Bond Flows at Risk: Global, Local, and Pipes Factors in Latin America[1]

Manuel Ramos-Francia
CEMLA

Santiago García-Verdú
Banco de México and CEMLA

Manuel Sánchez-Martínez
Banco de México and CEMLA

Serafín Martínez-Jaramillo
Banco de México and CEMLA

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Abstract

We estimate bond flows' densities and bond flows at risk, for Brazil, Chile, Colombia, Mexico, and Peru, based on quantile panel regressions. We do so as functions of global (push), local (pull), and so-called pipes factors. The local factor plays a comparable role across the intermediate quantiles of the densities, whereas the global factor is more relevant for their left tail. The pipes we explore affect such densities significantly. In addition, central to this study is whether the sensitivity of the bond flows' densities to changes in the global variable is regime dependent. Our findings indicate that under a low-volatility regime, such a sensitivity is small and, for some quantiles, nonexistent. Under a high-volatility regime, its magnitude increases markedly, particularly, for the left tail of the density. In addition, we propose a statistical divergence between densities to quantify the relative importance of the factor shocks affecting bond flows densities. Finally, we examine bond flows densities under some of the policies that central banks have undertaken in response to the COVID-19 crisis, providing evidence for their effectiveness.

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1. Introduction

It is worth describing from the outset why there has been a keen interest in capital flows since the Global Financial Crisis (GFC). This interest has had, at least, two major aspects. The first aspect entails the capital flows' level and volatility, while the second one relates to the remarks made by policymakers and the policy responses to capital flows along these years. The GFC was a watershed for capital flows worldwide. It has had profound economic and financial implications.

Consider how the patterns of capital flows, relative to GDP, have changed (García and Stracca, 2021). Bank loans diminished after the GFC, and have not recovered since then. This has been part of a substantial shift in the composition of capital flows. For their part, equity and bond flows have kept a relatively lower level. With respect to emerging market economies (EMEs), capital inflows have been maintained. Asian EMEs have led as major recipients of capital flows. Although capital flows have slowed down during some periods, these events have been transitory. In any case, their pre-GFC positive trend was substituted by a volatile dynamic.

Latin America saw its level increase in 2010, relative to pre-GFC, and since then, has maintained a fairly volatile dynamic. What is more, the capital flows' configuration has been transformed. Similarly, an important shift has taken place in the flows' composition, specifically from bank to investment funds' intermediation. As we have argued, this reflects the transformed nature of the players behind capital flows.

The second major aspect is the remarks made by policy makers and the policy responses along these years, in the case of both capital inflows and outflows. In this context, we underline the possibility of capital flows extreme events. Remarks by officials conveyed the zeitgeist at the time, especially in the years following the GFC. In effect, they coined terms such as "competitive easing", "currency wars," and "liquidity tsunamis." Capital flows earned a bad name, as some policymakers highlighted their costs and none of their benefits.

As for the policy responses, for instance, in the case of significant capital inflows, as a first response the exchange rate could be allowed to appreciate (see, e.g., IMF, 2012). This, however, could lead to unwarranted tight monetary conditions. Having to deal with real exchange rate misalignments is also a potential issue.

For their part, macroprudential policies have been considered as an option for dealing with capital flows. Post-GFC, such policies gained attention for several reasons. From the theoretical perspective, papers such as those by Korinek and

Sandri (2016) and Mendoza (2016), explore the role of macroprudential policies in dealing with financial amplification mechanisms, owing to global spillovers, including capital flows. The latter paper underscores the inherent challenges in implementing macroprudential policies in practice effectively.

The possible materialization of an extreme capital flows scenario has been an acute concern for investors and policy makers alike. Given the characteristics of financial markets in EMEs, on the one hand, capital inflows can lead to pressures on the real exchange rate, unwarranted changes in relative prices, and unsustainable shifts in credit supply, among others. On the other hand, abrupt capital outflows have the potential to generate financial disruptions, increase liquidity risk in EMEs and, at times, lead to full-fledged crises (Calvo, 1998).

In this context, an interest in understanding the determinants of capital flows has been intense. One potential approach classifies them into three types of factors: push (global), pull (local), and pipes. Their main features are worth recapping (García and Stracca, 2021). First, push or global factors incentivize investors to seek opportunities beyond their country of residence. Importantly, they are exogenous to the recipient economies, which has policy and econometric implications. They relate to global economic and financial conditions, in particular, those that have a bearing on funding and its cost.

Second, pull or local factors reflect the characteristics of the recipient economy that have a role in enticing global capital. They capture the risk-return profile that the economy provides to global investors. For instance, economic growth, and sovereign debt rating are considered pull factors.

Third, pipes factors refer to the infrastructure through which capital flows transit. They encompass many aspects, from the nature of the financial intermediaries that manage them to the regulations they need to follow. It is worth highlighting that, pipes at times, not only interact with each other but also with other factors.

We would like to underscore the following features of pipes. They tend to be more relevant in EMEs, as their financial markets are shallow. However, pipes have, however, been important on some occasions in AEs. Consider that they can contribute toward herd-like dynamics of capital flows due to the presence of asymmetric information, informational cascades, and/or rational speculative bubbles among investors could be present and intensify such dynamics.

Similarly, pipes can exacerbate capital flows' volatility considerably, and increase liquidity risk intensely. For instance, a significant portion of asset trading takes place on anonymous automatic electronic platforms and trading is done by algorithms (Nagel, 2016), which in times of financial stress tend to be net liquidity demanders.

A quid to understand capital flows is that their determination depends on several elements that operate concurrently. Accordingly, to gain a better understanding of their general equilibrium aspects, one can contextualize them by alluding to a Global Monetary Game (Feroli et al. 2014, Morris and Shin, 2014), a useful approach for understanding capital flows´ dynamics.

In this game, the main players are active investors who compete against each other and are averse to ranking last due to, for example, reputational concerns. They can invest their capital in a risk-free asset of a core economy (e.g., an AE) or in a risky asset of the economies on the periphery (EMEs).[2] The risk-free return depends on the monetary policy stance in the core economy.

For its part, the risky asset price depends not only on the peripheral country´s domestic monetary policy rate, but also —and crucially— on the active investors' positions in this asset. This feature can be motivated by the shallow financial markets in EMEs. Thus, their financial market characteristics, combined with an aversion to ranking last on the part of the active investors, makes herd-like dynamics more likely, which can in turn affect bond flows' densities in substantial ways.

Relatedly, for the past few years, most AEs' central banks have maintained a very accommodative monetary stance. With some exceptions, the setting has been characterized by abundant global liquidity and, accordingly, a very active search-for-yield by global investors. Some of such exceptions have been the European Debt Crisis, the Taper Tantrum, the Brexit Referendum, and the COVID-19 financial turmoil in early 2020.

Nevertheless, currently, a global policy pivot seems to be taking hold, making it likely that several AEs' central banks will eventually move toward normalizing their monetary policy stances. Most importantly, some of this already seems to be already taking place in the U.S., which has had recent episodes of inflation jitters. A lively debate on the persistence of inflation has ensued.

[2] Feroli et al. (2014) consider a closed economy, so in their model the risk-free asset and risky asset are within the same economy. Thus, our interpretation here is more general. We have assumed the existence of AEs and EMEs in which global investors can allocate their capital in a risky asset. In addition, we have assumed the existence of monetary authorities in both economies.

Against this backdrop, we examine bond flows' densities in five economies in the Latin American region, which we denote by LAC-5. Our main contributions are as follows. First, we focus on the role of pipes, particularly on how they affect bond flows´ densities. Pipes factors are of concern for EMEs, as the infrastructure of their financial systems is not as developed as that of AEs. These factors also interact with others and, in many cases, could lead to an increase in liquidity risk. Now, given our interest in pipes factors, we have used a weekly frequency, at which such factors should have a more relevant bearing.

Second, we explore whether the global factor follows a regime-switch, which would affect the sensitivity of bond flows' densities to such a factor. To the best of our knowledge, this is the first paper to contemplate whether a regime switch might affect bond flows' densities.[3] In addition, taking a hint from the Jensen–Shannon divergence, we put forward a statistical divergence to quantify the relative contribution of the global factor and regime switching to bond flows' densities.

Third, we consider some more general models that could explain our results. We believe this provides a richer structure, which is useful to gaining a better understanding of the factors affecting capital flows, in general, and bond flows in particular.

In sum, whereas other papers have focused on the dynamics of capital flows in terms of local and global factors, macroprudential policies and capital control management, relatively less attention has been paid to pipes and to the changing nature of global factors.

2. An Abridged Literature Review

Given the considerable benefits and costs that capital flows entail, the literature has paid attention to the factors determining their dynamics. For instance, Cerutti et al. (2015) examine capital flows in terms of global factors, also known as push factors and those that are local, also known as pull factors. Under such a characterization, policy makers, in principle, be interested in two matters: the extent to which they could decrease their economies' sensitivity to adverse global factors, and whether they could positively affect local factors.

[3] García and Stracca (2021) argue that pipes affect capital flows sensitivity to other factors. Thus, our exercise can also be seen as an exploration of pipes.

On the econometric model, we have the following remarks. Adrian et al (2019) propose the concept of growth at risk (GaR), which is similar to that of the value at risk (VaR). While the former refers to economic growth, the latter typically refers to the value of a company or the value of an investment portfolio. To operationalize GaR, they use quantile regressions. In particular, they estimate the effects of the local financial conditions on the density of GDP growth. They document that the lower quantiles of the economic growth densities are more susceptible to financial conditions. Adrian et al (2019) contend that macroeconomic conditions are not sufficient to obtain a differentiated effect across the associated quantiles.

The applications of quantile regressions in the economic literature are numerous. We would like to highlight the following ones: i) the differentiated effect on the wage distribution in terms of unionization levels -not all wage levels are affected similarly (e.g., Chamberlain, 1994); ii) the estimation of returns to education, whereby educational outcomes depend on several characteristics, a degree might be beneficial to most, but unfavorable to some individuals (e.g., Arias et al, 2002); (iii) the consideration of heterogeneous elasticities of consumption (e.g., Deaton, 1997); and, the economics of wealth distribution and inequality (e.g., Conley and Galenson, 1998; Gosling et al., 2000).

Close to this paper, Gelos et al (2019, 2021) use quantile regressions to estimate the probability distribution of capital flows to EMEs, based on current domestic and global financial conditions. They find that FX and macroprudential policies mitigate downside risks to portfolio flows due to adverse global shocks. They examine the implications of some factors that relate to pipes, such as financial depth.

For their part, Eguren-Martin et al. (2020, 2021) obtain the distribution of capital flows for an EMEs' panel, conditional on information contained in financial assets. They use quantile regressions to examine push and pull factors, which they estimate with principal component analysis, to find that the effects across the distribution of capital flows are heterogeneous. These authors document that the effects of pull factors are more persistent than those associated with push ones are, and the macroprudential and capital flows management measures are associated with changes in such densities.

Norimasa et al. (2021) use panel quantile regression to examine the risk of capital outflows for several EMEs. Their analysis shows that changes in financial conditions in AEs and in the U.S. monetary policy stance affect the risk of capital outflows for some economies. Using government debt as a measure of vulnerability, they find that a rise in government debt increases the risk of capital outflows in times of

financial stress. We will compare our key results with the main ones in Gelos et al (2019), Eguren-Martin et al (2020), and Norimasa et al (2021).

3. Data, Model, and Fitting the Densities

3.1 Data

We have a keen interest in understanding the underlying factors behind bond flows dynamics in Latin America. To explore them, we estimate panel quantile regressions that include Brazil, Chile, Colombia, Mexico, and Peru. This is a sensible approach, because these economies concentrate the largest volume of capital flows in the region, and their bonds can be characterized as an asset class.

We use weekly bond flows data from EPFR Global from January 7, 2004 to January 27, 2021. These measures are based on surveys.[4] Their use could be questioned on the grounds that they do not account for total bond flows. In particular, they do not match other data sources that incorporate more information, such as the BOPs' statistics.

However, while their levels certainly do not match, EPFR Global provides indicators that are timely measures of bond flow dynamics. In effect, investors and portfolio managers can have prompt access to them. In contrast, for instance, official macroeconomic statistics are accessible at a lower frequency and are published only with a considerable time lag.

We focus on bond flows for a plethora of reasons. They are more fickle than equity flows are and more so than foreign direct investment (FDI) is. Bond flows are more responsive to changes in monetary policy stances (Ramos-Francia et al. 2017), a feature we in which are interested. Centrally, government bond prices are fundamental for financial asset prices in an economy, particularly so in EMEs. Accordingly, they should also be of interest for financial stability reasons.

[4] Three comments are in order. First, according to EPFR Global's description we have: "[…] EPFR helps financial professionals understand where money is moving, how fund managers are investing that money, and what impact those shifts are having on geographies, sectors, industries and securities." Second, their data are aggregated from more than 135,000 traditional and alternative funds domiciled globally, from approximately $49.5 trillion AUM of EPFR-tracked assets. Third, gross inflows are net sales of domestic financial instruments to foreign residents. Gross outflows are net purchases of foreign financial instruments by domestic residents. Net capital flows are the difference between gross inflows and gross outflows. Our database captures sales and purchases of domestic financial instruments to and by foreign residents.

In our paper, we use the following as explanatory pull and push factors: the difference between the 10-year local term premium (Ramos-Francia et al., 2020) and the U.S. term premium (Adrian et al., 2013) is used as a proxy for an all-encompassing pull factor, while the VIX index is used as a corresponding push factor. While the alluded difference is not purely local because it depends on the U.S. term premium, it can be interpreted as a proxy to a measure of the marginal contribution to the risk of adding local bonds to a U.S. bond portfolio. From a macroeconomic perspective, the term premium contains information on inflation, fiscal, and liquidity risks. We did not include more regional economies because we were not able to obtain the data to estimate the term premiums for more of them.

The VIX is the implicit volatility of one-month maturity options on the S&P 500 index. The volatility of the underlying asset is a key parameter for the value of any financial option. The implicit volatility of an option is the value of the volatility parameter such that the theoretical price of the option matches its market price. We use it as a measure of global or push factors. The VIX is widely seen as a measure of global investors' risk-appetite. It has been used to explain global financial conditions. For instance, Rey (2015) uses this index as an indicator of the global financial cycle.

The EPFR Global bond flows have a weekly frequency. EPFR data points have their date stamp on Wednesdays. Their datum measures bond flows from Thursdays to Wednesdays. Thus, we consider the average of the daily data from the previous Thursday to the respective Wednesday. For comparison purposes, we divide the time series by their respective standard deviations. This is somewhat similar to the standardization with GDP when considering data at lower frequencies (as in, e.g., Gelos et al., 2019). We consider movements of such variables in terms of their common deviations.[5]

In some cases, we explore the bond flows' densities for individual economies of Brazil, Chile, Colombia, Mexico, and Peru. These are useful for comparison purposes.

[5] Standard deviations of the time series. Bond flows (mill. USD): BRA 138.06; CHI 28.26; COL 119.88; MEX 118.25; and PER 33.15. Term premium differences (%): BRA 1.96; CHI 0.72; COL 0.93; MEX 0.92; PER 1.12. VIX index (points): 9.07. Proportion of local currency debt held by non-residents (%): BRA 3.9; CHI 6.2; COL 10.5; MEX 8.4; and PER 10.7. Changes in international reserves excluding gold (mill. USD): BRA 4,426.7: CHI 976.5; COL 395.9; MEX 2,506.0; PER 951.4. EMTA bond trading volume (bill. USD): 224.4.

3.2 The Model

To obtain the bond flows densities, we use panel quantile regressions. As discussed, (e.g., in Koenker and Hallock, 2001), such regressions allow one to examine the effects that the explanatory variables have across a distribution and not only, for example, on the mean, as more common models do. Such a model also allows considering of different forecasting horizons. That being said, we focus on the current distribution and, in some cases, consider a one-week horizon. More concretely, a quantile regression is a statistical method that estimates conditional quantile functions; that is, "*[M]odels in which quantiles of the conditional distribution of the response variable are expressed as functions of observed covariates*" (Koenker and Hallock, 2001).

The regression for the τ th quantile is estimated by minimizing the sum of the tilted absolute residuals:

$$\widehat{\boldsymbol{\beta}}^{(\tau)} = \underset{\boldsymbol{\beta} \in R^k}{\operatorname{argmin}} \sum_{t=1}^{T} \rho_\tau\left(Y_{t+h} - \boldsymbol{X}_t \boldsymbol{\beta}^{(\boldsymbol{\tau})}\right)$$

where $\rho_\tau(\cdot)$ is the tilted absolute value function, which penalizes positive deviations by τ and negative deviation by $(1-\tau)$; Y_{t+h} is the dependent variable $h \in \mathbb{N}$ periods ahead and $\boldsymbol{X}_t$ is a vector of k independent variables, with $t = 1, \ldots, T$. For instance, in the case of the median, the function $\rho_{0.5}(\cdot) = |\cdot|/2$ allocates equal weights to negative and positive deviations. If $h = 0$, then the quantile regression infers a descriptive distribution of Y_t; and if $h > 0$, then the regressions imply a distribution of Y_t at some point in the future. Again, we consider $h = 0$ and, in a few cases, $h = 1$ week.

Computationally, this optimization problem is equivalent to minimizing the following linear function:

$$\begin{cases} Min_\beta \sum_t^T \rho_\tau(\epsilon_t) \\ \epsilon_t = Y_{t+h} - \boldsymbol{X}_t \boldsymbol{\beta} \; \forall t \end{cases} = \begin{cases} Min_{\boldsymbol{\beta}} \sum_t^T (\tau \epsilon_t^+ + (1-\tau)\epsilon_t^-) \\ \epsilon_t^+ - \epsilon_t^- = Y_t - \boldsymbol{X}_t \boldsymbol{\beta} \; \forall t \\ \epsilon_t^+, \epsilon_t^- \geq 0 \end{cases}$$

We describe our benchmark panel model for the conditional quantiles of bond flows h periods ahead: KF_{t+h} as a function of the VIX and the term premium differences. Then, our model is as follows.

$$Q_{KF_{t+h}\,|\,VIX_t, TP_i - TP_{US}}\left(\tau \middle| VIX_t, TP_i - TP_{US}, \boldsymbol{P_{i,t}}\right)$$
$$= \alpha_i(\tau) + \beta_1(\tau)VIX_t + \beta_2(\tau)(TP_i - TP_{US})_t + \boldsymbol{\beta_3'(\tau)P_{i,t}} + \epsilon_{i,t}\,,$$

where α_i's are the time-invariant fixed effects for country i, TP stands for term premium, $P_{i,t}$ are the pipes factors, and $\epsilon_{i,t}$ is the error term.

Quantile regression models have been used in economics to estimate conditional distributions, instead of just the mean as in an OLS model. This is relevant when the effects of the explanatory variables on the dependable variables are subject to the quantile being considered. In effect, changes in the explanatory variables can modify the shape of the distribution in a heterogeneous way. In addition, how well the distribution is characterized largely depends on the horizon as well as whether the regressors being considered are suitable for such a horizon.[6]

3.3 Fitting the Distribution

Once we obtain the quantiles, we fit a complete probability distribution. There are parametric methods such as those used in Adrian et al. (2019) in which a *t-skewed* distribution is fitted to the quantiles. These distributions are flexible and can capture important features of the data, such as the asymmetry of extreme bond flows.

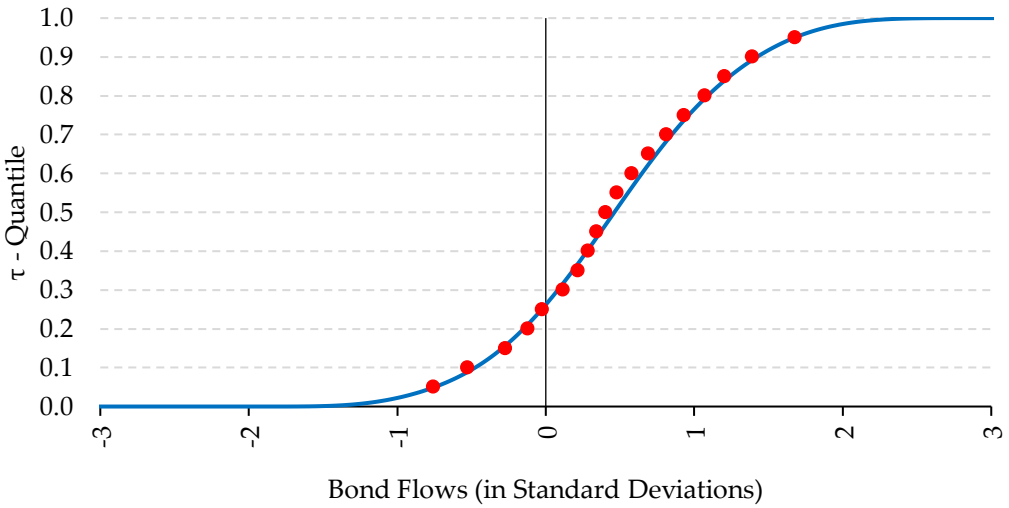


Figure 1. Example of Estimated Bond Flows Distribution (h=0).
Notes: Red dots represent the estimated quantiles from each regression. The green line is the estimated cumulative distribution based on our nonparametric approach.
Date: September 20, 2017. Country: Brazil.

[6] Moreover, these densities are conditional in that they depend on the explanatory variables, because in an ordinary regression $\boldsymbol{\beta'x}$ stands for $\boldsymbol{E}(y|\boldsymbol{x})$. Evidently, any statistic based on the distribution is conditional on the regressors.

We use a nonparametric method, given its flexibility and because it is computationally less intensive. This last characteristic is relevant because we have about 4,400 weekly observations, counting five economies. Thus, we use a tri-weighted kernel choosing a smoothing bandwidth as in Fan and Gijbels (1996).[7] In Figure 1, we provide an example of a density being fitted to a set of quantiles.

4. Benchmark Model and Models' Overview

We present our benchmark model's results, compare them to the main results in key papers in the literature, and briefly explicate the more general models we have estimated.

To set the stage, we first consider the coefficients of the panel quantile regressions with the global and local factors as explanatory variables. We refer to it as the benchmark model.[8] The following remarks are in order. The coefficients associated with the global factor are all negative. Yet, the factor matters more for the left tail of the bond flows' density, as the coefficient for the lowest quantile has the largest magnitude. The global factor has a homogenous influence on the rest of the density. In short, a rise in the VIX deteriorates the bond flows' density.

For their part, the coefficients associated with the local factor are all negative, and statistically significant for the intermediate quantiles. Thus, an increase in the difference deteriorates the bond flows' density. This factor is not as important for the tails of the density, as the coefficients associated with the extreme quantiles are not statistically significant. The global factor appears to be quantitatively more relevant that the local one is.

Next, we consider some of the mechanisms that could be behind these results. At the risk of oversimplifying, consider the following ones. Suppose that an extreme bond outflow takes place, leading to a drop in bond prices. A global investor with a position in local bonds could decide to follow suit. This might be the case for several reasons. Alternatively, the investor might fear gaining a lower return as prices dropped. Or, it could reason that the investors behind the outflow know something

[7] Numerically, the bandwidth h is given by

$$h = \left(\frac{8\pi}{3}\right)^{1/5} (2.0362)\left\{[\text{quantile}(X, 0.75) - \text{quantile}(X, 0.25))/1.349]^{\frac{2}{3}}\right\} n^{-\frac{1}{5}},$$

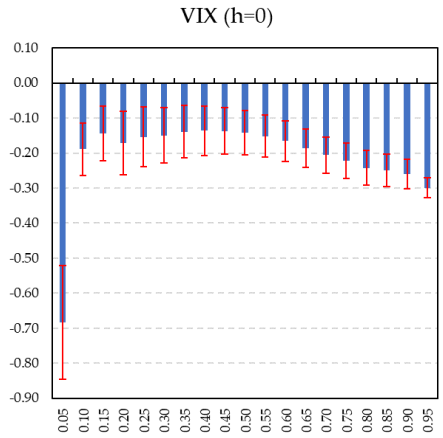
where $\text{quantile}(X, \tau)$ is a function that funds the τ quantile of vector X, and n is the number of data points.

[8] For each explanatory variable, there are 19 coefficients, each associated with one of the 19 quantiles in {0.05, 0.10, …, 0.95}. They could be called percentiles, as quantiles strictly are {0.25,0.50,0.75}.

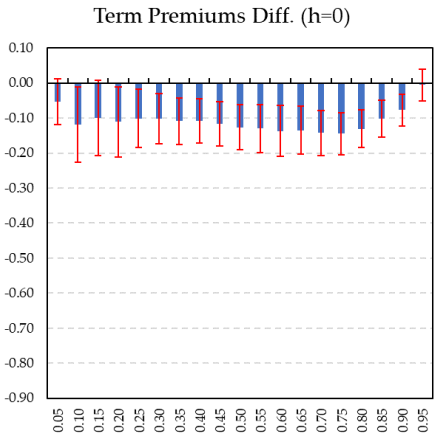
it does not. It could even think that the outflow is not due to a change in an economic fundamental, but nonetheless, it anticipates that investors will follow suit, as several investors might think the same. This could cause herd-like dynamics to ensue.

Consistent with this, some of the empirical regularities that we observe are negative skewness and fat left-tails in bond flows' densities. The conceivable presence of herd-like dynamics could explain the marked difference between the coefficients associated with the 0.05 and 0.10 quantiles for the global factor. If these dynamics are present, then small changes in the global factor could lead to pronounced changes in bond outflows. In this context, a lack of liquidity could very likely become a problem. It is possible that only a few or even no investors would be willing to take the other side of the exiting position.[9] In this context, pipes can become crucial.

We next consider a more general panel regression model, in which we have included three pipes, in addition to the basic push and pull factors. This implies that we have as regressors the VIX index, the difference in term premiums (i.e., local minus U.S.), changes in international reserves, EMEs' bond trading volume, and the proportion of non-resident local currency bondholders (relative to the total).



Panel A: Quantile regressors for the VIX index.



Panel B: Quantile regressors for the difference between local and U.S. term premiums.

Figure 2. Quantile Regressors.
Note: Red error bars indicate confidence intervals at a 10% level. We consider an explanatory horizon; i.e., $h = 0$.
Source: Own estimates with data from EPFR Global and Bloomberg.

[9] Thus, an authority acting as a liquidity provider of last resort might be warranted.

If we consider each pipe factor separately, then our benchmark results are maintained and key coefficients associated with each factor are statistically significant. When we include these three pipes *jointly*, then results are maintained except for that of EMEs' bond trading volume, whence most of the associated coefficients lose their statistical significance. That said, the coefficients associated with the right-hand tail of the density maintain statistical significance.

	Benchmark Model			**Benchmark Model + Pipes**		
	Quantile			Quantile		
	0.05	**0.50**	**0.95**	**0.05**	**0.50**	**0.95**
Term Premium Diff.	-0.05	-0.13	-0.01	-0.11	-0.07	0.02
t-stat	-1.35	-3.24***	-0.18	-1.23	-1.99**	0.39
VIX	-0.68	-0.14	-0.30	-0.57	-0.18	-0.29
t-stat	-6.94***	-3.64***	-17.27***	-4.19***	-3.51***	-6.16***
Change in Foreign Reserves ex. Gold				0.26	0.06	0.07
t-stat				2.24**	1.59	1.48
LC Bonds Held by Non-residents				-0.31	-0.03	0.14
t-stat				-4.00***	-0.58	1.29
EMTA Trading Volume				-0.15	0.01	-0.12
t-stat				-1.31	0.86	-4.34***

Table 1. Overview of Our Models' Estimations
Note: We have selected estimates for our benchmark model, and the benchmark model + the pipes factors. * p<0.10, ** p<0.05, *** p<0.01.
Source: Own estimations using data from EPFR Global, Bloomberg and Valmer.

Table 1 provides an overview of the benchmark, and benchmark and Pipes estimated models. Note that, by way of summary, we have included three quantiles (0.05, 0.5, and 0.95) for each explanatory variable. The effects associated with the global and local factors largely remain the same across these models. Pipes have, in general, statistically significant coefficients. Comparing the benchmark model (Column 1) and the one that also includes the pipes (Column 2), it appears that the global factor is largely uncorrelated with these pipes; else, we would have observed a substantial change in the estimates between the benchmark and the latter model. This is expected because the global factor is exogenous. The local factor is somewhat correlated with the pipes, because its coefficients vary when the pipes are included.

	Benchmark Model			Benchmark Model + VIX Regimes			Benchmark Model + 2 Pipes + VIX Regimes		
	Quantile			Quantile			Quantile		
	0.05	**0.50**	**0.95**	**0.05**	**0.50**	**0.95**	**0.05**	**0.50**	**0.95**
Term Premium Diff.	-0.05	-0.13	-0.01	-0.06	-0.12	-0.01	-0.10	-0.07	0.04
t-stat	-1.35	-3.24***	-0.18	-1.17	-3.28***	-0.22	-1.56	-2.06**	0.92
VIX	-0.68	-0.14	-0.30						
t-stat	-6.94***	-3.64***	-17.27***						
Change in Foreign Reserves ex. Gold							0.15	0.06	0.06
t-stat							1.90*	1.75*	1.16
LC Bonds Held by Non-residents							-0.32	-0.02	0.15
t-stat							-5.91***	-0.32	1.38
EMTA Trading Volume									
t-stat									
Low-Regime VIX				-0.06	-0.09	-0.23	-0.12	-0.12	-0.20
t-stat				-1.18	-3.24***	-13.32***	-1.84*	-3.30***	-4.73***
High-Regime VIX				-1.21	-0.22	-0.45	-1.20	-0.28	-0.36
t-stat				-6.89***	-3.70***	-16.94***	-6.17***	-3.68***	-5.02***

Table 2. Overview of Our Models' Estimations including VIX Regimes
Note: We have selected estimates for our Benchmark Model, The Benchmark Model + The VIX Regimes, and The Benchmark Model + 2 Pipes + The VIX Regimes. * p<0.10, ** p<0.05, *** p<0.01.
Source: Own estimations with data from EPFR Global, Bloomberg and Valmer.

Several macroeconomic and finance time series are, at times, subject to structural changes in their dynamics. A common approach to modeling such series is considering a regime-switch, which affects a specific feature of the model (Hamilton, 1994). In this context, we are interested in whether the sensitivity of bond flows to one of the factors is shifting. In effect, some of our times series could be subject to regime-switching. Accordingly, as a central model, we estimate a regime-switching model, which affects the coefficient associated with the VIX factor (Table 2, Columns 2 and 3).

We next compare our results with key ones in the literature. To this end, we will use the benchmark model. Notably, Gelos et al. (2019) explore the ways various economic policies affect capital flows, focusing on capital flows at risk. They use as the global factor either the U.S. corporate BBB spread, the U.S. 10-year yield or the DXY index of the U.S. dollar, and as a local factor, GDP growth.

The U.S. corporate BBB spread is a compensation for corporate risk. It is somewhat comparable to the VIX index, which we use. The DXY index relates to the cost of funding and of debt service in U.S. dollars. The coefficients associated with the U.S. BBB spread are not statistically significant. The 10-year yield and DXY's coefficients are negative for the intermediate quantiles. Their 0.10-quantile coefficient is negative and statistically significant. These are comparable to our results with the VIX.

Eguren-Martin et al. (2020) use principal component analysis (PCA) to obtain their factors. Given the presence of a relationship, using principal components (PCs) will typically contribute to obtaining statistically significant coefficients. Their results are consistent with ours in various respects. The global and local factors both have the expected signs. Global factors play a more important role in the lowest quantiles. Quantitatively, local factors have a less relevant role compared to global ones. However, the use of PCs might not be fully compatible with an interest on capital flows at risk, as they are not be amenable to modelling extreme events (Taleb, 2020).

Norimasa et al. (2021) have explored capital flows at risk in EMEs. They consider the corporate BBB spread and the shadow federal funds rate as global factors, and GDP growth rate and government debt as local ones. The BBB spread effect on the debt flows is, having obtained negative coefficients for the lowest quantiles, broadly consistent with our results.

Nevertheless, they estimate positive coefficients for the highest quantiles. While plausible, we do not find this result to be very intuitive. A larger BBB spread implies a greater level of the corporate interest rate in the U.S., all else being equal. It is not direct why investors would be enticed to invest more locally. For the shadow interest rate, their coefficients are not statistically significant. While a shadow interest rate is useful to assess the monetary policy stance when the reference rate is in negative territory, it is unclear whether investors take this into account. For its part, the GDP growth rate should relate more FDI than it does to foreign portfolio investment (FPI).

Our benchmark model's results are for the most part in line with the key results in the cited papers. We tend to obtain statistically significant coefficients in general, compared with other estimations that use observable variables. These comparisons have some caveats. Notably, our frequencies differ, whereas Gelos et al. (2019), Eguren-Martin et al. (2020), and Norimasa et al. (2021) use a quarterly frequency, we use a weekly frequency. In addition, their explanatory variables are macroeconomic, whereas ours mainly entail financial ones.

Our factors convey important investment information. As said, from a financial point of view, the difference of the term premiums can be seen as a proxy to the marginal risk contribution of adding local bonds to a U.S. bond portfolio. From a macroeconomic perspective, the term premium contains information on inflation, fiscal, liquidity, and political risks.

Next, we briefly explore the individual quantile regressions with our benchmark model (the corresponding figures are in Appendix A4.1). For Brazil, the global factor matters more as the quantiles increase does. The local factor matters less as the quantiles decrease. For both factors, the coefficients associated with the smallest quantiles are not statistically significant. Quantitatively, their effect is somewhat larger than that of the global factor.

For Chile, the global factor matters for intermediate and high quantiles. Hence, a rise in the global factor reduces the probability mass of the density's right-hand side. For its part, an increase in the local factor affects the high quantiles adversely, whereas the low quantiles are somewhat favored. We found this latter effect counterintuitive. That said, on average, the effect is as expected, as an increase in the local factor deteriorates the density.

For Colombia, the global factor maintains a small, albeit statistically significant, role in the right tail of the density. The local factor affects the low and high quantiles with opposite signs. It affects low ones negatively and high ones positively. Thus, a rise in the local factor increases the kurtosis. We note that for Chile and Colombia the average effect of the term premiums' difference -each with respect to that of the U.S. term premium- is, as expected, negative.

The cases of Peru, Mexico, and that of the panel regression are similar. In sum, we have shown the quantile regression estimates associated with the global and local factors, our benchmark model. We have presented the more general models we have estimated, which feature pipes as well as a regime-switching model. We will describe the latter two in more detail in the following sections.

Complementary, in the appendix, we explore how a set of time series –based on the bond flows' densities– have reacted to key economic events. We also examine the dynamics of a VAR model based on the time series from our benchmark model. We implement these latter exercises to verify that our model estimates are, in various respects, reasonable.

5. Pipe Factors: A Closer look

As we mentioned, pipes refer to the infrastructure through which capital flows transit. They encompass several aspects, such as the financial intermediaries that manage them, the regulations they have to follow, and the trading platforms they use, among others.

It is critical to understand that these factors, at times, interact with each other as well as with global and local factors. For example, given the regulations implemented in the aftermath of the GFC, banks face investment restrictions on where they could invest their capital, which led global asset management companies to take a more prominent role in capital flows, which end up changing the nature of the investors behind capital flows.

In this context, we explore how specific variables, which measure various aspects of the infrastructure of the financial system, affect the bond flows' densities. To that end, we have added three pipes to the benchmark quantile panel and assessed their implications.[10]

- We explore the (month-to-month changes in) international reserves, excluding gold. While international reserves are macroeconomic factors, they relate to pipes because they can be seen protecting pipes. Evidently, they serve other purposes as well, including protection against contingencies unrelated to pipes.
- We examine the role of EMEs' bond trading volume. This variable is telling of several aspects of pipes. For instance, it relates to the depth of EMEs' financial markets. That said, a low trading volume is not necessarily a bad signal. Yet, a persistent low volume might be indicative of a weak fiscal position.
- We also use the proportion of government bonds denominated in local currency held by non-resident investors, relative to their total.[11] This is an important indicator because it reflects confidence in investing in the local currency. In tandem, some resident investors might have to be holders for regulatory reasons, such as a pension fund or an insurance company. That said, a low proportion is not necessarily a bad omen.

Under an adverse bond flows' scenario, having a large proportion could turn out to be counterproductive. For instance, if there is little liquidity and a segment of non-resident investors wants to abandon its position, then bond flows' densities might deteriorate faster, as global investors anticipate an extreme bond outflow event.

We next explore the role of international reserves, underlining that they are not *bona fide* pipes. In effect, they are a macroeconomic factor. One could argue that they

[10] When considering monthly variables, we assume that the datum does not change during the corresponding month for our weekly estimates.

[11] Samples vary due to data availability. Brazil and Peru: December 2007 – January 2021. Mexico: January 2008 – January 2021. Colombia: January 2010 – January 2021. Chile: March 2013 – December 2020.

relate to pipes in at least two ways. They are a self-insurance mechanism and central banks utilize them under certain contingencies.

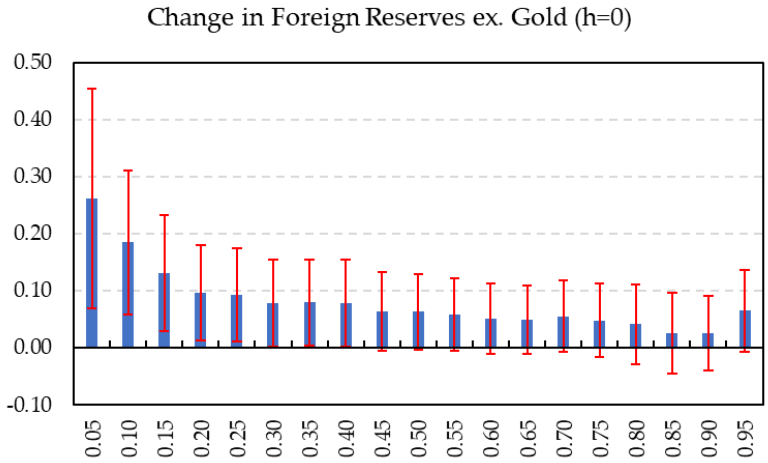


Figure 3. Quantile Regressors for the Change in Foreign Reserves excluding Gold.
Notes: Quantile regressions including the VIX index, the difference between local and U.S. term premiums, the changes in foreign reserves excluding gold, EMTA bond trading volume, and the proportion of local currency debt held by non-residents. Red error bars indicate confidence intervals at a 10% level. We consider an explanatory horizon; i.e., $h = 0$.

Source: Own estimates with data from EPFR Global, Bloomberg, IFS, EMTA, and the and the corresponding Finance Ministries and Central Banks.

Based on the quantile panel regression (Figure 3), we find that (changes in) international reserves matter most for the left-hand tail of the bond flows' density. They seem inconsequential for the right-hand tail, as all coefficients are small and most are not statistically significant. At an individual level, save for Chile, a rise in the level of international reserves positively affects the left tail of the bond flows' density (though note that we do not report these figures).[12]

Two comments are in order. First, the economies we have considered have a floating exchange rate regime. Second, relatedly, under a floating regime, the result is not a mechanical one. If capital flows would affect international reserves directly, then more capital inflows would lead to an increase in international reserves. If that were

[12] Chile seems to be less affected by the changes in their international reserves. It has some negative coefficients on some of the highest quantiles, but they are quantitatively small.

the case for bond flows, then we would have obtained negative (positive) coefficients for the left (right)-hand tail of the density, as a reduction (increase) in international reserves would be associated with bond outflows, which we do not obtain.

Such results echo the self-insurance motive of holding international reserves and demonstrate the benefits of doing so in terms of this dimension. Moreover, under a bond outflow episode, the FX market might be adversely affected. This could prompt a central bank to intervene in the foreign exchange market due to liquidity concerns. The overall objective of these interventions is, in many cases, to avoid a bad equilibrium. In an extreme case, there might be few or no investors willing to buy bonds from global investors, a setting in which the central bank may need to act as a liquidity provider of last resort.

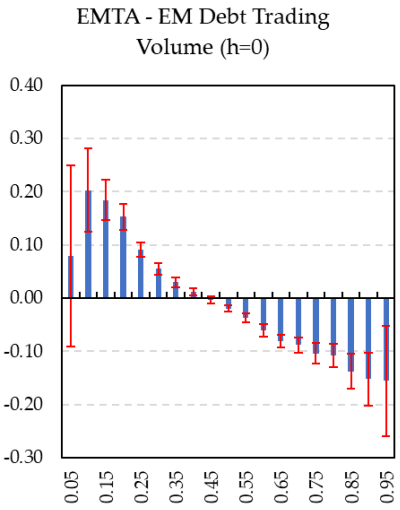
We next explore the role of the EMEs' bond trading volume, which is indicative of the depth of the financial market. As a caveat, we see such a variable as a crude proxy for the weekly bond trading volume of each individual economy, because it includes all EMEs and has a quarterly frequency. In effect, it is a common variable for all of our economies, and we have obtained a monthly frequency time series based on the Chow-Lin (1976) disaggregation method. We assume that the datum does not change during the corresponding month for the weekly estimates. The bond trading volume could be measured relative to the other indicators. Yet, considering it is a crude proxy, we opted for no further standardizations for this series.

We first estimate our benchmark model having as the only additional explanatory variable the volume traded in EMEs' bonds based on the EMTA surveys (Figure 4, Panel A). After this, we consider the benchmark model having added all three pipes (Figure 4, Panel B). The reason we show both is that in the latter case, the volume as an explanatory factor loses statistical significance in an important way.

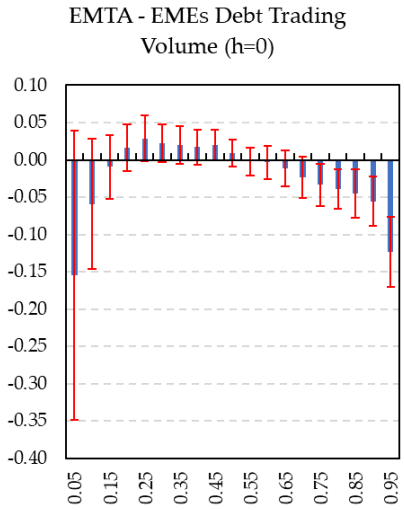
Based on the quantile panel regression (Figure 4, Panel A), a rise in the trading volume affects the low quantiles positively and the high ones negatively. Thus, a variation in the volume should lead to an approximately mean-preserving shift in the bond flows' density. Accordingly, a rise in the volume implies that its variance is reduced. Something similar happens with the kurtosis, as both tails of the density lose probability mass. We have the skewness remaining (approximately) constant.

Empirically, more volume leads to a density with smaller variance and kurtosis. If trading volume is higher, then having global investors changing their positions in

local bonds is less of a worry, including liquidity concerns. However, when we include all pipes, this particular variable loses statistical significance (Figure 4, Panel B).



Panel A. Individually included in the Benchmark Model



Panel B. Including the three pipes in the Benchmark Model

Figure 4. Quantile Regressors for the EMTA Emerging Markets Debt Trading Volume.
Notes: Quantile regressions including the VIX index, the difference between local and U.S. term premiums, the changes in foreign reserves excluding gold, EMTA bond trading volume, and the proportion of local currency debt held by non-residents. Red error bars indicate confidence intervals at a 10% level. We consider an explanatory horizon; i.e., $h = 0$.

Source: Own estimates with data from EPFR Global, Bloomberg, IFS, EMTA, and the corresponding Finance Ministries and Central Banks.

For the individual cases, which results we do not report, we have that for Chile, Colombia, and Mexico, a rise in the EMEs' bond trading volume decreases the variances of the bond flows' densities. A similar change occurs for the kurtoses. In effect, the coefficients associated with the quantiles have a similar pattern to that of the panel regression. Brazil and Peru's bond flows density do not seem to be notably affected by this factor.

We next consider a third pipe. This one refers to the proportion of government bonds denominated in local currency that are held by non-residents. The proportion is with respect to their total quantity, held by residents and non-residents.

All else being equal, if the proportion is higher (lower), then under adverse conditions, the probability of a notable bond outflow will be higher (lower) because

more (less) investors would prefer to exit their position in local bonds. In general, a greater proportion of non-residents holding local bonds could be seen as reflecting favorably with respect to pipes. That said, neither a high nor a low proportion by themselves should be interpreted in absolute terms.

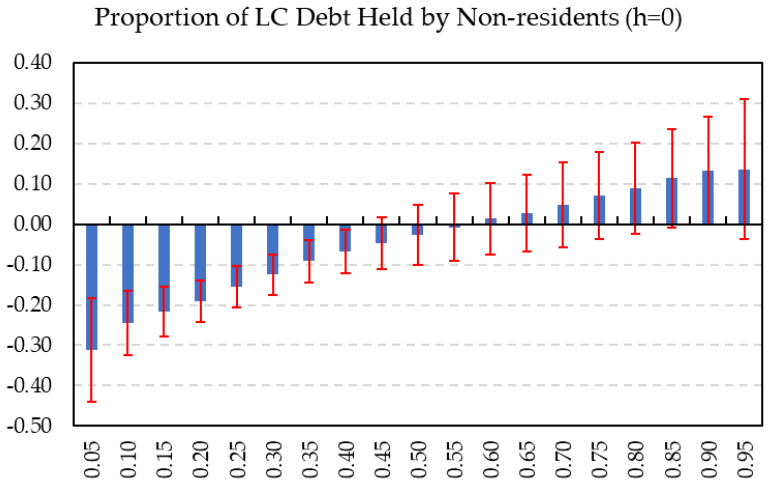


Figure 5. Quantile Regressors for the Proportion of Local Currency Debt Held by Non-residents.
Notes: Quantile regressions including the VIX index, the difference between local and U.S. term premiums, the changes in foreign reserves excluding gold, EMTA bond trading volume, and the proportion of local currency Debt Held by Non-residents. Red error bars indicate confidence intervals at a 10% level. We consider an explanatory horizon; i.e., $h = 0$.

Source: Own estimates with data from EPFR Global, Bloomberg, IFS, EMTA, and corresponding finance ministries and central banks.

Considering that non-resident investors are subject to different incentives and face different risks. In effect, they are more skittish. Under this setting, liquidity will more likely be an issue, because they could demand liquidity from both the bond and FX markets. The implications of this factor are thus not immediate and probably entail several effects in tandem.

We obtain that the proportion of non-residents holding local bonds deteriorates the bond flow density the most at the lowest percentile (Figure 5). In effect, in the quantile panel regression, the coefficients associated with the left-hand side of the density are negative and statistically significant. In contrast, most of the coefficients associated with the right-hand side of the density, while positive, are not statistically significant. However, we note that the 0.90 quantile is statistically significant.

As the left-hand quantiles decrease and the right-hand quantiles increase, they partially offset each other. Moreover, an asymmetry in the coefficients seems to be present. The 0.10 quantile is twice the size of that of the 0.90 quantile, and both are statistically significant. One could interpret this difference as an asymmetry in the net benefits of global investors, along this specific dimension. This implies that a higher proportion leads to a greater skewness. We underscore that such an effect affects the kurtosis as well.

In sum, having non-resident investors comes with benefits and costs for bond flows' densities. This is akin to the effect of bond trading volume, when regressed as the only pipe, *but in the opposite direction*. Broadly speaking, they are helpful in good times, but they are a risk factor in bad ones, where we associate good times with bond inflows and bad ones with outflows.

Such a proportion can be seen as the empirical proxy to the active investors in the Global Monetary Game approach, which we described earlier. The effect this factor has on the bond flows density is in line with one of the model's key predictions. An investor with a position in an EME's risky asset knows that its return will be affected if other investors leave their position in the same financial asset.

If a group of investors anticipates a significant bond outflow event will occur, then they will have the incentive to exit first, as this will secure them a higher return compared to that of its peers. However, if it reacts in an untimely way, then its return will be low. Thus, given a change in factors, more bond outflows could be precipitated, which will adversely affect the left tail of the bond flows' density.

Additional factors could be at play, such as trading volume through via algorithms, which varies across asset classes. As a proportion of the total, it is high in commodity, equity, and FX markets. Relatedly, the microstructure issues in one market might affect those in others. For instance, changes in the non-residents' positions in the local bond markets can affect the FX market. Empirically, EMEs interest rates and exchange rates can co-move strongly (Hofmann et al., 2020).

We have thus explored the implications of including three variables as factors in proxy pipes: international reserves, bond-trading volume, and the proportion of non-resident investors. They each share one common characteristic, namely, they affect the variance, skewness, kurtosis, and bond flows at risk.

Among the factors that affect bond flows, pipes are perhaps the most challenging to measure. Thus, we think it is useful to collect some of our previous topics, explain how they relate to these results, and show how they might relate to each other.

To that end, consider, first, the nature of the main players that intermediate bond flows in EMEs nowadays. Prior to the GFC, banks were mostly responsible for bond flows. In the GFC's aftermath, partially because of regulation, global asset management companies (GAMs) started being the dominant player.

GAMs' investment process is permeated with agency problems. In essence, a long chain of principal agent relations separates the owners of capital from those who make the actual investment decisions (e.g., portfolio managers). A monitoring device can mitigate the agency problems. Comparing portfolio managers has been used as such a device. Thus, managers compete callously against their peers. If one ranks last, it incurs reputational losses.

Other features make herd-like behavior likely. Consider the following ones. First, although competition among portfolio managers might be fierce, there is a significant degree of concentration among GAMs them. Second, GAMs have similar risk management and portfolio selection tools. Third, there has been a noteworthy increase in the use of automatic trading platforms, including algorithmic and high frequency trading. In episodes of intense stress, algorithmic provided liquidity can dry up very quickly and such platforms tend to be net liquidity demanders, recall the presence of kill-switches.

A point worth noting is that complexity has increased, given the wider use of financial technology. This brings new pipes to the setting. Financial technology adds another new dimension of operational risk to trading, which has yet to be fully understood, in particular, in terms of regulation.[13] For policy makers, it makes regulation more intricate and, possibly, more costly.

Consider then that the three pipes that we included in our exercises have a common pattern: unfavorable changes in the pipes deteriorate the variance and kurtosis of the bond flows' densities. Their effect depends on the percentile, which bespeaks the presence of differentiated effects. Moreover, the fact that the variance deteriorates, given changes in pipes, is in line with the referred interactions. The result whereby

[13] To provide an example, think of the challenges that the Boeing Co. has had with the 737 Max. In essence, these challenges emerged due to the airplane's complexity.

the kurtosis decreases is indicative of the potential presence of herd-like dynamics among global investors.

As an important remark in this section, we could have included more pipes. Yet, first, they are challenging to measure (e.g., because of crowded trades). Second, some of the variables we are considering already account for the operation and the net effects of several pipes, as we described earlier.

Finally, we assess if a typical shock on each of our factors: local, global and pipes changes the main moments in our bond flows densities. More specifically, our exercises assess whether a one standard deviation shock on each factor changes the main moments of the density, compared to the density corresponding to the average conditions of all the factors.

Table 3 shows our results based on permutation t-tests. Such a test starts with the difference between the same statistic based on two samples, say, their skewness. Then, one estimates the difference of the same statistic based on a permutation of the original data set, this is, relabeling which observations belong to either sample.

Note that if the difference between the same statistic based on the two sample is close to zero, the relabeling will be inconsequential. After repeating the process, a sufficiently large number of times one can estimate a t-test over the density of the differences of the corresponding quantities.[14]

We note that while the changes in the means are all statistically different, in terms of magnitude, the one associated with the shock on the VIX is the greatest in magnitude. As for the changes in the standard deviation, the one associated with the shock on the proportion of non-resident bondholders is the greatest in magnitude.

[14] We use 10,000 samples and 500 for the BaR-05.

	Mean	Std. Dev.	Skewness	Kurtosis	BaR-05
Average Conditions (before shocks)	0.20	0.78	-0.22	2.90	-1.17
Diff. TP Shock	0.13 ***	0.81 ***	-0.15 **	2.85	-1.29 ***
VIX Shock	-0.02 ***	0.80	-0.52 ****	3.40 ***	-1.51 ***
Non-Res. Holders Shock	0.17 **	0.94 ***	-0.21	2.69 ***	-1.45 ***
Change in Reserves Shock	0.28 ***	0.75 ***	-0.09 ***	2.78 ***	-0.99 ***
Trade Volume Shock*	0.18 **	0.78	-0.33 ***	2.96	-1.21

Table 3. Main Moments of the Bond Flows' Densities.

Notes: Based on densities estimated using the average of each factor, and adding a corresponding one standard deviation shock. All units are in typical (standard deviations) bond flows movements. The test is based on 10,000 permutations of the densities before shocks, and after the corresponding shock. Green (red) numbers indicate an improving (worsening) in the respective moment after the shock. A statistically significant value indicates that such a quantity is statistically different from the one from the density before shocks. * p<0.10, ** p<0.05, *** p<0.01.

6. On the Sensitivity to Global Factors: A Regime Switching Approach

Bond flows have been subject to abrupt changes. As underscored, significant changes in their dynamics and their determination have been a concerned for policy makers and investors. In tandem, some of the factors that might explain them have also been subject to notable changes in their dynamics. Prominently, the VIX index has been subject to structural changes in its dynamics. One thus wonders whether a bond flows sensitivity to other factors might be subject to notable changes.

To explore this, we consider the following approach.[15] We start from the VIX index and adjust a (Markov) regime-switching model to its time series, where the regime state affects the volatility of the shock to an AR(1) process. We obtain a high-volatility regime and a low-volatility regime for the VIX index (Figure 6). That said, a high volatility in the shocks is associated with a high volatility in the VIX time series.

These regime states, although they have a direct econometric interpretation, can be associated with certain market conditions, providing more economic intuition to them. Under a low-volatility regime, we could expect a mood where investors are more willing to invest in EMEs, and more abundant liquidity exists. In contrast, under a high-liquidity regime, investors are less willing to invest and liquidity is scarcer. In effect, the different regime states reflect sudden changes in investors' risk

[15] Relatedly, Ye et al. (2016) propose the use of regime switching in a quantile regression model. They focus on the detection of financial crisis contagion between the U.S. and some European countries.

appetite. This is the case when a regime state goes from low- to high-volatility. This contrasts with changes from high- to low-volatility, as they are not as abrupt.

As a second step, we consider the associated state probabilities, rounded to their nearest integers, which determine the dummy variables: $D_{t,low}$ and $D_{t,high}$. We note that $D_{t,low} = 1 - D_{t,high}$. Analytically, $D_{t,high} = \text{round}(\Pr(S_t = high\ \sigma^2))$.

We then estimate the following panel quantile regression model:

$$Q_{KF_{t+h}\,|\,VIX_t, TP_i - TP_{US}}\left(\tau \middle| VIX_t, TP_i - TP_{US}, \boldsymbol{P_{i,t}}\right) = \alpha_i(\tau) + \beta_{1,low}(\tau) D_{t,low} VIX_t + \beta_{1,high}(\tau) D_{t,high} VIX_t + \beta_2(\tau)(TP_i - TP_{US})_t + \boldsymbol{\beta_3'}(\boldsymbol{\tau})\boldsymbol{P_{i,t}} + \epsilon_{i,t}.$$

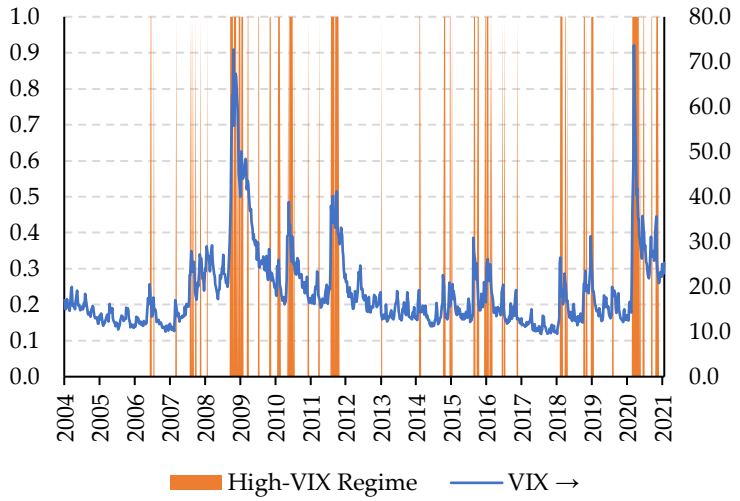


Figure 6. High VIX Regime Probability and the VIX Index
Notes: Low-volatility and high-volatility regimes for the VIX index based on an AR(1) model assuming an underlying Markov regime-switching model is affecting the shock's variances.
Source: Own estimates with data from Bloomberg.

Our key premise is that the sensitivity of the bond flow distribution with respect to the global factor depends on the VIX regime state. Specifically, this means that $\beta_{1,low}(\tau)'s$ and $\beta_{1,high}(\tau)'s$ exhibit different patterns.

To be clear, first, the regime is based on the dynamics of the VIX index. Second, all else being equal, part of the bond flows density changes are directly due to a shift in the actual level of the VIX. Having said that, as we will see, $\beta_{1,high}(\tau)$ is markedly different from $\beta_{1,low}(\tau)$, in effect, such a difference is statistically significant.[16]

Following with our economic interpretation, their difference reflects the change in the investors' mood among states. In effect, some global episodes have occurred during which a change to less risk-appetite is intense, yet short-lived. Most of the time, abundant liquidity has been predominant.

We next examine how the bond flows' densities respond to a switch from the high-volatility to the low-volatility regimes (Figure 6). In all cases, the densities are shifted to the left, indicating their overall deterioration. Similarly, their variances increase, reflecting unstable bond flows.[17] Their skewness become more negative, heralding a higher probability of bond *outflows*. Their kurtoses increase as the regime switches, indicating that extreme bond flows are now more probable. In sum, a regime switch from the high to the low-volatility affects the densities along several dimensions. Such a switch-shift deteriorates the densities.

We next need to assess more precisely how the associated coefficients change with the regime. This could support our hypothesis on how the regime affects the coefficients' patterns in such a way that they are conducive to the further deterioration of the bond flows' densities.

We then want to explore how the $\beta_{1,low}(\tau)$ s compare to the $\beta_{1,high}(\tau)$ s. This is not about the individual coefficient given a quantile; rather, it is about all of the coefficients and whether, in general, $\beta_{1,high}(\tau) > \beta_{1,low}(\tau)$. This would mean that the investors' sensitivity to changes in the VIX would be larger under the high volatility regime. Thus, the change in a regime to the high volatility state magnifies the impact of a change in VIX values are larger, and also the associated coefficients will be greater, thus further deteriorating the bond flows' densities.

[16] It might be the case that $\beta_{1,low}(\tau) = \beta_{1,high}(\tau)$ or perhaps $\beta_{1,low}(\tau) > \beta_{1,high}(\tau)$ in which case the rise in the VIX might be stave off by the reduction in the associated coefficients.

[17] To be clear, the variance refers to that of the bond flows densities, and the volatility to the VIX.

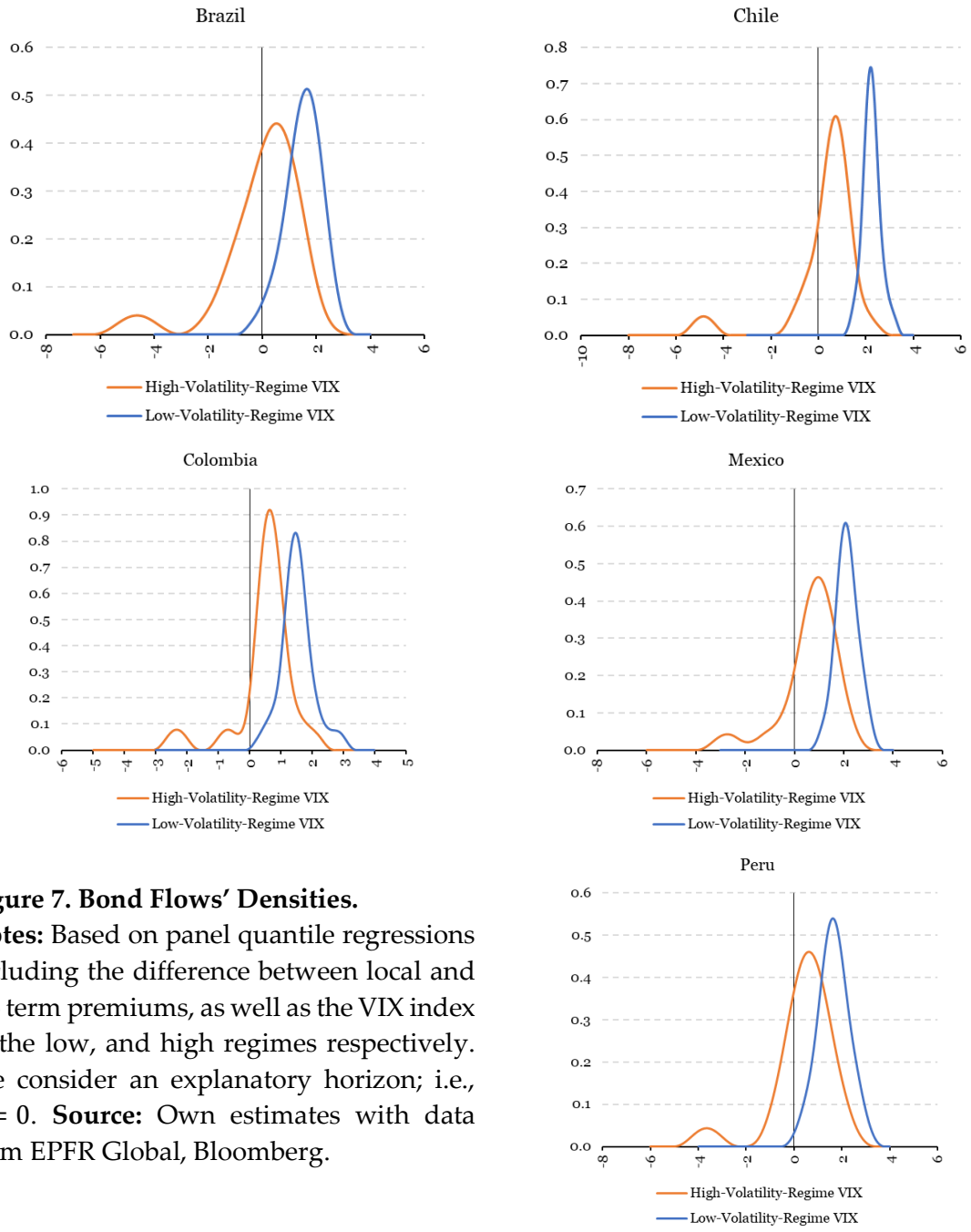
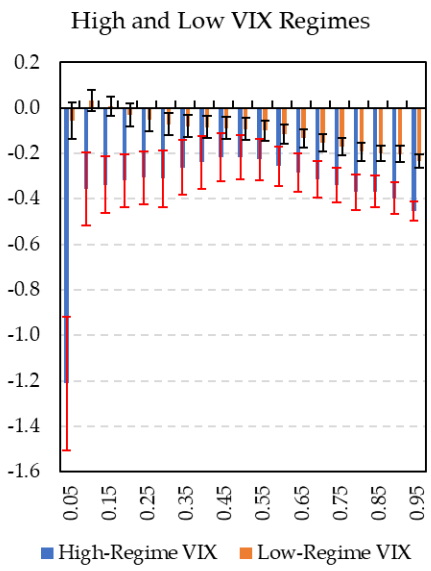
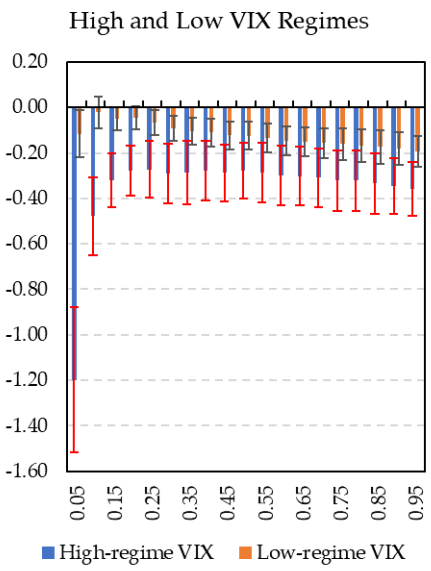


Figure 7. Bond Flows' Densities.
Notes: Based on panel quantile regressions including the difference between local and US term premiums, as well as the VIX index in the low, and high regimes respectively. We consider an explanatory horizon; i.e., $h = 0$. **Source:** Own estimates with data from EPFR Global, Bloomberg.



Panel A. Benchmark Model + VIX Regimes.



Panel B. Benchmark Model + the three pipes factors + VIX Regimes

Figure 8. Quantile Regressors for the High- and Low-regime VIX index.
Notes: Based on panel quantile regressions including the Difference between the local and US term premiums. Red and black error bars indicate confidence intervals at a 10% level. We consider an explanatory horizon; i.e., $h = 0$.

Source: Own estimates with data from EPFR Global, Bloomberg, and the corresponding central banks.

Remarkably, the coefficients of the quantile regressions differ visibly across regimes. Under the low-volatility regime, the magnitudes of the coefficients are, on average, smaller. Those associated with the five smallest quantiles are not statistically significant.

In contrast, under a high-volatility regime, we observe three key features. First, the bond flows at risk (BaR) increase more than 10 times their magnitude as the regime switches. In fact, its statistical significance changes, becoming statistically significant under the high-volatility regime. Second, under the low-volatility one, the coefficients associated with the lowest quantiles lose their statistical significance. Under the high volatility regime, all of the coefficients are statistically significant. Third, under the lower volatility regime state, on average (i.e., comparing their OLS estimates), the coefficients' magnitudes are smaller, in some cases, as if global investors were nearly oblivious to the global factor.

A central question is whether changes in the magnitude of the coefficients across *regimes* are statistically significant. To explore this question, we consider their individual confidence intervals. For the six lowest quantiles and for the two highest ones, we observe that their confidence intervals do not overlap (Figure 8). This provides support for the role of a regime-switch in the determination of bond flows.

Several characteristics of the regime model are worth underscoring. Given the global macroeconomic conditions in our sample period, the low-volatility regime is much more prevalent and persistent. The latter can be measured with the diagonal elements of the transition probabilities matrix. In effect, the probability of remaining in this same state is close to 1. Assuming that the associated stationary distribution exists, this means that the expected time of permanence in such a regime state is long.

The nature of the regime switch of the VIX could be enticing global investors into having positions in Latin American bonds, as long as the low-volatility regime state prevails. Thus, for instance, with low interest rates, the possibility of carry trade, and a low-volatility regime, global investors have an incentive to take positions in an EME's bond. The longer the low-volatility regime is in place, the more global investors will take positions in the EME's local asset.

It is worth collecting some of the elements we have discussed and analyzing how they come together in this model. First, portfolio managers aggressively compete against one other and are averse to ranking last. In addition, GAMs assets under management have increased, the existing low natural interest rates of AEs and, for various reasons, EMEs have greater interest rates. All of these factors give place to an intense search for yields based on allocating capital overseas, borrowing from AEs with low interest rates and investing in a EMEs with high interest rates (i.e., carry trade).

In this context, one plausible interpretation is that global investors become "complacent," until the regime switches to the high-volatility state and the bond outflows become more common. This is in line with the regime switch affecting the density in significant ways, reflected by changes in the magnitude of the coefficients and the increase in the probability mass under the left-hand tail of the density.

6.1 Quantifying the Changes in the Bond Flows' Densities

The bond flows' densities can change for several reasons, as recently shown. A change might be the product of several shifts, such as the combination of a regime switch and a VIX shock. In this context, we want to quantify *ex post* what portion of

the change is due to a regime switch and what portion is due to a change in the VIX itself.

A plausible option is to use the Kullback–Leibler divergence (KLD), which is based on the notion of entropy. The KLD between two densities p and q is given by:

$$KLD(p|q) = \int_{-\infty}^{\infty} p(x) \ln(p(x)/q(x))\, dx$$

Intuitively, the KLD is the sum of the discrepancy between two densities p and q, weighted by the density p. For a given event, one much pay attention to the discrepancy between p and q if the discrepancy itself is quantitatively large and the event is probable when measured with p.[18]

A problem we face is that the KLD measure of a sequence of density changes (for example, given by a sequence of shocks and regime shifts) *is not invariant to their order*. More concretely (see Figure 9), if we first consider the KLD of the original density and the VIX-shocked density, then the KLD of the VIX-shocked density as well as the VIX-shocked density plus the regime shifted density, this will have a different result than if we first consider the KLD of the original density and the regime-shifted density, then the KLD between the regime-shifted density and the regime-shifted density plus the VIX-shocked density.

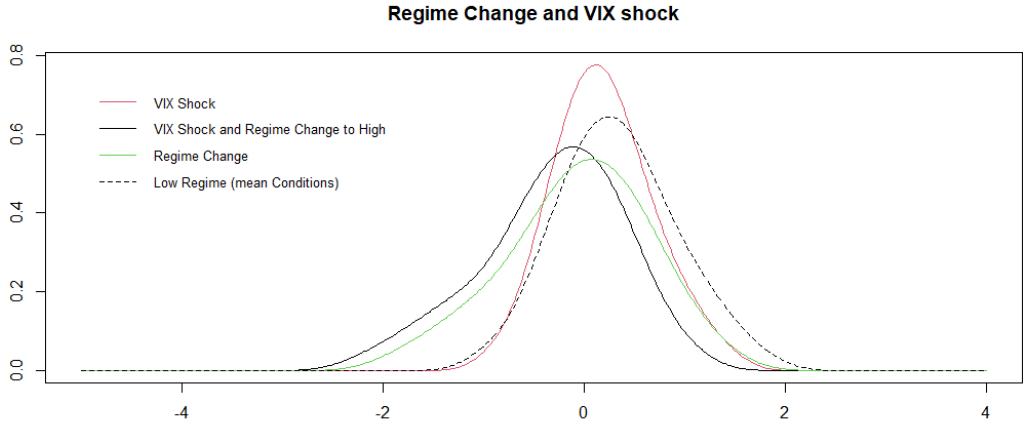


Figure 9. Decomposing the Changes in the Bond Flows' Density

[18] If the discrepancy is large but its probability is low, then do not pay much attention to it. Likewise, if the probability is high but the discrepancy is small, then do not pay much attention to it.

Notes: The density in a black dotted line is the one prevalent under a low volatility regime, with the average value for the VIX. The density in a green line is the one under a shift to a high volatility regime. The density in a red line is the one prevalent under a shock on the VIX. The density in a black plain line is the one prevalent under a shift to a high volatility regime *and* under a shock under the VIX.

KLD (Averages):	KLD (**Δ**VIX → **Δ**Regime):	KLD (ΔRegime → ΔVIX):
Average **Δ**VIX: 0.20 × Direct	**Δ**VIX: 0.24 × Total [Dashed → Red]	**Δ**Regime: 0.39 × Total [Dashed → Green]
Average: **Δ**Regime: 0.67 × Total	**Δ**Regime: 0.94 × Total [Red → **Black**]	**Δ**VIX: 0.16 × Total [Green → **Black**]
Total: 0.87 × Total	Total: 1.18 × Total	Total: 0.55 × Total

Source: Own estimations with data from Bloomberg and EPFR.

In other words, the KLDs depend on the *order* of the shifts/shocks. Thus, we take a hint from the Jensen–Shannon divergence (JSD), and instead of the KLD, we consider the average of the KLD from each density change associated with the same total shift in factors and *consider both possible sequences*.[19] This provides a divergence that does not depend on the order of the shifts/shocks, as when the KLD is used.

In our case, $p(x)$ is the result of subjecting $q(x)$ to a regime shift (q_r) and then a shock (q_{sr}) or to a shock (q_s) and then a regime shift (q_{rs}). Thus, our divergences, based on KLD, are equal to:

$M_r = 0.5(KLD(q_r|q) + KLD(q_{rs}|q_s))$; (the divergence due to the regime switch)
$M_s = 0.5(KLD(q_s|q) + KLD(q_{sr}|q_r))$, (the divergence due to the VIX shock)

Note that each considers both possible sequences in which the change (be it a VIX shock or a regime shift) can take place. Again, the example shown is in Figure 9.

[19] Recall that the JSD between $p(x)$ and $q(x)$ is defined as $JSD(p|q) = 0.5(KLD(p|r) + KLD(q|r))$ where $r = (p + q)/2$. To be clear, we do not use the JSD.

Based on the above, we have two comments. First, the extent to which the KLD can differ when one considers different orders and, relatedly, it depends on the specific (ordered) sequence of the shifts considered. Second, for its part, it is clear that the regime switches accounts for the bulk of the total change between the original density (dashed) and the final density (black).

Second, this underscores the relevance of including a regime to capture bond flows dynamics. In effect, the regime switch affects the bond flows' density the most overall. This adds to the evidence supporting its relevance.

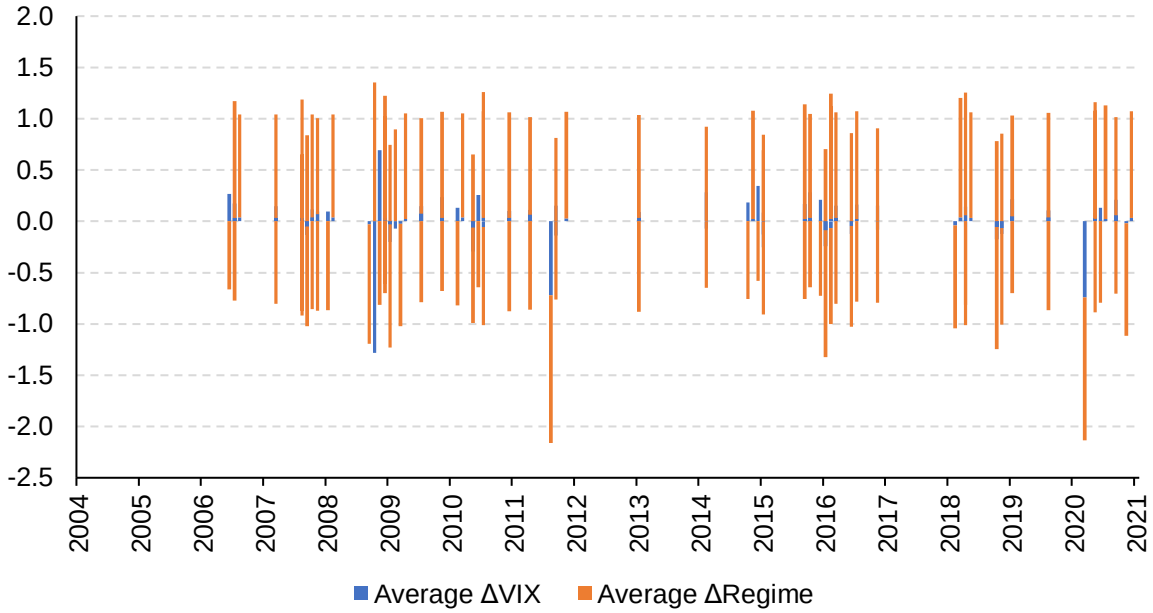


Figure 10. Decomposing the Changes in the Bond Flows' Density

Notes: Given that a regime change occurs, we depict the relative contribution of the regime shift and the change in the volatility. The relative contribution of the regime shifts is much more important for explaning the shifts in the bond flows' densities vs the changes in the VIX.
We have standardized the KLD of the total change to a unit.

Source: Own estimations with data from Bloomberg and EPFR.

Figure 10 shows the decomposition of the changes in the bond flows' densities given that a regime switch occurs. For convenience, we have standardized the KLD of the total change to a unit. Again, we observe that the regime switches account for the bulk of the total change. It is only during particular periods, such as those in the

years of 2008, 2011, and 2020, that we observe VIX shocks having a relatively more important role.

Note that we have not included periods in which only a change in the VIX occurred. This is mainly because in such cases, no decomposition exists, as the total change amounts to the change due to the VIX.

7. Policy Responses, Global, and Local Ones During the COVID-19 Financial Turmoil

We explore how bond flows' densities have responded to global and local policies in key weeks during the COVID-19 financial turmoil in early 2020. For that end, we use direct approaches. Our main results are that they work in terms of reducing key statistics of the bond flows densities. This would not necessarily be the case had we not considered all of the bond flows density but rather only its mean or mode.[20]

We take two approaches. The first one compares the bond flows' densities from the week before the announcement and those densities from the week of the announcement. The second one, an event study, uses dummy variables. We think such an approach can be useful in the context of quantile regressions. For this latter exercise, we focus on the cases of Chile and Mexico. Our only reason for doing so is econometrical. Both economies implemented their main policies during weeks different from that of the Federal Reserve, thus making their effects relatively more direct to identify.

We revert to our model without regimes to simplify the presentation. We are able to do so without loss of generality, as the high-volatility regime was the prevalent one from March to May 2020. Thus, the inclusion of the VIX regime model in the quantile panel regressions should not change our main conclusions. In other words, the shifts in the densities were not due to a regime switch.

7.1 Bond Flows and Global Policy Responses: U.S. Federal Reserve

The relevance of the USD relates, of course, to its status as the reserve currency. As is known, the role of the USD goes further. First, global trade is largely invoiced in USD. Thus, changes in the USD liquidity can affect trade. The role of the USD is not only in terms of trade, but also in terms of the global financial markets. Second, an important portion of credit related to the global supply chains is denominated in USD. Thus, USD global liquidity can have a bearing on this type of credit. Third,

[20] In the appendix, we present the results for three sets of policies; one related to the GFC. One associated to the European Debt crisis; and, the final one related to the COVID-19 crisis.

centrally, a substantial portion of debt that EME corporates issue is denominated in USD. These are among main reasons why the USD liquidity provision is key to the global financial stability.

In this context, we compare the bond flows' densities during the week prior to the policy announcement against the bond flows' densities in the week of the announcement. Specifically, first, we compare the bond flows' densities in the week of March 18, 2020, with that of March 25, 2020.

During the second week, the following were the main policy announcements: the Central Bank Liquidity Swaps, Primary Market Corporate Credit Facility, Secondary Market Corporate Credit Facility, Term Asset-Backed Securities Loan Facility, and The Main Street Lending Program, among others.[21] Recall that the time stamp for the bond flows falls on Wednesdays. This means that we identify weeks by their Wednesday dates, referring to the week prior, starting on the Thursday and ending on the referred Wednesday.

Such an assessment underestimates the total effect as it accounts for the effect of the announcement and the most immediate effects. We have the medium and long-term effects, which are harder to measure but should be there. Based on the panel quantile regressions, BaR are reduced across the board, whereas the effect is nil for the mode. This is a good case to illustrate the usefulness of considering the whole distribution.

In the case of Brazil, the left tail of the distribution shifts to the right once the policy measures are announced. In particular, the BaR shift from -5.2 to -4.6. As for Chile, the BaR is reduced, from -5.2 to -4.6. For Colombia, the BaR is reduced from -5.4 to -4.7. For Mexico, for those same weeks, the left part of the distribution shifted to the right. The BaR were reduced, from -5.3 to -4.7. Similarly, for Peru, the BaR is reduced from -5.2 to -4.6 (see Figure in Appendix A7.1)

This provides evidence that the Federal Reserve's policy measures were successful in reducing the probability of a left-tail risk bond flow event for EMEs. However, in some cases, such a measure did not seem to affect the central part of the density. This assures on the general effectiveness of these measures. The set of policy

[21] Some facilities announced in the previous days: Commercial Paper Funding Facility (March 17) the Primary Dealer Credit Facility (March 17), and the Money Market Mutual Fund Liquidity Facility (March 18). Nonetheless, we consider that the set announced on March 19, 2020 is more relevant for the Latin American region.

measures that the Federal Reserve has put in place has an impact on the liquidity of the USD, particularly the international swap lines with central banks.

7.2 Bond Flows' Densities and Local Policy

We next assess the effects of local policy events on the respective bond flows densities. To that end, we consider the benchmark model by individual economies, as well as a dummy variable based on the policies being implemented. We focus on the cases of Chile and Mexico, as the dates of the announcements of their key policies do not coincide with those of the Federal Reserve. Thus, consider the following local policy events.

Chile 1 (28-may, 17-jun):

The end of May and the beginning of June were active weeks for Chile in terms of policy. On May 29, 2020, Chile learned about the approval of a two-year Flexible Credit Line (FCL) for US $ 23,930 million (SDR 17,443 million) from the International Monetary Fund (IMF).

On June 1, the Ministry of Economy, Development and Tourism, launched the National Tourism Plan, which included financing, health protocols, and joint work with the sector, to reactivate tourism's SMEs, which the COVID-19 crisis affected, including subsidies of $ 7 billion in grants to be delivered.

On June 1, the Ministry of Labor and Social Welfare established the "Short Law," which complemented the Employment Protection Law and, among other changes, increased the percentage for the calculation and payment of social security contributions and health during the suspension of the employment contract. It expressly prohibits the distribution of profits, and limits the compensation of executives at the companies that have used this measure.

On June 3, the Central Bank of Chile requested the Federal Reserve to be part of the temporary Foreign and International Monetary Authorities (FIMA) REPO Facility. The Central Bank was accepted on June 24.

On June 3, the Central Bank of Chile announced that it would reduce its position in their non-deliverable forwards, as the exchange rate volatility was greatly reduced.

On June 8, the Ministry of Economy, Development and Tourism Launched the "Pymes en Línea" platform to provide SMEs and midsize enterprises with training in areas such as electronic commerce, social networks, e-commerce, the marketplace,

payment methods, and digital marketing to bolster their online presence and sales during the pandemic.

If one considers the Chilean bond flows densities, expectedly, the local policy event leads to an overall improvement in the bond flow density. This is more notable in the BaR and in the right-hand part of the density. Thus, quantitatively the Chilean density improves (Figure at Appendix A7.2).[22]

Mexico: April 16, 2020 to May 6, 2020

Next, consider the following local policy events. From March 27 to May 15, 2020, the National Banking and Securities Commission (CNBV) issued temporary exceptional accounting standards (regulatory forbearance) to credit institutions. It also offered the flexibility of liquidity requirements for banks and other temporary flexibilities, including those applicable to listed companies, general financial warehouses, and Financial Support Entities.

On April 21 the Central Bank substantially expanded its liquidity facilities, thus making them more affordable. It also accepted a broader range of collateral, and expanded the range of eligible institutions. In particular, the Central Bank opened a facility to repurchase government securities at longer maturities than those of regular open market operations for up to 100 billion pesos.

On April 21, the undersecretary of Prevention and Promotion of Health announced the beginning of phase 3 epidemic in Mexico. The national lockdown program was extended until May 30.

On April 21, the monetary policy rate was lowered by 50 basis points to 6%, which is 125 basis points lower than the policy rate at the beginning of the year 2020.

On April 22, government workers could apply to personal loans at a low cost, offered by the social security system for the state's workers (ISSSTE).

On April 30, the Ministry of Economy granted loans with optional repayments to SMEs that maintain employees on payroll, the self-employed and domestic workers (this was credit allocated with no legal contract; the government trusted one's word).

[22] ***Chile 2 (18-jun, 8-jul):*** The weeks of Jun 18, 2020 and July 8, 2020, featured an important event for Chile. This time saw the inclusion of Chile in the Federal Reserve's FIMA. The coefficients for the Chilean economy are not statistically significant at the 10% confidence level. This indicates that a possible effect was previously priced in by the market. Alternatively, the effect could be completely captured by the term premiums' differences.

Most of the effect takes place on the left tail of the bond flows densities. The coefficient is largest for the Mexican case, compared with the other economies. That said, it is somewhat adversely affected in its right tail.

8. Final Remarks

Capital flows have been a matter of keen interest for investors, policy makers, and scholars alike. For all of the benefits they bring, they also entail significant risks. They became a significant issue as the AEs' policy responses to the GFC took form, which contributed to giving global investors the incentives to allocate capital in risky assets in EMEs.

Financial institutions have actively sought returns from abroad, because AEs bond yields positioned themselves near their all-time lows, possibly reflecting low natural interest rates in most of these economies. This had as a key repercussion that the EMEs bond flows' volatility increased notably. We have obtained bond flows' densities, based on a panel, for the LAC-5 economies, and in some cases for the individual cases of Brazil, Chile, Colombia, Mexico, and Peru.

We have examined three key aspects closely: the effects that pipes might have on the bond flows' density, whether the sensitivity of bond flows to changes in the global factor has been subject to a regime-switch, and how bond flows' densities have reacted to the set of measures of the Federal Reserve and of some local central banks in the context of the COVID-19 financial turmoil in early 2020.

We document that the pipes factor we have considered affect the bond flows' densities, skewness, kurtosis, and bond flows at risk significantly. Briefly, changes in international reserves are relevant for the left tail of such densities. A rise in the proportion of foreign residents holding locally denominated bonds increases the variance and the kurtosis of the density. More bond trading volume appears to reduce the variance, skewness and kurtosis, and mitigate extreme bond flows events (albeit not statistically robust).

We have argued that these pipes factors measure the net effect of various pipes responsible for bond flows dynamics. For instance, international reserves have been accumulated for self-insurance purposes. A rise in international reserves leads to smaller skewness and bond flows at risk. This is consistent with the idea that a greater availability of resources for liquidity provision by the central bank diminishes the possibility of herd-like dynamics. The proportion of non-resident is beneficial in good times, and it is a risk factor in bad times.

Many of these factors could complicate macroeconomic management in EMEs in various respects, many of which we initially mentioned: they might lead to the pressures of large and abrupt depreciations of the exchange rate, unwarranted changes in relative prices, sudden decreases in the credit supply, and a deterioration of financial stability, among others. On the other hand, bond outflows could lead to important liquidity problems in the local bond market and, brings to the table the potential role of the liquidity provider of last resort-the role that an authority in an EME would need to assume.

We find that the sensitivity of bond flows' densities to changes in the global variable appears to be regime dependent. We present evidence that under the low volatility regime, the sensitivity to the global factor is none or, if present, very small. Nonetheless, under the high volatility regime, it increases markedly.

Additionally, we provide evidence of the effectiveness of the implementation of some of the central banks' policies as a response to the COVID-19 crisis. More specifically, we find support for the hypothesis in which economic and policy events affect the bond flows' densities in a heterogenous way. Thus, using quantile regressions to account for the effects across the whole distribution allows for a refined analysis.

Finally, the use of quantile regressions has been advocated to distinguish the effects through the entire density. For the most part, we agree with this point. Having said that, the inclusion of the regime switching model to capture the effects of extreme economic and notable policy events raises a parallel point. The regression coefficients vary not only through quantiles, but also across regimes.

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APPENDICES

Appendix A4.1.

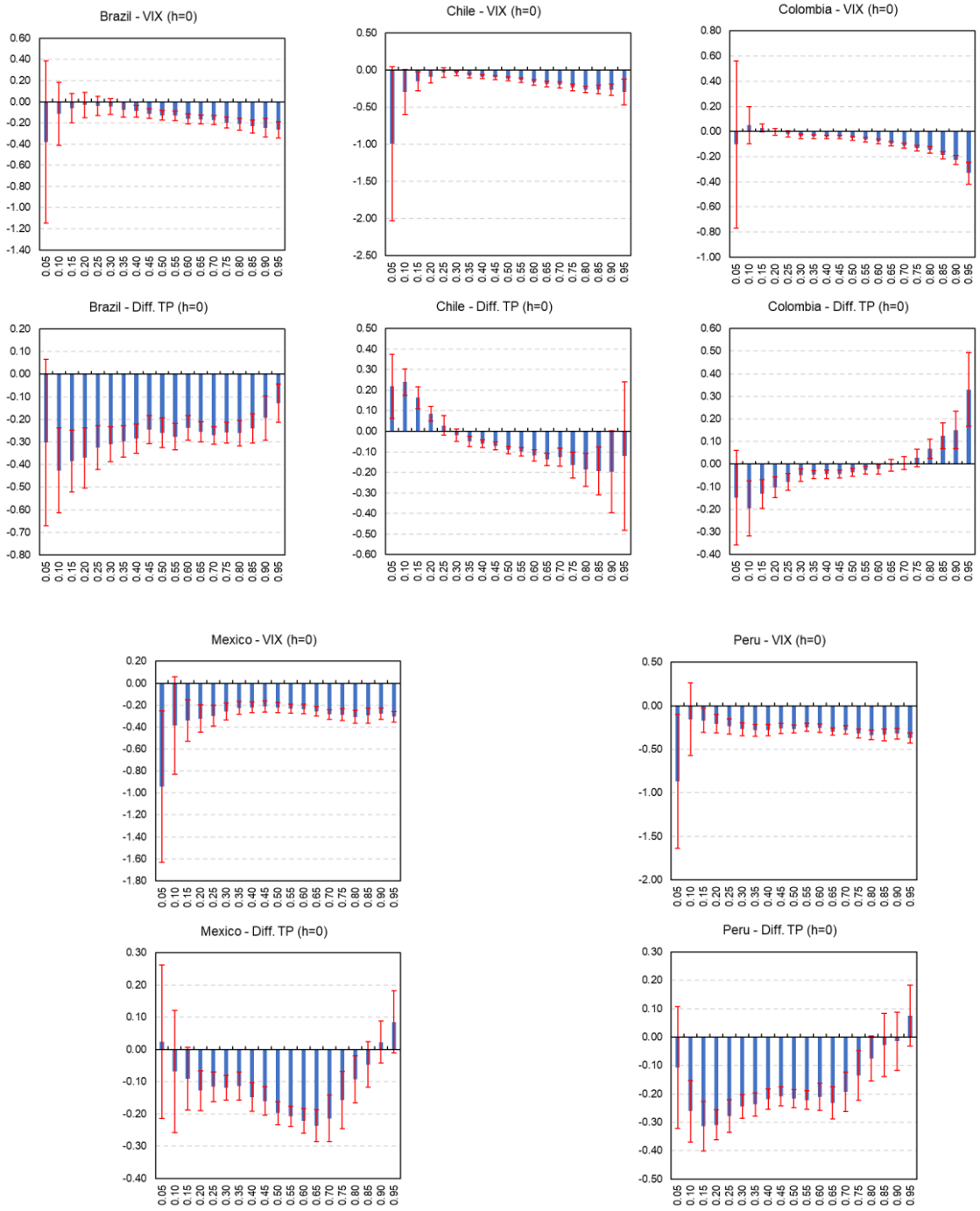


Figure A4.1. Initial Individual Quantile Regression Estimations
Note: Red error bars indicate confidence intervals at a 10% level.
Source: Own calculation with data from EPFR Global and Bloomberg

Appendix A7.1.

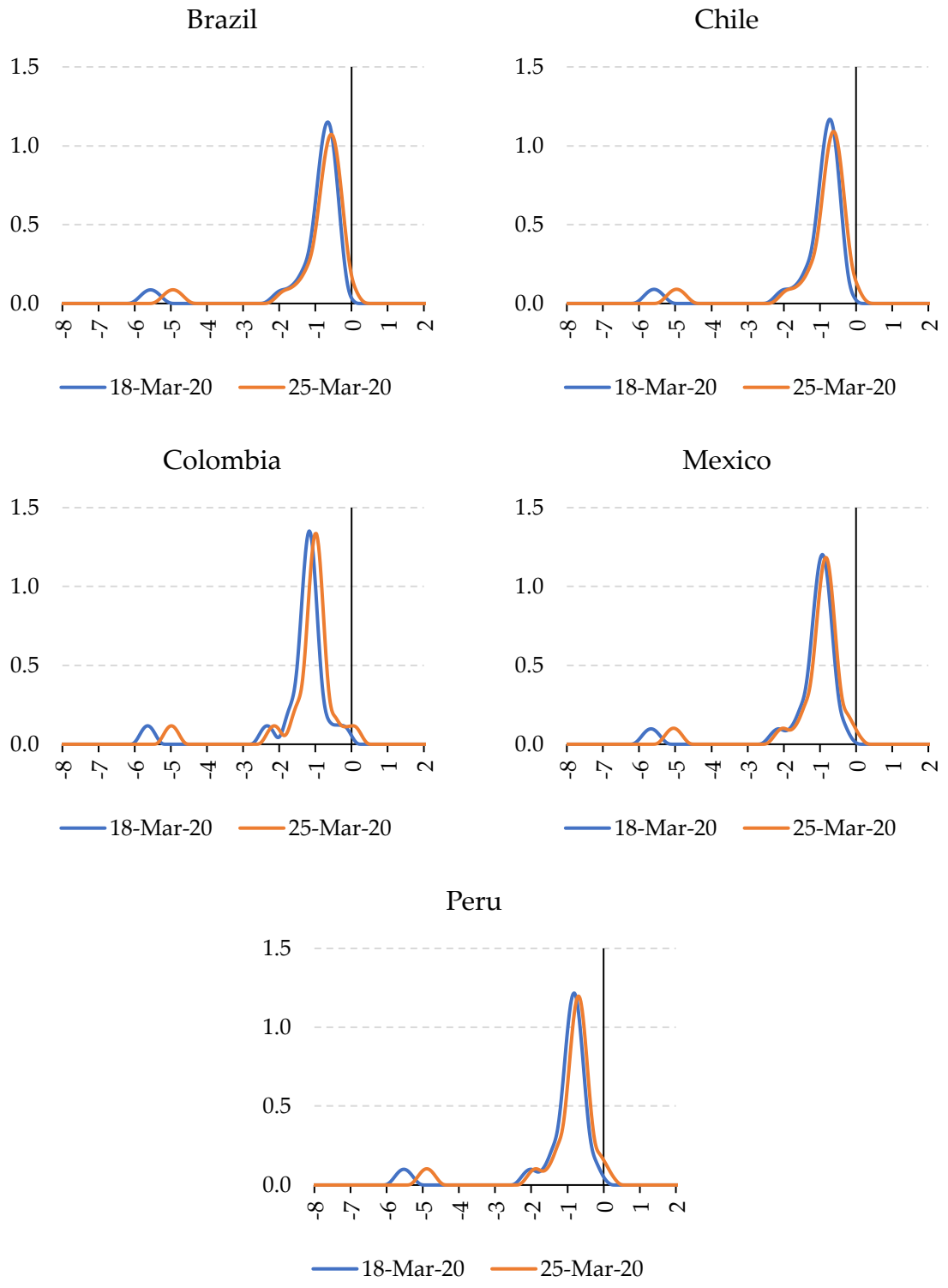


Figure A7.1. Bond Flows Distribution under Global Policy Responses
Note: Based on panel quantile regressions.
Source: With data from EPFR Global, and Bloomberg.

Appendix A7.2

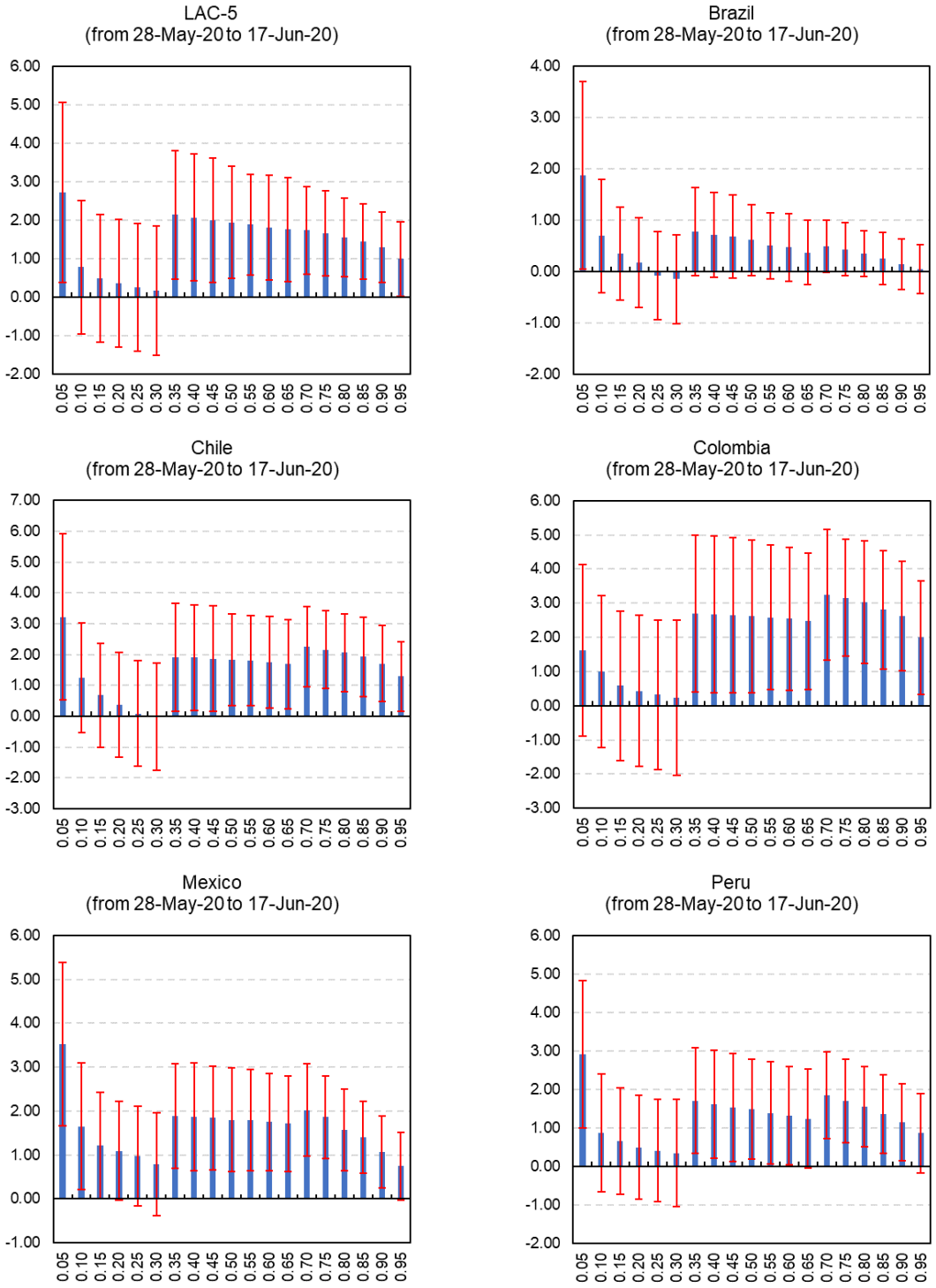


Figure A7.2. Results for a dummy from May 28, 2020 to June 17, 2020.
Note: Based on individual quantile regressions. Red error bars indicate confidence intervals at a 10% level.
Source: With data from EPFR Global, and Bloomberg.

Appendix A7.3

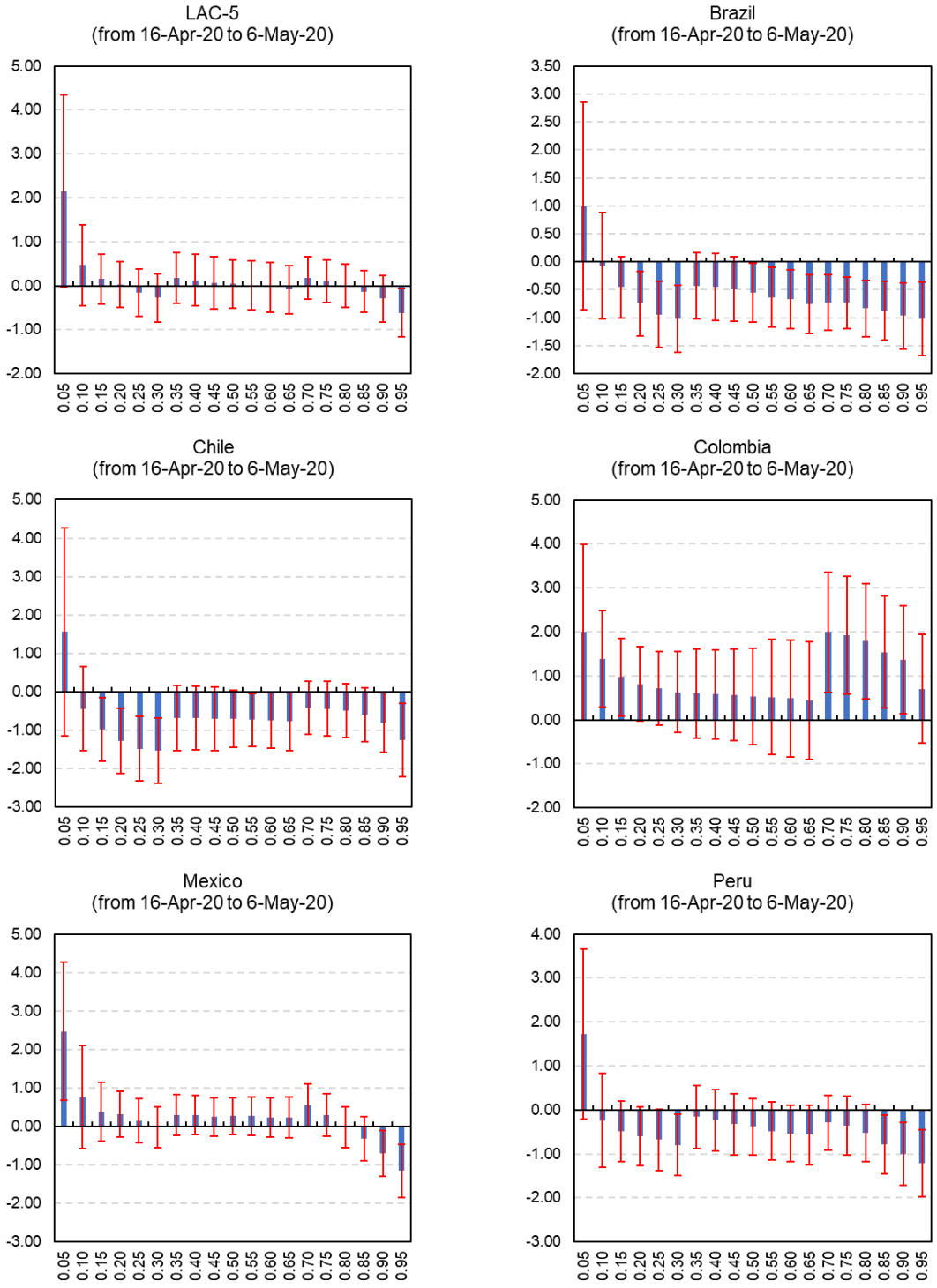


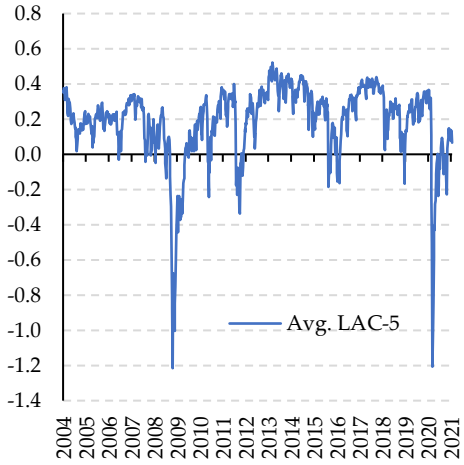
Figure A7.3. Results for a dummy from April 16, 2020 to May 6, 2020.
Note: Based on individual quantile regressions. Red error bars indicate confidence intervals at a 10% level. **Source:** With data from EPFR Global, and Bloomberg.

Appendix B1. Bond Flows Distributions' Time Series

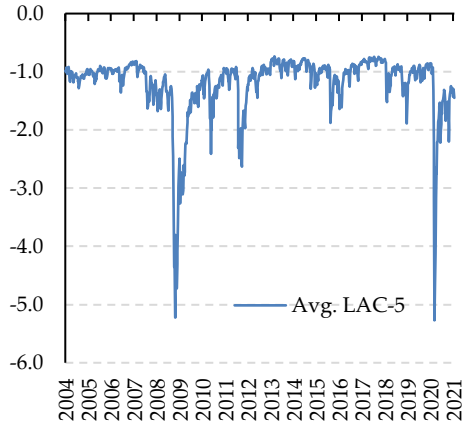
We briefly explore the time series of the average of the means of the bond flows distributions and that of the 5% BaRs, among others, based on the benchmark model. We focus on how the distribution itself has fared through key economic events. Our aim is to explore the extent to which the referred time series have reacted to economic and policy events, and the extent to which such reactions are reasonable.

Consider the magnitude of the average of the individual means for our LAC-5 economies' bond flows distributions in two key episodes: the GFC, and the COVID-19 shock. They both present a similar magnitude. Moreover, their second, third, and fourth moments are close to each other (the figures are not reported).[23] In effect, both the GFC and the COVID-19 episodes presented significant bond outflows' means.

Next, we examine the periods associated with the GFC and the COVID-19 episodes for which the mean of the distribution was below -0.5. The periods related to the GFC lasted for about six months, while those for the COVID-19 lasted for less than a month. As for the periods for which the BaRs were below -2.0, it took more time for the BaR to recover in the GFC, reflecting a more persistent process and, conceivably, a more effective policy response in the COVID-19 episode. On the BaR for different horizons, 0- and 1-week, the GFC and COVID episodes fared similarly. The BaRs in the GFC episodes had distinct magnitudes; in particular, the 1-week's magnitude is smaller.



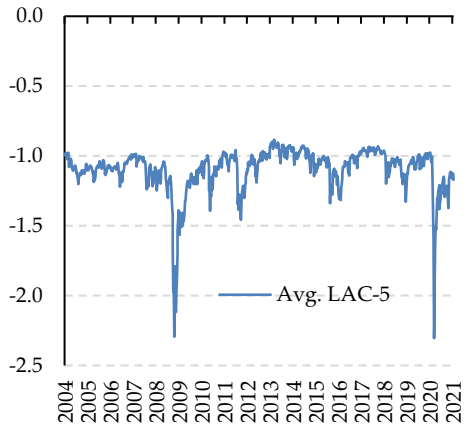
Mean with h=0



5% BaR with h=0

[23] Bad times are associated with smaller means, greater volatility (standard deviation / variance), more negative skewness, and greater kurtosis.

Figure B1.1. Average mean, BaR_0, and BaR_1 time series for LAC-5.
Notes: Based on panel quantile regressions. We average over the individual estimates of Brazil, Chile, Colombia, Mexico, and Peru. The variables used as explanatory factors are the VIX as global and the difference of term premiums as local. 5% BaR. Forecast horizon *h* in weeks. **Source**: Own calculation with data from EPFR Global and Bloomberg.



5% BaR with h=1

Appendix B2. VAR

Exploring the key variables with a VAR allows us to check on the model's consistency in a dynamic setting. We use our benchmark model. Our main objective is to examine the time series' general consistency. For any VAR, there are two key aspects. The determination of its lag, for which we use the Bayesian Information Criterion (BIC). The other one is the identification, for which we use a recursive one.

To that end, we make the following assumptions. In terms of shocks, VIX, being a global financial variable, contemporaneously affects all others. What is less clear is the order of term premiums' difference with respect to the BaR. Yet, the term premiums' difference depends on macro variables and expectations, while BaR largely depends on expectations. We assume that the term premiums' difference affects the BaR contemporaneously, but not the other way around.

On the impulse-response functions (IRF) for the LAC-5 case, we have that a shock on the VIX leads to a rise in the difference of the term premiums and a decrease in the BaR (IRFs presented in Appendix A4.3). The response of the difference, while small, is persistent and positive for 12+ weeks. The response of the BaR, with about the same magnitude as the VIX, is negative and persistent. A shock on the difference of the term premiums leads to a decrease in the BaR, which, albeit small, is statistically significant for about six months.

The response of the VIX is not statistically significant. This is as anticipated, as these are all small open economies and the VIX is a global variable. A shock on the BaR does not induce a response from the VIX or the term premiums' difference. A shock on the VIX or a shock on the term premiums' difference leads to similar responses in the individual cases. This is similar in terms of signs, magnitudes, and dynamics.

Two distinctive results are, first, the responses of the BaR to a shock on difference of the term premiums for the cases of Chile and Mexico as they are positive, albeit small. The individual magnitudes are larger compared to the case of LAC-5. One could understand this difference thinking of LAC-5 as a diversified portfolio based on several economies and, thus, delivering a smaller BaR response, which is a sensible result.

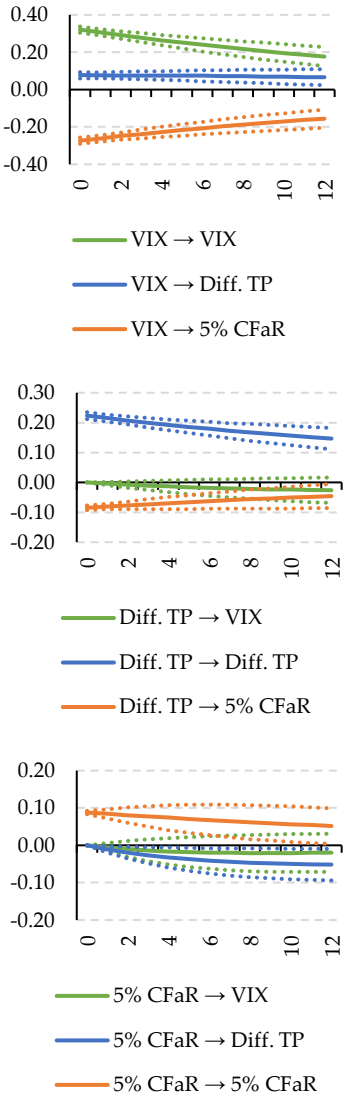


Figure 4A. LAC-5

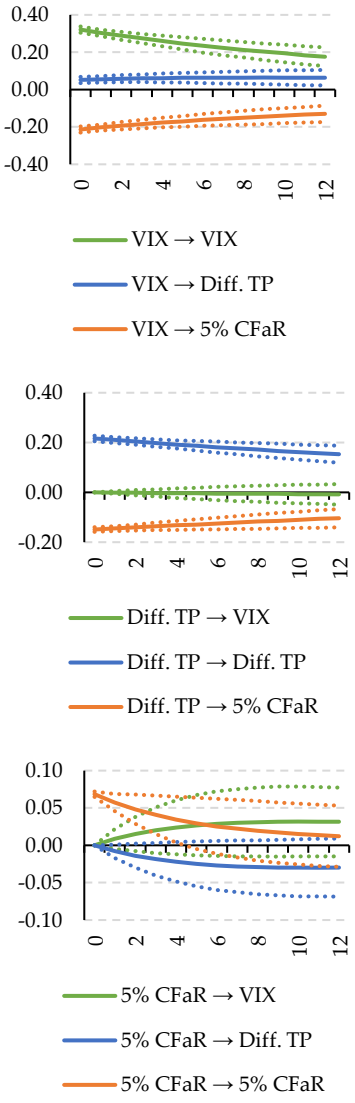
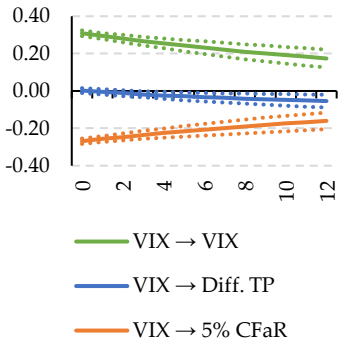
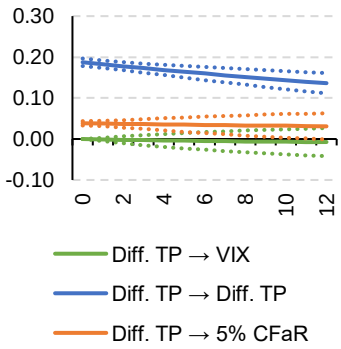


Figure 4B. Brazil

Figure B2.1a. Impulse Response Functions based on the VAR.
Source: Own calculation with data from EPFR Global and Bloomberg.





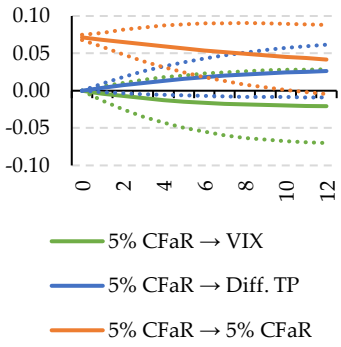
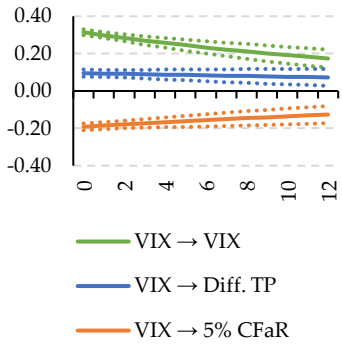
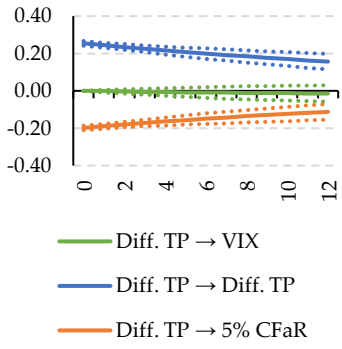


Figure 4C. Chile





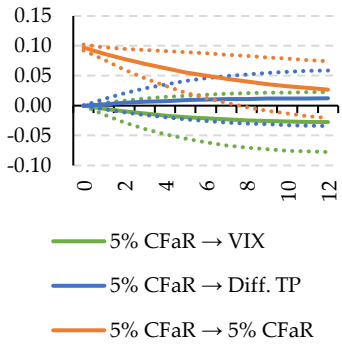
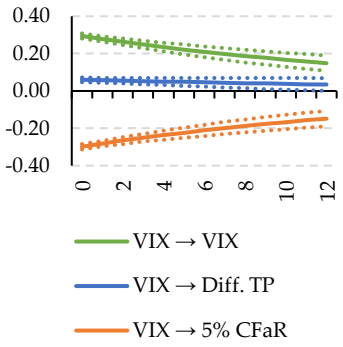
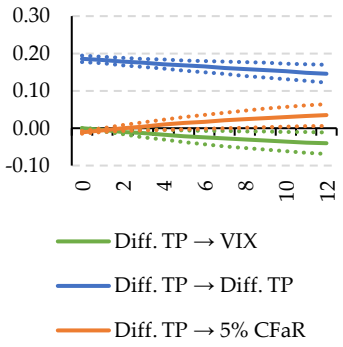


Figure 4D. Colombia

Figure B2.1b. Impulse Response Functions based on the VAR.
Source: Own calculation with data from EPFR Global and Bloomberg.





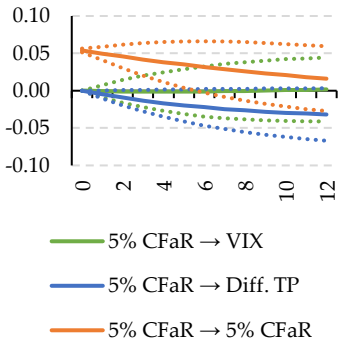
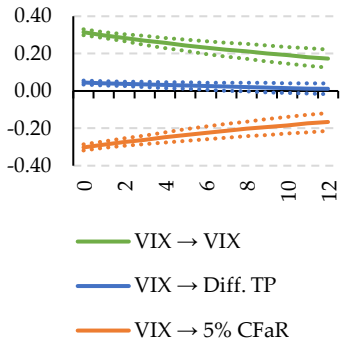
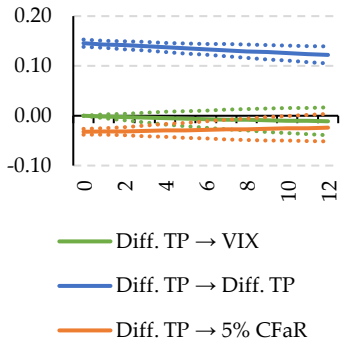


Figure 4E. Mexico





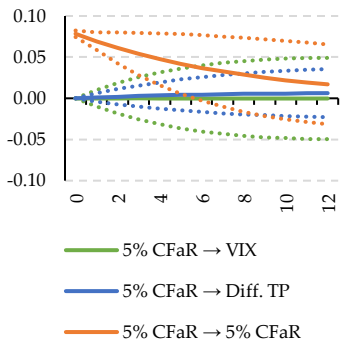


Figure 4F. Peru

Figure B2.1c. Impulse Response Functions based on the VAR.
Source: Own calculation with data from EPFR Global and Bloomberg.

Appendix B3. The COVID-19 Bond Flows Outlook

We first compare the bond flows distribution prior to two set of policy responses, in GFC and COVID-19 episodes, respectively. Second, we incorporate three economic episodes explicitly in the quantile regressions. This provides evidence that, at the outset, the COVID-19 bond flows prospects were at least as bad as in GFC. Recall that the BaR level for COVID-19 deteriorated as much as in the GFC (Figure 1).

B3.1 COVID-19 vs. GFC Bond Flows Distributions

We next compare the bond flows distribution in the week of the September 17, 2008, a couple of days after the demise of Lehman Bros., with that of the week in March 18, 2020, just before key COVID-19 policy announcements.[24] It is worth mentioning that pointing out a week in which the COVID-19 crisis had a full-fledged beginning is harder than in the case of the GFC.

The bond flows distribution for COVID-19 shows a way worse picture than that of the GFC. An important statistic to this comparison is the BaR, which is noteworthy greater for March 18, 2020. This can be interpreted a tail risk scenario presenting a potentially higher level of outflows in the case of COVID-19's financial turmoil.

Based on the bond flows distributions, we can conclude that the COVID-19 outlook was in many ways as bad as that of the GFC.

[24] The U.S. Federal Reserve announced the implementation of the following programs: Temporary U.S. dollar liquidity arrangements (swap lines), Primary Market Corporate Credit Facility, Secondary Market Corporate Credit Facility, Term Asset-Backed Securities Loan Facility, and Main Street Lending Program, among others.

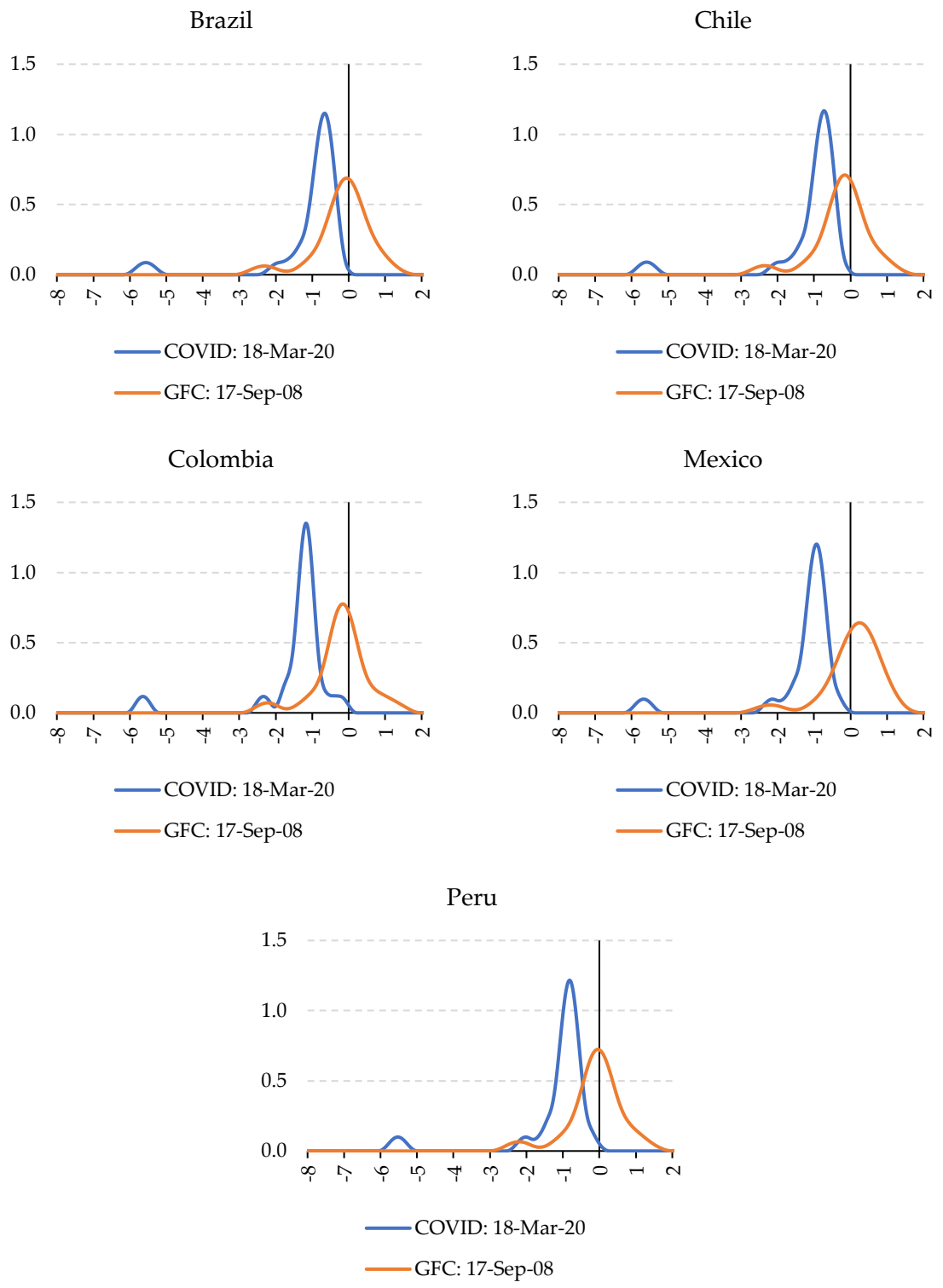


Figure B3.1. Bond Flows Distribution GFC vs COVID-19

Notes: Means of directed Kullback-Leibler divergences. Brazil: 0.0226. Chile: 0.0224. Colombia: 0.0384. Mexico: 0.0352. Peru: 0.0298.

Note: Based on quantile panel regressions including the VIX index and the difference of Local and US Term Premiums. **Source**: Own calculation with data from EPFR Global and Bloomberg.

B3.2 Accounting for Economic and Policy Events Explicitly

We provide further evidence that the COVID-19 initial outlook was worrying. To that end, we incorporate key economic and policy events explicitly in the quantile regressions. We do this by constructing dummy variables based on such economic and policy events, and incorporating them explicitly as explanatory variables in our quantile regressions. To be clear, we consider global and local variables as explanatory variables and, in addition, incorporate the following dummy variables.

We consider three episodes, one associated with the GFC, one with the Taper Tantrum, and one with the COVID-19. We explore the coefficients associated with the three dummy variables. In what follows, we abuse the terminology as we refer to the dummy variables in terms of GFC, Taper Tantrum, and COVID-19, while such variables are associated with very specific episodes that took place during such events. For the GFC, we consider the weeks between September 24, 2008 and October 1, 2008 (inclusive). It thus starts in the week just after the Lehman Brothers' collapse. We note that bonds outflows increased markedly at the time for our LAC-5 aggregate.

We construct the Taper Tantrum dummy considering the weeks of: June 19 and 26, 2013. We note that although the Federal Reserve announcement was on May 22, 2013 (Bernanke's testimony to Congress). It was during those weeks of June 2013 FOMC, that the financial markets deterioration really took hold as investors expected that the FOMC would adopt a more hawkish stance as long-term interest were rising. Markets were in for a surprise.

As for the COVID-19 dummy, we consider the weeks of March 4 and 11, 2020. Recall that on March 3, 2020, Chairman Powell, announced a 50-bps cut in the Federal Funds Rate target in light of "evolving risks to economic activity" due to the development of the COVID-19 pandemic. This took place before March 18, 2020, which is associated with the largest bond outflow in our sample. Thus, we have that the results are not being driven by this particularly bonds outflow event. In addition, it did not include the week in which the previously mentioned package of measure was announced between March 19 and 25, 2020.

One could ask what validates not modeling other events in the estimation sample with additional dummy variables. A working assumption is that those events within the estimation sample that were omitted were approximately uncorrelated to those we did include. If this is the case, the estimates of the coefficient of interest are unbiased.

On the LAC-5, the VIX has a small effect on a few quantiles. A rise in the VIX shifts such quantiles left. That said, albeit negative, the smallest quantiles are not statistically significant. This contrasts with the regression in which we did not include the aforementioned events as dummy variables, for which the most relevant coefficient was that associated with the smallest quantile. These new variable gains much of the global variable's explanatory power.

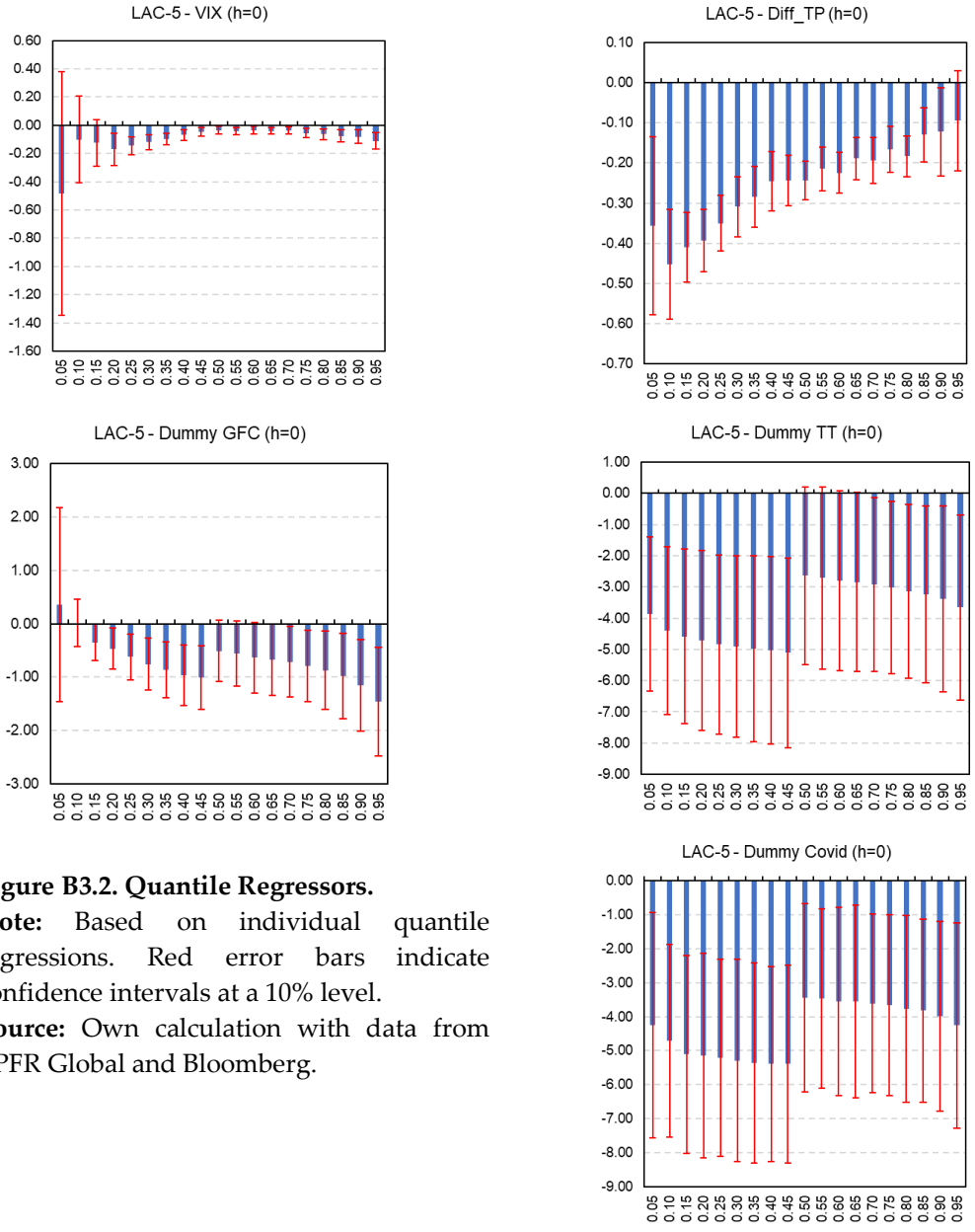


Figure B3.2. Quantile Regressors.
Note: Based on individual quantile regressions. Red error bars indicate confidence intervals at a 10% level.
Source: Own calculation with data from EPFR Global and Bloomberg.

Most coefficients for the local factor are negative and statistically significant, except for some related to the smallest quantiles. In terms of magnitude, some quantiles on the sides are the largest ones. A deterioration in the term premiums' difference affects the right tail mainly. In sum, in terms of the local factor, this model and the one presented before (i.e., without the dummies) are similar.

For the GFC, all the statistically significant coefficients have negative signs. Those associated with the two smallest quantiles are not statistically significant. Thus, the distribution deteriorated almost uniformly during the GFC. For the Taper Tantrum, save for some intermediate ones, most are negative and statistically significant. Their magnitudes are notable. For COVID-19, except for the smallest one, all are negative and statistically significant. Their magnitudes are more notable than those of the Taper Tantrum. In sum, for the dummy variables, those associated with the Taper Tantrum and the COVID-19 episode affect the bond flows distributions most in their left tail. The effect of the GFC seems to be more uniform along the quantiles.

In the case of Brazil, for the VIX, the smallest coefficients are not statistical significance, as in the LAC-5 case. The rest of the coefficients maintain a uniform albeit small magnitude. For the term premium differences, a similar pattern is maintained (relative to the model without dummies). For GFC dummy, all statistically significant coefficients are negative. For the Taper Tantrum dummy, the coefficients in the 0.05-0.45 range and those in the 0.85-0.95 range are negative and statistically significant. Thus, at the time, the bond flows distribution deteriorated markedly, especially the left tail. For COVID, save for the smallest quantile, all coefficients are statistically significant and negative. Their magnitudes are larger, more so than other similar coefficients.

For the case of Chile, for the VIX and the term premium differences, the coefficients pattern is broadly maintained between models. For the GFC, the dominant coefficients, associated with the highest quantiles, are negative and statistically significant. The GFC deteriorated the upside risks of the bond distribution.

For the Taper Tantrum, the coefficients associated with the left side of the distribution and those associated with the largest ones are negative and statistically significant. In the Taper Tantrum episode, the bond flows distribution gained a fatter left tail. As for the COVID, the associated coefficients are negative and statistically significant. In terms of the magnitudes, this seems to be the most relevant event.

For the Mexican case, as for the VIX, the coefficient associated with the smallest quantiles loses its statistical significance. The rest keep their statistically significant

but are small. As for the term premium differences, the coefficients in the 0.05-0.25 range are statistically significant and negative, then the 0.45-0.65 range gains statistically significant but turn out to be small. As for the GFC, the 0.20-0.45 and 0.85-0.95 ranges are negative and statistically significant. As for the Taper Tantrum, most coefficient are negative and statistically significant. As for the COVID episode, all coefficients are statistically significant, and their magnitudes are prominent, as those associated with the Taper.

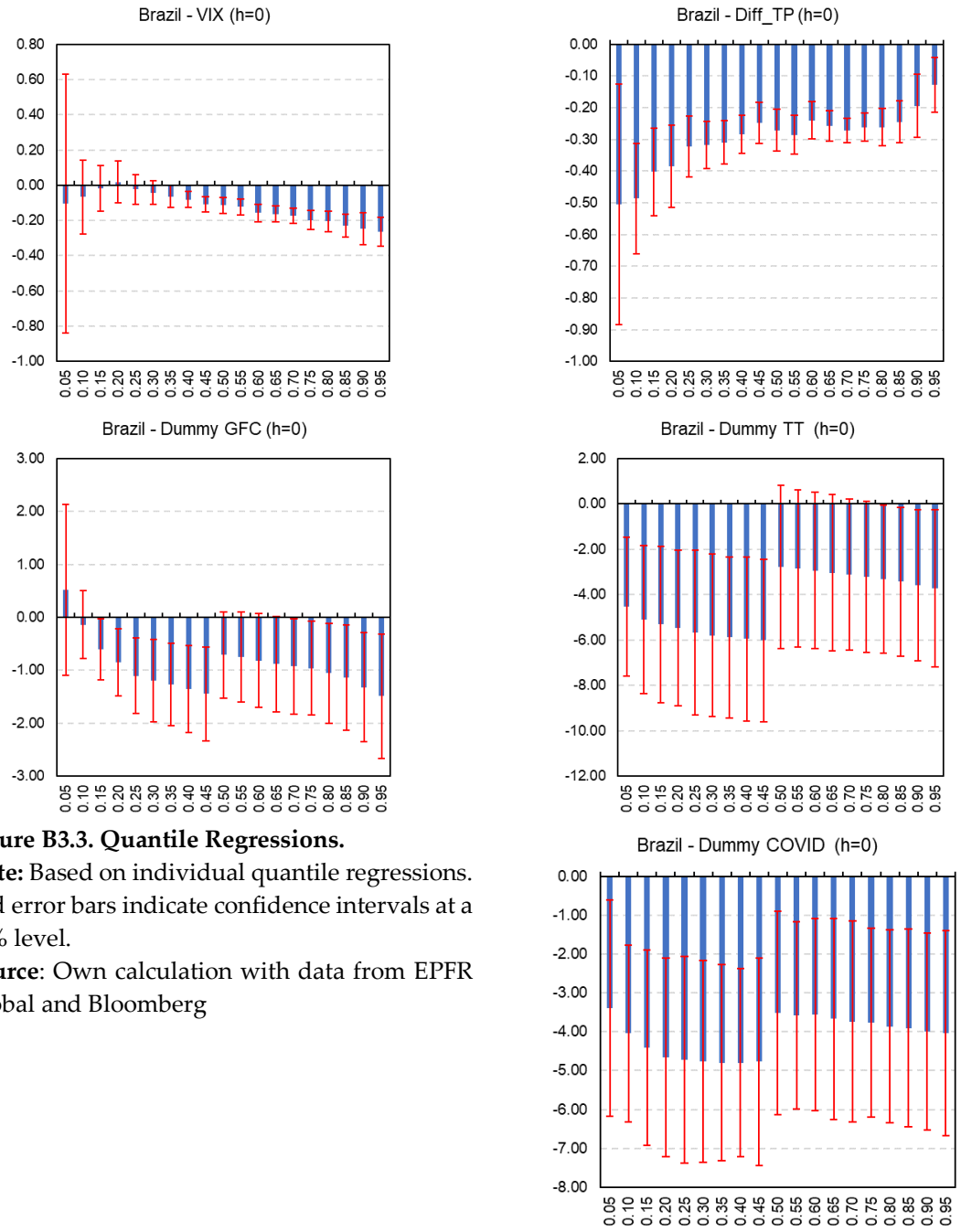


Figure B3.3. Quantile Regressions.
Note: Based on individual quantile regressions. Red error bars indicate confidence intervals at a 10% level.
Source: Own calculation with data from EPFR Global and Bloomberg

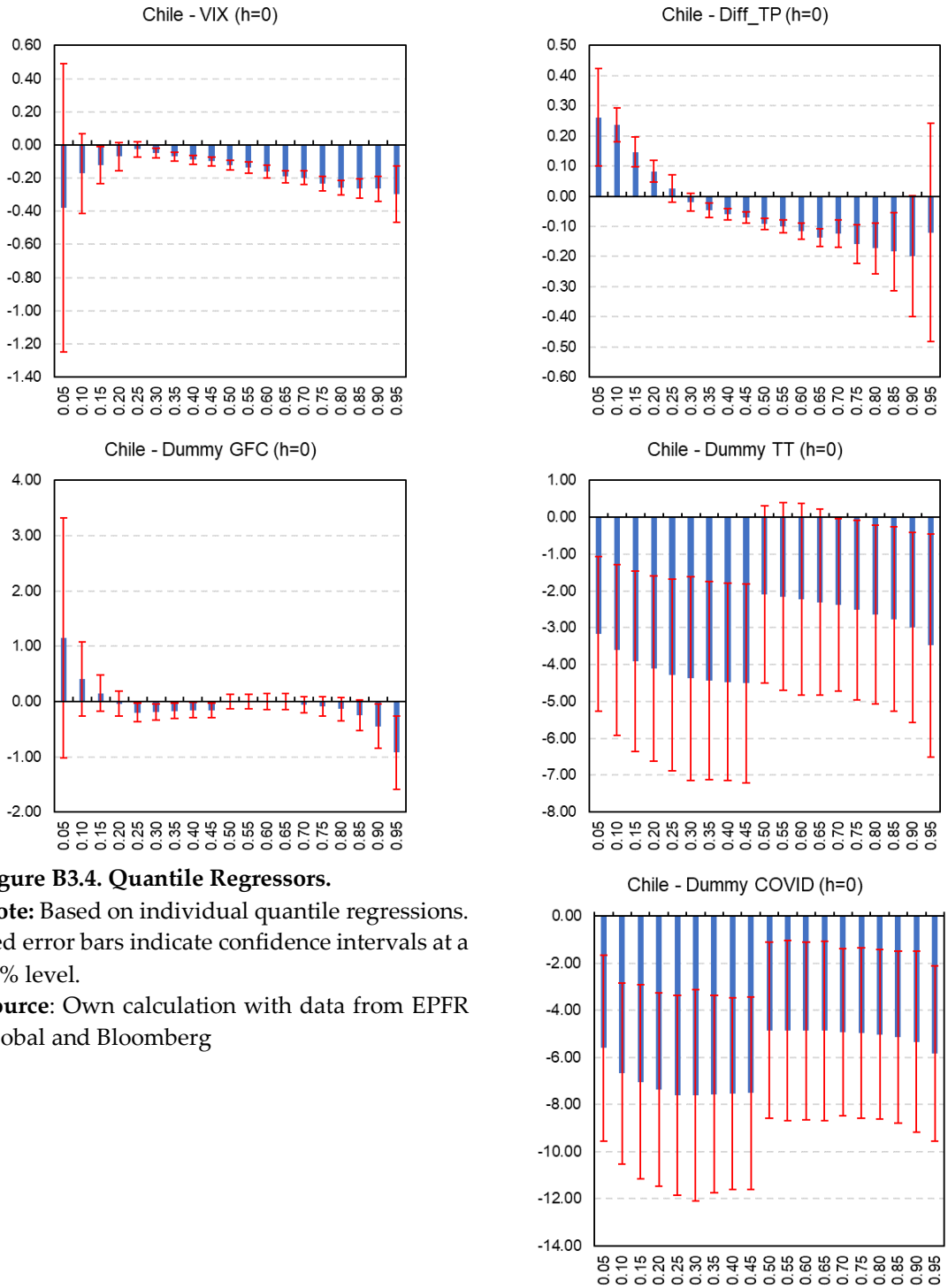


Figure B3.4. Quantile Regressors.

Note: Based on individual quantile regressions. Red error bars indicate confidence intervals at a 10% level.

Source: Own calculation with data from EPFR Global and Bloomberg

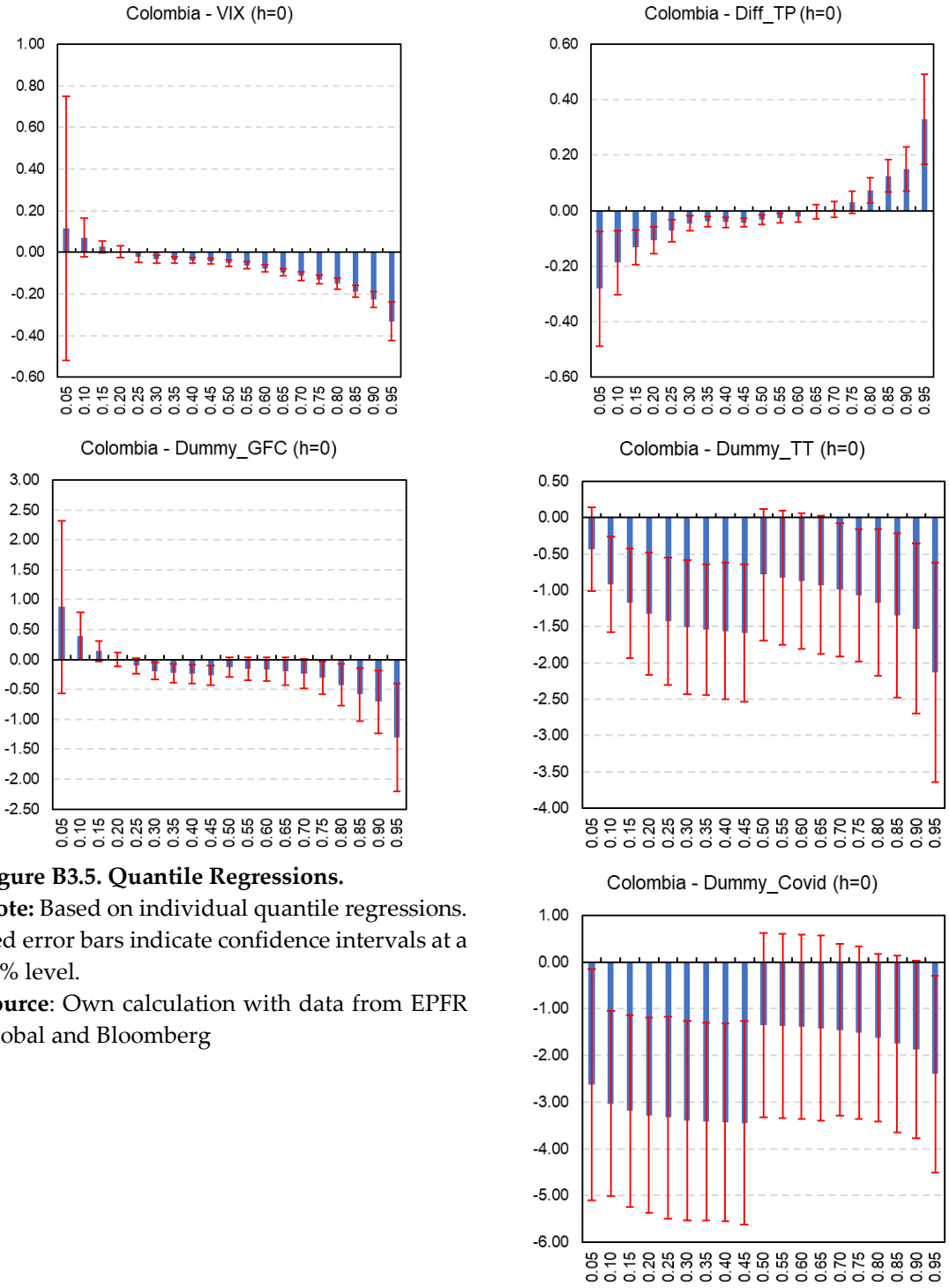


Figure B3.5. Quantile Regressions.
Note: Based on individual quantile regressions. Red error bars indicate confidence intervals at a 10% level.
Source: Own calculation with data from EPFR Global and Bloomberg

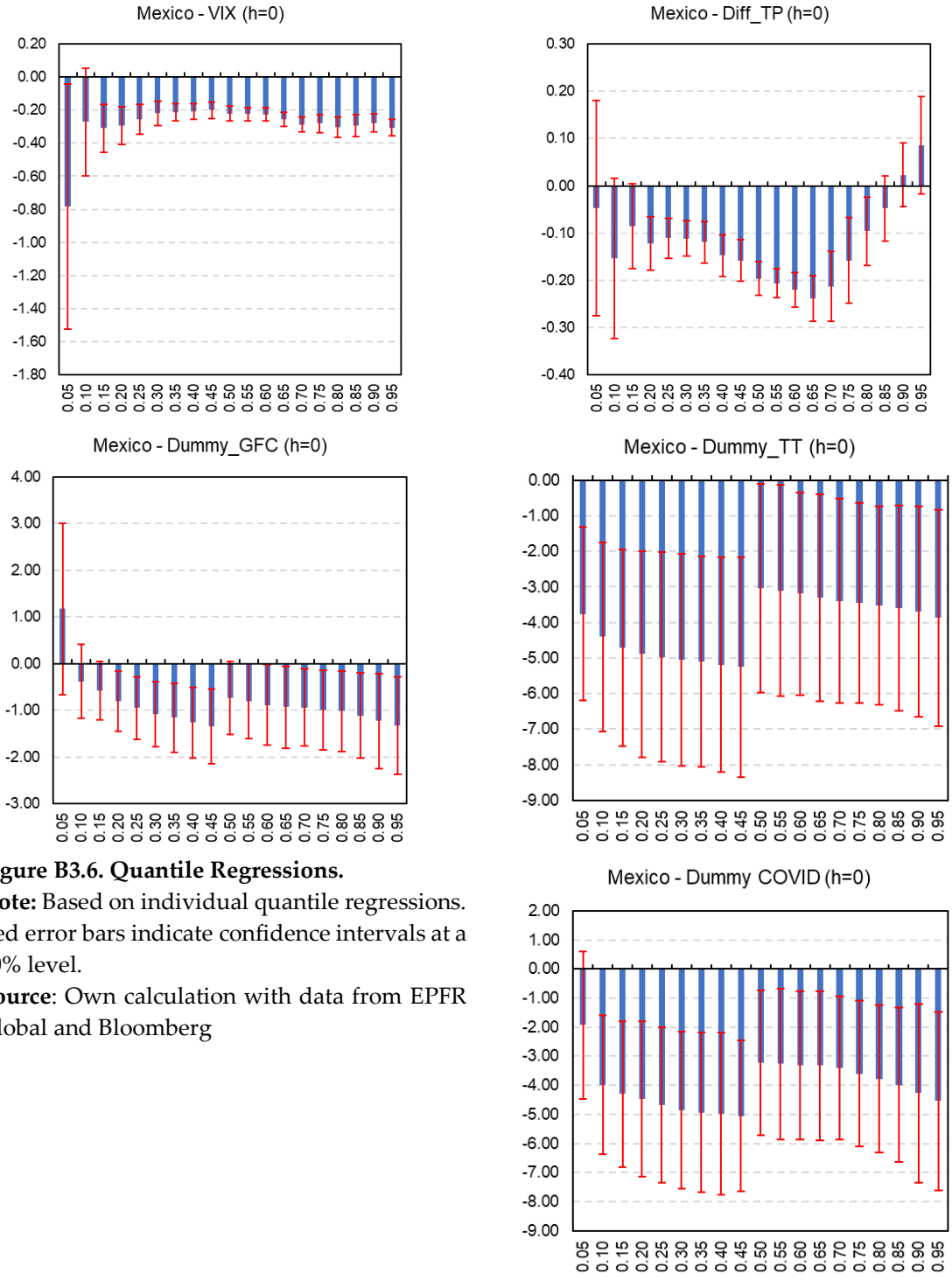


Figure B3.6. Quantile Regressions.
Note: Based on individual quantile regressions. Red error bars indicate confidence intervals at a 10% level.
Source: Own calculation with data from EPFR Global and Bloomberg

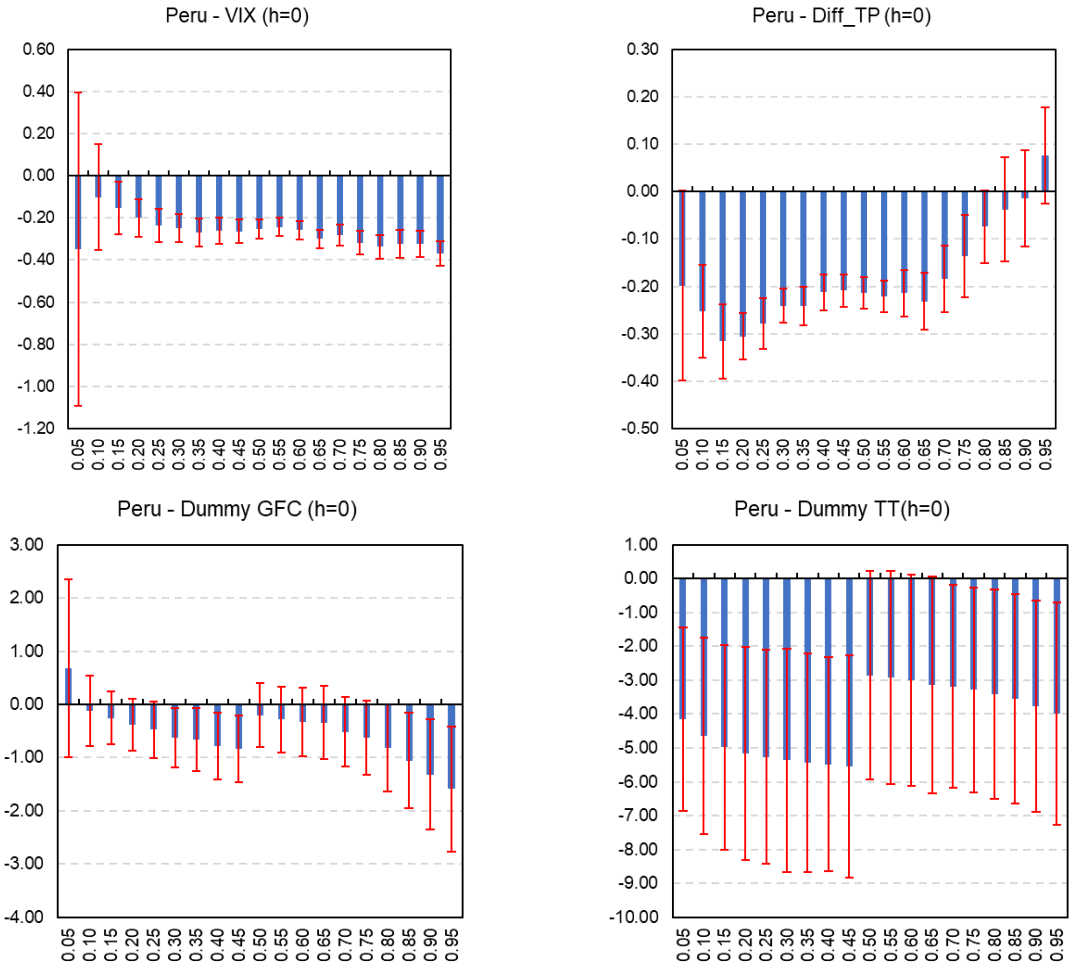


Figure B3.7. Quantile Regressions.
Note: Based on individual quantile regressions. Red error bars indicate confidence intervals at a 10% level.
Source: Own calculation with data from EPFR Global and Bloomberg

Interestingly, considering the GFC, the Taper Tantrum, and the COVID-19 periods as explanatory variables in the quantile regressions provides a different view of our initial estimations. This happens notably with the global factor, the VIX. The explanatory power it had in our initial models is largely replaced by the referred dummies. More specifically, when comparing the models with and without the dummies, a portion of the effects associated with the lowest quantiles for the VIX are explained by the dummies instead. On the other hand, the coefficients associated with the term premium differences are similar across models (i.e., those without and with dummies).

This bespeaks to the status of the episodes considered. Perhaps, more importantly, it underscores that the quantile coefficients of the global and local variables (without the crisis dummies) are largely driven by specific economic episodes. This is similar to the criticism of overlooking the effects of different quantiles when one uses ordinary regressions. Thus, from a time series' perspective, overlooking the effects of significant episodes explicitly might adversely affect the results when one uses quantile regressions.

This leads to the following questions: what justified not including dummy variables that captures a specific event when we only used the global and local variables? In not including them, one makes one of two implicit polar assumptions. First, the global and local factors were sufficient statistics to obtain the distributions. In short, any event would affect such factors and, in turn, they would impact the bond flows' distribution. Second, any event could be uncorrelated to such factors. If this were the case, the estimated coefficients would be unbiased even when not including the dummy variables. In the respective estimation, we learned that this is not necessarily the case. Such factors are not sufficient to explain all of the bond flows distribution. In short, the dummy variables have additional information by themselves.

A related relevant question is regarding the forecasting capacity of the explanatory variables vs. the forecasting horizon of the distribution. As a general result, the forecasting capacity of a given variable depends on the forecasting horizon and the nature of factor. Some might be better forecasting the medium horizon than the short horizon. That said, all else equal, the longer the horizon the less the forecasting capacity of a model, captured potentially by the distribution shifting closer to a non-informative one. [25]

[25] In this context, it is worth mentioning that the pseudo R^2 deteriorate as the horizon increases. This is reasonable considering the explanatory variables we are using. This is also one of the reasons why we decided to stop short of exploring longer horizons.

All in all, we have just provided evidence supporting that the COVID-19 financial turmoil was expected to be at least as bad than GFC in terms of bond outflows. That being said, we will argue that the apparent tail risks did not fully materialize.

To that end, we bring two points to the table. First, we will recall some of the results we have just presented. Second, we will compare the cumulative bond flows dynamics weeks before and after the referred financial market episodes, that of the GFC and that of the COVID-19 one. This comparison comes with a caveat. Our indices are standardized to 100 in a week previous to the bond outflows. That said, relative to the initial level of accumulative bond flows, the recovery has been swifter in the case of the COVID-19 financial turmoil in the early months of 2020.

B3.3 Revisiting the Bond Flows Time Series

Recall that the magnitudes of the BaRs in the GFC and the COVID-19 crisis reached about the same maximum level. Nonetheless, in the case of COVID-19, the time series of the BaR was less persistent and recovered much more quickly as it reached small levels much rapidly.

Based on this and other information we have presented, we conjecture that while the expectations for COVID were that the bond flows could deteriorate as bad as in the GFC crisis did, the associated risk of an extreme bond outflows episode during COVID did not materialize. Moreover, it might have been due to more timely and effective policy responses.

B3.4 The Accumulated Bond Flows

Consider the periods associated with the GFC and the COVID-19 crisis. We depict indices capturing the accumulated bond flows, before and after, the first week of such events (Figure 10).

The magnitude and the persistence of the former episode are relatively more severe. Note that although having the same initial date, such indices are standardized with respect to the initial cumulative bond flows prior to each episode. During the GFC, the equivalent of the bond flows accumulated since 2004 were withdrawn from the LAC-5 economies. What is more, the accumulated bond flows recovered its initial levels only after about a year.

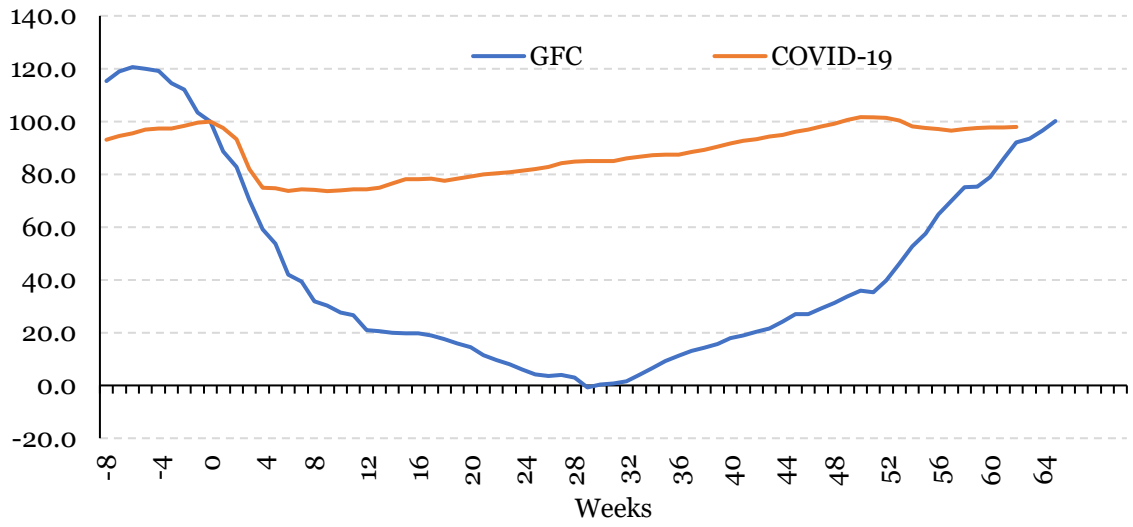


Figure B1.8. GFC vs COVID-19.
Notes: The zero level at the Y-axis means that all the bond flows since 2004 were withdrawn from the LAC-5 economies. **X-axis Zeros:** Sep 15, 2008 for the GFC, and February 26, 2020 for the COVID shock.
100 indicates the cumulative level of bond flows at the respective origin date stamps.
Source: With data from EPFR Global.

Several indicators signaled that the COVID-19 financial outlook in terms of bond flows could be as bad as in the GFC. At least, initially this seemed to be the case. Nonetheless, the recovery in terms of bond flows was in relative terms better.

B4. Considering Cross-Terms

Another variation to our main model is to include cross-terms. While we have explored several configurations, we have only found one reasonable model. This model includes the global (VIX) and local factors, as pipes, the proportion of non-resident bond holders, and the cross-term between the VIX and our pipes factor. The interpretation of the cross-term is intuitive.

The VIX and the proportion of local nominal bond holding contribute to a deterioration of the bond flows' densities. In effect, given a fixed set of pipes, under a situation in which there are bond outflows, more volatility in financial market deteriorates the density. Seeing the coefficients as partial derivatives, a larger VIX, augments the adverse effect of the proportion and likewise, a larger proportion of non-resident holdings, augments the adverse effect of the VIX.

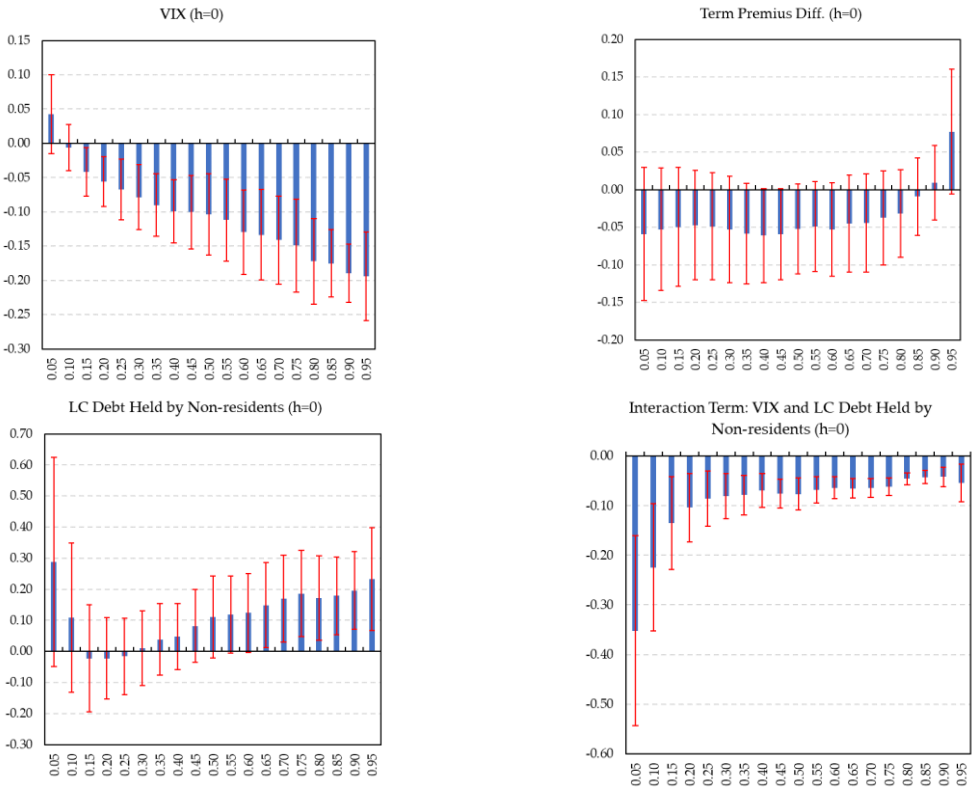


Figure B4.1. Quantile Regressors for the Benchmark model including Pipes and a Cross-Term.

Note: Red error bars indicate confidence intervals at a 10% level. We consider an explanatory horizon; i.e., $h = 0$. **Source:** Own estimates with data from EPFR Global, Bloomberg, and the corresponding Finance Ministries and Central Banks.

In addition, while the individual coefficients associated with the VIX and the proportion of bondholders vary, but, they do so in a consistent way once the cross-term is considered. While we only present the results of the model that includes one pipes factor and one-cross term, a more general model that includes the three pipes factors and the referred cross-term largely maintains the results.