Clogged capital flows pipes? Non-bank global investors and the stability of bond flows

Manuel Ramos-Francia[a], Matias Ossandon Busch[a,b], Ricardo Montañez-Enríquez[a]

(a) CEMLA; (b) IWH

Motivation

- A striking fact of the post-financial crisis period has been the changing nature of capital flows' dynamics, especially in the case of Emerging Market Economies (EMEs).
- Critically, in the case of EMEs, there has been an increase in capital flows' volatility.
- Two factors have been referred to as possible drivers of this trend:
    1. A shift from banks to Global Asset Managing Companies (GAMs) as key players in cross-border flows.
    2. The rise of passive investing (and of automated trading, including algorithmic and high frequency).
- These dynamics can have far-reaching implications for the stability of capital flows.

Total volume of assets under management

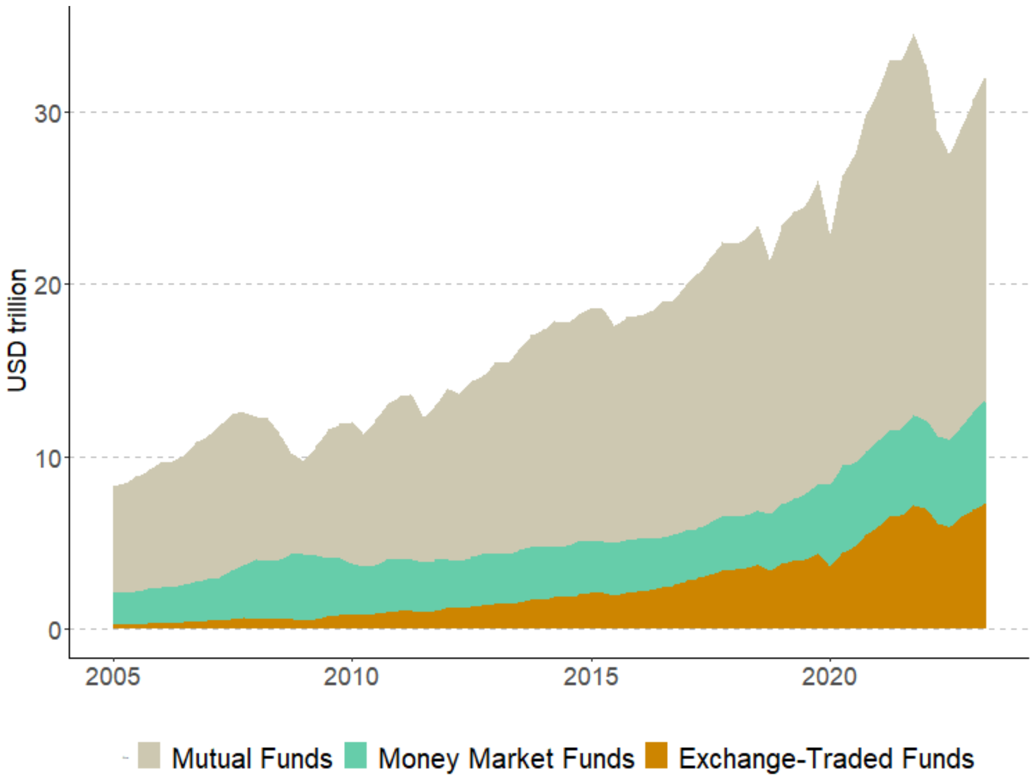

Figure 1: Total volume of funds globally. Source: Own calculation based on data from IMF.

Share of EMEs' bond holders by type

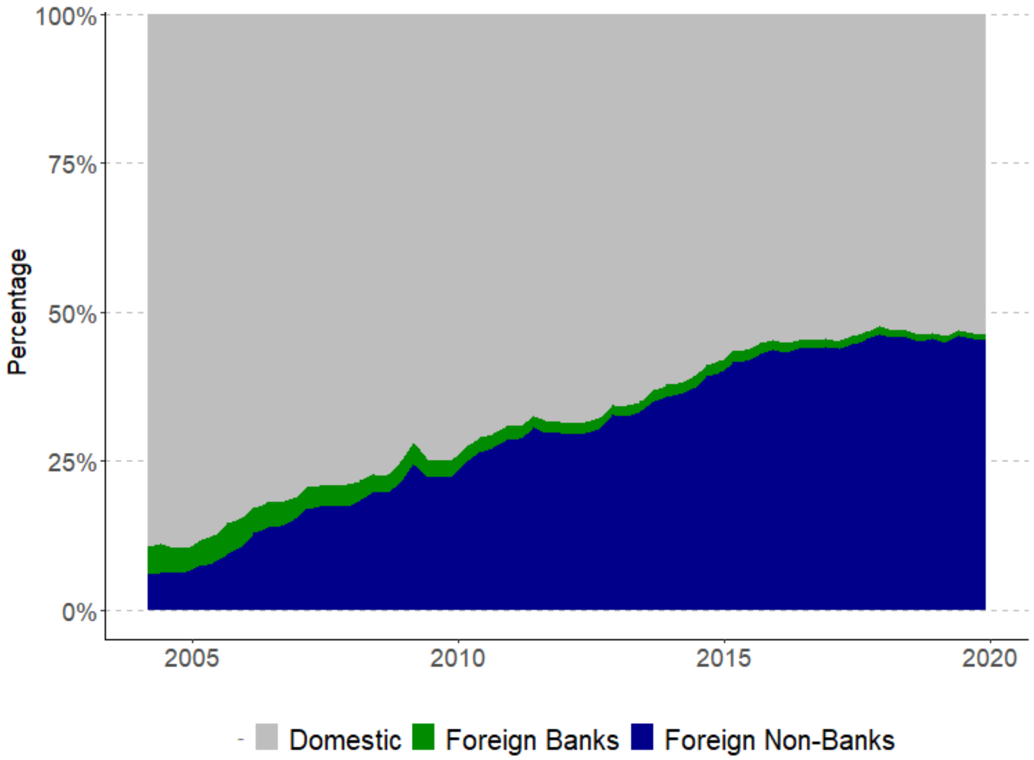

Figure 2: Percentage of bond holders in EMEs. Source: Own calculation based on data from the US Federal Reserve Board.

- ETFs have observed an eightfold increase since 2010 (left); Foreign NBFI went from representing 10% of EMEs debt holders as of 2005, to more than 45% as of 2020 (right).

Motivation

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Net weekly bond flows (Brazil, Chile, Colombia, Mexico, Peru)

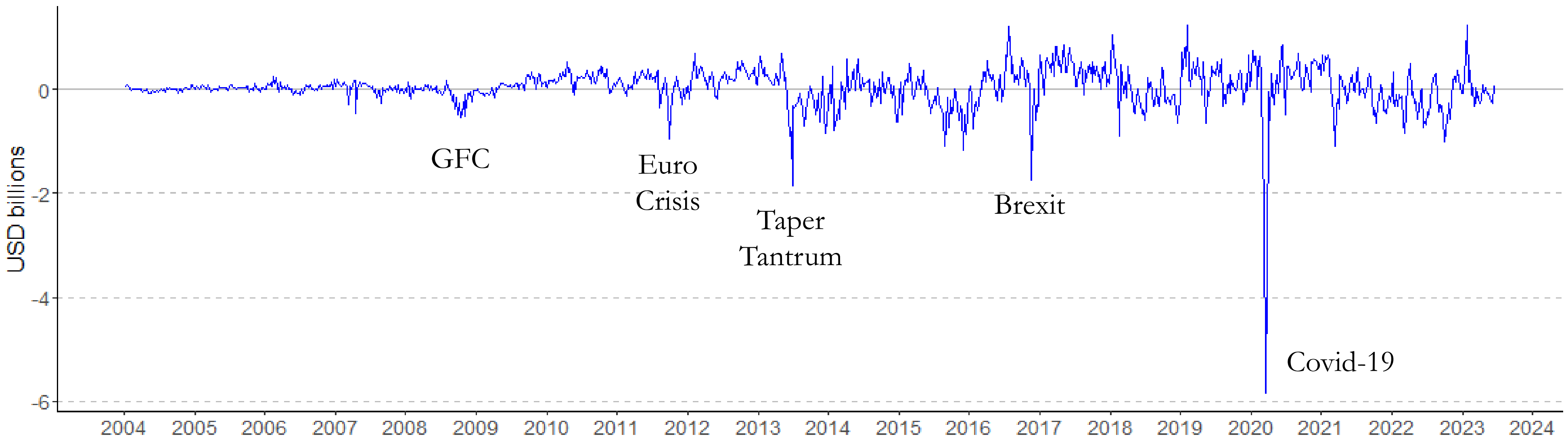

Figure 3: Total weekly bond flows for the countries in the panel (Brazil, Chile, Colombia, Mexico and Peru). Source: Own calculation based on data from EPFR Global. "GFC" marks outbreak of the Great Financial Crisis with the collapse of Lehman Brother on September 15, 2008. "Euro Crisis" marks cut in Italy's credit rating by one notch to A+ from AA− and the cut in Spain's rating to AA− from AA+ by Fitch on October 7, 2011. The "Taper Tantrum" marks the intended end of the U.S. Fed's massive bonds' purchases program, as announced on May 22, 2013 by Ben Bernanke. "Brexit" marks the period following UK's referendum on leaving the EU on June 23, 2016. The lowest value in the series coincides with Theresa May's announcement to trigger EU's Article 50 on October 2, 2016. "Covid-19" marks the outbreak of the Covid-19 pandemic on March 15, 2020 (first lockdowns announced in the U.S.).

- The volatility and the magnitude of extreme negative events have been **increasing with time**.
- EMEs are **vulnerable to non-resident bond holders** and to global financial events.

Research question

Global Monetary Game → **Δ^+GAMs**

Central Banks

Institutional characteristics.

- Principal-agent relationship. **Aversion to ranking last. Herding.**
- Non-leveraged funding.
- Outside of regulatory perimeter.
- **Unrestricted redemptions.**

From active to passive investments. Automated trading.

- Index-based portfolios.
- **Concentration, crowded trades.**
- **Algorithmic provided liquidity under stress?**
- Kill switches.

EMEs limited fiscal firepower → thinner, shallower markets.

Δ^+ CF Volatility $\stackrel{?}{=}$ **Δ^+Liquidity Risk**

- 1) This increase in liquidity risk creates incentives to accumulate FX reserves, which is complicated in the context of fiscally-constrained EMEs. 2) Also, makes it necessary in some cases to be supported with liquidity provision from core CB. → **Moral hazard?**

- **<u>This paper</u>: Do these post-2008 changing patterns in international financial markets affect the stability of bond flows to EMEs?**

- We expand the literature by assessing the role of three policy-relevant factors:

1. First, we shift the focus from traditional **pull and push factors** to the role of capital flows **pipes' resilience and interconnectedness**.*
2. Second, we assess the impact of **1)** GAMs, **2)** debt markets' exposure to ETF portfolios, and of **3)** changes in central banks´ IR on the **probability of extreme bond outflows** from EMEs.
3. Third, we explore whether **4)** **central banks' liquidity provision under conditions of stress** (e.g. direct spot market, NDFs; bilateral FX swaps, Repo facilities) attenuate the link between global factors and bond flows.

* Pipes refer to the institutional infrastructure through which capital flows transit, as well as the financial intermediaries that use and manage them, the laws they follow, etc.

Research design

- We follow a research design based on **two main building blocks**:
  - A baseline Growth-at-Risk (GaR) model adjusted to account for global and domestic factors affecting the shape of **bond flows' expected densities**.
    - ✓ Variables capturing the resilience and interconnectedness of pipes-related factors as drivers of bond flows' expected densities.
  - A database on macrofinancial variables for five Latin American countries: **Brazil**, **Chile**, **Colombia**, **Mexico**, and **Peru**
    - ✓ Countries in LAC with long-term (10y) local currency bonds.
    - ✓ Bonds with a sizable share of non-resident holders, and extensively used in indexed products, such as ETFs.

Research design – GaR approach

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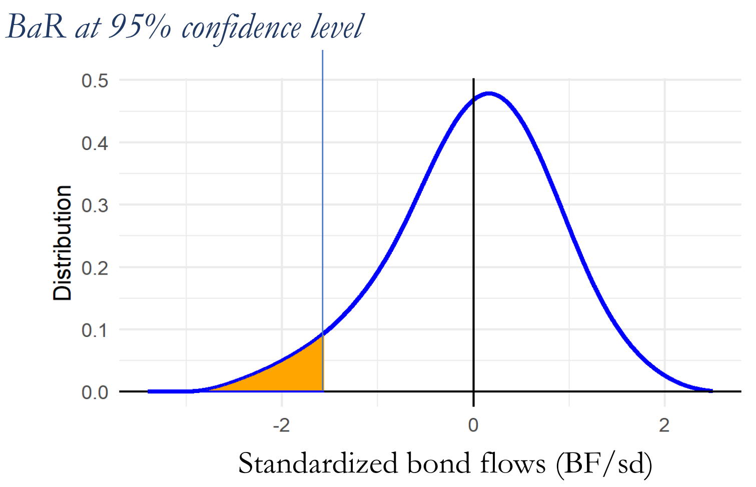

Example: Weekly BaR estimation for Mexico as of June 2023

S.d. of Mexican-bond flows	118.9	million USD
Mexico's BaR in s.d.	1.2	
Mexico's BaR in USD	143.3	million USD

- Following the Growth-at-Risk methodology, we quantify changes or impacts in bond flows distributions by computing the **5th percentile** of estimated distributions. **This allows us to focus on the possible realization of extreme outflows at a given time horizon.**
- **We will refer to this measure as *Bond Flows at Risk* or *BaR*.** To ease interpretation, we estimate the **standardized bond flows**, measured as the ratio of bond flows to country-level standard deviations.

Research design: Data

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- The sample spans from January 2004 to June 2023 and includes five Latin American economies: Brazil, Colombia, Chile, Mexico, and Peru.

- Main variables of interest:

  - Weekly bond flows from EPFR Global.
  - VIX index (global **push factor**).
  - Spread between domestic and U.S. 10-year term premium (domestic **pull factor**).
  - **Pipes' proxies**: 1) change in international reserves; 2) share of non-resident held bonds; 3) exposure to ETFs; 4) central banks' domestic and cross-border liquidity interventions.

- Variables are transformed to ratios of the original value with respect to the country-specific standard deviation.

Benchmark specification with quantile (τ) (panel) regressions at horizon *h*:

$$BF_{i,t+h}(\tau) = \alpha_i(\tau) + \beta_{1,h}(\tau)VIX_t + \beta_{2,h}(\tau)TPS_{i,t} + \beta_{3,h}(\tau)NRB_{i,t} + \beta_{4,h}(\tau)\Delta IR_{i,t} + \beta_{5,h}(\tau)ETF_{i,t} + \varepsilon_{i,t}(\tau)$$

Where:

- $BF_{i,t+h}$ are the bond flows at week $t+h$ of country i.
- We will consider contemporary effects, i.e., $h = 0$.
- α_i are country fixed effects.
- VIX_t is the CBOE Market Volatility Index at week t.
- $TPS_{i,t}$ is 10-year term premium spread between country i and U. S. at week t.
- $NRB_{i,t}$ is the share of non-resident bond holders in country i at week t.
- $\Delta IR_{i,t}$ is the monthly change in international reserves held at country i's central bank
- $ETF_{i,t}$ is country i's exposure to ETFs computed as the sum of weekly changes in the net asset value of the top-5 ETFs trading EMEs bonds weighted by countries' share in each ETF.
- $\varepsilon_{i,t}$ is the error term.

Baseline model (1) estimation

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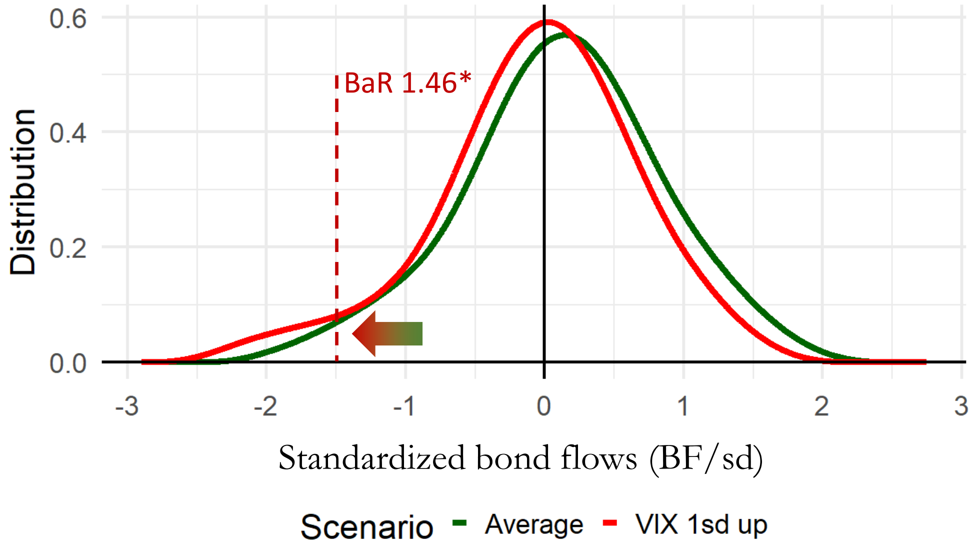
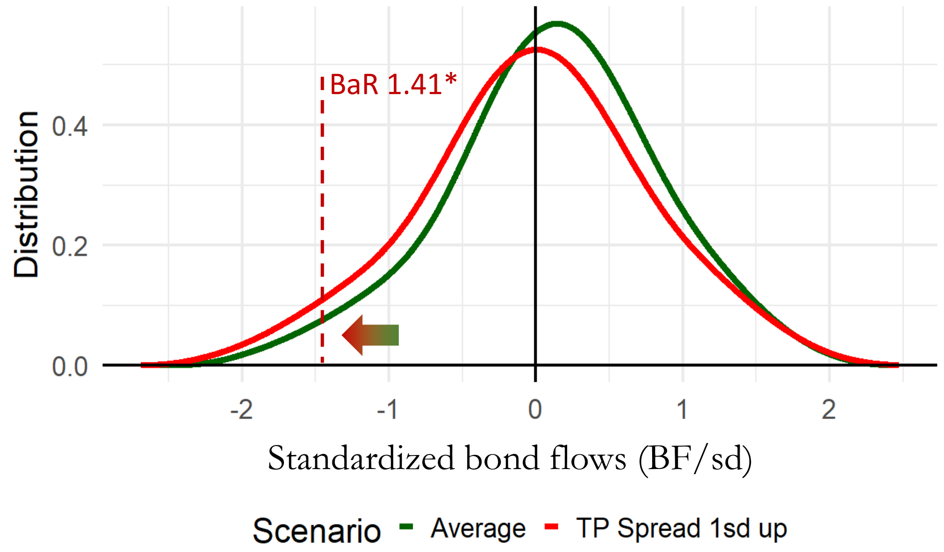
A. Shock to the VIX index



B. Shock to the spread in TP



- We estimate a baseline scenario distribution at the mean values for the VIX index and the term-premia spreads. (**green curves**). Then, we stress each variable separately by increasing it by one standard deviation (**red curves**).
- The BaR changes from **1.20** to **1.46*** s.d. of bond flows following a shock to the VIX (Panel A), and to **1.41*** s.d. following a shock to the term-premia spread (Panel B).

Notes: * Statistically significant effects on the 5th percentile of the bond flows' distribution. Based on quantile panel regressions. Source: Own estimates with data from EPFR Global, Bloomberg, IFS, CBOE, ETF websites, and the and the corresponding Finance Ministries and Central Banks.

Baseline model (1) estimation

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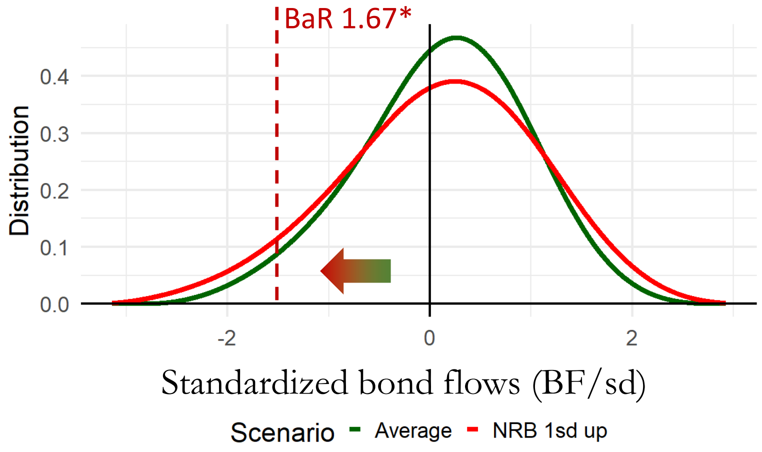
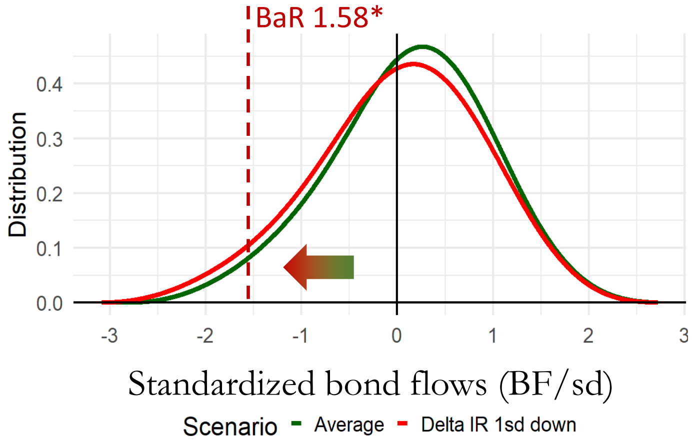
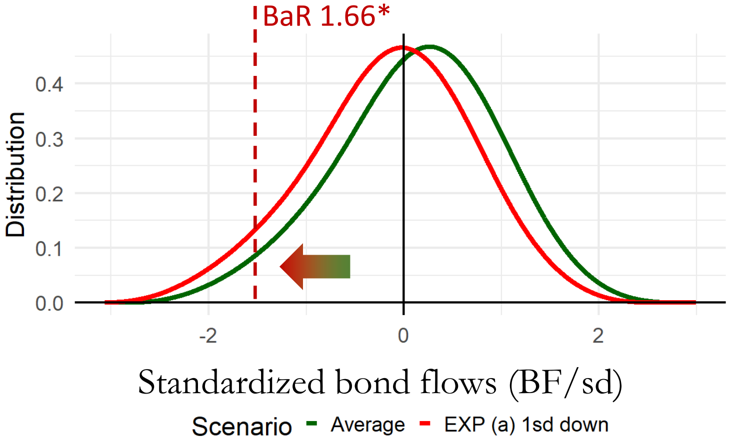
A. Share of non-resident bond holders



B. Δ International reserves



C. Exposure to losses in ETFs' market values



- A **higher vulnerability** in terms of a higher share of non-resident bond holders (Panel A), a large decrease in international reserves (Panel B), or a large decrease in the market value of ETFs' holding bonds of country i shifts the expected distribution of bond flows to the left.
- The BaR changes from a baseline of **1.38 sd** (**green curves**) to **1.67*** sd (Panel A), **1.58*** sd (Panel B), and **1.66*** sd (Panel C). * marks statistically significant effects on the 5th percentile of the bond flows' distribution.

Notes: Based on quantile panel regressions. Source: Own estimates with data from EPFR Global, Bloomberg, IFS, CBOE, ETF websites, and the and the corresponding Finance Ministries and Central Banks.

Baseline model (1) results

- An increase in the VIX index causes an **uneven left shift throughout the distribution**.
- Its effect is **sizable on the left tail**, compared to the right tail, and tamer to the central percentiles, implying a larger probability of extreme bond outflows when shocks to the VIX index hit.
- Larger term-premia spreads also shift the distribution to the left.
- The results are in line with previous findings on the effect of **pull and push factors on capital flows**.
- **Changes in pipes' characteristics shift the expected bond flows' distribution with the expected signs.**

The role of pipe characteristics (2)

We extend the baseline specification as follows:

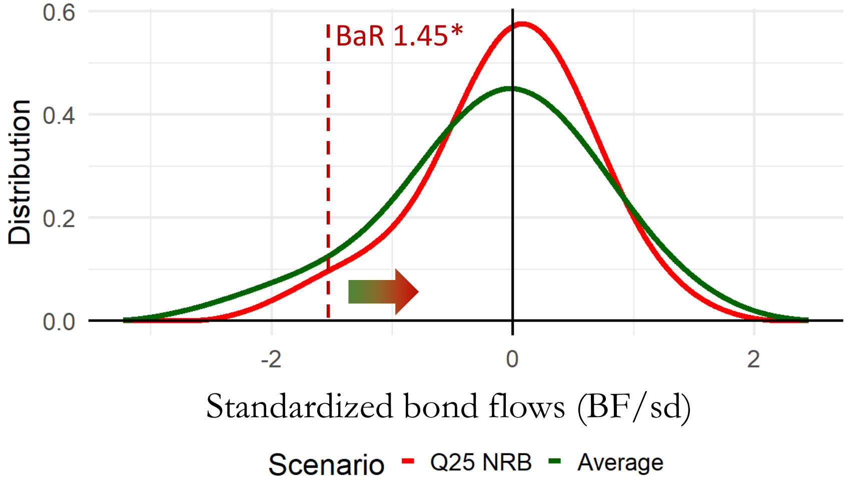
$$BF_{i,t+h}(\tau) = \alpha_i(\tau) + \beta_{1,h}(\tau)VIX_t + \beta_{2,h}(\tau)TPS_t$$
$$+\boldsymbol{\beta'}_{3,h}(\tau)\boldsymbol{Pipe}_{i,t} + \boldsymbol{\beta'}_{4,h}(\tau)(\boldsymbol{Pipe}_{i,t} \times VIX_t)$$
$$+\varepsilon_{i,t}(\tau)$$

The variable $Pipe_{i,t}$ refers to a vector of three **pipe characteristics**:

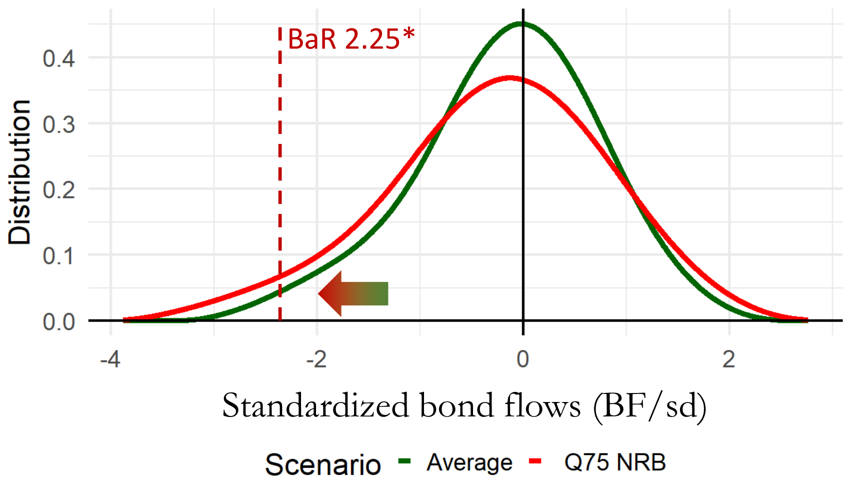
- $NRB_{i,t}$ percentage of Non-Resident Bond holders
- $ETF_{i,t}$ exposure to ETFs
- $\Delta IR_{i,t}$ change in International Reserves
- **Interaction $\boldsymbol{Pipe}_{i,t} \times VIX_t$ captures non-linear effects of shocks to the VIX index depending on pipes' characteristics.**

Pipes' scenario (2) analysis: NRB

A. Low share of non-resident bond holders



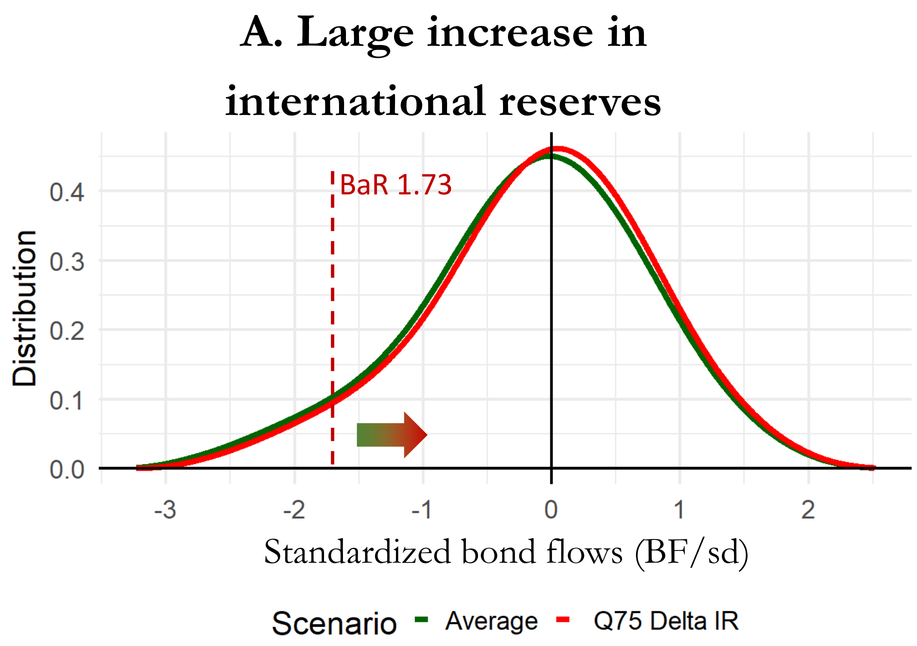
B. High share of non-resident bond holders

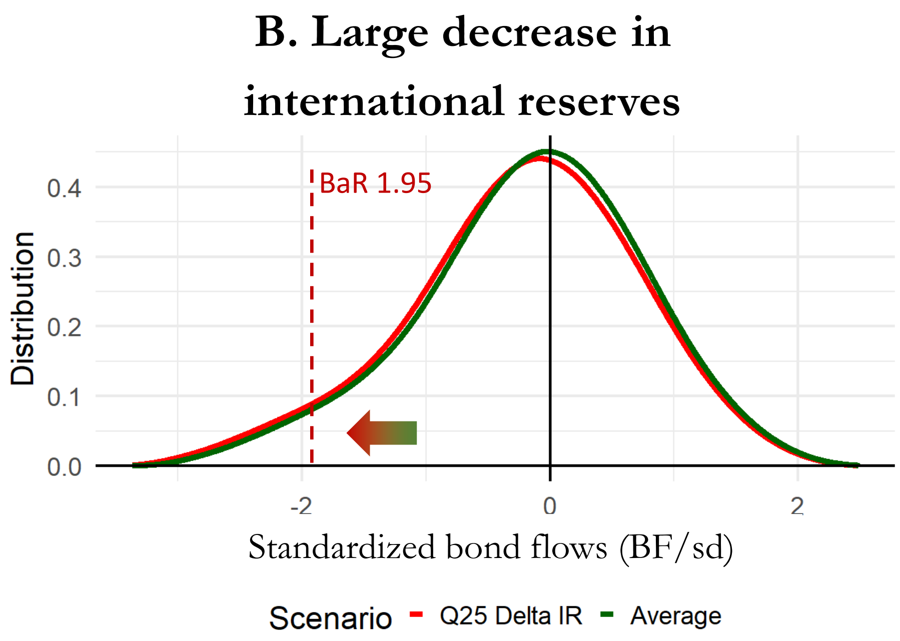


- <u>We estimate **three scenarios**: an average baseline scenario absent of shocks; one following a shock (up) to the VIX index for countries at the 25th percentile of the the pipe variable (Panel A); and another at the 75th percentile (Panel B)</u>.
- Compared to an average baseline scenario (**BaR at 1.84, green curves**), a 1 s.d. up shock to the VIX index shifts the bond flows' distribution to the left (Panel B) **(2.25*)** if the share of non-resident bond holders is large (**red curve**).
- **Thus, more interconnected pipes – as proxied by a large share of NRB – exacerbate the impact of adverse global financial conditions on the probability of extreme bond outflows.**

Note: The BaR changes from a baseline of 1.84 sd (green curves) to 1.45 sd (Panel A) and 2.25 sd (Panel B). * marks statistically significant effects on the 5th percentile of the bond flows' distribution. Source: Own estimates with data from EPFR Global, Bloomberg, IFS, CBOE, ETF websites, and the and the corresponding Finance Ministries and Central Banks.

Pipes' scenario (2) analysis: ΔIR



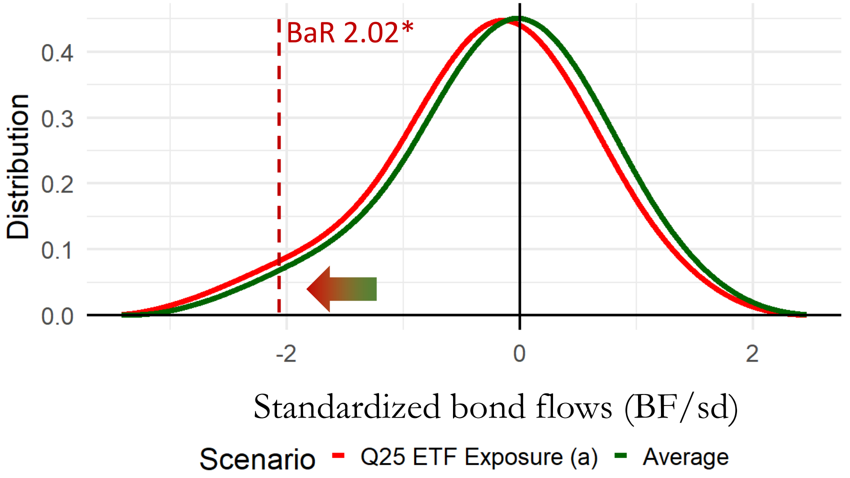


- Compared to an average baseline scenario (**BaR at 1.84, green curves**), a <u>1 s.d. shock (up) to the VIX</u> index shifts the bond flows' distribution to the left (**red curve (1.95)**, Panel B) if countries experience contemporaneously a **large decrease in international reserves**.
- **Thus, more liquid pipes – as proxied by increases in international reserves – mitigate the impact of adverse global financial conditions on the probability of extreme bond outflows.**

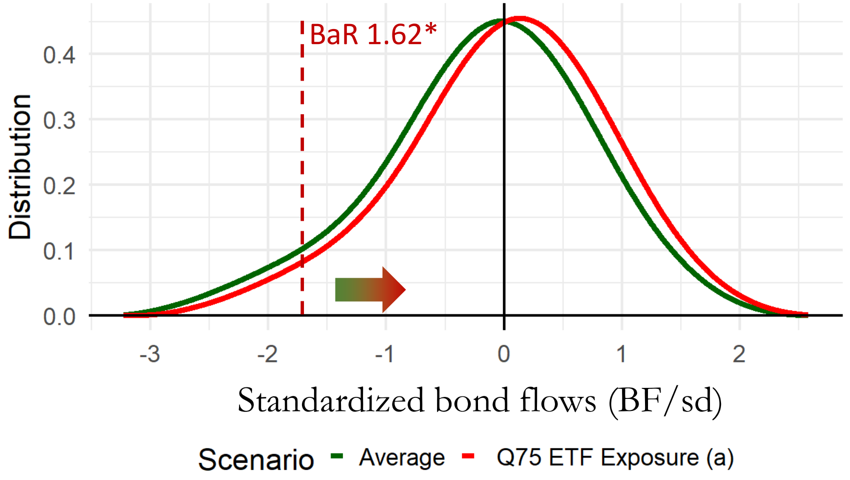
Notes: The BaR changes from a baseline of 1.84 sd (green curves) to 1.73 sd (Panel A) and 1.95 sd (Panel B). * marks statistically significant effects on the 5th percentile of the bond flows' distribution. Source: Own estimates with data from EPFR Global, Bloomberg, IFS, CBOE, ETF websites, and the and the corresponding Finance Ministries and Central Banks.

Pipes' scenario (2) analysis: ETF

A. Reductions in the market value of ETFs investing in countries' bond markets



B. Increases in the market value of ETFs investing in countries' bonds markets



- Compared to an average baseline scenario (**BaR at 1.84, green curve**), a 1 s.d. shock (up) to the VIX index shifts the bond flows' distribution to the left (**red curve, 2.02*** Panel A) if ETFs investing in a country's bond market lose market value.
- **Thus, countries' exposure to GAM passive investing – as proxied by their exposure to ETFs– exacerbates the impact of adverse global financial conditions on the probability of extreme bond outflows.**

Notes: The BaR changes from a baseline of 1.84 sd (green curves) to 2.02 sd (Panel A) and 1.62 sd (Panel B). * marks statistically significant effects on the 5th percentile of the bond flows' distribution. Source: Own estimates with data from EPFR Global, Bloomberg, IFS, CBOE, ETF websites, and the and the corresponding Finance Ministries and Central Banks.

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Announcement Dates

COVID-19 (2020)

	Domestic liquidity interventions	Cross-border liquidity interventions
Brazil	March 25	March 18; October 29
Chile	March 25; July 29	June 24
Colombia	March 11; May 6	April 22
Mexico	March 20; April 21	May 13; June 24
Peru	March 16; June 10	

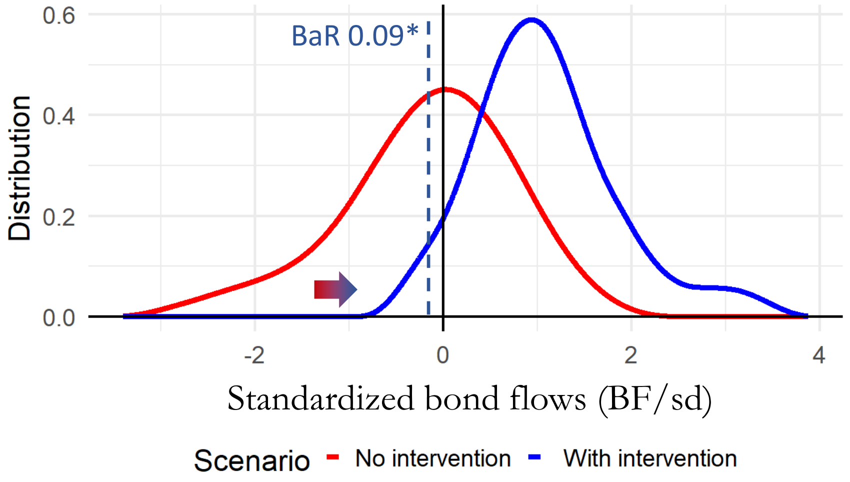
Global Financial Crisis

Mexico & Brazil		October 29, 2008

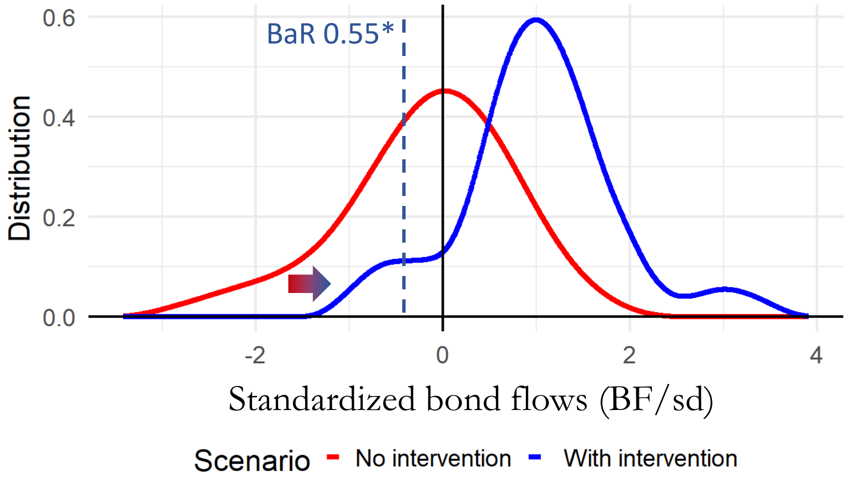
- Since the Global Financial Crisis (e.g.,, during the COVID-19 pandemic), different jurisdictions put in place emergency **liquidity provisions** – both domestic and cross-border – to prevent a dry-up in financial markets.
- We grouped these measures as domestic or cross-border liquidity interventions.
- Cross-border liquidity interventions include, e.g., bilateral FX Swaps and/or access to the FIMA facility. Domestic liquidity interventions include, e.g., spot market interventions, interventions through NDFs, etc.

$$BF_{i,t+h}(\tau) = \alpha_i(\tau) + \beta_{1,h}(\tau)VIX_t + \beta_{2,h}(\tau)TPS_t + \boldsymbol{\beta'}_{\mathbf{3},\boldsymbol{h}}(\tau)\boldsymbol{Pipe}_{\boldsymbol{i},\boldsymbol{t}} + \boldsymbol{\beta'}_{\mathbf{4},\boldsymbol{h}}(\tau)\left(\boldsymbol{Policy}_{\boldsymbol{i},\boldsymbol{t}}\right) + \boldsymbol{\beta'}_{\mathbf{5},\boldsymbol{h}}(\tau)\left(\boldsymbol{Policy}_{\boldsymbol{i},\boldsymbol{t}} \times \boldsymbol{VIX}_{\boldsymbol{t}}\right) + \varepsilon_{i,t}(\tau)$$

A. Effect of adverse global financial conditions with/without *domestic* liquidity interventions



B. Effect of adverse global financial conditions with/without *cross-border* liquidity interventions



- Following a **shock to the VIX index (1 s.d. increase)**, the probability of extreme bond outflows increases to a lesser extent in the 4 weeks following the announcement of Liquidity interventions (**blue curves**), both **domestic** (Panel A) and **cross-border** (Panel B), compared to a non-intervention scenario (**BaR 1.92; red curves**).

Notes: The BaR changes from a baseline of 1.92 sd (red curves) to 0.09 sd (Panel A) and 0.55 sd (Panel B). * mark statistically significant effects on the 5th percentile of the bond flows' distribution.
Source: Own estimates with data from EPFR Global, Bloomberg, IFS, CBOE, ETF websites, and the and the corresponding Finance Ministries and Central Banks.

Pipes' models (3) results

- In times of global market stress, a higher exposure to **non-resident investors** exacerbates the probability of **extreme** bond outflows.

- Large market-value losses by **ETFs investing in countries' bond markets** are associated with increases in the probability of extreme bond outflows. These losses exacerbate the effect of **adverse global financial conditions** on the probability of extreme outflows.

- More **liquid and resilient pipes** – as captured by increases in **international reserves** – reduce the probability of extreme outflows, mitigating the effect of shocks to global financial conditions.

- **Liquidity provision** – done (directly in spot market) with IR from central bank or through derivatives (NDFs), or from cross-border facilities (swap lines, FIMA repo facility) – significantly mitigate the effect of adverse global financial conditions on the probability of extreme outflows.

Final remarks

- Since the GFC, complex market dynamics sometimes arise from **perverse demand responses.**
- We document that the probability of extreme bond outflows from EMEs under adverse global financial conditions is amplified by countries' exposure to Global Asset Managing Companies (GAMs), and by the increase in passive investing and automated trading (e.g., algorithmic and high frequency).
- Negative externalities of GAMs arise from their nature (aversion to ranking last), the use of investment vehicles like ETFs (and automated trading), and the availability of almost **immediate redemptions** → **Dramatic increase in liquidity risk under stress conditions.** **(Redemption fees?)**
- These volatile dynamics may be attenuated by capital flows' pipes that are more resilient, that is, liquid and less saturated by global investors.
- Particularly, timely provision of liquidity (in FX and sometimes in bond markets) under conditions of market stress crucial to ensure the proper functioning. However, **moral hazard** needs to be considered.

Appendix

Quatile panel regressions

- We use quantile panel regressions to model conditional quantiles of bond flows BF_t as function of VIX, term premium differences, and pipe factors $\boldsymbol{Pipe_{i,t}}$:

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

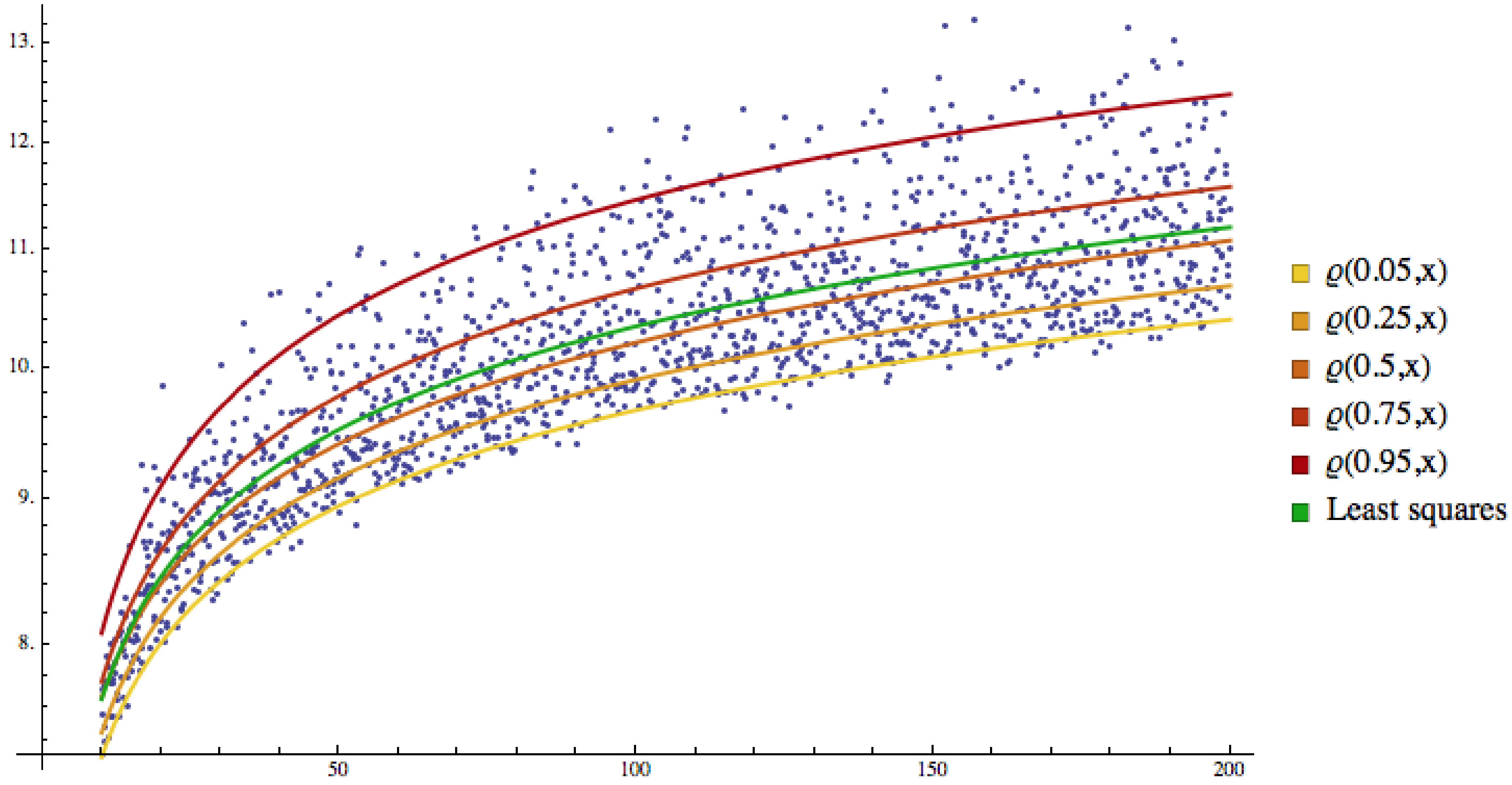
- α_i are time-invariant fixed effects for country $\boldsymbol{i}$, and $\epsilon_{i,t}$ are the error terms.

- Thus, we have to estimate the quantile coefficients $\widehat{\boldsymbol{\beta}}(\tau)$such that:

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

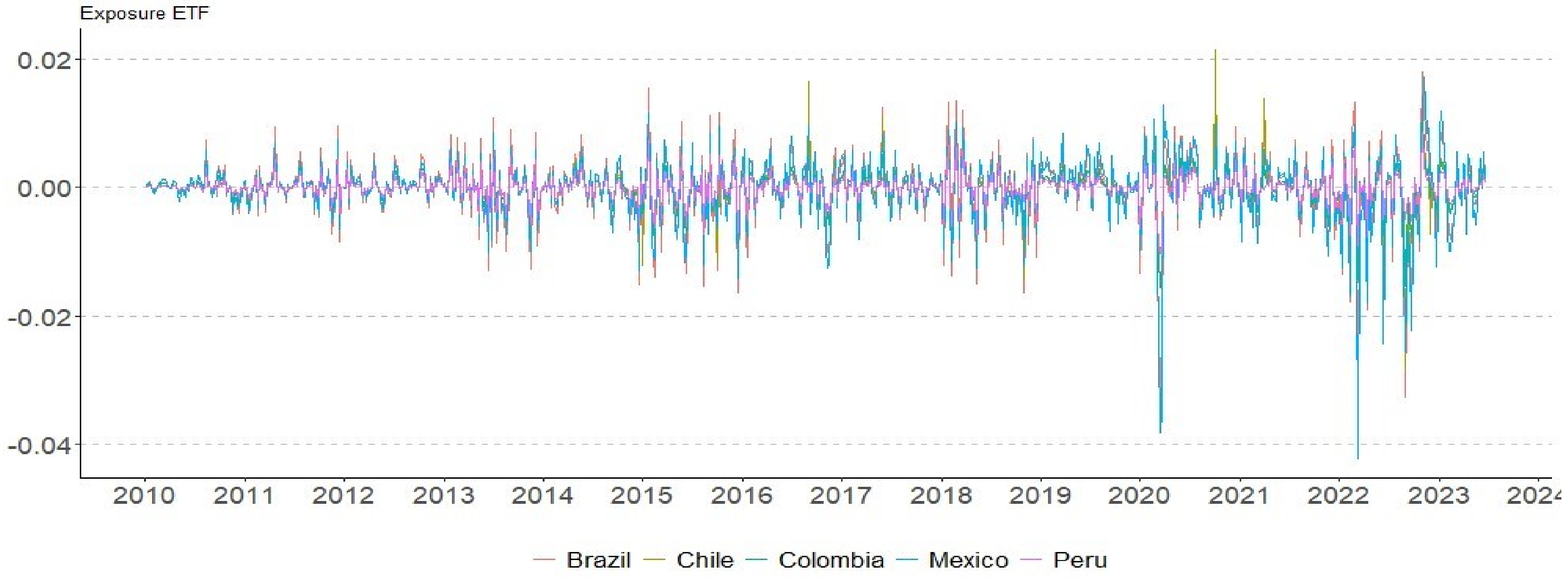
$$= \underset{\boldsymbol{\beta} \in R^k}{\operatorname{argmin}} \sum_{t=1}^{T} \tau \left(BF_{t+h} - \boldsymbol{X}_{i,t}\boldsymbol{\beta}(\tau)\right)_{BF_{t+h} > \boldsymbol{X}_{i,t}\boldsymbol{\beta}(\tau)} + (1-\tau)\left(BF_{t+h} - \boldsymbol{X}_{i,t}\boldsymbol{\beta}(\tau)\right)_{BF_{t+h} < \boldsymbol{X}_{i,t}\boldsymbol{\beta}(\tau)}$$

Representation of quantile regressions



Note: Figure from Mathematica for prediction algorithms. [URL](URL).

Exposure to ETFs



The figure illustrates countries' exposure to ETFs according to the proposed metric.

Source: Own calculation with data from:

- Vanguard FTSE,
- Emerging Markets ETF VWO,
- iShares Core MSCI Emerging Markets ETF,
- iShares JP Morgan USD Emerging Markets Bond ETF,
- VanEck J.P. Morgan EM Local Currency Bond ETF,
- Vanguard Emerging Markets Government Bond ETF.

- The exposure to ETFs metric is given by: $$ETFa_{i,t} = \sum_{k=1}^{5} \Delta ETF_{k,t} \times s_{i,k}$$
- k indexes one of the top-5 ETFs specialized in EMEs.
- $\Delta ETF_{k,t}$ represents the change in the value of ETF k investing in bonds issued by country i at time t.
- $s_{i,k}$ is the share of bonds issued by country i in ETF k.

Estimating the term premia spread

- We consider as a domestic financial stress factor the spread between the 10-year domestic vs. U.S. term premium obtained from 10y zero-coupon interest rate. We consider as the long-term rate the 10y zero-coupon interest rate (in simple composition), as the short-term rate the 1-month interest rate, and the term premium (in simple composition):

$$\left(1+10\cdot i_t^{(10)}\right)=\left[\left(1+\frac{E_t i_t^{(1m)}}{12}\right)\dots\left(1+\frac{E_t i_{t+119m}^{(1m)}}{12}\right)\right]\left(1+10\cdot TP_t^{(10)}\right) \quad (1)$$

- We next define the risk-neutral interest rate as described in **Eq. (2)**:

$$\left(1+10\cdot i_t^{(10,*)}\right)\equiv\left[\left(1+\frac{E_t i_t^{(1m)}}{12}\right)\dots\left(1+\frac{E_t i_{t+119m}^{(1m)}}{12}\right)\right] \quad (2)$$

- Hence, we consider:

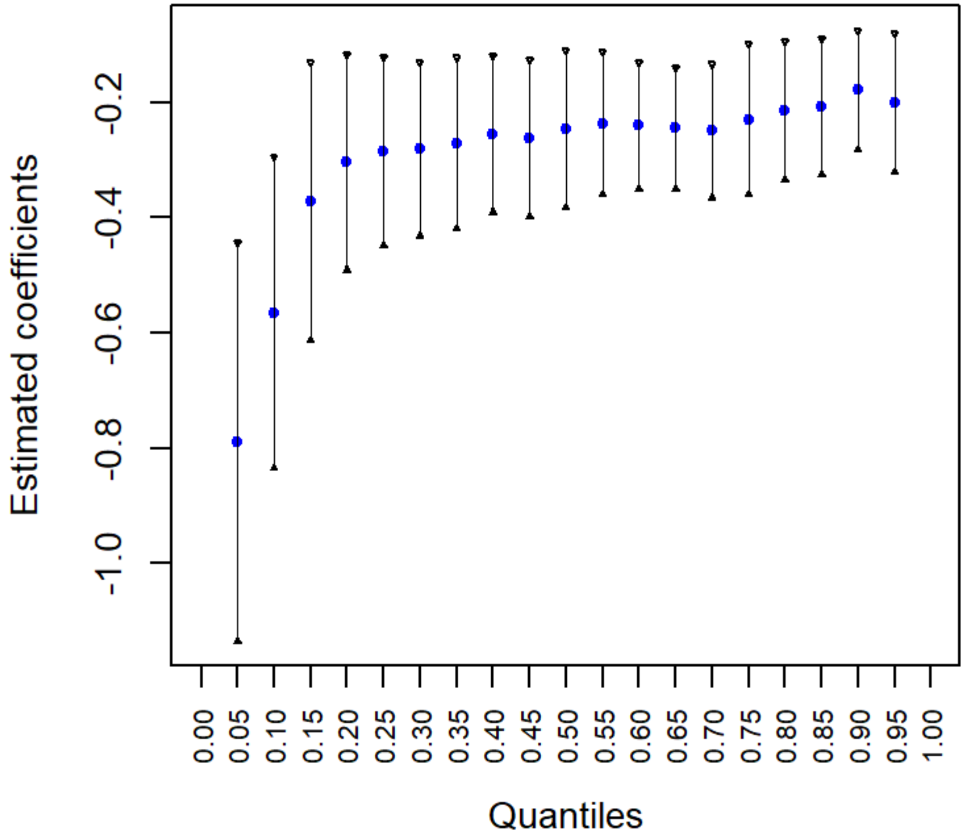
$$\left(1+10\cdot i_t^{(10)}\right)=\left(\mathbf{1}+\mathbf{10}\cdot \boldsymbol{i}_t^{(\mathbf{10},*)}\right)\left(1+10\cdot TP_t^{(10)}\right) \quad (3)$$

- Term premia are computed following the methodology proposed by **Adrian et al. (2013)**. While the alluded spread is not capturing purely domestic factors because of its link to the U.S. term premium, it can be interpreted as a proxy for the marginal contribution to the risk of adding EME bonds to a U.S. bond portfolio. This metric has been widely used to construct measures of the U.S. yield curve (see **Moench and Soofi-Siavash, 2022**, for a recent application). From a macroeconomic perspective, the spread in the term premium conveys information on inflation, fiscal, liquidity and other macro-financial risks.

Quantile regression estimation

$$BF_{i,t+h}(\tau) = \alpha_i(\tau) + \boldsymbol{\beta_{1,h}(\tau) VIX_t} + \beta_{2,h}(\tau)TPS_{i,t} + \beta_{3,h}(\tau)NRB_{i,t} + \beta_{4,h}(\tau)\Delta IR_{i,t} + \beta_{5,h}(\tau)ETF_{i,t} + \varepsilon_{i,t}\,(\tau)$$

Estimated $\boldsymbol{\beta_{1,h}(\tau)}$

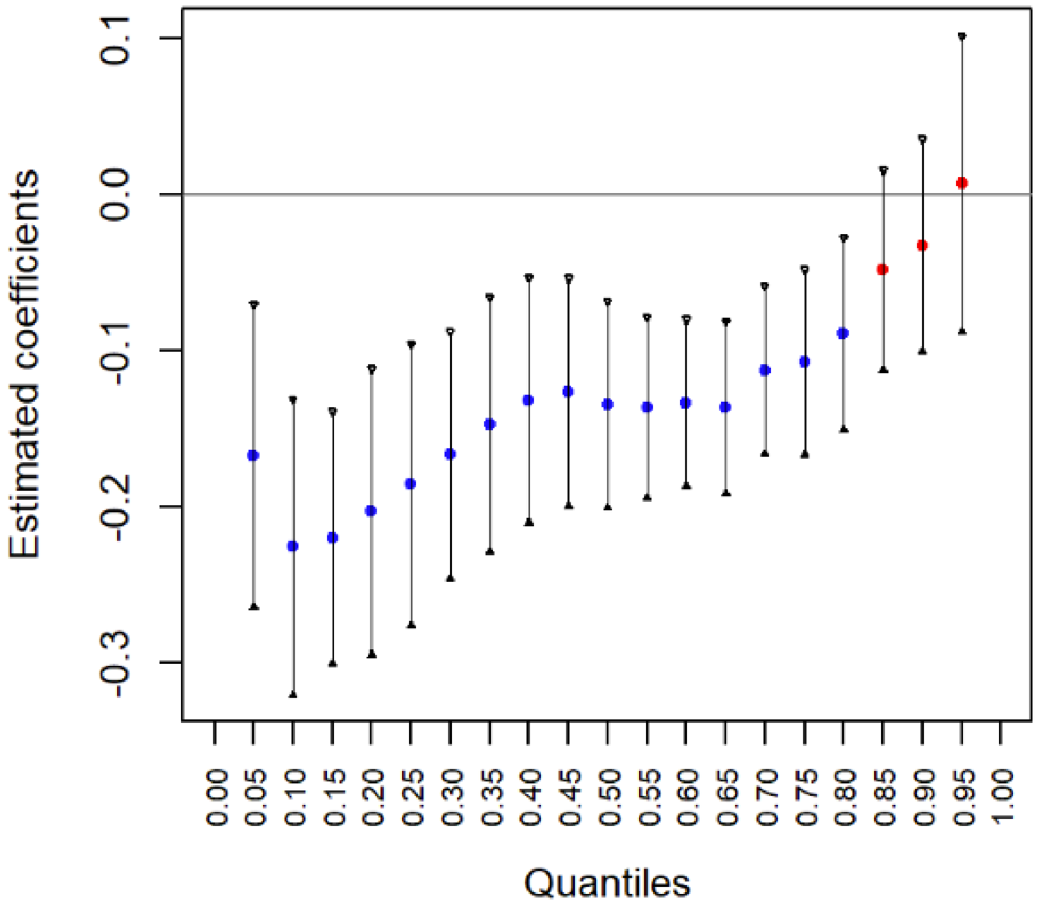


- This figure illustrates the estimated coefficients $\boldsymbol{\beta_{1,h}(\tau)}$ for different quantiles (τ) of the bond flows' distribution.
- Dots represent point estimates, whereas the brackets represent the confidence intervals of each estimation at the 95 percent conficence level.
- The leftmost estimated coefficient illustrated the effect of a one standard deviation increase in the VIX index on the 5th percentile of the bond flows' distribution.

Quantile regression estimation

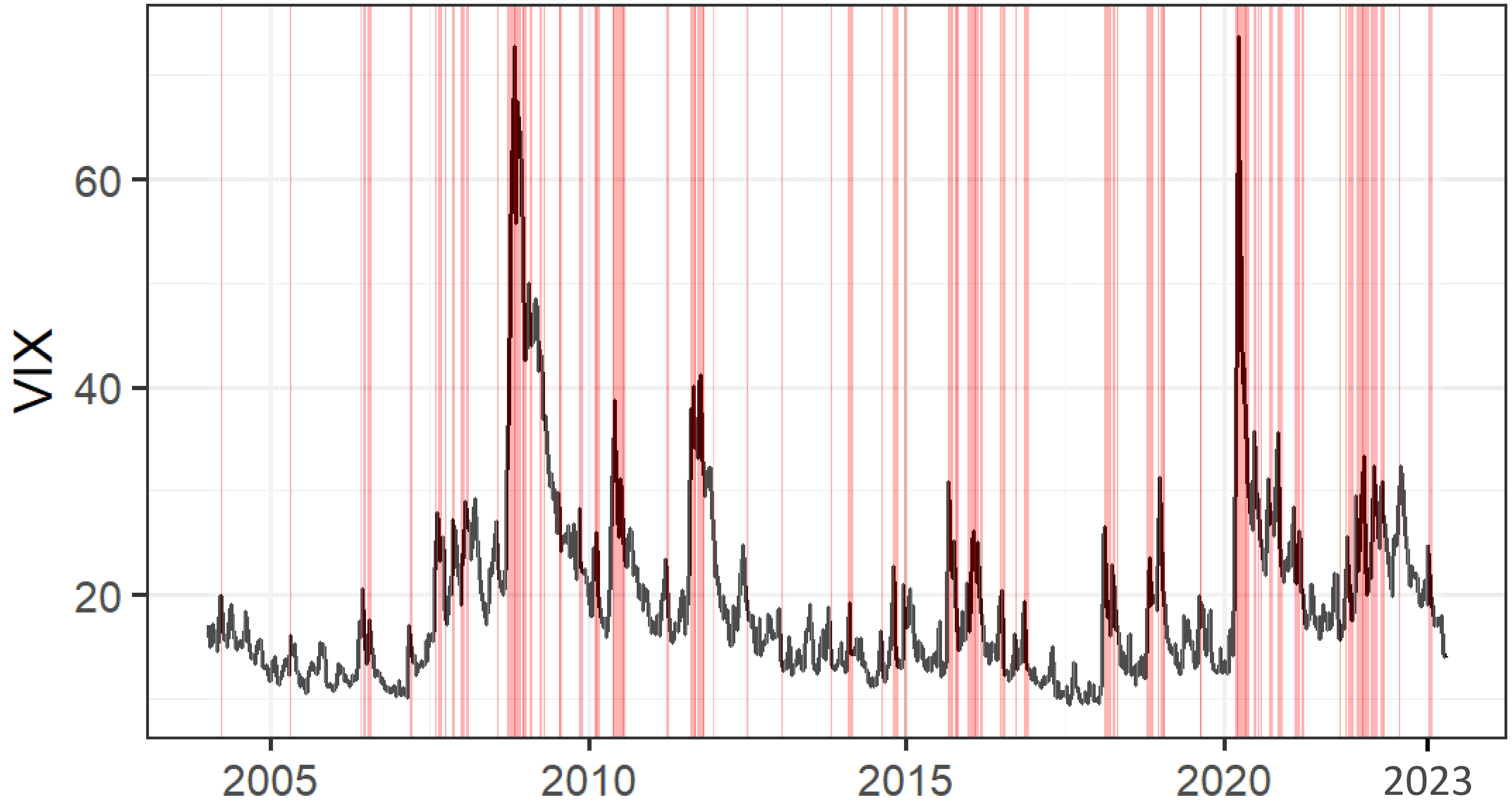
$$BF_{i,t+h}(\tau) = \alpha_i(\tau) + \beta_{1,h}(\tau)VIX_t + \boldsymbol{\beta_{2,h}(\tau)TPS_{i,t}} + \beta_{3,h}(\tau)NRB_{i,t} + \beta_{4,h}(\tau)\Delta IR_{i,t} + \beta_{5,h}(\tau)ETF_{i,t} + \varepsilon_{i,t}\ (\tau)$$

Estimated $\boldsymbol{\beta_{2,h}(\tau)}$



- This figure illustrates the estimated coefficients $\boldsymbol{\beta_{2,h}(\tau)}$ for different quantiles (τ) of the bond flows' distribution.
- Dots represent point estimates, whereas the brackets represent the confidence intervals of each estimation at the 95 percent conficence level.
- The leftmost estimated coefficient illustrated the effect of a one standard deviation increase in the TP Spread on the 5^{th} percentile of the bond flows' distribution.

Regime-switching model

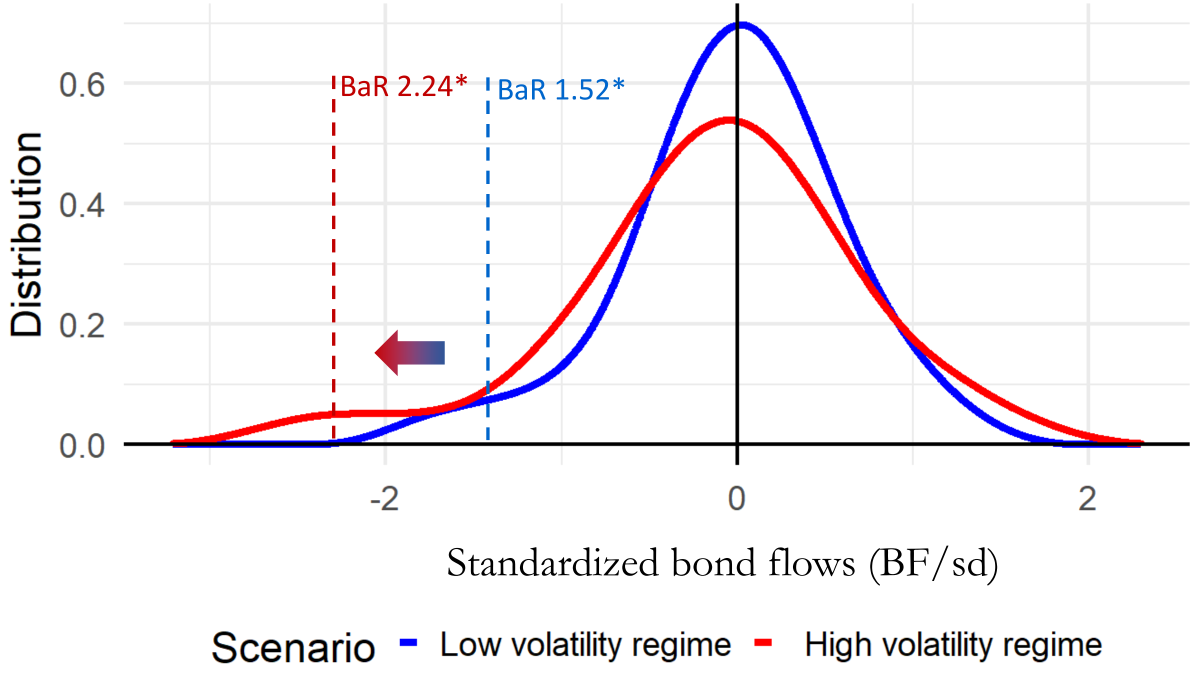


Notes: This figure shows the time series of the VIX index (solid black line) along with vertical lines representing weeks identified as being within a high volatility regime in the VIX index according to a Markov regime switching model.

- The VIX time series can be represented in a statistically significant way by a regime-switching model, with a high-volatility regime state and a low-volatility one.
- We start from the VIX index and estimate a Markov regime switching model to its time series. In it, 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. That said, a high volatility in the shocks is associated with a high volatility in the VIX time series.
- We consider the associated state probabilities, rounded to their nearest integers, which define the dummy variables: $D_{t,low}$ and $D_{t,high}$. We note that $D_{t,low} = 1 - D_{t,high}$. Analytically, $D_{t,high} = \text{round}(\Pr(S_t = high\ \sigma^2))$.

Regime-switching model

Effect of shock to the VIX index (1 s.d. up) by high vs. low volatility regimes



$$BF_{i,t+h}(\tau) = \alpha_i(\tau) + \beta_{1,h}(\tau)D_{t,high} + \beta_{2,h}(\tau)D_{t,high} \times VIX_t + \beta_{3,h}(\tau)TPS_{i,t} + \boldsymbol{\beta'}_{\mathbf{4,h}}(\tau)\boldsymbol{Pipe}_{\boldsymbol{i,t}} + \varepsilon_{i,t}\,(\tau)$$

- Following a 1 s.d. shock to the VIX index, the probability of extreme bond outflows increases the most **under high volatility regimes (red line)** in global financial markets (departing from baseline **BaR of 1.20**)

Notes: The BaR changes from a low-volatility scenario of 1.52 sd (blue curve) to a high volatility scenario of 2.24 sd (red curve). * marks statistically significant effects on the 5th percentile of the bond flows' distribution. Source: Own estimates with data from EPFR Global, Bloomberg, IFS, CBOE, ETF websites, and the and the corresponding Finance Ministries and Central Banks.