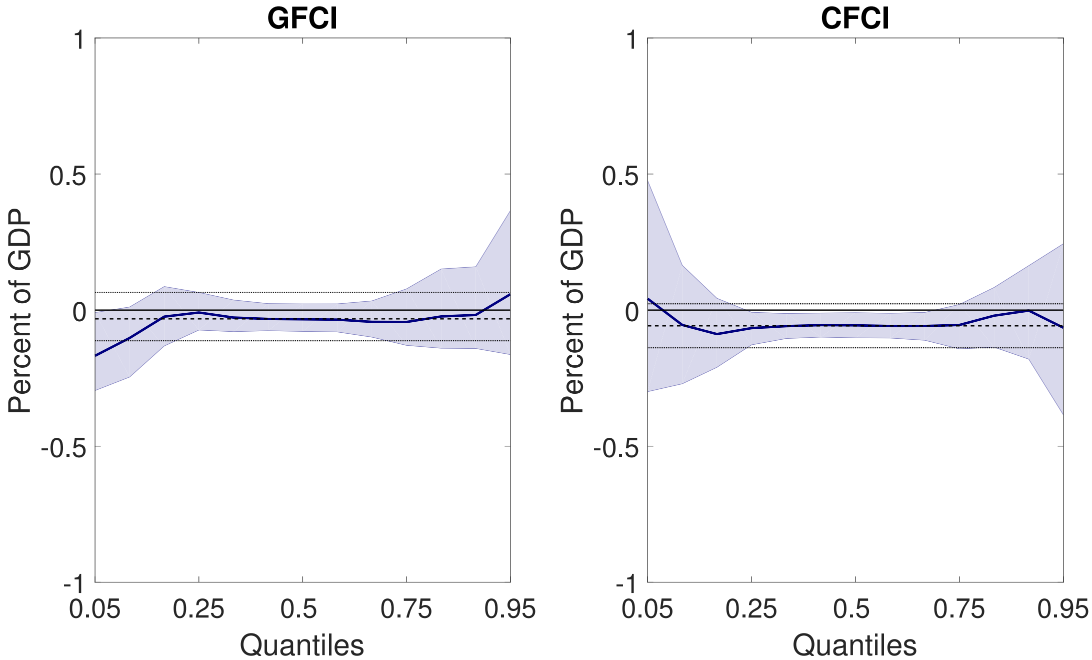
Figure C.2 Term structure of the effect of global and local financial conditions on the fifth percentile of FDI



Note: The chart shows the estimated effect of a one standard deviation tightening in global and local financial conditions on the fifth percentile of FDI across horizons. The one standard deviation confidence interval is based on block bootstrap methods following Fitzenberger (1998).

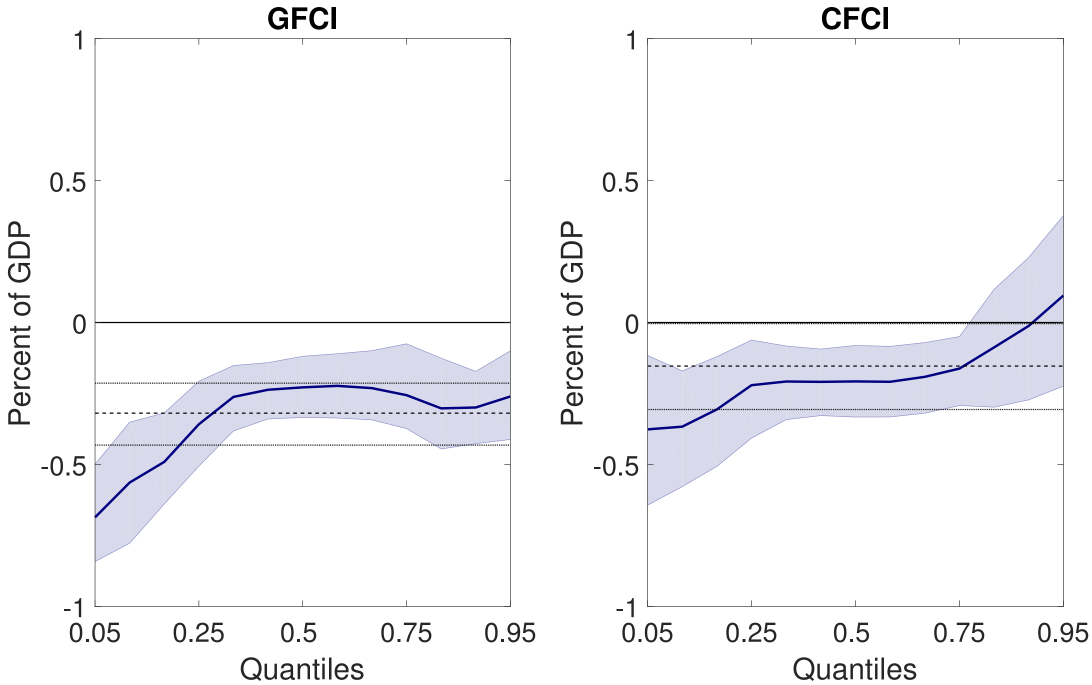
C.2 Resident flows

Figure C.3 The effect of global and local financial conditions on resident portfolio flows



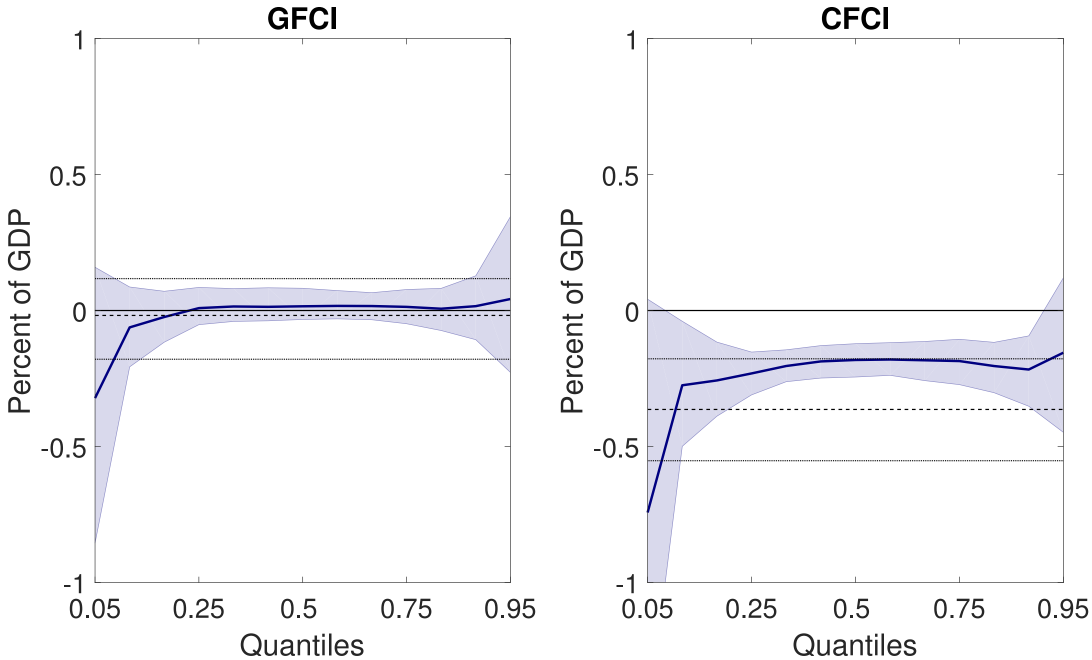
Note: The chart shows the estimated effect of a one standard deviation tightening in global and local financial conditions on resident portfolio flows (i.e. gross portfolio outflows). The one standard deviation confidence interval is based on block bootstrap methods following Fitzenberger (1998). Dashed lines show the OLS estimates and dotted lines the associated one standard deviation confidence bands.

Figure C.4 The effect of global and local financial conditions on resident banking flows



Note: The chart shows the estimated effect of a one standard deviation tightening in global and local financial conditions on resident banking flows (i.e. gross banking outflows). The one standard deviation confidence interval is based on block bootstrap methods following Fitzenberger (1998). Dashed lines show the OLS estimates and dotted lines the associated one standard deviation confidence bands.

Figure C.5 The effect of global and local financial conditions on resident FDI

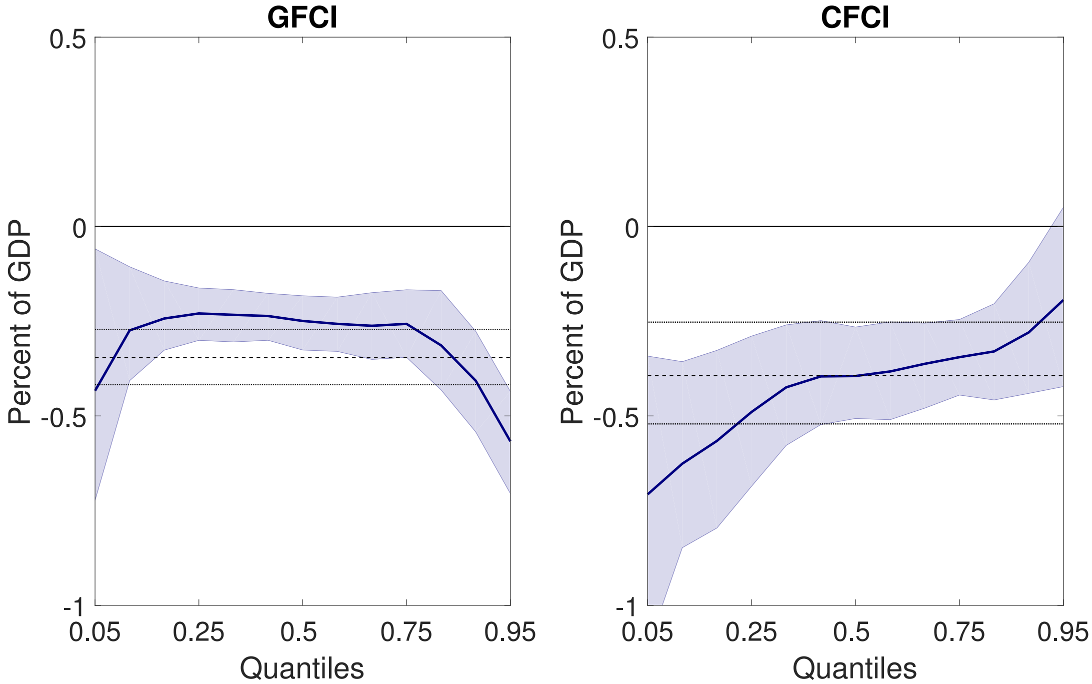


Note: The chart shows the estimated effect of a one standard deviation tightening in global and local financial conditions on resident banking FDI (i.e. gross FDI outflows). The one standard deviation confidence interval is based on block bootstrap methods following Fitzenberger (1998). Dashed lines show the OLS estimates and dotted lines the associated one standard deviation confidence bands.

C.3 Debt and Equity flows

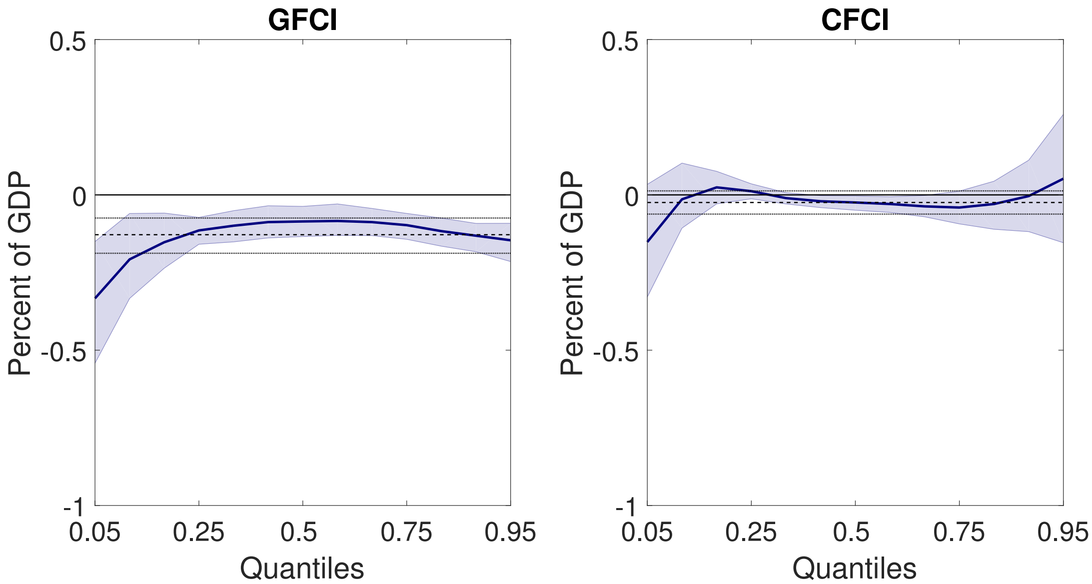
Several papers (e.g. Gelos et al. (2019)) have highlighted that portfolio debt flows and portfolio equity flows may show differential responses to push and pull factors. As figure C.7 shows, we find the left-tail response of equity and debt flows to be quite similar, with both contributing to a sharp increase of sudden stop risk when global financial conditions tighten. However, portfolio debt flows seem to respond more strongly than portfolio equity flows to push factors in the right tail.

Figure C.6 Effect of global and local financial conditions on portfolio debt flows



Note: The chart shows the estimated effect of a one standard deviation tightening in global financial conditions on portfolio debt flows. The one standard deviation confidence interval is based on block bootstrap methods following Fitzenberger (1998). Dashed lines show the OLS estimates and dotted lines the associated one standard deviation confidence bands.

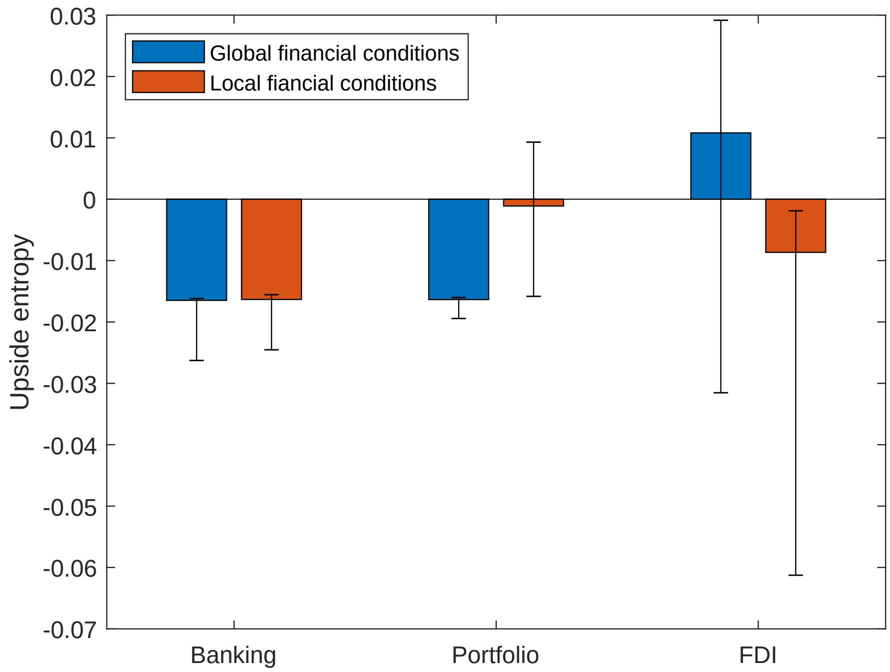
Figure C.7 Effect of global and local financial conditions on portfolio equity flows



Note: The chart shows the estimated effect of a one standard deviation tightening in global financial conditions on portfolio equity flows. The one standard deviation confidence interval is based on block bootstrap methods following Fitzenberger (1998). Dashed lines show the OLS estimates and dotted lines the associated one standard deviation confidence bands.

C.4 Upside entropy

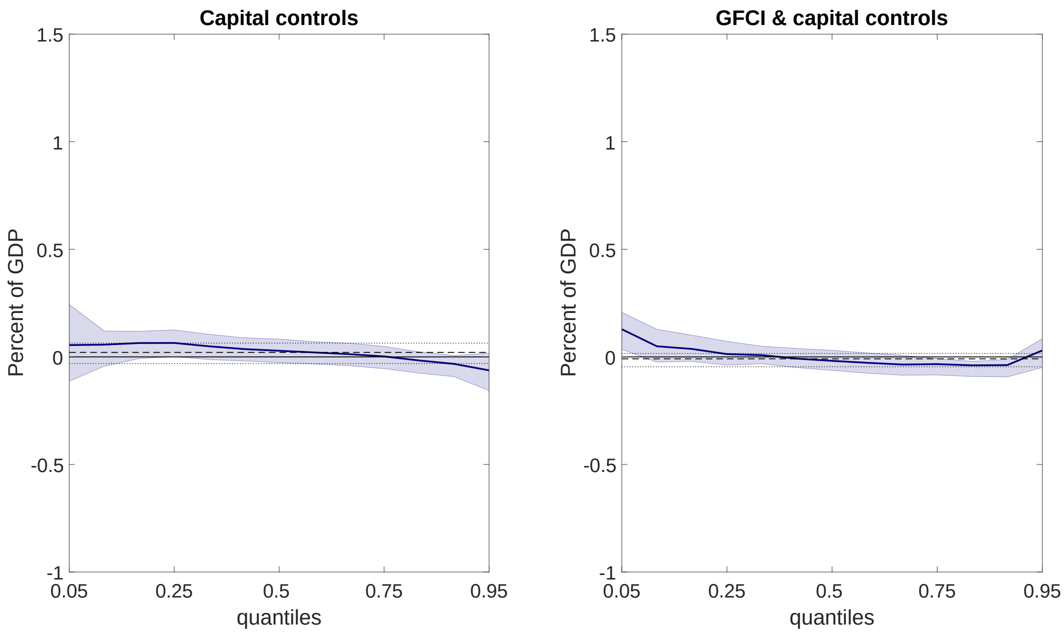
Figure C.8 Exposure of capital outflows to push and pull factors



Note: This chart shows the upside relative entropy (divergence in mass to the right of the 95th percentile) between a distribution of a particular type of gross capital flow (as labeled in x-axis) conditioning on average financial conditions and (i) one with tighter global conditions (and average local conditions) in blue and (ii) one with tighter local conditions (and average global conditions) in orange.

C.5 Aggregate Capital Flow management measures

Figure C.9 Effect of capital flow 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 interval is 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 Technical Appendix: Quantile regression, bootstrapping and relative entropy

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

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

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 $\hat{u_i}^{(0)}(\tau) = y_i - x_i\hat{\beta}^{(0)}(\tau)$ and construct a diagonal matrix of weights $w^{(t)}, t > 0$, whose diagonal elements are given by

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

We then obtain an updated estimate $\hat{\beta}^{(t)}(\tau)$, residuals $\hat{u}^{(t)}(\tau)$ and weights $w^{(t+1)}(\tau)$ using weighted least squares:

$$\hat{\beta}^{(t)}(\tau) = \left(x'w^{(t)}(\tau)'\,x\right)^{-1} x'w^{(t)}(\tau)'\,y$$

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 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.

The procedure works as follows: letting $z_t = [y_t, x_t]$ denote the original data, T the sample size and b a suitably chosen block length, a resample z^*_{it} 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^*_{it} yields an estimate of the quantile regression coefficients $\hat{\beta}^*_i(\tau)$ and can be used to compute all other statistics of interest, such as $\hat{V}_i(\tau)$ and thus $R^1(\tau)$ etc. Confidence intervals at level γ for $\hat{\beta}(\tau)$ and other quantities of interest are computed as

$$\left(2\hat{\beta}(\tau) - \hat{\beta}^*_{\frac{1-\gamma}{2}}(\tau), 2\hat{\beta}(\tau) - \hat{\beta}^*_{\frac{\gamma}{2}}(\tau)\right) \tag{D.3}$$

where $\hat{\beta}^*_p(\tau)$ denotes the $p-$th percentile of the bootstrapped draws $\hat{\beta}^*_i(\tau)$[34].

D.3 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

[34] In the computation of confidence intervals for $R^1(\tau)$ we instead compute directly percentiles from the bootstrapped draws to ensure non-negative values.

financial conditions, we compute downside and upside (relative) entropy outside of the central part of the distribution of $\hat{g}(x)$ as

$$\mathcal{L}^D = \int_{-\infty}^{\hat{G}^{-1}(0.05)} \log\left(\frac{\hat{f}(x)}{\hat{g}(x)}\right)\hat{f}(x)dx \tag{D.4}$$

$$\mathcal{L}^U = \int_{\hat{G}^{-1}(0.95)}^{\infty} \log\left(\frac{\hat{f}(x)}{\hat{g}(x)}\right)\hat{f}(x)dx. \tag{D.5}$$

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).