Capital Flows in Risky Times: Risk-on Risk-off and Emerging Market Tail Risk*

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ABSTRACT

Risk-on risk-off shocks have pronounced distributional impacts on capital flows, with managed funds playing an increasingly pivotal role in amplifying these effects. This paper demonstrates that among managed funds, passive funds, with their limited discretion and benchmarking mandates, significantly heighten susceptibility to extreme outflow realizations compared to active funds. These tail realizations create abnormal co-movements in emerging market flows and returns, resulting in outsized aggregate outcomes. This study highlights the distinct dynamics of passive fund flows in the face of changes in global investor risk bearing capacity and provides new insights into the changing mechanisms driving emerging market tail risks.

Keywords: Mutual Funds, ETFs, Emerging Markets, Risk-on/Risk-off, Extreme Events, Tail Risk, Portfolio Reallocation, Passive Investment.

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1 Introduction

This paper's key contribution lies in quantifying the degree to which passive investment flows aggravate extreme outflows and returns relative to the influence of active flows, thereby substantially affecting aggregate outcomes in emerging markets. We demonstrate that passive funds' limited discretion and benchmark-driven strategies amplify global risk shocks, creating outsized flow responses and spillover effects. These dynamics underscore the critical role of fund structure in driving contemporary tail risks in emerging market capital flows.

The mechanism we document operates through a specific causal chain. A global risk-off shock, originating in advanced economy credit, equity, or funding markets, triggers redemption requests from investors in emerging market funds. Fund managers must then respond, but their response is constrained by mandate. Active managers retain discretion: they can choose which countries to sell, hold cash buffers, or buy at a discount assets they view as fundamentally mispriced. Passive managers have no such latitude. They must mechanically rebalance to benchmark weights, selling every country in the index in proportion to its weight, regardless of that country's fundamental exposure to the underlying shock. These fund-level flows then aggregate to country-level capital flows, where the allocation is determined by index construction rules (e.g., MSCI EM Index weights) rather than by factors of broad economic importance. The result is that the institutional plumbing of how capital is intermediated, e.g., passive versus active mandates, open-end mutual funds versus ETFs, and the specific benchmark to which a fund is tied, shapes the distributional properties of aggregate emerging market capital flows in ways that standard models of portfolio rebalancing do not capture.

The April 2025 tariff shock provides a stark illustration. The sweeping reciprocal tariffs announced on Liberation Day imposed sharply different rates across trading partners, generating substantial cross-sectional variation in expected economic exposure. Yet, the passive fund channel we document implies that the resulting capital flow response need not respect this heterogeneity. To the extent that passive fund redemptions drive the flow response, an emerging market with high index weight but low tariff exposure may experience larger outflows than one directly targeted by the policy — a decoupling of the geography of capital flows from the geography of fundamental exposures that is invisible in aggregate flow data but central to understanding emerging market tail risk.

At the aggregate level, emerging market flows are characterized by episodes of sudden stops, surges, capital flight, and retrenchments (Forbes and Warnock (2012), Forbes and Warnock (2021)). A vast literature seeks to understand the extreme flow realizations but finds it difficult to explain the observed tail risk in emerging markets with fundamentals alone. Gabaix et al. (2006) show that a combination of news and trades by large investors can generate tail risk in illiquid markets, i.e., fat-tailed distributions of volumes and returns. Illiquid emerging markets provide an ideal setting to examine the tail risk impact of liquidity-motivated trading by large, foreign institutional investors on portfolio flows and returns, which is the subject of this paper.

Foreign institutional investors play an increasingly important role in emerging markets, with assets under management in global funds rising from $69 billion to $1.47 trillion between 2004 and 2025.[1] . Recent work by Rey, Planat, Stavrakeva, and Tang (2024) and Rey and Stavrakeva (2025) suggests that cross-border equity reallocations have become the *dominant* channel through which global shocks propagate across markets. Their framework, rooted in portfolio-balance accounting, shows that fluctuations in foreign investor demand for equities are transmitted jointly through exchange rates and local asset prices, with equity markets increasingly displacing debt as the key margin of adjustment.

At the same time, it is well known that redemption issues are a source of instability for professionally managed portfolios (Goldstein, Jiang, and Ng (2017); Falato, Goldstein, and Hortaçsu (2021); Coval and Stafford (2007)). Redemption requests from investors can occur as frequently as daily, implying very liquid open-end fund liabilities, while underlying emerging market assets range from moderately illiquid (many equity positions) to very illiquid (many bond positions). The liquidity transformation that occurs on the balance sheets of open end mutual funds implies that if the redemption requests are significant enough to swamp fund cash reserves, liquidating emerging market holdings can generate significant price impacts (see Jotikasthira, Lundblad, and Ramadorai (2012)). This vulnerability is compounded

[1] Bond funds rose from $11 billion to $352 billion over the same period, while equity funds rose from $58 billion to $1.12 trillion.

by currency exposure, which can amplify losses and trigger further investor withdrawals during periods of market stress. When redemption requests are large and indiscriminate, fund managers may be forced to liquidate assets systematically to meet outflows, often selling based on liquidity needs rather than asset fundamentals.

Similar to the portfolio adjustment mechanisms highlighted in Rey et al. (2024) and Rey and Stavrakeva (2025), our paper examines the impact of high-volume trading by open-end mutual funds and ETFs on tail-risk in emerging market capital flows. We further this agenda by emphasizing the increasing role of passive funds and the consequences thereof. Our contribution is to show that within this global portfolio network, the institutional mechanics of mutual funds—particularly passive investment in illiquid markets—can amplify those reallocations into nonlinear tail-risk outcomes for emerging markets.

To pin down a mechanism through which trading by foreign institutional investors can generate tail risk, we employ an identification strategy that considers global risk-on risk-off shocks as news that is plausibly exogenous to emerging-market destination-specific fundamentals. Here, index-benchmarked passive fund investments (mutual funds or ETFs), with little managerial discretion and acting in concert, provide a conduit through which global shocks generate sizeable price effects, spillovers, and elevated correlations. Specifically, given the well-known fund flow-performance relationship documented in Sirri and Tufano (1998), feedback loops can generate price-liquidity spirals if the investor base responds to falling prices by increasing redemption requests, leading to further liquidity-motivated sales, generating further price effects, and so on. In particular, liquidity mismatches between withdrawals from open-end mutual funds and illiquid assets can amplify market volatility and capital flows at risk when investors move to sell in unison, transmitting financial stress across borders. While there is an added layer underlying ETFs that may provide a transmission buffer relative to these theoretical open-end fund redemption pressures, ETFs can also be associated with important passthrough effects (see, for example, Ben-David et al. (2018) and Da and Shive (2018)).

Our focus on the link between global risk shocks and tail realizations in capital flows confers several sources of plausible exogeneity that facilitate identification. In our setting, (i) the shocks are global, originating in developed markets and acting on small open economies,

(ii) fund investors are domiciled abroad in advanced economies, and (iii) benchmark investing via passive open-end funds and ETFs closely track, by construction, the weights in benchmark indices such as the MSCI emerging markets index for equities or the JP Morgan's EMBI index for bonds.[2]

To formalize the conduit of large foreign institutional investor trading and to more fully characterize tail risk, we conduct a detailed exploration of the magnitude of risk-on risk-off (RORO) shocks impacts *across the entire distribution* of emerging market flows.[3] We employ an 'at-risk' framework (Gelos et al. (2019); Eguren-Martin et al. (2020)), an approach that is similar to that taken in Adrian et al. (2019), characterizing "GDP-at-Risk" effects that vary across quantiles.[4] Our distributional approach maps directly onto the taxonomy of extreme capital flow episodes established by Forbes and Warnock (2012) and Forbes and Warnock (2021): the 5th percentile flow realization in a given country-week corresponds to capital flight episodes, while the 95th percentile corresponds to sudden stops or surges. Our quantile regression framework captures how the entire distribution of these episodes shifts in response to global shocks, rather than counting events above or below an arbitrary threshold. This approach is more general and avoids the well-known sensitivity of event-study results to threshold choice.

To characterize the impact of RORO shocks on fund flow distributions we use the panel quantile regression approach of Machado and Santos Silva (2019) with a dataset of multilateral, high-frequency fund flows into and out of emerging markets from EPFR Global. These data let us consider the distributional implications for cross-border flows across asset classes (EPFR bond and equity mutual funds and ETFs). Further, these funds primarily represent investors (clients) domiciled in the U.S. and Europe. Data on equity and fixed-income emerg-

[2]These weights can significantly deviate from underlying economic fundamentals by instead under- or overweighting countries based on the specific selection criteria employed.

[3]As outlined above, global shocks to investor sentiment allow us to identify plausibly exogenous portfolio reallocations; at the same time, our focus on estimating the full distribution allows us to comment in particular on extreme such reallocations.

[4]Underscoring the importance of our agenda, the International Monetary Fund warned in October 2022 that non-bank financial intermediaries holding illiquid assets are a 'major potential vulnerability' posing a risk to the stability of the global financial system (IMF (2022)). "Pressures from these investor runs (sic corporate bonds, certain emerging market assets, real estate) could force funds to sell assets quickly, which would further depress valuations. That, in turn, would amplify the impact of the initial shock and potentially undermine the stability of the financial system." https://www.imf.org/en/Blogs/Articles/2022/10/04/how-illiquid-open-end-funds-can-amplify-shocks-and-destabilize-asset-prices

ing market returns come from MSCI country-level USD and local currency equity return indices, Bloomberg local currency bond indices, and USD Emerging Market Bond Indices from JP Morgan (these primarily represent sovereign bonds) for fixed-income returns.

Our main findings are as follows. First, across asset classes, we find that while adverse shocks engender negative median flow responses for both bonds and equities, we uncover important variations in the measured shock responses in the tails of the distribution. In so doing, we not only show that shifts in global investor risk bearing capacity, as captured by RORO, lead to outsized flow changes, but also that the emphasis on measures of central tendency in the existing literature on capital flows masks significant underlying heterogeneity in the distributional impacts of global risk shocks. To illustrate the implications of different tail reactions to RORO shocks, we complement our regression results with a quantitative example through the lens of various risk-off events, that highlights the economic significance of our approach.[5]

Second, consistent with Gabaix et al. (2006), we present evidence that links large fund flows to asset returns. We find sizable and statistically significant correlations between fund flows (as a percent of total market capitalization) and aggregate equity returns, fixed income returns, and currency returns. The associated magnitudes are striking. A one standard deviation equity liquidation representing 0.021% of market capitalization ($92M) is associated with a 23 basis point depreciation of the currency and a 65-80 basis drop in aggregate equity returns. A one standard deviation liquidation of 0.024% in fixed income ($100.4M) is associated with a drop in currency and fixed income returns of 22 basis points and 18–28 basis points, respectively. These patterns display significant differences across asset classes and within asset classes; for example, U.S. dollar indices are more sensitive than local currency indices, indicative of significant impacts on currency returns. Given the clear endogeneity between volumes and prices, this evidence corroborates the notion that liquidations by large or numerous coordination funds have significant implications for asset prices (Gabaix et al. (2006)). Consistent with inelastic markets, the return impacts of a liquidation rise with the amount of AUM attributable to passive vehicles.

[5]Similar exercises can be done for the full sample, on a country-by-country basis, for different crisis episodes, and so on.

Third, we find that mechanical rebalancing by index-benchmarked passive fund investments (mutual funds or ETFs) plays a central role in engendering extreme flow realizations and increase cross-country return correlations. With little managerial discretion and acting in concert, these funds, therefore, provide a conduit through which global shocks can drive emerging market tail risk. Passively managed funds play a rapidly increasing role in facilitating emerging market investing (see Figure 1); this is a long-standing reality for equities that is now growing rapidly for fixed income. Within the category of passive flows we see that an important part of that evolution in both equity and fixed income classes is tied to the rise of emerging market ETFs. Given the rise of ETFs among fund flows, we dig deeper into the role of passive management by further splitting EM passive funds into index funds and ETFs. Despite the fact that ETFs are associated with additional pressure absorption capacity, the significant responses to global risk shocks in the passive space appear most closely tied to ETFs.

While low-cost passive investing facilitates emerging market access (and the good that can come from it), an unexpected consequence is that passive fund flows react much more than active fund flows to global shocks. This suggests that the investor populations across active and passive funds are very different in their risk-bearing capacity. Under the null that investor populations are the same for both types of funds, one would expect greater and more dispersed flow sensitivity from active funds for the simple reason that their performance is likely to be more diverse, which should drive higher flow sensitivity in the tails. We find the opposite in that the limited discretion afforded to the passive fund manager, linked to benchmarking, creates a passthrough effect that engenders abnormal co-movements in emerging market flows and returns.

To wit, we also document that the passive investment channel has implications beyond the level of flows. Countries with higher passive fund representation exhibit significantly elevated cross-country return correlations during risk-off episodes. At current levels of passive penetration, the RORO-induced increase in return correlations falls in the top decile of the historical distribution. This finding suggests that the growth of passive investing is itself a source of the global financial cycle, not merely a transmission mechanism for underlying shocks, but an amplifier that generates excess comovement unrelated to fundamentals.

Finally, we document flows into Treasury money market funds in response to global risk

Figure 1: The composition of emerging market fund flows (% assets under management)

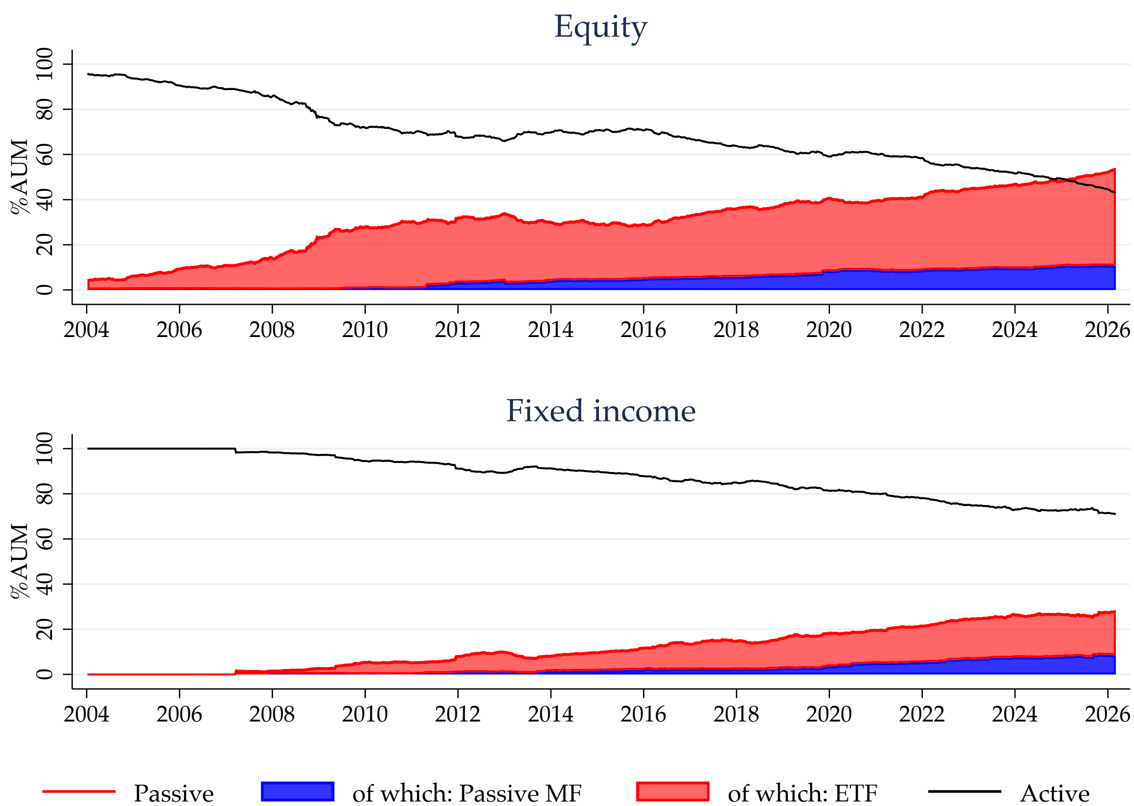


Figure 1 shows the proportion of equity and fixed income assets under management attributable to passive fund flows (decomposed into ETFs and passive mutual funds) and active fund flows.

shocks, consistent with flight to safety dynamics. In a manner that complements what we observe for risky emerging market assets, we detect the opposite flow responses to safe assets.[6]

In sum, we see a wide-ranging coalescence around the importance of variation in global shocks for EM portfolio flows. Critically, however, we emphasize these shocks to the foreign institutional investor base as a potential vector through which open-end funding pressures—or the complementary pressures associated with the ETF machinery—manifest. Next, we provide a brief review of the related literature before turning to our empirical analysis.

[6]These effects are also more pronounced for institutional money market funds, in contrast to retail-focused money market funds.

1.1 Related Literature

Our findings align with the previous literature on the financial fragility implications of mutual fund liquidity mismatches, organizational structures, and trading strategies especially during times of market turmoil (Chen, Goldstein, and Jiang (2010); Goldstein et al. (2017); Falato et al. (2021); Affinito and Santioni (2021); Stein (2009); Manconi, Massa, and Yasuda (2012); Financial Stability Board (2017); Cella, Ellul, and Giannetti (2013)). Further evidence suggests that the increase in benchmark-driven investing may explain the increased sensitivity of fund flows to global financial conditions (Financial Stability Board (2022); Raddatz, Schmukler, and Williams (2017); Arslanalp and Tsuda (2015); Converse, Yeyati, and Williams (2020); Arslanalp et al. (2020); Moro and Schiavone (2022); Kacperczyk, Nosal, and Wang (2022)).[7] Our paper suggests that the volume of liquidity-motivated trading by foreign institutional investors, especially passive funds and ETFs, associated with risk appetite variation can drive tail risk in emerging market capital flows (like surges or retrenchments), with significant attendant asset price impacts.

Our paper also contributes to the literature that examines the mechanisms by which risk shocks impact the risk-bearing capacity of foreign investors and propagate across borders, which emphasize advance economy monetary policy shocks (Bruno & Shin, 2015b); Chari, Dilts Stedman, and Lundblad (2021); Gourinchas and Obstfeld (2012); Bekaert, Hoerova, and Duca (2013); Miranda-Agrippino and Rey (2020a); (2020b); Fratzscher, Lo Duca, and Straub (2018); and Schularick and Taylor (2012)), the role of liquidity in dollar-funding markets Avdjiev et al. (2019); and Acharya and Steffen (2020)), and the link between portfolio flows and exchange rates (Gabaix and Maggiori (2015); Chari et al. (2021); Hofmann, Shim, and Shin (2020); Chari, Dilts Stedman, and Lundblad (2020); Forbes and Warnock (2021); Lilley et al. (2022); and Goldberg and Krogstrup (2023)).

Finally, the paper is related to a broader literature on the international portfolio balance channel, with contributions by Coeurdacier and Rey (2013); Caballero, Farhi, and Gourinchas (2016); Gabaix and Maggiori (2015); Bacchetta, Davenport, and Van Wincoop (2022); Camanho, Hau, and Rey (2022); Jiang, Richmond, and Zhang (2022); Koijen and Yogo (2020).

[7] Emerging market crisis-focused literature documents international investor-induced return co-movement during high volatility periods and crisis contagion (Kodres and Pritsker (2002); Boyer, Kumagai, and Yuan (2006); Jotikasthira et al. (2012)).

Relatedly, numerous studies document benchmark inclusion effects; a non-exhaustive list includes the works of Chen, Noronha, and Singal (2004); Cremers, Ferreira, Matos, and Starks (2016); Hau, Massa, and Peress (2010); Raddatz et al. (2017); Broner, Martin, Pandolfi, and Williams (2021); Hau (2011); Basak and Pavlova (2013); and Kashyap, Kovrijnykh, Li, and Pavlova (2021).

2 Data

2.1 Capital Flows and Returns

We use the Country Flows dataset from EPFR Global to measure aggregate fund flows. EPFR Global publishes weekly portfolio investment flows by more than 22,000 equity funds and more than 10,500 bond funds, with more than $38 trillion USD of capital under management. The Country Flows dataset combines EPFR's Fund Flow and Country Weightings data to track the flow of money into world equity and bond markets. While fund flow data reports the amount of cash flowing into and out of investment funds, the country weightings report tracks fund manager allocations to each of the various markets in which they invest. Combining country allocations with fund flows produces aggregate fund flows into and out of emerging markets (see Jotikasthira et al. (2012)). Because the country flows comprise the sum of fund-level aggregate re-allocations, they come cleansed of valuation effects and therefore represent real quantities.

The EPFR country flow data confers a number of benefits in our chosen setting. A key strength lay in the high frequency of the data, which allows for a tight temporal link between the measured flows and the daily redemption stresses we aim to estimate. Moreover, the granular reporting of the data enables us to explore the role of passive investment strategies and indexing in aggravating tail events. Finally, and importantly, the data covers a large proportion of all fund assets under management. Still, the data has some shortcomings. Two particular concerns stand out. First, institutional investors like sovereign wealth funds, pension funds, hedge funds, and banks' proprietary trading desks which typically purchase EM securities directly are generally not reflected in EPFR data. While it would be useful to observe the behavior of these investors, our focus on fund investor behavior as a mechanism itself implies that the exclusion of these additional investors does not render our findings inert. We merely, then, issue the caveat that these findings may not extend to all institutional investors. Second, the country level flows data rely on some less-than-ideal simplifying assumptions. For example, not all funds report the country-level portfolio allocations needed to estimate country flows at the fund level, so EPFR applies the average country allocation of one fund group to all funds in this case. In another example, valuation changes affecting the country allocations from one week to the next are assumed to be zero. Despite these shortcomings, however, Koepke and Paetzold (2020) find the EPFR data well-suited to analyzing questions related to fund investor behavior.[8] Internet Appendix Figure 1 plots the distribution of the EPFR flows summed across the sample countries on a weekly basis, which we produce using the algorithm of Azzalini (2020). As in Adrian et al. (2019), we use the empirical quantiles of the data in each week to fit a skewed-t distribution (proposed by Azzalini and Capitanio (2003)). Visualizing the data in this way underscores the importance of our approach—while the mean clearly shifts from week to week, so does the *shape* of the distribution. The colors in the figure correspond to the financial distress measure of Romer and Romer (2017), which allows us to see that the weekly distribution looks more normal during tranquil times, pictured in blue/violet.

To measure returns on emerging market portfolio assets, we collect daily total returns from a number of well-known indices. Individual country returns on USD and local currency bonds come from J.P. Morgan's Emerging Market Bond Index (EMBI) and the Bloomberg Barclay's Local Bond Index, while we measure country-level equity returns using the Morgan Stanley Capital International (MSCI) local currency and USD indices. Table 1 displays summary statistics for return and flow measures.

Reflecting the availability of EPFR data, the sample runs from January 7, 2004 to Dec. 31, 2025.[9] The sample of countries comprises emerging markets appearing in each of the flow and return data sets. Of these, we include countries with widespread recognition as emerg-

[8]Another angle we would be remiss to ignore is EPFR's value as a proxy for portfolio flows writ large. Conceptually different from BOP data and covering a limited proportion of all investors, the country-aggregated fund flow data typically differ sibstantially from country-level portfolio flow data at the end of the quarter. However, Koepke and Paetzold (2020) find that EPFR has significant predictive content for within-quarter BoP portfolio flows despite the discrepancy. Thus, while we reiterate that we focus on fund flows as such, the predictive content of EPFR for flows writ large suggest that our findings may yet still hold implications for flows more broadly.

[9]The exception is local currency bond returns, which only become available in 2008.

Table 1: Summary Statistics

(a) RORO Summary Statistics

	Q5	Q50	Q95	Skewness	Kurtosis
RORO Index	-1.28	-0.05	1.49	1.66	21.84
Funding Liquidity	-0.93	0.00	0.87	0.82	76.09
AE Equity Returns/Volatility	-1.31	-0.06	1.51	1.07	17.77
Gold and Currencies	-1.61	-0.01	1.67	0.16	5.75
Corporate Spreads	-1.28	-0.05	1.31	2.23	33.31
Observations	5922				

(b) EPFR Country Flows

	Mean	St. Dev.	Q5	Q25	Q50	Q75	Q95	Skewness	Kurtosis
Equity flows, % of AUM(t-1)	0.04	0.4	-0.6	-0.1	0.0	0.2	0.7	-0.4	28.9
Equity Flows (Mil. USD)	7.89	112.8	-108.5	-8.0	1.0	16.5	153.1	0.5	31.0
Equity AUM (Bil. USD)	22.48	39.9	0.5	2.7	7.9	23.8	95.2	3.7	20.6
Bond flows, % of AUM(t-1)	0.09	0.6	-0.7	-0.2	0.1	0.4	0.9	-0.5	17.9
Bonds Flows (Mil. USD)	4.44	54.8	-63.0	-6.8	1.5	19.5	79.9	-4.2	83.7
Bonds AUM (Bil. USD)	9.29	10.4	0.1	1.3	6.1	13.1	34.5	1.7	5.9
Observations	25036								

(c) Returns

	Mean	St. Dev.	Q5	Q50	Q95	Skewness	Kurtosis
Exchange rate return	0.03	4.02	-0.87	0.00	0.92	335.99	117163.01
MSCI LC Return	0.05	1.47	-2.15	0.00	2.24	-0.28	19.04
MSCI USD Return	0.05	1.72	-2.56	0.00	2.58	-0.34	19.05
EMBI Return	0.02	0.79	-0.71	0.02	0.75	-3.59	1033.44
LC Bond Return	0.03	0.73	-0.45	0.01	0.52	33.83	5774.77
Observations	131616						

Table 1 displays summary statistics of (a) RORO shocks from Chari et al. (2025), (b) country fund flows and assets under management from EPFR, and daily returns from the MSCI (LC and USD), EMBI, and Bloomberg local bond total return indices.

ing market economies.[10] The final set of countries includes Argentina, Brazil, Chile, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Pakistan, Peru, the Philippines, Poland, Qatar, Russia, South Africa, Taiwan, Thailand, Turkey, and the United

[10]We exclude China due to its unique characteristics related to investor access. In the domestic A-share market, access to qualified investors has been limited, despite more recent liberalization including the Hong Kong Connect program. Many global mutual funds instead build Chinese equity exposures *indirectly* through various Hong Kong or U.S. cross-listed securities

Arab Emirates.[11]

2.2 Characterizing risk-on/risk-off

Since the global financial crisis, a colloquial (and somewhat imprecise) risk-on / risk-off terminology has become pervasive in the financial press and among policymakers. In this framework, shocks to investors' *risk appetite* induce portfolio rebalancing away from so-called "risk assets" (towards safe assets) with important implications for risky (and safe) asset price determination.

A natural starting point for an analysis of the implications of global shocks for emerging market capital flows and returns is the VIX index. The international finance literature has popularized the use of the VIX index as a measure of global risk aversion (Avdjiev et al. (2019); Rey (2013)). However, recent evidence suggests a weakened relationship between the VIX and other key variables since 2008 (Forbes (2020); Miranda-Agrippino and Rey (2020a); Erik et al. (2020)). The declining role of the VIX may be related to (i) the shifting composition of global capital flows (Avdjiev et al. (2019)) and (ii) may be limited to crisis episodes (Cerutti, Claessens, and Rose (2019)). A breakdown in the negative relationship between bank leverage and risk appetite since 2009 suggests that the VIX is no longer a reliable proxy for the price of bank balance sheets (Erik et al. (2020)). Forbes and Warnock (2021) and Miranda-Agrippino and Rey (2020a) highlight the VIX's declining role in explaining credit growth and capital flows.

The VIX's limitations stem from its narrow focus: the market participants who use S&P 500 options to hedge against U.S. equity volatility measured by the VIX index may have characteristics that do not extend to all market participants or risk assets impacted by changes in a risk environment. As such, the VIX may miss crucial signals from credit markets, funding conditions, and currency dynamics that affect a broader array of market participants. Instead, we use the Risk-on/Risk-off (RORO) index, which provides a broad summary statistic of risk-seeking/aversion behavior reflecting high frequency shifts in investors' willingness to take on, retain or offload risky assets (Chari et al. (2025)). RORO captures risk signals relevant to

[11] EM classifications considered include the IMF, BRICS + Next 11, FTSE, MSCI, S&P, EMBI, Dow Jones, Russell, Columbia University EMPG and BBVA.

diverse investor types—equity investors, fixed income allocators, and leveraged intermediaries—each responding to different risk sources (equity volatility, credit spreads, liquidity stress, currency movements) that assert time-varying importance across different crisis episodes. The index comprises the first principal component of standardized changes across 14 financial variables spanning four categories: credit risk (corporate spreads), equity market volatility (returns and implied volatility like VIX), funding liquidity (TED spread, LIBOR-OIS), and safe currency/specie (USD, gold). Details of index's construction, properties, and validation can be found in Chari et al. (2025).[12]

Variables included in the index are normalized such that an increase imply risk-off behavior. As such, positive values of the RORO reflect a decline in risk bearing capacity, similar to the sign interpretation of the VIX. Figure 2 displays the RORO index, cumulatively summed to levels in Panel (a), and then decomposed into its various sub-indices in panels (b) and (c). Table 1a shows that the index and its subcomponents are skewed towards downside risk and fat-tailed. In addition to skewness and excess kurtosis, Figure 2c shows that the index and its subcomponents also exhibit time varying volatility. With fat tails, destabilizing extreme events like capital flight or surges become more probable and potentially more destabilizing. Predictably, both risk and risk aversion show large spikes during the global financial, the European debt, and the COVID-19 crises.

2.2.1 Control variables

The literature on patterns of international capital flows separates determinants into common, global "push" factors associated with external shocks, and "pull" country-specific factors. Following this literature on capital flow determinants (see, for example, Calvo et al. (1993); Fratzscher (2012); Fratzscher et al. (2016); Passari and Rey (2015); Milesi-Ferretti and Tille (2011); Forbes and Warnock (2012)), the capital flow and return regressions include a measure of advanced market returns (obtained from Kenneth French's website), the monetary policy stance of advanced economies as measured by the shadow rate, and advanced economy in-

[12]In the spirit of Avdjiev et al. (2019) and Rey (2013), we replicate our baseline quantile regressions replacing RORO shocks with log changes in the VIX. The results, presented in Internet Appendix Table 9, are qualitatively similar to our baseline results below — global risk shocks, broadly defined, engender significantly negative bond and equity portfolio flows, particularly in the left tail.

Figure 2: Decomposing the RORO Index into its Sub-Components

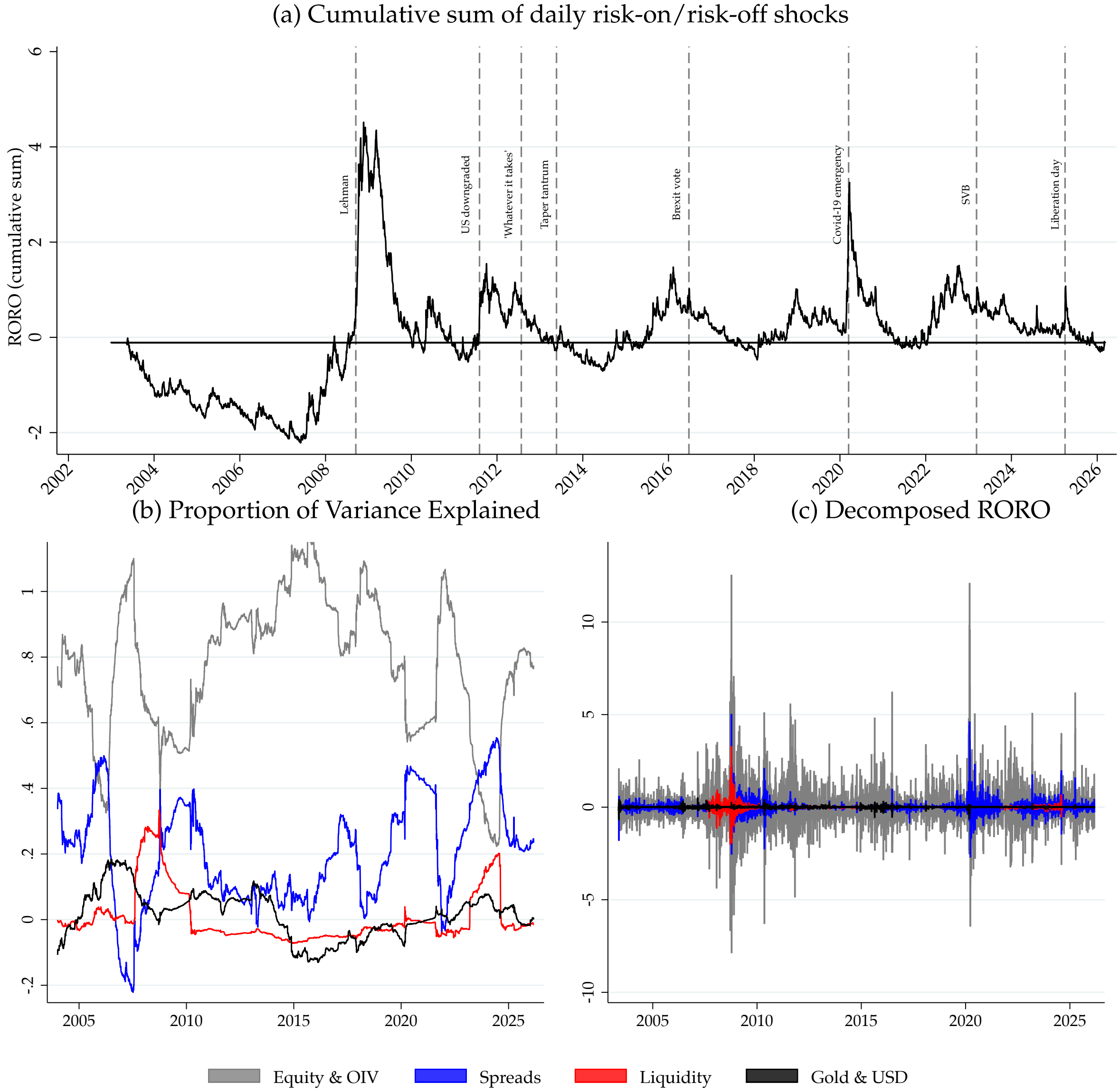


Figure 2a displays the RORO index in levels, summing cumulatively from the start of the index. Below, panel (b) shows the proportion of the RORO index's variation that is explained by each of its subindices, calculated over a rolling sample of 520 business days. Panel (c) decomposes the daily RORO shocks into contributions from the subindices by multiplying the explained variation in Panel (b) by the daily RORO measure. The decomposition method is detailed in Chari et al. (2025)

dustrial production growth.[13] We use year fixed effects to control for global conditions more broadly, as well as a lag of the left-hand-side variable to account for the autocorrelation introduced by scaling over lagged positions. Time fixed effects account both for slow moving

[13] All advanced economy variables comprise a USD real GDP-weighted average of the United States, the UK, the euro area and Japan.

business cycles and structural changes in the market for ETFs and mutual funds.

Country-specific (pull factor) controls include local policy rates, real GDP growth, and the broad real effective exchange rate (REER). To control for the influence of local macroeconomic news in the intervening week or day, we include the Citigroup Economic Surprise Index (CESI) for emerging markets. The CESI tracks how economic data compare to expectations, rising when economic data exceed economists' consensus forecasts and falling when data come in below forecast estimates.[14]

With the exception of emerging market news surprises, all control variables enter with a lag to rule out simultaneity.[15] Both sets of controls affect capital flows and returns, but also likely react directly to changes in risk sentiment. In fact, our advanced economy push variables not only react to our relevant global shocks but likely also drive them. All daily variables enter as the weekly moving average leading up to the week's EPFR reporting date; thus, lagged variables consist of the weekly moving average ending on the date one week before the report of the measured flow.

Before turning to the results, it is worth setting a prior about what we expect to see. In advanced economies, the long-run correlation between equity and government bond returns is effectively zero: bond returns are driven primarily by discount-rate and duration effects tied to policy and inflation, while equity returns load heavily on cash-flow shocks that often offset those denominator effects. The emerging market context is different. EM sovereign bonds carry considerable political and credit risk that bears directly on expected cash flows, and the correlation between EM equity and sovereign bond returns approaches 0.5, on average. Given this common cash-flow exposure across asset classes, one natural prior is that the distributional implications of RORO shocks for EM equity and fixed-income flows should look broadly similar. As we show below, they do not — and the divergence is itself informative about the channel through which these shocks operate, an observation we return to when we decompose flows by fund type in Section 3.3.

[14]Indices are defined as weighted historical standard deviations of data surprises (actual releases vs. Bloomberg survey median) and are calculated daily in a rolling three-month window. The weights of economic indicators are derived from relative high-frequency spot FX impacts of one standard deviation data surprises. The indices also employ a time decay function to replicate the limited memory of markets.

[15]While news surprises likely drive capital flows and returns, it is unlikely that the risk shock drives news surprises or vice versa on any given date.

3 Estimation and Results

To identify plausibly exogenous variation in these reallocations, we regress weekly EPFR country-level flows onto RORO global risk shocks using the panel quantile regression approach of Machado and Santos Silva (2019). We include country and time fixed effects and control for previously described "push" and "pull" factors. Country-level flows enter as a percent of the previous week's allocation. As stated in the data description, in the EPFR flow regressions, changes in the risk measures are aggregated by a moving average over the week.

$$k_{it}^{(q)} \quad = \quad \alpha_i^{(q)} + \delta_t^{(q)} + \rho k_{it-1}^{(q)} + \beta^{(q)} RORO_t + \gamma_1^{(q)} PUSH_{t-1}^k + \gamma_2^{(q)} PULL_{i,t-1}^k + \epsilon_{i,t} \tag{1}$$

where $k_{it}^{(q)} = \left(\frac{K_{it}}{H_{it-1}} * 100\right)$. k_{it} is either equity or bond flows (K_{it}) scaled by holdings of the same, H_{it-1}. We cluster bootstrapped standard errors by country to account for serially correlated error terms.[16]

In general, global risk shocks have important implications for the median emerging market flows and the tails of the distribution. In each case, a global shock of either type decreases flows across the distribution. In each case, the "worst" realizations (in the left tail) change more than the median realization, and the "best" (right tail) realizations change less than the median, lengthening the tails of the distribution. That is, ($|\beta^{(.05)}| > |\beta^{(.5)}| > |\beta^{(.95)}|$). Increases in downside risk signify capital flight or retrenchments captured by the left tail, and decreases in upside risk correspond to capital inflow slowdowns captured by the right tail.

Figure 3 summarizes the results. The left panels of Figure 3 plot the quantile regression coefficients for both bonds and equities with 95% confidence intervals using bootstrapped standard errors. For reference, the distance from zero captures the magnitude of the negative impact of a risk-off shock for bond and equity flows. The quantile coefficient curve's slope reflects the shock's dispersive effect. The flatter the quantile curve, the more uniform the shift in the distribution in response to a one standard deviation risk-off shock and, conversely, the steeper the curve, the more dispersive the impact. A flat-sloped quantile curve would be consistent with a uniform shift in the distribution. Table 2 provides point estimates and standard

[16]We draw bootstrapped standard errors from 5,000 replications. We also use bootstrap replications to test that the quantile-specific parameter values are statistically different from one another and find that each case is different. These results are readily available on request.

errors for selected quantiles.

Across quantiles, the effects are economically meaningful. A one standard deviation RORO shock moves the median of the fixed income (equity) fund flow distribution by 11.2 (9.5) basis points. For context, the average weekly change in flows across the sample is 0.08 - .1 basis points. Consulting the summary statistics, a median-sized reaction to a one unit RORO shock would put the resulting flow in the bottom quartile of historical observations. With respect to the distribution, two patterns stand out. First, fixed income reacts more forcefully to the shock compared to equity across most quantiles. The only quantile we report where equity reacts more lay in the reaction of the 95th percentile, which generally represents the largest inflow realizations. Second, the steep, positively inclined quantile coefficient curve for bonds is consistent with a more dispersive impact in the direction of downside risk, i.e., capital flight on the left and an inflow slowdown on the right. The distribution of equity flows also displays a dispersive impact, albeit less exaggerated than that of fixed income flows.

Table 2: The impact of a one standard deviation RORO shock on EPFR flows (% of AUM)

(a) Bond flows

	Q5	Q25	Q50	Q75	Q95
RORO	-0.165***	-0.129***	-0.112***	-0.0948***	-0.0635***
	(0.00318)	(0.00270)	(0.00319)	(0.00403)	(0.00583)
Observations					23452

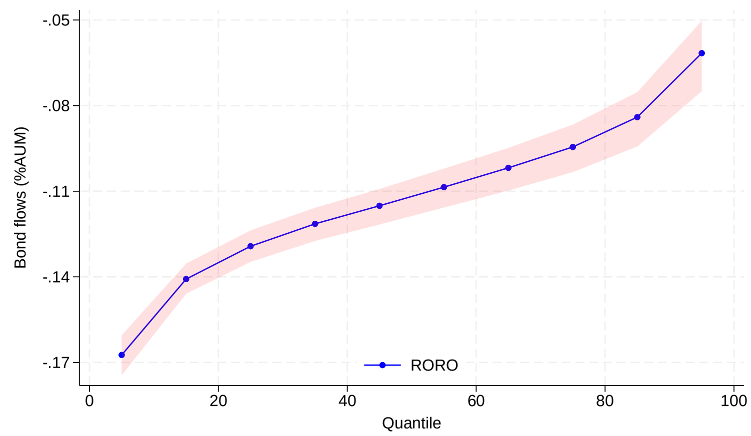
(b) Equity flows

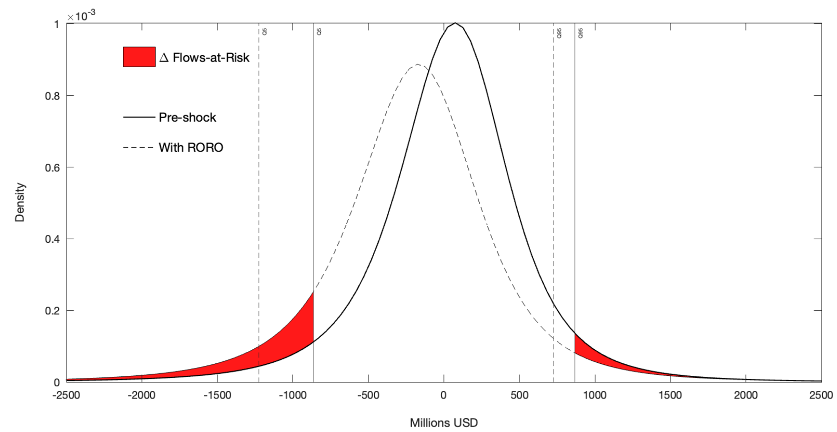
	Q5	Q25	Q50	Q75	Q95
RORO	-0.110***	-0.0997***	-0.0948***	-0.0901***	-0.0805***
	(0.00433)	(0.00300)	(0.00300)	(0.00354)	(0.00547)
Observations					23484

Table 2 summarizes the results of quantile regressions of a) bond flows and b) equity flows on RORO shocks from Chari et al. (2025). The specification includes the full set of control variables, country fixed effects, and year fixed effects. Full results can be found in the Internet Appendix. Bootstrapped standard errors are clustered by country and shown in parentheses. *, **, and *** signify a statistically significant effect at the 10%, 5%, and 1% levels, respectively.

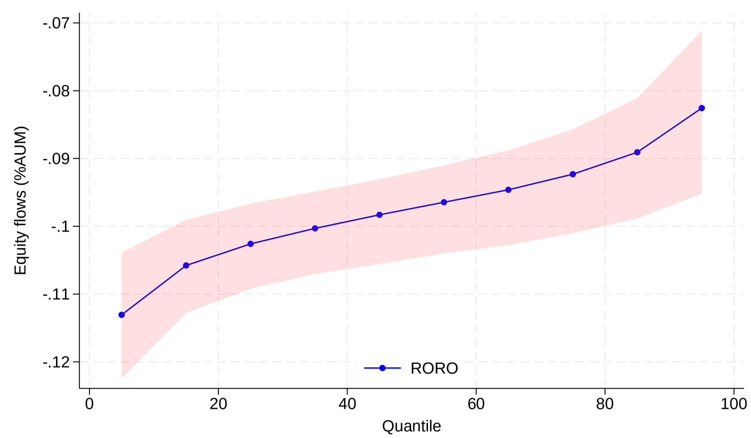
The right panels of Figure 3 visualizes the changes to the fund flow distribution brought on by RORO shocks, fitting a skewed-t distribution to the estimated quantiles as in Adrian et al. (2019) and others. The solid black lines show the predicted density of flows in the absence

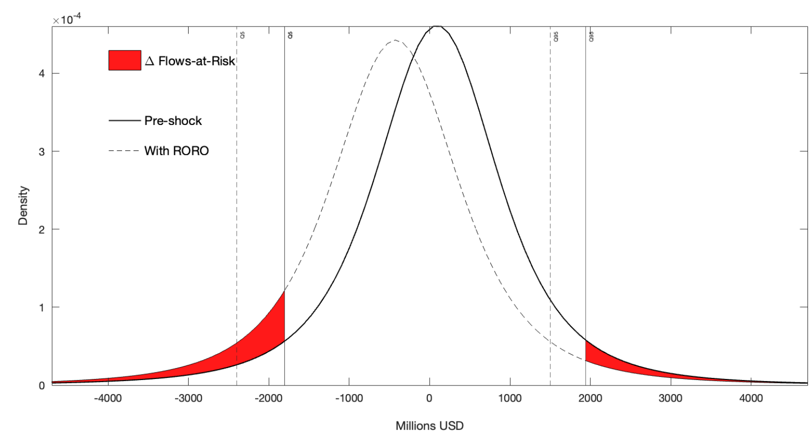
Figure 3: The distributional impact of RORO shocks on EPFR bond and equity flows (% of AUM)





(a) Bond flows (% of AUM_{t-1})





(b) Equity flows (% of AUM_{t-1})

Figure 3 summarizes the impact of a one standard deviation RORO shock on emerging market bond and equity flows, respectively. The left panels plot the quantile coefficients for quantiles $q = \{5, 15, 25, \ldots, 95\}$. Error bands represent 95% bootstrapped confidence intervals clustered by country. The right panels plots the results from fitting the distribution of emerging market equity and fixed income fund flows conditional on a shock to RORO to a skewed-t probability distribution using the algorithm of Azzalini (2019). The specification pictured includes the full set of control variables, country fixed effects, and year fixed effects. Full results can be found in the Internet Appendix. Bootstrapped standard errors are clustered by country.

of risk shocks. The dotted lines show that same predicted density with the fitted contribution from risk-off shocks added in. The red area shows how the change in the quantiles translates to changes in the dollar value of flows following a risk-off shock. Vertical solid and dotted lines mark the 95th and 5th quantiles of the pre- and post-shock densities, respectively.

Starting with fixed income in the top panel, the baseline results confirm two key patterns. First, risk shocks shift the distribution in its entirety, with additional impact on downside risk captured by the mass in the left tail. This dispersive impact arises because risk-off shocks exacerbate the worst outflow realizations, amplifying downside risk. The clearest indication of this is the distance between the solid and dotted lines; while the 95th quantile has moved, the distance between the pre- and post-shock 5th quantile is twice as large.[17] Comparing the right tail with the left demonstrates that the change in flows overall emanates more from the growth of the left tail than from the diminution of the right tail; that is, the overall change in observed fund flows following a risk-off shock results more from an increase in gross outflows than from a cessation in gross inflows.

To summarize, RORO shocks shift the entire distribution of emerging market fund flows, but add disproportionate weight to the left tail — the worst outflow realizations. This pattern is consistent across asset classes with a negative shock triggering retrenchment or flight. Where bond and equity flow distributions differ is in the degree of dispersion: bond flows fan out (tails-out) more compared to equity flows, a distinction we return to when we decompose flows by fund type.

3.1 Persistence of risk-on risk-off shocks

Thus far, we have provided evidence on the impact of RORO shocks in the week immediately following a shock. Given that capital reallocations may not react immediately to shocks, the fund flows likely display a lagged response. Second, for the shock effects to be truly consequential, they should prove persistent. To shed light on the dynamic reaction of fund flows to

[17] Internet Appendix Figure 2 visually summarizes the changes in the capital flow distributions for quantile coefficients on the left tail (q^5), the median (q^{50}), and the right tail (q^{95}). The approach confirms the pattern underlying the heterogeneous reactions of the equity and fixed-income distributions.

RORO shocks, we repeat our baseline exercise as a series of local projections:

$$k_{it+h}^{(q)} = \alpha_i^{(q)} + \delta_t^{(q)} + \rho k_{it-1}^{(q)} + \beta_{1,h}^{(q)} RORO_t + \gamma_1^{(q)} PUSH_t^k + \gamma_2^{(q)} PULL_{it}^k + \epsilon_{i,t} \tag{2}$$

where $h = 0, \ldots, 12$ is the horizon for the impulse response and k_{it+h} is the cumulative flow between time t and $t + h$. To smooth the excess variability of the estimator, we apply a compound moving median smoother to the estimated series $\hat{\beta}_j = \{\hat{\beta}_{j,0} \ldots \hat{\beta}_{j,H}\}$.[18]

Figure 4 displays the results. Some common patterns stand out. First, the effects are largely persistent. In each case, the impact of the shock dissipates between weeks 10 and 12, indicating that these high-frequency shocks exhibit long-lasting effects. In terms of distribution, the observed patterns for fixed income flows and equity flows are distinct. For fixed income, persistence is even more pronounced in that the worst outflow realizations largely deteriorate for longer than the median or the highest inflow realizations. Specifically, the 5^{th} quantile falls more (and for longer) than the 95^{th}. Contrast this with equity flows, wherein the worst outflow realizations deteriorate more than median and inflow realizations in the first five months, and the outflow realizations (Q5) recover before those of the equity inflow realizations (Q95) on the right tail. The second panel in Figure 4 shows that the decline in inflows steadily worsens for about 10 weeks before recovery begins.

The patterns suggest that bond flows are accompanied by persistent retrenchment in response to a one standard deviation risk-off shock, while equity flows display a pattern more akin to a sudden stop or the drying up of equity inflows.

Taken together, the persistent nature of these global shocks suggests at least two facts. First, RORO shock impacts are consequential in that their effects do not immediately dissipate or reverse. Second, our results warrant a deeper examination, outside of the scope of this paper, on the interplay between the distributional effects of these shocks and the role for revisions in expectations about cash flows and risk premia (both commonly examined in the asset pricing literature).

[18] Smoothing is an exploratory data-analysis technique for making the general shape of a series apparent (Tukey (1977)). Specifically, we first apply a 3-spline moving median smoother with repetition to convergence, followed by a Hanning linear binomial smoother. Smoothed values are obtained by taking medians of each point in the estimated horizon and the two points around it. The number of points used is called the span of the smoother. Thus, the IRFs pictured show the medians of β_{h-1}, β_h, and β_{h+1}. We then repeat the process with binomial weights.

Figure 4: Dynamic Effects using local projections

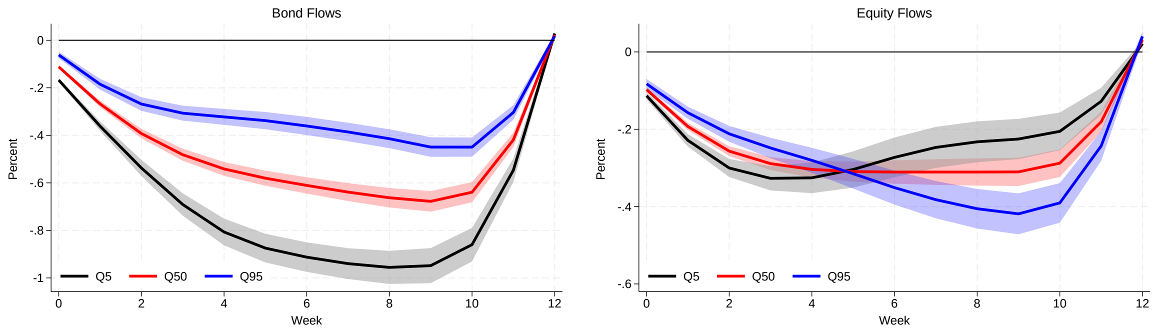


Figure 4 summarizes the impact of a one standard deviation shock to the RORO index on emerging market bond and equity flows over a 12 week-horizon. Thick lines show the path of the smoothed estimate for the path of $\hat{\beta}_{i,0}, \ldots, \hat{\beta}_{i,25}$ using a compound moving median smoother. The shaded areas indicate smoothed confidence intervals at 95% confidence intervals. The specification pictured includes the full set of control variables, country fixed effects, and year fixed effects. Full results can be found in the Internet Appendix. Bootstrapped standard errors are clustered by country.

3.2 Application: Emerging market flows during crisis

To illustrate the implications of different tail reactions to RORO shocks, we present examples of various high-volatility episodes through the lens of observed emerging market flows. Table 3 shows the quantitative impact of the largest shocks in each of the Global Financial Crisis, the initial period of the Covid-19 crisis, and Liberation Day on the distribution of bond and equity fund flows into the emerging markets in our sample. The sub-panels shows the distributional consequences of a RORO shock. The advantage of our approach is that we can conduct such quantitative exercises for the implications of different risk-on or risk-off episodes, by asset class, for individual countries, or we can aggregate across countries.

For each episode, the first row shows the 5th, 50th, and 95th quantile of observed fund flows to emerging markets over the previous five years. The second row shows the product of the a risk-off shock in the 95th percentile of RORO observations in that episode and the parameter values from our quantile regressions, $\sigma^{(95)} \times \hat{\beta}^{(q)}$. Row three translates the impact into dollar terms by multiplying $\sigma^{(95)} \times \hat{\beta}^{(q)}$ by the average emerging market AUM in each asset class in the five years preceding the shock ($\hat{\beta}^{(q)} \times \sigma \times H$). This value shows how much the 5th, 50th, and 95th quantiles shift in response to a shock of size $\sigma^{(95)}$, which in the 5th quantile approximates a notion of increased value-at-risk. Finally, the fourth row in each event sums

Table 3: The effect of RORO shocks on the distribution of emerging market EPFR flows

	Panel i: Bonds	Q5	Q50	Q95	Panel ii: Equity	Q5	Q50	Q95
β*Liberation Day								
$\sigma(q^{95}) = 4.55$	Flow Quantiles: 2020 - 2024	-96.71	-2.38	71.05	Flow Quantiles: 2020 - 2024	-98.03	0.03	134.86
	% of AUM/week	-0.754	-0.509	-0.289	% of AUM/week	-0.499	-0.432	-0.367
	Est. Change	-112.42	-75.91	-43.13	Est. Change	-162.71	-140.79	-119.58
	Est. Flow Quantiles	-209.1	-78.3	27.9	Est. Flow Quantiles	-260.7	-140.8	15.3
β*GFC								
$\sigma(q^{95}) = 4.65$	Flow Quantiles: 2002 - 2006	-11.66	0.64	25.21	Flow Quantiles: 2002 - 2006	-63.13	1.59	136.13
	% of AUM/week	-0.77	-0.52	-0.30	% of AUM/week	-0.51	-0.44	-0.37
	Est. Change	-11.49	-7.76	-4.41	Est. Change	-42.04	-36.37	-30.89
	Est. Flow Quantiles	-23.1	-7.1	20.8	Est. Flow Quantiles	-105.2	-34.8	105.2
β*CovidPeak								
$\sigma(q^{95}) = 7.06$	Flow Quantiles: 2015 - 2019	-71.61	5.01	111.70	Flow Quantiles: 2015 - 2019	-116.92	0.87	142.69
	% of AUM/week	-1.17	-0.79	-0.45	% of AUM/week	-0.77	-0.67	-0.57
	Est. Change	-148.16	-100.04	-56.84	Est. Change	-192.87	-166.88	-141.74
	Est. Flow Quantiles	-219.8	-95.0	54.9	Est. Flow Quantiles	-309.8	-166.0	1.0

Table 3 shows the counterfactual quantiles of the post-shock distribution of emerging market fund flows and compare them to the distribution from the five years preceding the shock (shown in the first row of each section). The first row displays empirical quantiles of the flow distribution in the five years preceding the episode. In the second row, we take the 95th quantile RORO shock from each of the GFC, and the initial Covid period, and Liberation Day and multiply it by our estimated parameter values. The estimated change in the third row is the value in row 2 multiplied a five year average of AUM preceding the shock to generate a dollar value for the flow, $\hat{k}^q = k^q + \hat{\beta}^q \times shock \times H$. Row 4 sums rows 1 and 3 to show a sample conditional distribution prevailing as a result of the risk shock.

rows one and three to give an estimate of the subsample conditional distribution of flows prevailing as a result of the shock, $\hat{k}^{(q)} = k^q + \hat{\beta}^{(q)} \times \sigma \times H$.

In addition to contextualizing the magnitudes of the changes we document, this exercise further elucidates the distinction in the changing shape of the capital flow distribution conditional on risk-on risk-off shocks. To see this, consider the impact of the Covid-19 RORO peak on bonds versus equity fund flows. The bottom row of Table 3 shows that both distributions have shifted left, deeper into outflow space. However, the bond flow distribution has widened considerably relative to pre-pandemic, while the equity distribution has largely retained the length of its range.

More specifically, Q95 (the right tail) of the bond flow distribution has shifted somewhat, decreasing by $56.8M per week, while Q5 (the left tail) has shifted markedly more, by $148.2M per week. Thus, while the unconditional 95th quantile ($111.7M) in the first row is halved in the post-shock estimate ($54.9M), the 5th quantile of bond flows has worsened by a factor of three (-$71.6M to -$219.8M per week). Comparing the estimated change among Q5, Q50 and Q95, the worst outflow realization worsen almost 48% more then the median realizations, and the median realizations have fallen by 43% more than the highest inflow realizations. In this example, we can see more concretely that a dispersive tail response does not imply that inflows increase in response to a risk-off shock, only that they decrease by less than the median and lower quantiles.

In contrast, the equity distribution has shifted more than reshaped in response to a RORO shock. The 95th quantile falls by $141.7M per week to near zero ($142.7M to $1M per week), signifying a massive capital inflow slowdown. The 5th quantile, which captures extreme outflow realizations, moves away from the median by 26%, and the median realization falls 25% more than the 95th quantile.

As foreshadowed at the end of Section 2, the prior of similar bond and equity flow responses fails, and the failure points directly to the prevalence of passive equity investing in emerging markets, to which we now turn.

3.3 Passive versus Active Flows

Figure 1 suggests a sizable and increasing role for passively managed funds in facilitating EM access for global investors. Around 52% of assets under management in EM equity funds are passively managed as of 2025 (from nearly zero two decades earlier), and a similar trajectory has begun for EM fixed income funds.

Given this important development in the machinery of modern fund management, we examine the role of managerial discretion in driving emerging market tail risk. One potentially complicating factor is the extent to which emerging market passive funds mechanically invest in the various indices to which they are tied. As a result, in the absence of managerial discretion in asset allocation, the funding pressures passive vehicles face engender a mechanical passthrough to the underlying markets in which these funds invest. Hence, to examine the role for passive management in driving the distributional implications of global shocks that we document above, we re-run our quantile regressions by separating the flows attributed to active funds from those attributed to passive funds.

Figure 5, panel (a) summarizes the results, with accompanying point estimates and standard errors displayed in subfigures 5b - 5e. Figure 5 suggests that investor flows into passive funds (left) react far more strongly to global risk shocks than for active funds (right). As a reminder, the EPFR country flow data combine information about cash flowing into and out of EM investment funds with manager-reported country weightings to gauge fund country re-allocations. Investor subscriptions and redemptions are then a critical ingredient to this measurement. The increased sensitivity shows that investors in passive funds are far more reactive (in terms of their redemptions and subscriptions) to global risk shocks than those invested in active funds, where both passive fixed income and equity funds show net outflows from a shock. These pressures then disproportionately pass through to the countries in which passive EM funds invest.

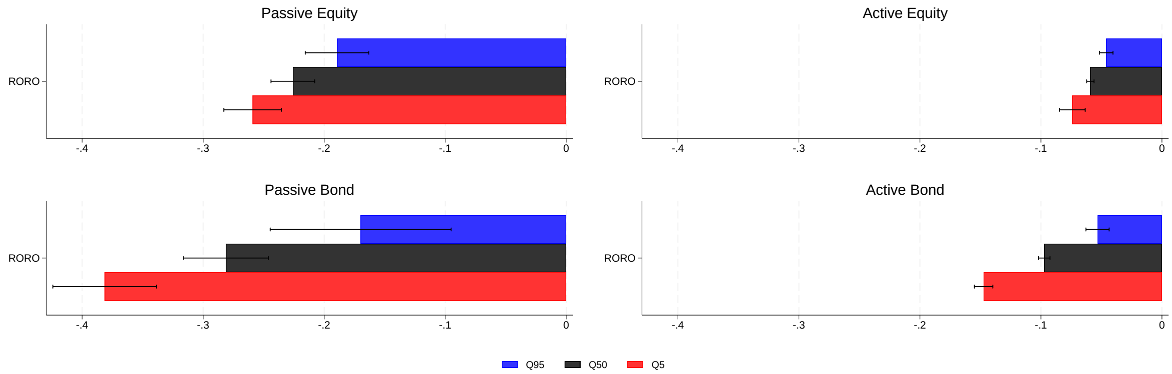
Furthermore, we find that the tails-out reaction from the baseline extends to both passive and active flows. The fall in passive flows is particularly noteworthy in fixed income–the worst outflow realizations (Q5) fall at 2.3 times the rate of inflow realizations (Q95). We might expect active flows to show a more uniform shift—active managers have discretion buy at a discount those assets that experience price affects from shock but which have strong fundamentals. In fact, the tails of the active flow distribution widen a bit more than the passive flows in terms of percent spread between the 5th and 95th percentiles.

Given the importance of index construction in driving passive fund activity, Internet Appendix Table 4, panel (a) shows the relevant index weights for the popular MSCI EM Index that is a common reference point for many EM index investors. We also present the proportion of each country's assets in the EPFR sample total passive fund AUM. There are, at least, two important takeaways.

First, Internet Appendix Table 4, panel (b) presents the correlation between EPFR realized equity allocation weights and the MSCI EM Index weights (we focus on an equity index for illustration). The correlation shows a very high association between the weights in the MSCI EM Index and the actual portfolio allocations of passive equity funds. The finding is, of course, consistent with our priors for passive funds. However, notice that these realized allocation weights differ markedly from, say, GDP weights; namely, the spillover effects that we document will then impact countries in a manner consistent with whatever rules govern index construction as opposed to factors of broad economic importance. The centrality of index construction is an important ingredient to any understanding of financial market spillovers in

Figure 5: Distributional impact of RORO shocks on active and passive bond and equity flows

(a) The impact of a one standard deviation RORO shock on tail and median flows (% of AUM)



(b) Estimate detail: Passive Bond flows

	Q5	Q25	Q50	Q75	Q95
RORO	-0.375***	-0.303***	-0.276***	-0.246***	-0.168***
	(0.0228)	(0.0169)	(0.0164)	(0.0188)	(0.0311)
Observations					19942

(c) Estimate detail: Active Bond flows

	Q5	Q25	Q50	Q75	Q95
RORO	-0.142***	-0.110***	-0.0947***	-0.0800***	-0.0529***
	(0.00424)	(0.00255)	(0.00271)	(0.00344)	(0.00531)
Observations					23452

(d) Estimate detail: Passive Equity flows

	Q5	Q25	Q50	Q75	Q95
RORO	-0.253***	-0.230***	-0.218***	-0.206***	-0.179***
	(0.0140)	(0.0107)	(0.0103)	(0.0109)	(0.0147)
Observations					23471

(e) Estimate detail: Active Equity flows

	Q5	Q25	Q50	Q75	Q95
RORO	-0.0696***	-0.0608***	-0.0572***	-0.0538***	-0.0462***
	(0.00611)	(0.00293)	(0.00178)	(0.00123)	(0.00303)
Observations					23484

Figure 5 summarizes the impact of a one standard deviation RORO shock on emerging market passive and active fund flows, respectively, with 90% confidence intervals. Sub-tables 5b - 5e show point estimates and standard errors. The specification includes the full set of controls, country fixed effects, and year fixed effects. Full results can be found in the Internet Appendix. Bootstrapped standard errors are clustered by country and shown in parentheses. *, **, and *** signify a statistically significant effect at the 10%, 5%, and 1% levels, respectively.

international economics.

Second, somewhat as an aside, an equally large correlation for active emerging market equity funds allocations with index weights is somewhat surprising. Despite a much greater degree of managerial discretion to deviate from the benchmark index weights, active funds appear to be, at least on average, closet indexers.[19]

The Liberation Day tariff shock offers a concrete application of this finding. Because the reciprocal tariffs announced on April 2, 2025 varied dramatically across trading partners, one might expect the capital flow response to mirror this cross-sectional variation in economic exposure. Our results suggest otherwise. The outsized sensitivity of passive flows documented above — combined with the tight link between passive fund allocations and benchmark index weights shown in Internet Appendix Table 4 — means that a country's realized outflow during the episode is better predicted by its MSCI EM Index weight than by its tariff rate. The tariff episode thus provides a concrete illustration of how the passive fund channel can decouple capital flow responses from underlying fundamentals, with the distributional consequences we quantify in Table 3.

3.4 Open-End Funds versus ETFs

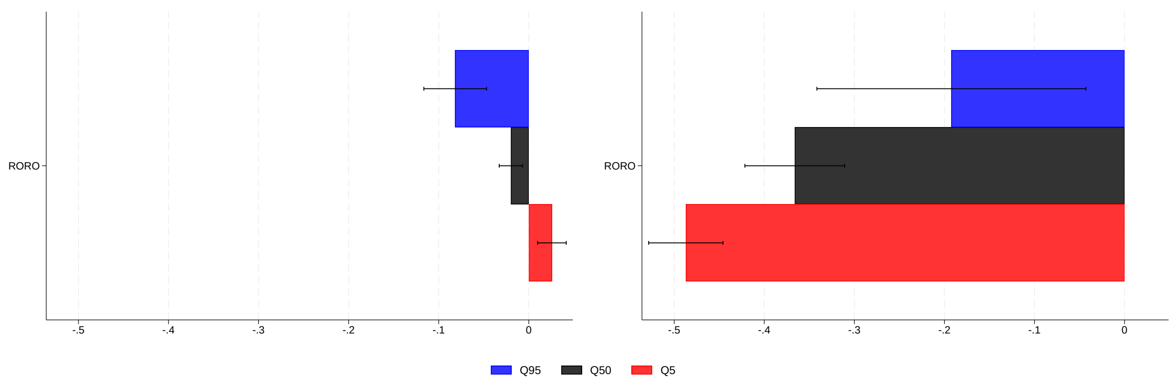
Given that we uncover an important role for passive funds as a transmission mechanism for global shocks to emerging market tail risk, we should also acknowledge that the mechanisms of open-end mutual funds and ETFs differ in important ways. Specifically, in the analysis presented above, we combine open-end index funds and ETFs into the passive category. However, as mentioned earlier, the arbitrage process (and the associated tracking error) for ETFs may provide a transmission buffer against spillovers relative to the inflexibility of the open-end index funds.

To investigate further, we separate EPFR passive funds into open-end index funds and ETFs. In Figure 6, we present the tail and median impacts of RORO shocks on emerging market country flows associated with all mutual funds on the left and ETFs on the right.

[19] In pursuit of this point, we also conditioned the impact of global shocks on equity flows and returns on the weight assigned to market i in the MSCI EM Index (no such weights are available to us in fixed income). While we do not observe any impact of the weight on the conditional response of flows to shocks, we do see that the impact of shocks on MSCI USD returns (and to a lesser extent local currency returns) increases with the weight of the market in the index. Results from this exercise are available on request.

Figure 6: The Variation in Responses to Risk Shocks within Passive Flows (ETFs versus Mutual Funds)

(a) Passive Bond Mutual Funds (b) ETFs



(c) Passive Equity Mutual Funds (d) ETFs

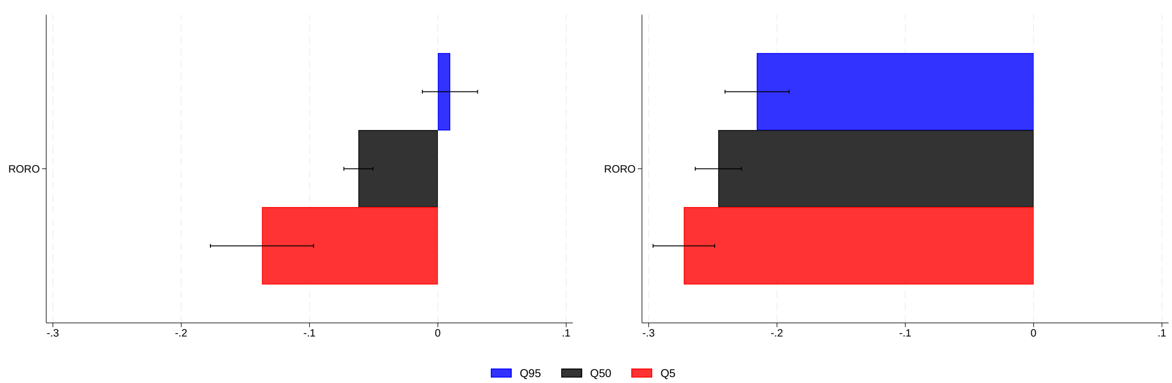


Figure 6 summarizes the results of quantile regressions of passive bond fund flows and passive equity fund flows flows, split into passive mutual funds (panels (a) and (c)) and ETFs (panels (b) and (d)) on the RORO index. Each specification includes the full set of control variables, country fixed effects, and year fixed effects. Full results can be found in the Internet Appendix. Bootstrapped standard errors are clustered by country and black lines correspond to 90% confidence intervals.

Perhaps the most interesting pattern we see here is that ETFs react more than passive mutual funds to a risk-off shock. For passive equity funds, Panel B shows a negative median response to RORO shocks across both index funds and ETFs, with statistically significant negative responses in the right tail — indicating sudden stops or inflow slowdowns. The pattern of coefficients across passive equity vehicles is consistent with the comparatively even cross-quantile response we documented for passive equity flows in aggregate. For passive bond funds, the picture is starker. RORO shocks elicit negative and statistically significant responses across quantiles, with magnitudes substantially larger for ETFs than for index mutual funds.

Taken together, the significant responses to RORO shocks in the passive space appear most closely tied to ETFs. While this finding builds on Converse et al. (2020)), our results capture the full distributional implications of global shocks on portfolio flows. The importance of ETFs is interesting as we may have thought these vehicles would have additional pressure absorption capacity facilitated by the arbitrage process and any associated tracking error. Despite that, like open-end index funds, the ETF holding basket does not permit discretion, and the passthrough pressures from sizable ETF trading remain.

The passive asset management industry is a key driver replacing traditional active management. As this part of the asset management industry continues to grow rapidly, this evolution does raise questions about the implications of passive fund management for cross-border capital flow correlations and tail risks.[20]

3.5 Implications of fund flows for aggregate returns

In what follows, we conduct three exercises: linking aggregate flows to country-level returns, conditioning that link on the degree of passive penetration, and examining how RORO shocks reshape cross-country return correlations as passive representation grows.

First, we conduct an additional exercise based on Gabaix et al. (2006), which suggests that a combination of news and trades by large investors can generate out-sized movements in volumes and returns. To quantify large volumes, we scale our fund flow data by the size of

[20] Converse et al. (2020)) argue that there might be important clientele effects drawn more naturally to active versus passive vehicles, and ETFs in particular; we leave this important question to future research.

the underlying asset market. We then regress aggregate returns on these proportions, along with the previously described "push" and "pull" factors, year fixed effects, and country fixed effects.

$$R_{i,t} = \alpha_i + \beta \frac{K_{i,t}}{M_{i,t-1}} + \gamma_1 PUSH_{t-1} + \gamma_2 PULL_{i,t-1} + \delta_t + \epsilon_{i,t} \tag{3}$$

Here, $R_{i,t}$ is the weekly return on the exchange rate (LC/USD), EMBI, LC Bond index, MSCI LC or MSCI USD indices, $K_{i,t}$ is the contemporaneous equity or fixed income fund flow, and $M_{i,t-1}$ is country i's equity market capitalization or bond market size.

As highlighted in the introduction, Table 4 shows a statistically significant, large, positive relationship between fund flows as a percent of total market capitalization and aggregate returns. A one standard deviation equity liquidation representing 0.021% of market capitalization ($71.8M) is associated with a 23 basis point depreciation of the currency and a 65 - 80 basis drop in aggregate equity returns. A one standard deviation liquidation of 0.032% in fixed income ($91.1M) is associated with a drop in currency and fixed income returns of 22.5 basis points and 18 - 28 basis points, respectively. To be clear, these flow-return correlations are suggestive rather than causal, but the magnitudes are economically large enough to warrant attention regardless of the precise identification. Further, our results join Aldunate, Da, Larrain, and Sialm (2022) in lending empirical support to the inelastic market hypothesis of Gabaix and Koijen (2021), which predicts that aggregate asset prices can and do react to day-to-day investment flows.

Table 4b links the impact of these liquidations explicitly to the prevalence of passive investment in fund flows:

$$R_{i,t} = \alpha_i + \beta_1 \frac{K_{i,t}}{M_{i,t-1}} + \beta_2 Z\left(\frac{H^p_{i,t-1}}{H_{i,t-1}}\right) + \beta_3 \frac{K_{i,t}}{M_{i,t-1}} \times Z\left(\frac{H^p_{i,t-1}}{H_{i,t-1}}\right) \dots$$
$$+ \gamma_1 PUSH_{t-1} + \gamma_2 PULL_{i,t-1} + \delta_t + \epsilon_{i,t} \tag{4}$$

Where $Z\left(\frac{H^p_{i,t-1}}{H_{i,t-1}}\right)$ captures the proportion of overall fund AUM invested in country i that can be attributed to passive funds, in z-scores. As such, β_1 is the reaction of aggregate returns to a RORO shock when passive assets under management as a percent of total is at the sample

Table 4: The impact of fund-driven liquidation on asset returns

(a) Impact of a one standard deviation decrease in fund flows (% of total market capitalization) on aggregate returns

	FX Return	MSCI LC	MSCI USD	FX Return	EMBI	LC Bonds
Δ market cap (1SD)	0.232***	-0.649***	-0.798***			
	(0.0459)	(0.0979)	(0.123)			
Δ market cap (1SD)				0.225**	-0.282***	-0.181***
				(0.0839)	(0.0607)	(0.0246)
Policy Rate (t-1)	0.0199***	0.00565*	0.00737**	0.0270*	0.0130**	0.0187***
	(0.00429)	(0.00274)	(0.00333)	(0.0132)	(0.00586)	(0.00473)
REER (t-1)	0.00771***	-0.00582***	-0.00875***	0.0114**	-0.00102	0.000216
	(0.00197)	(0.00202)	(0.00154)	(0.00492)	(0.00273)	(0.00147)
Real GDP Growth (t-1)	-0.00142	0.0156*	0.0202*	-0.0125**	0.00540	-0.000527
	(0.00424)	(0.00804)	(0.0116)	(0.00582)	(0.00410)	(0.00230)
Emerging Mkt. News	-0.00423***	0.0213***	0.0260***	-0.00757***	0.0119***	0.00284
	(0.00148)	(0.00260)	(0.00293)	(0.00163)	(0.00221)	(0.00243)
Adv. Mkt. Index (t-1)	0.00120***	-0.00456***	-0.00580***	0.00202***	-0.00225***	-0.00121***
	(0.000262)	(0.000483)	(0.000656)	(0.000272)	(0.000292)	(0.000158)
Observations	23515	22493	22493	16879	14164	13647

(b) Impact of fund-driven liquidation on asset returns conditional on passive AUM (% of total)

	FX Return	MSCI LC	MSCI USD	FX Return	EMBI	LC Bonds
Δ market cap (1SD)	0.273***	-0.713***	-0.899***			
	(0.0381)	(0.0743)	(0.0812)			
Δ market cap (1SD)				0.235**	-0.298***	-0.183***
				(0.0840)	(0.0635)	(0.0243)
% passive AUM (1SD)	0.0413	-0.0121	-0.0265			
	(0.0393)	(0.0953)	(0.102)			
Δ market cap (1SD) × % passive AUM (1SD)	0.0709***	-0.111**	-0.174***			
	(0.0250)	(0.0459)	(0.0547)			
% passive AUM (1SD)				0.142*	0.0420	0.00256
				(0.0725)	(0.0578)	(0.0386)
Δ market cap (1SD) × % passive AUM (1SD)				0.0702***	-0.0729**	-0.0280
				(0.0208)	(0.0290)	(0.0174)
Constant	-1.100***	2.252***	2.880***	-2.539***	0.724*	0.523**
	(0.254)	(0.358)	(0.418)	(0.679)	(0.389)	(0.199)
Observations	23502	22480	22480	15038	12678	13647

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 shows the impact of a one standard deviation decrease in fund flows as a percent of total market capitalization on weekly exchange rate (LC/USD) returns, local currency returns, and dollar-denominated returns in equity and fixed income markets, respectively. Table 4b shows the impact of a one standard deviation decrease in fund flows as a percent of total market capitalization, conditional on the percent of AUM in passive funds, expressed in z-scores. All controls are included. Interaction terms show the effect of changing from an average level of passive AUM (as a percent of total AUM) to a one standard deviation above average passive AUM. All specifications include country and year fixed effects, with standard errors clustered by country.

mean, whereas $\beta_1 + \beta_3$ shows the reaction of aggregate returns to a liquidation when passive representation is one standard deviation above the mean. Columns 1 - 3 show that the return reaction is 15 - 20 percent larger when passive AUM as a percent of total equity is one standard deviation above the mean. Columns 4 - 6 repeat the exercise for fixed income. Interestingly, exchange rate returns and returns on dollar denominated bonds react more strongly to passive penetration than equity returns (25 - 30 percent more), although it carries the expected sign, passive penetration in fixed income has no statistically significant bearing on local currency bond returns. Because fund investment local currency fixed income is a relatively recent phenomenon, it is likely that this last specification is underpowered.

To the extent that passive investment induces race-to-the-exits behavior, which in turn sets off price-quantity spirals, we also expect a higher proportion of fund AUM in passive vehicles to induce larger return comovements in the face of risk-off shocks. We test this hypothesis directly in the following manner. With daily country-level returns in hand, we generate a bilateral correlation between each pair of countries by taking the product of their daily return z-scores. Individual observations of this object can be thought of as the marginal contribution of that day's realization to the full-sample Pearson correlation coefficient between the two countries, ρ_{ijt}. We then sum the product of country i and j's z-scores over j for each i to produce a daily measure of how the correlation between the returns of country i with all of the other EMs in the sample evolve over time:

$$\Phi_{i,t} = \sum_{j=1} \rho_{i,j,t}$$

Because the units do not have a natural interpretation, we use the z-scores of this object to express how correlated country i's returns are with other EMs, $Z(\Phi_{i,j,t})$. We then regress return correlation on RORO shocks, conditional in passive prevalence in AUM:

$$Z(\Phi_{i,t}) = \alpha_i + \beta_1 RORO_t + \beta_2 Z\Big(\frac{H^p_{i,t-1}}{H_{i,t-1}}\Big) + \beta_3 RORO_t \times Z\Big(\frac{H^p_{i,t-1}}{H_{i,t-1}}\Big) \dots$$
$$+ \gamma_1 PUSH_{t-1} + \gamma_2 PULL_{i,t-1} + \delta_t + \epsilon_{i,t} \quad (5)$$

Table 5 displays the results. Starting with the unconditional impact of RORO shocks on return correlations in odd numbered columns, we see that a one unit RORO shock raises equity and fixed income return correlations by 0.08 - 0.26 standard deviations. While the sign is not surprising—return correlations ought to rise in the face of risk-off shocks—the magnitudes are striking. For context, Internet Appendix table 6 shows that the difference between the 75th and 25th percentile of the MSCI USD, MSCI LC and EMBI correlation variables is only 0.19, 0.18 and 0.11 standard deviations, respectively.

Even-numbered columns condition the return correlation impact of RORO shocks on the percent of AUM attributable to passive funds. For this exercise, passive percent in AUM is normalized to show the impact of a RORO shock conditional on 10% AUM in passive vehicles, so that we can easily see how the return correlation scales up with passive fund presence. Going from zero passive representation to 10% of AUM in passive vehicles raises the equity and fixed income correlation variables by .03 - .11 standard deviations over the base case of zero passive fund representation.[21] Unconditional values in odd columns match the marginal impact evaluated at the sample mean. For example, the unconditional effect of a RORO shock raises the MSCI USD return correlation variable by .26 standard deviations. We see in the summary statistics included in the internet Appendix that the sample average proportion of AUM in passive vehicles is 30.2%. A back of the envelope calculation reveals that a level of passive funds accounting for 30% of AUM is associated with an RORO-induced increase in equity return correlation of 0.25 standard deviations—the unconditional value in Table 5a ($0.17 + 0.03 \times 3 = 0.26$). A more interesting comparison, however, relates the average passive AUM penetration displayed in Figure 1 with the marginal effects displayed in the table. In the last year of the sample, the average passive AUM proportion among fixed income and equity funds stood at 26 and 52.5 percent, respectively. This degree of passive representation is associated with a change in return correlations of .31 - .35 standard deviations in the face of a risk-off shock. Among fixed income return correlations, an increase of this size would fall in the top 95% of all historical observations, while the increase in equity return correlations would fall in the top 90% of historical observations.

Next, we refine our correlation exercise to account for the benchmark-driven nature of passive investment strategies by integrating index weights into the analysis. In the baseline

[21] Internet Appendix Table 6b scales up the impact of passive representation in intervals of 10 percentage points.

Table 5: The effect of RORO shocks on return correlations, conditional on passive AUM (% of total)

(a) Equally weighted

	(1) MSCI USD	(2) MSCI USD	(3) MSCI LC	(4) MSCI LC	(5) EMBI	(6) EMBI	(7) LC Bonds	(8) LC Bonds	(9) Exch. Rate	(10) Exch. Rate
RORO	0.26***	0.17***	0.25***	0.11***	0.18***	0.04***	0.08***	-0.03***	0.08***	0.11***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Passive(t-1)		0.10***		0.10***		0.14***		0.09***		0.04***
		(0.01)		(0.01)		(0.03)		(0.02)		(0.01)
RORO×Passive(t-1)		0.03***		0.05***		0.11***		0.09***		-0.01***
		(0.00)		(0.00)		(0.01)		(0.01)		(0.00)
Policy Rate (t-1)	0.00	0.00	0.00	0.00	0.00	-0.00	0.00	0.00	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
REER (t-1)	0.00	-0.00	0.00	0.00	-0.00	-0.00	-0.00*	-0.00	-0.00*	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Real GDP Growth (t-1)	0.00	0.00*	0.00**	0.00***	0.00**	0.00**	0.00	0.00	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Emerging Mkt. News	-0.00	-0.00	-0.00*	-0.00	-0.00***	-0.00***	-0.00**	-0.00*	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Adv. Mkt. Index (t-1)	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AE IP Growth (t-1)	-1.09***	-1.04***	-0.71**	-0.71**	-0.30	-0.51	-0.63*	-0.75**	-1.66***	-1.59***
	(0.29)	(0.29)	(0.29)	(0.29)	(0.36)	(0.36)	(0.34)	(0.34)	(0.28)	(0.28)
AE Avg. Shadow Rate (t-1)	0.01	0.02*	0.03***	0.03***	0.01	0.02*	0.00	0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.64***	0.64***	0.58***	0.59***	0.91***	0.91***	0.88***	0.88***	0.33***	0.33***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.09)	(0.09)	(0.07)	(0.07)	(0.04)	(0.04)
Observations	22364	22364	22365	22365	16314	16314	15345	15345	22428	22428

(b) Scaled by MSCI index weights

	MSCI USD	MSCI USD	MSCI LC	MSCI LC	EMBI	EMBI	LC Bonds	LC Bonds	Exch. Rate	Exch. Rate
RORO	0.23***	0.21***	0.21***	0.13***	0.17***	0.05***	0.08***	-0.02*	0.08***	0.14***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Passive(t-1)		0.10***		0.10***		0.12***		0.06***		0.04***
		(0.01)		(0.01)		(0.03)		(0.02)		(0.01)
RORO×Passive(t-1)		0.00		0.03***		0.09***		0.08***		-0.02***
		(0.00)		(0.00)		(0.01)		(0.01)		(0.00)
Constant	0.66***	0.66***	0.59***	0.59***	0.92***	0.91***	0.88***	0.81***	0.36***	0.36***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.08)	(0.09)	(0.07)	(0.07)	(0.04)	(0.04)
Observations	22364	22364	22365	22365	16314	16314	15345	15345	22428	22428

Table 5 reports parameters from regression changes in equally weighted (panel a) and MSCI-weighted (panel b) cross country correlations on risk-on/risk-off shocks, conditional on the proportion of fund AUM attributable to passive funds. The dependent variable for each country is sum of its bilateral return correlations (MSCI LC, MSCI USD, EMBI, local currency bond, and exchange rate) with the other EMs in the sample, expressed in z-scores. Daily contributions to sample correlation are measured using the product of z-scores. Passive penetration is the percent of total fund AUM which is attributed to passive vehicles. This variable is normalized to show the impact of a RORO shock when passive representation goes from 0 to 10%. All specifications utilize country and year fixed effects. Standard errors are shown in parentheses. *, **, and *** signify a statistically significant effect at the 10%, 5%, and 1% levels, respectively.

specification, we construct the return correlation measure by summing the bilateral product of Pearson z-scores. This amounts to equally weighting bilateral correlations across all country pairs and effectively treating each pair of countries as equally important contributors to aggregate co-movement. However, benchmark-based investing allocates capital according to index weights rather than equally across markets. To better align the empirical specification with the proposed mechanism, we construct an alternative measure that weights bilateral return correlations by countries' representation in the MSCI Emerging Markets index prior to aggregation:

$$\Phi_{i,t} = \sum_{j=1} \rho_{i,j,t}\omega_{j,t}$$

Where $\omega_{j,t}$ is the weight of country j in the MSCI. Because we only have weights for the MSCI EM, we use these weights to contemplate correlations between fixed income returns and exchange rate returns as well.

The results, which are displayed Table 5b, reveal a nuanced pattern. For local-currency equity returns, the interaction between RORO shocks and passive fund penetration remains positive and statistically significant, although the magnitude is somewhat attenuated relative to the equal-weighted specification. In contrast, the corresponding effect for U.S. dollar-denominated equity returns becomes statistically indistinguishable from zero, and the interaction term on EMBI returns, while still statistically significant, is diminished. This distinction suggests that exchange-rate dynamics may play an important role in mediating the impact of passive investment on return comovement.

To explore this possibility directly, we repeat the exercise using exchange rate return correlations as the dependent variable. While risk off shocks still increase exchange rate comovement, we find that greater passive penetration dampens this response ($\beta_1 > 0$, $\beta_3 < 0$). That is, although adverse global shocks generally increase currency return correlations, the incremental impact of passive ownership is negative. This cushioning effect is present in both the equal-weighted and benchmark-weighted specifications, although it becomes economically larger and statistically stronger once bilateral correlations are weighted by MSCI representation.

Taken together, these findings suggest that benchmark-weighted specifications sharpen, rather than overturn, the baseline interpretation. Passive benchmark investing appears to synchronize local risky asset pricing during periods of heightened global risk aversion, generating coordinated repricing across emerging market equity markets. At the same time, exchange-rate responses are comparatively more heterogeneous across countries, likely reflecting differences in reserve management, exchange-rate regimes, monetary policy responses, commodity exposure, and other country-specific characteristics. Consequently, exchange-rate dynamics partially offset common movements in local asset returns when measured in U.S. dollar terms.

This distinction refines the interpretation of the benchmark channel. Rather than uniformly increasing cross-country correlations across all dimensions, passive investing appears to compress differentiation in local asset pricing while leaving broader macroeconomic adjustment mechanisms comparatively less synchronized.

These findings speak to the broader debate on the global financial cycle Rey (2013) and Miranda-Agrippino and Rey (2020a). The literature has emphasized U.S. monetary policy and global risk appetite as drivers of cross-border comovement. Our evidence adds a complementary channel: the institutional plumbing through which capital reaches emerging markets. As passive fund penetration grows, the mechanical transmission of shocks through benchmark rebalancing generates excess return comovement that is unrelated to fundamental similarities across countries. In this sense, the rise of passive investing is not merely a response to the global financial cycle—it is increasingly a source of it.

3.6 Flight to Safety

A question that naturally arises when examining the relationship between risk appetite and the allocation to, or pricing of, risky assets relates to the complementary implication for so-called ”safe” assets. A safe asset is a simple debt instrument expected to preserve its value across various states of the world, including adverse, possibly systemic events. Under this definition, the categorization of what assets exactly are to be considered ”safe” remains a point of discussion (see Gorton (2016) and Caballero et al. (2017) as examples, among many others). However, U.S. Treasury bonds are generally considered safe under this definition, so that we will focus on these here.

Accordingly, we test the degree to which our RORO shocks elicit flight-to-safety responses by repeating the above exercises replacing EPFR emerging market (risky asset) flows with the growth rate of assets held in U.S. money market mutual funds. The Investment Company Institute publishes these data, reporting money market fund assets weekly to the Federal Reserve. To isolate safe assets, we focus on the subset of funds that invest in U.S. government debt.

To be clear, the global shocks we consider are certainly not exogenous to U.S. money market flows in the same way they might be for emerging market portfolio flows. Acknowledging this limitation, we also retain most of our global ”push” variables: advanced economy market returns, advanced economy GDP growth, and the average advanced economy monetary stance as measured by the shadow rate as controls in this exercise. We also retain year-fixed effects, and we run the following regression:

$$g_t^{(q)} = \alpha^{(q)} + \delta_t^{(q)} + \beta^{(q)} RORO_t + \gamma_1^{(q)} PUSH_t^k + \epsilon_t \quad (6)$$

Where $g_t^{(q)}$ is the weekly growth rate of government money market assets in quantile q. We retain the “push” controls and year fixed effects from our baseline specification.

Table 6 displays the results. A RORO shock positively affects flows into government money market funds, consistent with a flight to safety. The effect is concentrated in the right tail of the distribution, indicating that the largest safe-asset inflow realizations are disproportionately associated with risk-off episodes. This pattern complements what we observe for risky emerging market assets and confirms that global risk shocks simultaneously drive capital away from emerging markets and toward safe havens.

Finally, the Investment Company Institute money market flow data permit a separation into two subsets of government money market funds, those available to institutions vs. those available to retail investors. Despite some possible measurement noise, this important delineation offers an additional degree of granularity that deserves scrutiny in that it may facilitate a better understanding of the moving parts driving our key results. Interestingly, we find that the largest effects documented in Internet Appendix Table 8 are associated with institutional

Table 6: The impact of a one standard deviation risk-off shock on the distribution of government money market fund assets

	(1) Q5	(2) Q50	(3) OLS	(4) Q95
RORO Index	0.09***	0.13***	0.20***	0.35***
	(0.01)	(0.01)	(0.04)	(0.07)
AE Mkt. return	-0.00	0.00**	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
AE Industrial production (t-1)	-8.21***	-5.51***	-7.36***	-30.95***
	(1.52)	(2.07)	(2.84)	(8.25)
AE Shadow short rate (t-1)	-0.30***	-0.12	-0.13	0.05
	(0.08)	(0.08)	(0.11)	(0.22)
Constant	0.55	0.19	1.63***	3.06
	(0.34)	(0.50)	(0.62)	(3.98)
Observations	774	774	774	774

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6 summarizes the results of quantile regressions of changes in government money market funds on our RORO index. Specification includes year fixed effects.

money market fund flows. Retail flows are considerably less sensitive to global risk shocks. Institutional money, and the fund machinery through which it operates, appears to be an important ingredient behind our tail risk results.

4 Conclusion

This paper opens the black box between global risk shocks and emerging market capital flows. While the existing literature has established that shifts in global risk appetite drive capital flow episodes—sudden stops, surges, flight, and retrenchment—far less attention has been paid to the institutional vehicles through which these shocks are transmitted. We show that these vehicles are not passive conduits: they shape, amplify, and distort the distribution of capital flows to emerging markets.

Using panel quantile regressions applied to high-frequency fund flow data, we document three main findings. First, global risk-off shocks shift the entire distribution of emerging market fund flows — a pattern we illustrate through the GFC, the Covid peak, and the Liberation Day tariff episode — with left-tail effects substantially exceeding those at the median. The result holds across equity and fixed income but the shape differs: bond flows fan out (tails-out), consistent with capital flight, while equity flows exhibit more of a cross-quantile shift, a difference we attribute to mechanical rebalancing by passive funds.

Second, the institutional structure of fund intermediation matters profoundly. Among managed funds, passive vehicles, with their limited managerial discretion and benchmark-driven allocation mandates, react far more strongly to global shocks than active funds, particularly in the tails. The finding points to a structural amplification channel: when a risk-off shock triggers redemptions, passive fund managers sell every country in the benchmark, regardless of that country's fundamental exposure to the underlying shock. The result is a mechanical passthrough of funding pressures that generates outsized and correlated outflows across the emerging market universe. Within the passive space, ETFs play a particularly significant role despite the arbitrage-based pressure absorption capacity that should, in principle, buffer them.

Third, this machinery has aggregate consequences. Fund-flow liquidations move country-level equity, bond, and exchange rate returns by economically large magnitudes, consistent with the inelastic markets hypothesis of Gabaix and Koijen (2021), and countries with higher passive penetration exhibit elevated cross-country return correlations during risk-off episodes — suggesting that the growth of passive investing is itself a source of the global financial cycle. The same shocks simultaneously drive flight-to-safety flows into U.S. government money market funds, most prominently among institutional vehicles, confirming that RORO operates symmetrically across risky and safe assets.

These findings carry implications for both researchers and policymakers. For researchers, our results suggest that models of international capital flows that abstract from fund structure may miss an increasingly important source of tail risk and cross-country comovement. The ongoing shift from active to passive management is not merely a change in investment style; it is a structural transformation in the plumbing of international finance that alters the distributional properties of aggregate flows.

For policymakers, several questions arise. First, as the share of passive AUM continues to grow, the amplification channel we document will strengthen, raising the question of whether existing reserve buffers and capital flow management tools are calibrated to a world in which an increasing fraction of cross-border flows is non-discretionary and benchmark-driven. Second, the tight link between passive flows and index construction means that decisions by index providers—such as MSCI's periodic rebalancing of country weights or its inclusion and exclusion of markets—function as de facto macro-prudential events, reshaping the distribution of capital flows across countries in ways that are decoupled from underlying economic fundamentals. Third, the elevated cross-country return correlations associated with passive fund penetration suggest that the diversification benefits of emerging market investment may be eroding precisely as access to these markets expands, leading to an unintended consequence of the low-cost passive revolution that warrants further investigation.

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