Global Fund Flows and Emerging Market Tail Risk

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ABSTRACT

Global risk and risk aversion shocks have distinct distributional impacts on capital flows with salient consequences for tail risk in emerging markets. Open-end mutual fund trading provides a key mechanism linking shocks facing global investors to extreme capital flow realizations. The effects are heterogeneous across asset classes and fund types. The limited discretion and higher conformity of passive fund investments linked to benchmarking amplify pass-through effects that engender abnormal co-movements in emerging market flows.

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1 Introduction

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 and that 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 $1.15 trillion between 2004 and 2020,[1] . 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). 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 paper examines impact of high-volume trading by open-end mutual funds and ETFs on tail risk emerging market capital flows. 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 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

[1] Bond funds rose from $11 billion to $383 billion over the same period, while equity funds rose from $58 billion to $759 billion.

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. 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 pass-through effects (see, for example, Ben-David et al. (2018) and Da and Shive (2018)).

Our focus on the link between micro-founded 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 global risk shock impacts *across the entire distributions* 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]

To characterize the impact of global risk and risk aversion shocks on capital flow distributions we use the panel quantile regression approach of Machado and Santos Silva (2019). To do so, we use a dataset of multilateral, high-frequency fund flows into and out of emerg-

[2]These weights can significantly deviate from underlying economic fundamentals by instead under- or over-weighting 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 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 emerging 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 macro uncertainty and investor risk sentiment 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 different global shock types. We see that variation in the quantity of global risk is, on average, significantly more influential for the tails of the emerging market mutual fund flow distribution than variation in risk aversion (or the price of risk). Empirical measures that conflate risk and risk aversion, like the VIX, mask this observation. While our main results focus on the immediate reaction of the flow distribution to relevant global shocks, we also employ a local projections approach to shed light on the dynamic reaction of fund flows.

Second, consistent with the arguments in 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 0.023% of market capitalization ($71.8M) is associated with a 23 basis point depreciation of the currency and a 71-88 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 12 basis points and 22–26 basis points, respectively. These patterns display significant differences across asset classes and within asset classes, 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 suggestive evidence corroborates the notion that sizable liquidations by large funds imply have significant implications for asset prices (Gabaix et al. (2006)).

Third, to illustrate the implications of different tail reactions to global risk shocks, we complement our regression results with a quantitative example through the lens of a representative emerging market (Brazil), that highlights the economic significance of our approach.[5]

Fourth, we find that mechanical rebalancing by index-benchmarked passive fund investments (mutual funds or ETFs) plays a central role in engendering extreme flow realizations. 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. Further, the figure shows that an important part of that evolution in both asset classes is tied to the rise of emerging market ETFs.

While low-cost passive investing facilitates emerging market access (and the good that can come from that), an unexpected consequence is that passive fund flows react much more (in some cases as much as an order of magnitude 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 aversion or risk analysis. 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 pass-through effect that engenders abnormal co-movements in emerging market flows and returns.

Fifth, given the rise of ETFs mentioned above, 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 and risk aversion shocks in the passive space appear most closely tied

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

to ETFs.

Finally, we document flows into Treasury money market funds in response to global risk shocks, consistent with a flight to safety. In a manner that complements what we observe for risky emerging market assets, we detect the opposite flow responses to safe assets.[6]

To sum up, we see a wide-ranging coalescence around the importance of variation in important global shocks for portfolio flows, be they shocks to global risk or risk appetite. Critically, 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. Aiding identification in the current context, the time variation in either global risk or risk aversion facing the marginal global investor (say from the United States or Europe) is largely exogenous to emerging market fundamentals. Next, we provide a brief review of the related literature before turning to our empirical analysis.

2 Related Literature

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) and signifi-

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

[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)).

cant 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). 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).

3 The Data

3.1 Capital Flows and Returns

We use the Country Flows dataset from EPFR Global. EPFR Global publishes weekly portfolio investment flows by more than 14,000 equity funds and more than 7,000 bond funds, with more than USD 8 trillion 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 enable us to explore the role of passive investment strategies and indexing in aggravating tail events. Finally, and importantly, the data cover 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]

Figure 2 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

[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.

(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 Apr. 15, 2020.[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 emerging 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 Arab Emirates.[11]

3.2 Separating Global Risk and Risk Aversion

We use both structural and statistical approaches to microfound and quantify global risk shocks that are salient for emerging market fund investors.[12] Since the global financial crisis, a colloquial (and somewhat imprecise) risk-on / risk-off terminology has become pervasive in the

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

[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

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

[12]The literature heretofore identifies an important role for shocks to global investor risk appetite or the price of risk (Bruno and Shin (2015a); Bruno and Shin (2015b); Chari et al. (2021); and Bekaert et al. (2013)). Rey (2013) and Miranda-Agrippino and Rey (2020b), for example, suggest that global risk aversion is a key transmission vector that "exports" U.S. monetary policy shocks and with a significant source of cross-country asset return comovement tied to its variation

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, given that the index relies on traded option prices, this measurement choice does not permit the separate identification of variation in physical risk from variation in the price of risk. Further, 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.

To show the importance of this issue, Figure 3 provides a decomposition of the daily log changes in the VIX index into daily log changes in physical volatility (following Bekaert and Hoerova (2014)) and in the variance risk premium (reflecting variation in risk prices).[13] As we observe, these two rather different economic concepts are both important determinants of the shocks to the overall VIX index. Equally, the relative importance of the two shocks for the overall VIX index varies in the time-series. Our understanding of the implications of global shocks for emerging market flows and returns requires a disentangling of the quantity and price of risk.

Given these limitations, we instead follow Bekaert et al. (2022) (hereafter BEX (2022)) by considering an alternative measurement approach that permits the separation of realized

[13]To operationalize the exercise, for each day, we regress the log change in the VIX index on the log changes in physical risk and the variance risk premium over the previous two-years. We then calculate the variance of the model fitted log VIX change and use the two-year regression to measure the proportion explained by physical risk and the risk premium, respectively. For each day, we multiply that day's daily log change in the VIX index by those two-year proportions and present a decomposition of that day's shocks.

variation in global risk from global investor risk appetite. BEX (2022) propose a dynamic no-arbitrage model for equities and corporate bonds where fundamentals (such as industrial production, consumption earnings ratios, and corporate loss rates) display time-variation in conditional variances and higher order moments.

Employing a wide set of macro and financial market data, they develop a habit-based asset pricing model decomposition (see, for example, Campbell and Cochrane (1999)) to structurally distinguish the price of risk (risk aversion) from the quantity of risk (economic uncertainty).[14] They assume that stochastic time variation in risk aversion is less than perfectly correlated with fundamentals allowing a role for pure preference shocks. While this approach has the advantage of disentangling risk aversion from risk, absent for other risk aversion measures commonly used in the literature (such as the VIX index), inference about this separation may, of course, be contaminated by any model mis-specification.[15]

Figure 4 presents this model-based structural decomposition into changes in risk aversion or the price of risk (Panel C) and the quantity risk (D). The model-based measures are skewed towards downside risk and fat-tailed. In addition to skewness and excess kurtosis, these measures also exhibit time varying volatility (see Table 1a). 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.

3.2.1 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

[14]Thanks to Nancy Xu for making these daily data available. https://www.nancyxu.net/risk-aversion-index

[15]External validation exercises show that the extracted stochastic risk aversion series loads positively and significantly on the equity variance risk premium proxied by the risk-neutral equity variance, credit spreads, and the realized corporate bond variance. Importantly, there is a strong correlation between the stochastic risk aversion with consumer confidence and Sentix investor emotions indices (Bekaert et al. (2022)). The extracted physical risk series is highly correlated with both credit spreads and corporate bond volatility. Further, term spreads have a significant negative effect on the quantity of risk consistent with a flattening yield curves signaling future economic downturns.

(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 the advanced economy industrial production growth.[16] 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 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.[17]

With the exception of emerging market news surprises, all control variables enter with a lag to rule out simultaneity.[18] 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.

4 Estimation and Results

To identify plausibly exogenous variation in these reallocations, we regress weekly EPFR country-level flows onto our global risk and risk aversion *shocks* using the panel quantile regression approach of Machado and Santos Silva (2019). We include country and time fixed

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

[17]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.

[18]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.

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.

$$k_{it}^{(q)} = \alpha_i^{(q)} + \delta_t^{(q)} + \rho k_{it-1}^{(q)} + \beta_1^{(q)} Risk_t + \beta_2^{(q)} RA_t + \gamma_1^{(q)} PUSH_{t-1}^{k} + \gamma_2^{(q)} PULL_{i,t-1}^{k} + \epsilon_{i,t} \quad (1)$$

where $k_{it}^{(q)} = \left(\frac{K_{it}}{H_{it-1}} * 100\right)$. $Risk_t$ and RA_t are the risk and risk aversion shocks from Bekaert et al. (2022), respectively, that enter the specification in a nested manner. k_{it} is either equity or debt 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.[19]

In general, global risk and risk aversion 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 and returns across the distribution. In many cases, 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. These patterns come with subtle caveats, highlighting the importance of separating risk from risk aversion and the implications for tail responses.

The left panels of Figure 5 plots the quantile regression coefficients for both bonds and equities. 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 catches 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 negatively sloped quantile curve signifies a compression of the distribution. The shaded areas represent confidence intervals at 95% using bootstrapped standard errors. Table 2 provides point estimates and standard errors for selected quantiles.

[19]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.

For fixed income, the steep, positively inclined risk aversion quantile coefficient curve for bonds is consistent with a dispersive impact in the direction of downside risk, i.e., capital flight on the left and an inflow slowdown on the right. However, the magnitude of the distance from zero of the quantile coefficient curve for uncertainty shocks suggests that the negative impact of physical risk shocks on bond flows is, on balance, more significant and more uniform.

For equities, we see a different pattern. The flatter, downward-sloping quantile risk aversion coefficient curve signals that capital outflows (q^5) slow down by less than the negative shift in the median (q^{50}). Still, capital inflows on the right tail (q^{95}) slow down significantly more. Together, these signify a compression of the distribution. In contrast, the quantile coefficient curve for uncertainty shocks for equity flows is positive and steep, counterbalancing the impact of the risk aversion shock on the left tail.

It is worth pointing out that from the magnitudes of the negative coefficients, we observe that the impact of physical risk shocks, or the quantity of risk, is significantly higher than that of risk aversion shocks across the distributions for equities and bonds. Focusing on the distributional consequences illustrates the differential responses of outflows and inflows captured by the tails and highlights differential responses across asset classes.

The right panels of Figure 5 visualizes the changes to the fund flow distribution brought on by shocks to risk and risk aversion, fitting a skewed-t distribution to the estimated quantiles as in Adrian et al. (2019) and others. 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 some additional impact on downside risk captured by the mass in the left tail. Risk aversion shocks leave the distribution's right tail anchored, i.e., inflow slowdowns contribute little to the changes in net flow. At the same time, the dispersive impact arises by exacerbating the worst outflow realizations, amplifying downside risk.[20]

We see the first pattern in the difference between the black, bold distribution (which shows the prediction less the impact of risk and risk aversion shocks) and the red line, which shows the prediction including the effects of physical risk-off shocks. In this instance, some mass is

[20]Online 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.

removed from the right tail (indicating a decrease in total inflow realizations). In contrast, a larger mass is added to the left tail (showing an increase in gross outflow realizations).

The impact of a risk aversion shock is shown in blue. Here we see almost no mass removed from the right tail, while mass is indeed added to the left tail signifying downside risk. The black dotted line contemplates the combined impact of the two shocks, which shifts the distribution to the left and removes mass from the distribution's right tail while placing more mass in the left tail. The combined effect shows net outflows resulting partly from diminished gross inflows but more significantly from exacerbated gross outflows, consistent with flight or retrenchment. Visualizing the results in this way helps to contextualize downside risk. Although there is a more dispersive impact on the distribution's tails relative to the median, both tails shift in a manner consistent with net outflows from a risk-off shock.

Turning to equity flows in panel (b), the results suggest a dominant role for physical risk, resulting in a dispersive impact in the tails relative to the median, and a more minor role for risk aversion, which slightly compresses the distribution. This latter pattern can be readily seen in the distribution plotted in blue, which again shows the predicted flow distribution conditional on a risk aversion shock. Although this plot lies mainly to the left of the unconditional distribution, it is also the narrowest depicted, with most of the reaction owing to decreased mass in the right tail (a sudden stop). At the same time, we see a minuscule diminution of outflow (left) tail risk relative to the unconditional density. Here again, the fitted distributions help us to interpret the parameter values—although the parameter value on the fifth quantile is positive, that realization does not imply an inflow but rather that gross outflows have slowed. The pattern suggests that capital outflows slow down, and inflows also slow down or stop. The net result is a compressed equity flow distribution conditioning on a risk aversion shock.

In contrast, a macro risk shock results in less mass in the right tail and substantial additional mass in the left tail, i.e., greater asymmetrically in the direction of downside risk. The net effect is shown with a dotted line, where we see less mass in the right tail (capital inflows slow down) and more mass in the left tail (capital flight), reflecting the flow density's stronger reaction to physical risk shocks.

To summarize, the variation in the quantity of risk or macro uncertainty has a more significant impact across the distribution and adds more weight to downside tail risk than risk aversion; this is the case across asset classes and is consistent with a negative shock triggering retrenchment or flight. Where bonds and equity flow (and thus also return) distributional changes differ is in the dispersive impact of risk aversion shocks. This distinction offers a window into common measures such as the VIX and enables us to consider risk measurement and co-movement more generally.

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 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.

$$R_{i,t} = \alpha_i + \beta \frac{K_{i,t}}{M_{i,t-1}} + \gamma_1 PUSH_{t-1} + \gamma_2 PULL_{i,t-1} + \delta_t + \epsilon_{i,t} \quad (2)$$

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 3 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 0.023% of market capitalization ($71.8M) is associated with a 23 basis point depreciation of the currency and a 71-88 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 12 basis points and 22–26 basis points, respectively. These parameter values, however, are merely suggestive given the clear endogeneity between volumes and prices. Even so, 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.

4.1 Persistence of risk shocks

Thus far, we have provided evidence on the impact of risk and risk aversion shocks in the week immediately following a shock. Given that capital reallocations may not react immediately to shocks, they 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 risk and risk aversion shocks, we repeat our baseline exercise as a series of local projections:

$$k^{(q)}_{it+h} \quad = \quad \alpha^{(q)}_i + \delta^{(q)}_t + \rho k^{(q)}_{it-1} + \beta^{(q)}_{1,h} Risk_t + \beta^{(q)}_{2,h} RA_t + \gamma^{(q)}_1 PUSH^k_t + \gamma^{(q)}_2 PULL^k_{it} + \epsilon_{i,t} \quad (3)$$

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 $\hat{\beta}_j = \{\hat{\beta}_{j,0} \ldots \hat{\beta}_{j,H}\}$.[21]

Figure 6 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 the distribution, this persistence is even more pronounces 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}.

Across the various cases, risk aversion shocks largely worsen the left tail of the distributions for longer than the median or the right tail. The worsening left tail response is also the case for the impact of uncertainty shocks on bond fund flows. The only exception is uncertainty's impact on equity flows, where gross inflows fall for longer than the median flow. However, at the trough of the median response, the reactions are generally tails-out on a cumulative basis.

Taken together, the persistent nature of these global shocks suggest, at least, two facts. One, these impacts are consequential in that their effects do not immediately dissipate or re-

[21]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.

verse. 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).

4.2 Application: Brazil

To illustrate the implications of different tail reactions to risk aversion and risk shocks, we present examples of various high-volatility episodes through the lens of a representative emerging market, Brazil. Table 4 shows the quantitative impact of the largest shock in each of the Global Financial Crisis, U.S. monetary policy normalization post-GFC, and the initial Covid-19 crisis on the distribution of bond and equity fund flows into Brazil. Panel A shows the distributional consequences of a risk aversion shock, while Panel B shows the implications of a physical risk 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 fund flows over the previous year. The second row shows the product of the maximum risk-off shock observed in that episode and the parameter values from our quantile regressions, $\sigma\hat{\beta}^{(q)}$. Row three translates the impact into dollar terms by multiplying $\sigma\hat{\beta}^{(q)}$ by the average Brazilian AUM in each asset class in the three months preceding the shock ($\hat{\beta}^{(q)} * \sigma * H$). This value shows how much the 5th, 50th, and 95th quantiles shift in response to a shock of size σ, which in the 5th quantile approximates a notion of value-at-risk. Finally, the fourth row in each event sums rows one and three to give an estimate of the subsample conditional distribution of flows prevailing as a result of the shock, $\hat{k}^{(q)} = k^q + \hat{\beta}^{(q)} * \sigma * H$.

In addition to contextualizing the magnitudes of the changes we document, this exercise furtther elucidates the distinction in the changing shape of the capital flow distribution conditional on global risk and risk aversion shocks. To see this, consider the impact of the Covid-19 risk aversion peak on bonds versus equity fund flows. The bottom row of Table 4, Panel A shows that both distributions have shifted left, deeper into outflow space. However, the bond flow distribution has widened considerably, while the equity distribution has narrowed.

More specifically, Q95 (the right tail) of the bond flow distribution has shifted very little, decreasing by $6.84M per week, while Q5 (the left tail) has shifted markedly more, by $146.4M per week. Thus, while the unconditional 95th quantile ($184.4M) is very similar to the post-shock estimate ($177.5M), the 5th quantile of bond flows has worsened by a factor of four ($48.8M to $195.2M per week). 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 narrowed in response to a risk aversion shock. The 95th quantile falls by $242.9M per week to less than half its 2019 value ($396.8M to $153.9M per week), signifying a massive capital inflow slowdown. The 5th quantile, which captures extreme outflow realizations, moves toward the median by $21.4M, which leaves the conditional 5th quantile at about 75 percent of its 2019 value (-$357.96 to -$236.5M per week), i.e., outflows remain relatively steady. This last point clarifies the results expressed as quantiles of flows in percent of AUM—a positive parameter value for the bottom quantiles does not imply an inflow but rather a slowing of outflows. At the same time, the highest equity inflow realizations have fallen, as in a "sudden stop."

This quantitative exercise also illustrates the distinction between a response that is roughly comparable across the distribution to one that significantly changes its shape. Here we can compare, for example, the differential response of bond fund flows to risk shocks (which affects all quantiles similarly) versus the response of these flows to a (highly dispersive) risk aversion shock. Looking at the bottom row in Panels A and B for bonds, we see that the left tail reacts similarly to the two different shocks. In each case, Q5 falls by slightly more than $141M per week. While quantile responses to a risk shock are relatively uniform, risk aversion elicits a more robust lenghtening tail response. Thus, although Q5 moves in a similar manner across measures, the highest inflow realizations (Q95) shrink markedly in response to a negative risk shock (-$122.7M per week) while moving very little in response to a risk aversion shock (-$6.8M per week). Similarly, the median flow is more adversely affected by risk shocks (-$131.7M) compared to risk aversion (-$73.6M)—almost double.

Finally, breaking down our estimates in this way across episodes allows us to distinguish between moments of elevated risk versus elevated risk aversion. Here, we use a hypothetical example. Appendix Table 5 repeats the exercise in Table 4, showing the hypothetical impact on the flow distribution in the face of a ”risk-dominant” event versus a ”risk aversion-dominant” event. This extension shows the counterfactual quantiles of the post-shock distribution of flows and compares them to the distribution from 2019 (shown in the first row of the table).

In the first row of each subsection, we take a hypothetical risk or risk aversion shock and multiply it by our estimated parameter values. The estimated change in the second row is the value in row two multiplied by Brazilian AUM in 2019 to generate a dollar value for the flow. Row three sums the top row and the second subsection row to show a sample conditional distribution prevailing due to the risk-off shock. The ” total ” row indicates the sum of the estimated change to the flow quantiles, conditional on risk and risk aversion shocks. We see that across asset classes, risk-dominant events generate more extreme tail movements. Finally, with this set of hypothetical risk shocks, the equity distribution under the risk aversion-dominant scenario displays a tails-in or compressed response.[22]

4.3 Passive versus Active Flows

Figure 1 suggests a sizable and increasing role for passively managed funds in facilitating EM access for global investors. Around 40% of assets under management in EM equity funds are passively managed in 2020 (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 EM 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 pass-through 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

[22]This example features a ratio of risk aversion to risk shocks of 3, but it is worth noting that any ratio less than 1.93 would give a net tails-out result compared to the 2019 unconditional distribution.

funds from those attributed to passive funds.

Figure 7 suggests that investor flows into passive funds (panel A) react far more strongly (in some cases as much as an order of magnitude more) to global risk shocks than for active funds (Panel B). 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 to either risk aversion or physical risk across both asset classes. These pressures then disproportionately pass through to the countries in which passive EM funds invest. Figure 8 translates the predicted quantiles into a skewed-t distribution, which punctuates the importance of physical risk in aggravating outflow realizations and of risk aversion in diminishing inflow realizations.

Furthermore, in our earlier analysis for which we do not separate active and passive funds, we find that the general distributions of both fixed income and equity flows widen (tails-out) in response to adverse physical risk shocks, whereas both distributions narrow (tails-in) in the face of an adverse risk aversion shock. In the equity space, where passive funds make up a significant fraction of assets under management as of 2020, this pattern is consistent with passive funds playing a large role in driving these baseline results (as shown in Figure 7). In fixed income, where active management remains more common, this strong tails-in response to adverse risk aversion shocks that we see in Figure 7 does not carry through to the earlier general results. However, as passive bond funds further penetrate emerging market fund management, one can speculate as to how this will affect overall country bond flows, with more episodes characterized by sudden stops.

Given the importance of index construction in driving passive fund activity, Table 5, 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, Table 5, 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 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.[23]

4.4 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 9, we present the tail and median impacts of global risk and risk aversion shocks on emerging market country flows associated with all passive funds (Column a, consistent with the left half of Figure 7 discussed above), open-end index funds (column b), and

[23] 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.

ETFs (column c). Row (i) shows this disaggregation for equity flows, and row (ii) shows the same for fixed income flows.

First, Panel A confirms that the median response to risk aversion shocks for emerging market bond flows associated with index funds and ETFs is consistently negative and significant. However, the sudden stop or capital inflow slowdown associated with passive bond funds, evidenced by the negative and significant coefficient on Q95 in response to risk aversion shocks, appears to be primarily driven by ETFs (ETF Q95). We do not see much statistical significance related to passive bond fund flow responses to risk aversion shocks on the left tail (Q5, M.F. Q5, ETF Q5). In contrast, physical risk shocks elicit a strong capital outflow response for passive bond funds, but this, too, appears to come from ETFs. In contrast, the coefficient on Q5 for passive mutual fund bond flows in response to physical shocks (M.F. Q5) is positive and significant, suggesting a slowdown in outflows.

For passive equity funds, Panel B shows a negative median response to risk aversion shocks for emerging market equity flows associated with index funds and ETFs. Further, we find that risk aversion shocks elicit a negative and statistically significant response on the right tail across the board, indicating sudden stops or inflow slowdowns. At the same time, the left tail response is positive and signals that outflows also slow down. The pattern of coefficients implies a tails-in response to risk aversion shocks across all types of passive equity funds.

Except for equity mutual funds on the right tail, the response to physical risk shocks is negative and significant across quantiles for passive equity flows. In terms of magnitudes, passive equity mutual fund responses to risk aversion shocks are significantly higher in both tails compared to ETFs. However, passive bond mutual funds and ETFs respond more strongly to risk aversion shocks across asset classes than their equity fund and ETF counterparts. In contrast, the response of passive equity flows to physical risk shocks is significantly higher than passive bond flows.

Taken together, the significant responses to global risk and risk aversion 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 pass-through pressures from sizable ETF trading remain.

The passive asset management industry is a key driver replacing traditional active management, where discretion is significantly more pronounced. 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.[24]

4.5 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 global risk or risk aversion 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 mon-

[24]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.

etary stance as measured by the shadow rate as controls in this exercise. We also retain year-fixed effects, and we run the following regression:

$$g_t^{(q)} = \alpha^{(q)} + \delta_t^{(q)} + \beta_1^{(q)} Risk_t + \beta_2^{(q)} RA_t + \gamma_1^{(q)} PUSH_t^k + \epsilon_t \quad (4)$$

Where $g_t^{(q)}$ is the weekly growth rate of government money market assets in quantile q, and $Risk_t$ and $R.A._t$, precisely as above, represent the risk and risk aversion decomposition.

Table 6 summarizes the results. A shock to physical risk positively affects flows into government money market funds. However, this effect is not consistent across the distribution and appears strongest at the median. Risk aversion shocks drive the left tail of the distribution toward the median, but we do not observe statistically significant impacts elsewhere in the distribution. Taken together, we detect some reactions to global shocks in the allocations to safe assets in a manner that complements what we observe for risky assets. As the effects are stronger for global risk shocks than risk aversion shocks, this distinction reiterates the importance of using a measurement strategy that facilitates the separation of these two very different economic concepts.

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 Table 6 are associated with institutional 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.

5 Additional Tests and Robustness Checks

5.1 Alternative Measures of Global Shocks

In recognition that the structural model-based approach used to derive our measures of variation in global physical risk and investor risk appetite may suffer from model misspecification, we consider two alternative measures of global risk appetite. First, we follow the literature and employ log changes in the VIX index as a proxy for global risk aversion shocks; Avdjiev et al. (2019) and Rey (2013), for example, document the sensitivity of portfolio equity flows to the VIX. Second, we construct a statistical risk-on/risk-off (RORO) index.[25]. Our RORO index comprises the z-score of the first principal component of daily changes across several relevant asset markets.

Our RORO index incorporates several series. To capture changes related to credit risk, we use the change in the ICE BofA BBB Corporate Index Option-Adjusted Spread for the United States and the Euro Area, along with Moody's BAA corporate bond yield relative to 10-year Treasuries. To capture changes in risk aversion emanating from advanced economy equity markets, we use the additive inverse of total daily returns on the S&P 500, STOXX 50, and MSCI Advanced Economies Index, along with associated changes in option implied volatilities from the VIX and the VSTOXX. To account for changes to funding liquidity, we include the daily average change in the G-spread on 2-, 5-, and 10-year Treasuries, along with changes in the TED spread, the 3-month LIBOR-OIS spread, and the bid-ask spread on 3-month Treasuries. Finally, we include growth in the trade-weighted U.S. Dollar Index against advanced foreign economies and the change in the price of gold. We normalize each component such that positive changes imply risk-off behavior. Then, before taking the first principal component, we scale these normalized changes by their respective historical standard deviations. A caveat to bear in mind is that while linked to variation in risk aversion, these two alternative measures still likely confound information about variation in risk appetite with variation in physical risk.

Table 7 presents results from quantile regressions of equity and bond flows, where we replace the global shocks derived from the structural model with either the VIX or the RORO

[25]See Cascaldi-Garcia et al. (2020) for a similar method.

index. To ease comparison, we present the coefficients of the BEX risk aversion and risk shocks on portfolio flows at the bottom of each table.

Table 7, Panel A provides the results for bond flows. First, while the bond flow magnitudes associated with VIX shocks are, on average, of a similar magnitude to the BEX structural shocks, the distributional implications are somewhat different. The tails-out behavior in bond flows associated with VIX shocks looks more like the patterns we observe from BEX risk aversion than physical risk, as seen at the bottom of the table. Recall that tails-out refers to capital outflows or retrenchments, while tails-in responses are consistent with sudden stops or capital inflows slowing down.

Second, the bond flow response to our alternative RORO index shocks is several times larger in magnitude than the BEX structural or VIX shocks. Further, the bond flow distributional implications of a RORO shock also capture the tails-out behavior uncovered with BEX risk aversion. While there are some quantitative differences across the various cases, our results are qualitatively consistent in that global risk shocks (broadly defined) engender significantly negative bond portfolio flows, particularly in the left tail of the distribution.

Similarly, Table 7, Panel B provides the results for equity flows. First, consistent with the results associated with the structural BEX global shocks (repeated at the bottom), we continue to observe significant negative equity flows associated with VIX shocks. However, the impact of VIX shocks across the equity flow distribution is relatively constant. The pattern differs from the results associated with structural shocks, where risk aversion exhibits tails-in equity flow behavior, while physical risk exhibits tails-out. The VIX shock results suggest a counterbalancing of the two effects, so the net impact is relatively constant.

Second, the baseline effects for equity flows are similarly larger in magnitude for the RORO index shocks, much like that reported for bond flows above. We also observe a largely uniform pattern across the distribution in that the coefficients are relatively constant, much like for the VIX shocks. For equity flows, at least, the decomposition of global shocks into components linked to risk and risk aversion appears particularly salient. However, all cases uncover important distributional implications for global shocks on equity flows.

Taken together, our main findings are not particularly sensitive to the BEX structural decomposition. All candidate measures of global shocks exhibit significant implications for portfolio flows. However, some more nuanced findings across the flow distributions potentially linked to the separation of risk from risk aversion require a model. In unreported results, we find similar magnitudes and patterns when we analyze the implications for passively managed bond and equity flow distributions across these candidate global shocks.

5.2 Large shocks

The turmoil caused by the onset of the Covid-19 pandemic set off a meltdown in international capital flows. To ensure that our results are not driven by this decidedly atypical shock, we repeat the baseline exercise including an indicator variable equal to one after January 20, 2020. This date corresponds to the first documented Covid cases in the United States.[26] Controlling for the early Covid period does somewhat dampen the measured impact of risk aversion and risk. This is unsurprising, given the out-sized movements in our risk-measures during the early part of 2020. That said, most of the broad patterns that we document from the baseline approach remain. The only exception is that, whereas a shock is associated with a mildly "tails-out" reaction of bond funds in the baseline, it appears to induce a mildly "tails-in" reaction when we control for Covid.

To more closely examine how extreme risk-off shifts in global risk aversion or uncertainty affect the distribution of flows, we modify our baseline to account for this potential non-linearity. We add to our regression an indicator variable equal to one when a risk or risk aversion shock is above the 75th percentile of its distribution, interacting this dummy with our risk and risk aversion shocks:

$$\begin{aligned} k_{it} = \alpha_i + \delta_t + \rho k_{it-1} + \beta_1 Risk_t + \beta_2 RA_t + \beta_3 \mathbb{1}[R_t > Q75] + \beta_4 \mathbb{1}[R_t > Q75] * R_t \ldots \\ \ldots + \gamma_1 PUSH_t^k + \gamma_2 PULL_{it}^k + \epsilon_{i,t} \end{aligned} \tag{5}$$

Where R_t is either risk or risk aversion. We test one interaction at a time to economize on parameters. While the results are formally presented in the online appendix Table 7, we report here that we do indeed observe a bigger flow impact associated with large risk-off shocks as

[26]Consulting Google trends, after January 20 searches for words like "covid", "corona", and "Wuhan" began to climb toward their mid-March peak.

compared to other shocks. This result at least partially explains the importance of the Covid period in our baseline examination.

6 Conclusion

The novel contribution of our paper is to characterize how risk and risk aversion shocks alter the range and shape of the distributions of emerging market capital flows associated with mutual fund and ETF trading. We document that global shocks to both the price and quantity of risk have important distributional implications for emerging market portfolio flows. While some differences exist in the impact across bond versus equity market flows, the effects associated with the left tail are generally larger than that on the median realization. Further, we find that the worst realizations are often disproportionately affected by shocks to the quantity of risk rather than shocks to the price of risk.

When mapping from global shocks to investment management funding pressures to emerging market capital flows, we highlight an important source of variation in the mutual fund organizational form; not all funds are alike. In response to global shocks, passively managed emerging market funds, which now represent a sizable fraction of assets under management, face different redemption pressures and benchmarking mandates from active funds. Specifically, we find that the amplification effects of higher conformity in global fund investments via passive fund benchmarking drive herd behavior and elevated correlations in response to global shocks. Further, additional results separating ETFs from active and passive mutual funds show that ETFs appear to play a critical role in driving our baseline results. In sum, the actual conduits facilitating investor flows to emerging markets are critical to understanding emerging market tail risk.

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

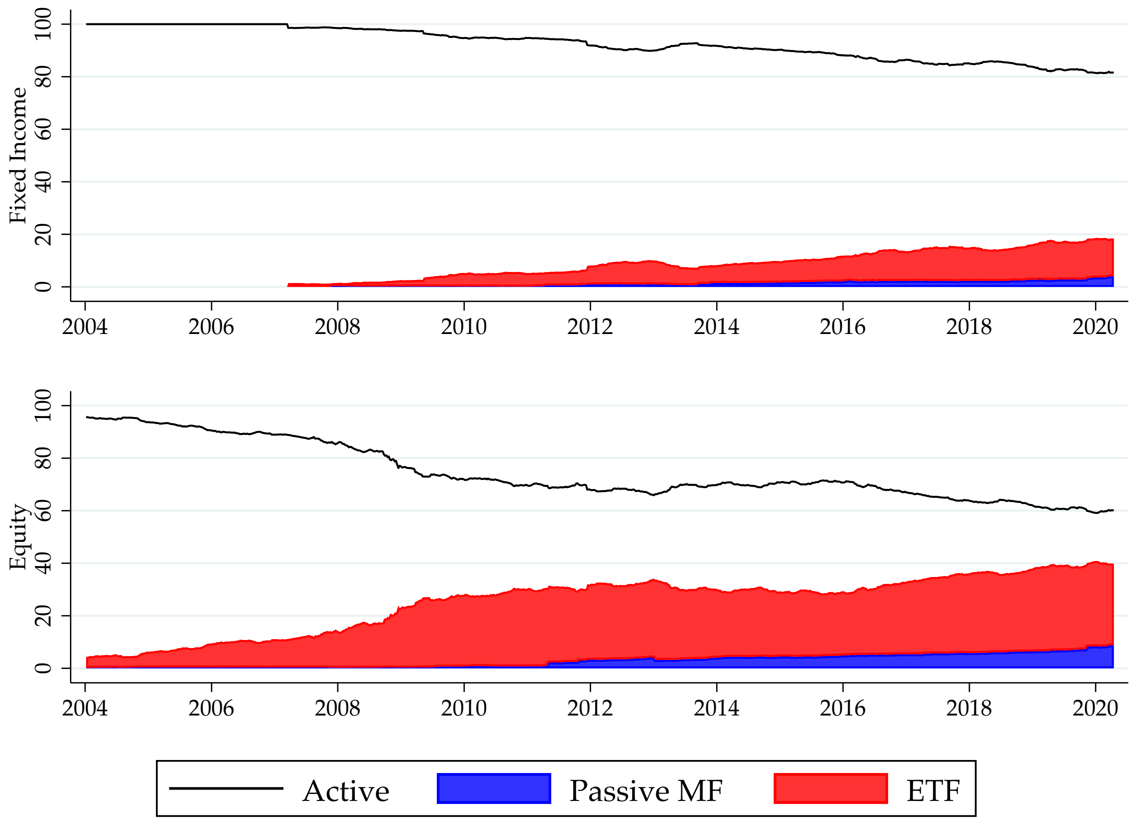
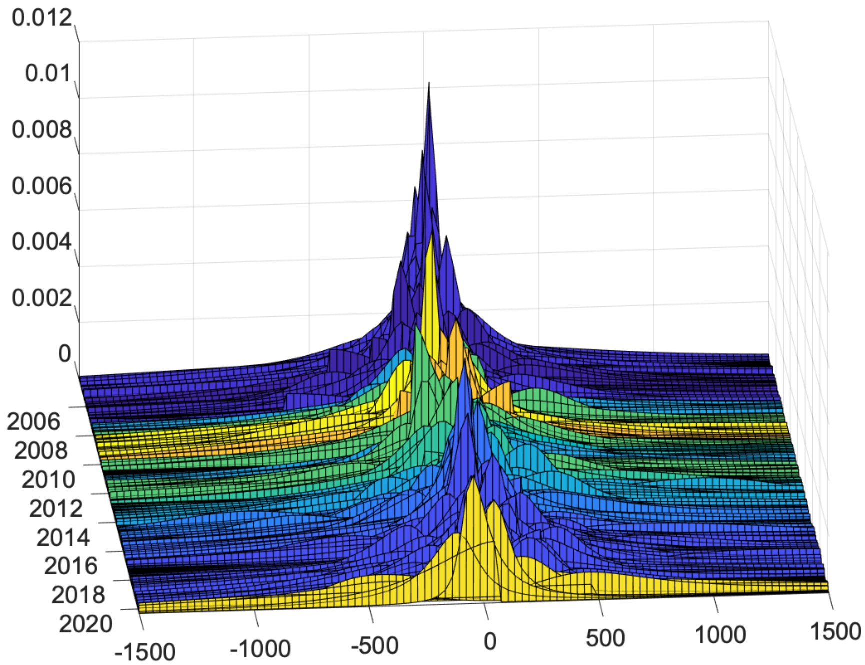
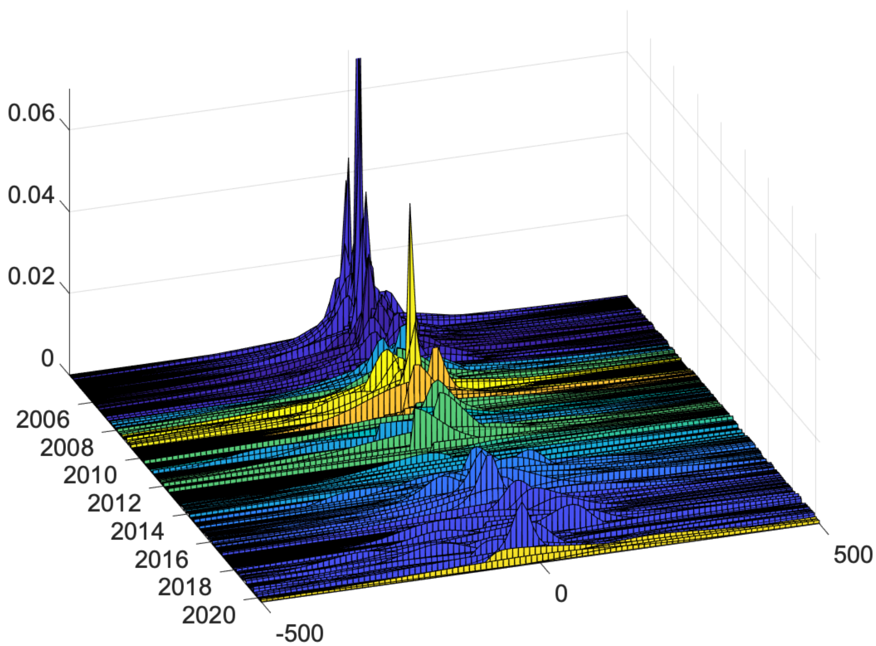


Figure 1 shows the proportion of equity and fixed income assets under management attributable to passive fund flows (decomposed into ETFs and passive mutual funds) and active fund flows.

Figure 2: Time varying fitted distribution of emerging market fund flows



(a) Equity



(b) Fixed Income

Figure 2 Plots the results from fitting the empirical distribution of weekly emerging market equity (panel a) and fixed income (panel b) fund flows to a skewed-t probability distribution using the algorithm of Azzalini (2019).

Figure 3: The Decomposition of VIX Shocks into the Price and Quantity of Risk

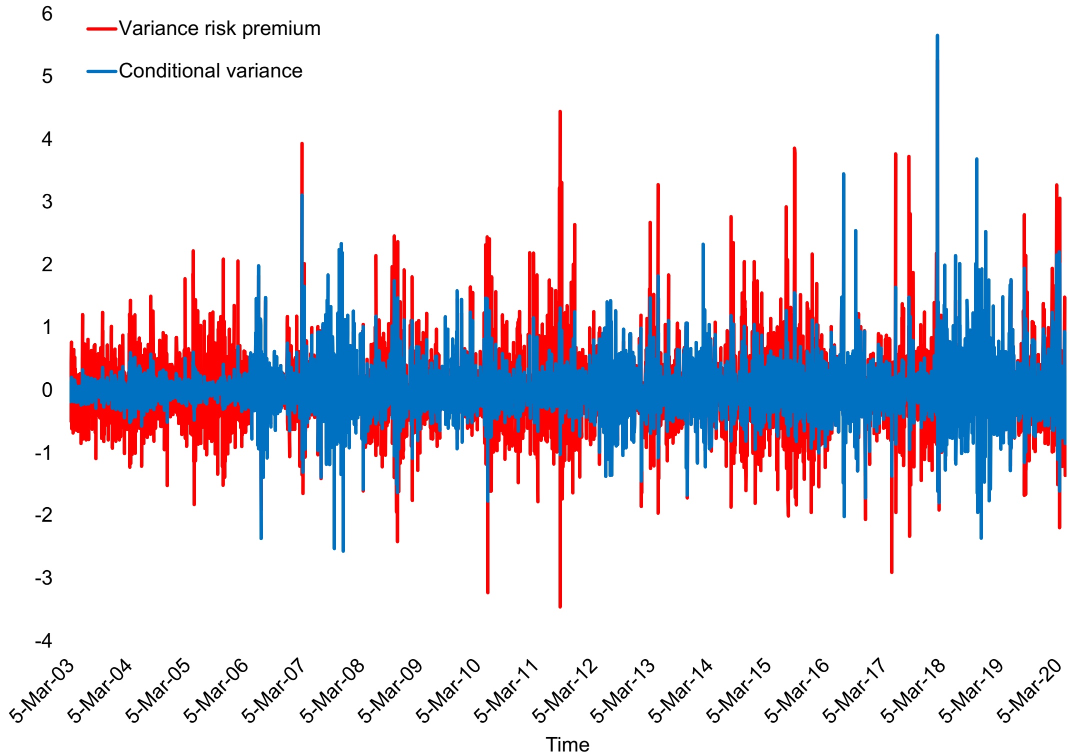
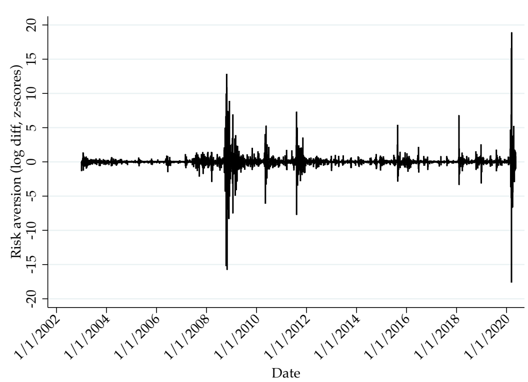
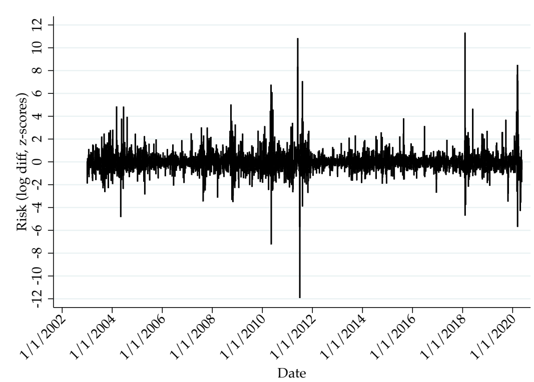


Figure 3 provides a decomposition of the daily log changes in the VIX index into daily log changes in physical volatility (following Bekaert and Hoerova (2014)) and in the variance risk premium (reflecting variation in risk prices).

Figure 4: Risk and Risk Aversion Shocks



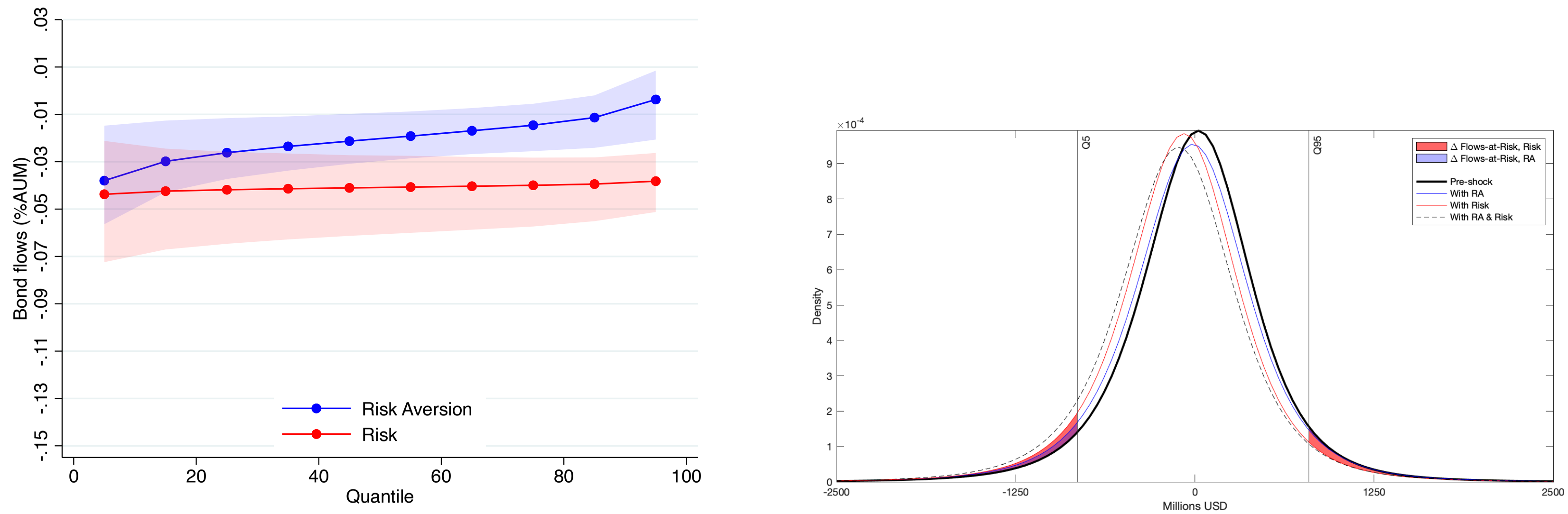
(a) Time Series (log difference): Risk Aversion



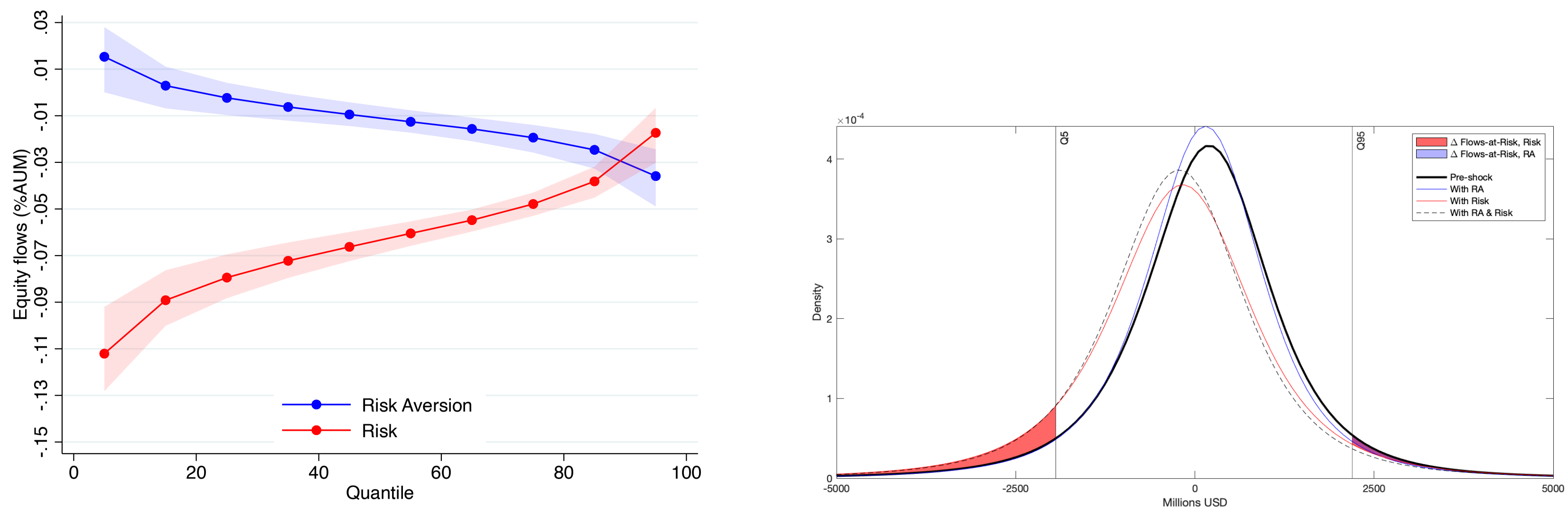
(b) Time Series (log difference): Risk

Figure 4 plots the log difference of risk aversion and risk from Bekaert et al. (2022).

Figure 5: The distributional impact of risk and risk aversion shocks on EPFR bond and equity flows (% of AUM)



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



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

Figure 5 summarizes the impact of a one standard deviation shock to risk and risk aversion on emerging market bond and equity flows, respectively. Risk and risk aversion are the log differences of the estimated series from Bekaert et al (2022) and enter the regressions as a weekly moving average. 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 risk aversion or risk 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.

Figure 6: Dynamic Effects using local projections

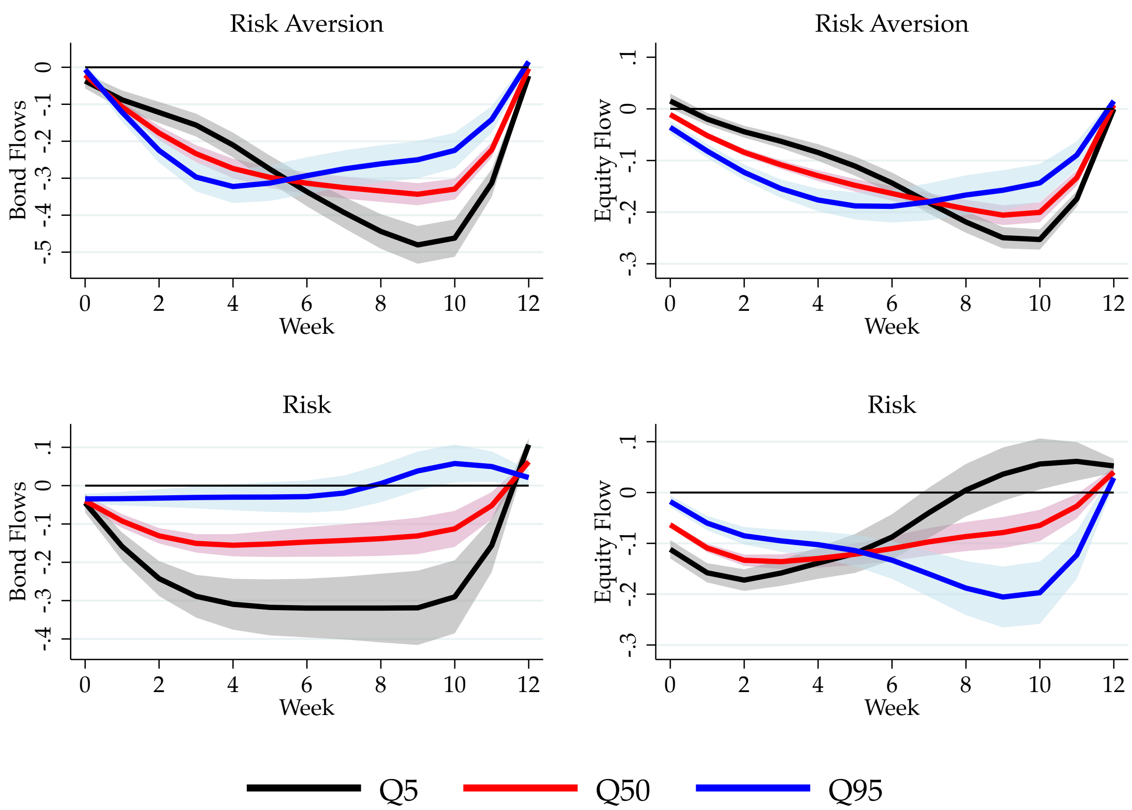
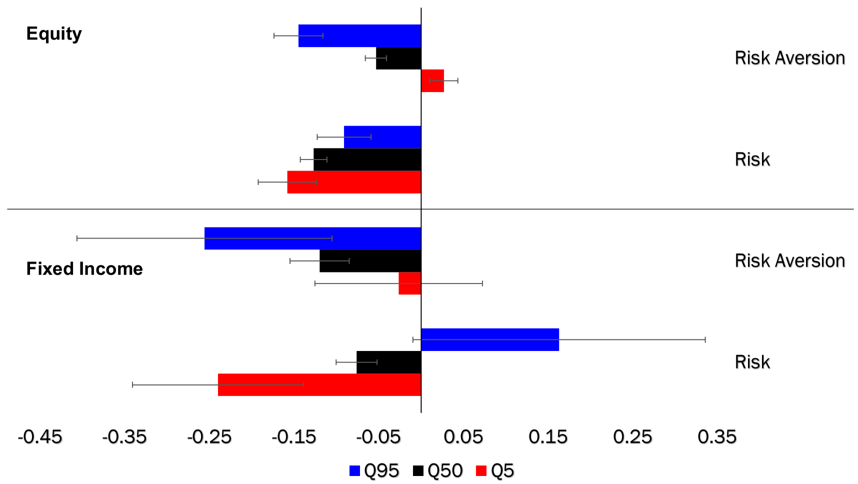
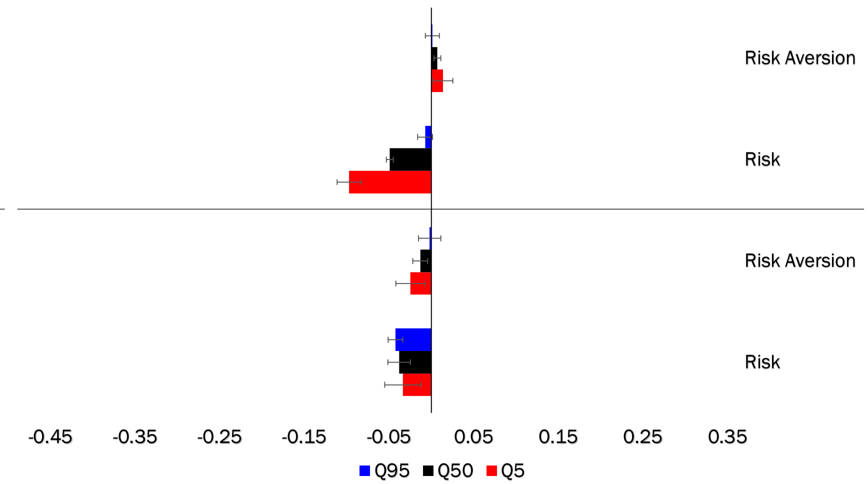


Figure 6 summarizes the impact of a one-standard deviation shock to risk and risk aversion on emerging market bond and equity flows, respectively, over a 12 week-horizon. Risk and risk aversion are the log differences of the estimated series from Bekaert et al (2021) and enter the regressions as a weekly moving average. 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.

Figure 7: The distributional impact of risk and risk aversion shocks on active and passive EPFR bond and equity flows (% of AUM)



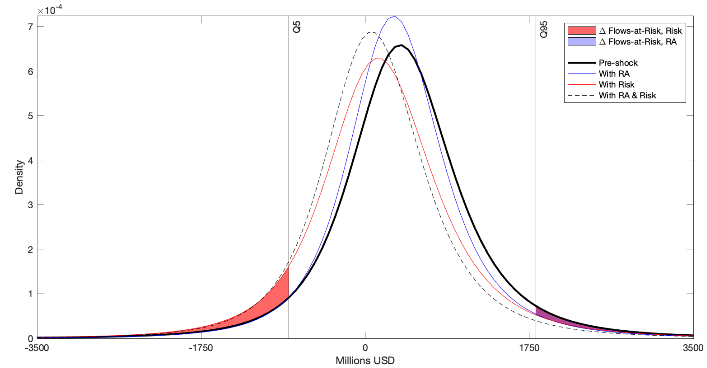
(a) Passive



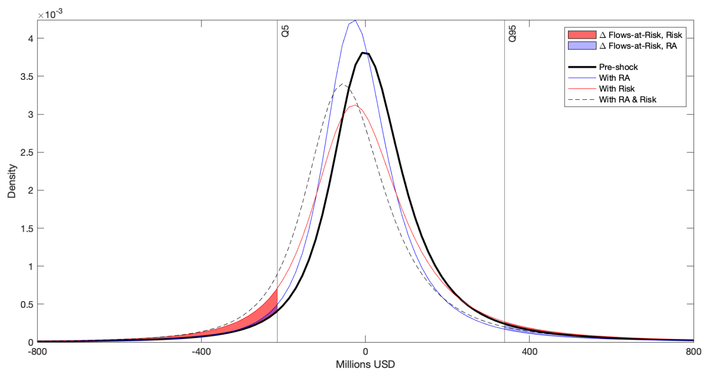
(b) Active

Figure 7 summarizes the impact of a one standard deviation shock to risk and risk aversion on emerging market passive and active fund flows, respectively. Risk and risk aversion are the log differences of the estimated series from Bekaert et al (2021) and enter the regressions as a weekly moving average. Panels (a) and (b) show the impact of a one standard deviation global risk on passive and active fund flows, respectively. 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.

Figure 8: Predicted Passive Flow Distributions Conditional on Risk Shocks



(a) Equity

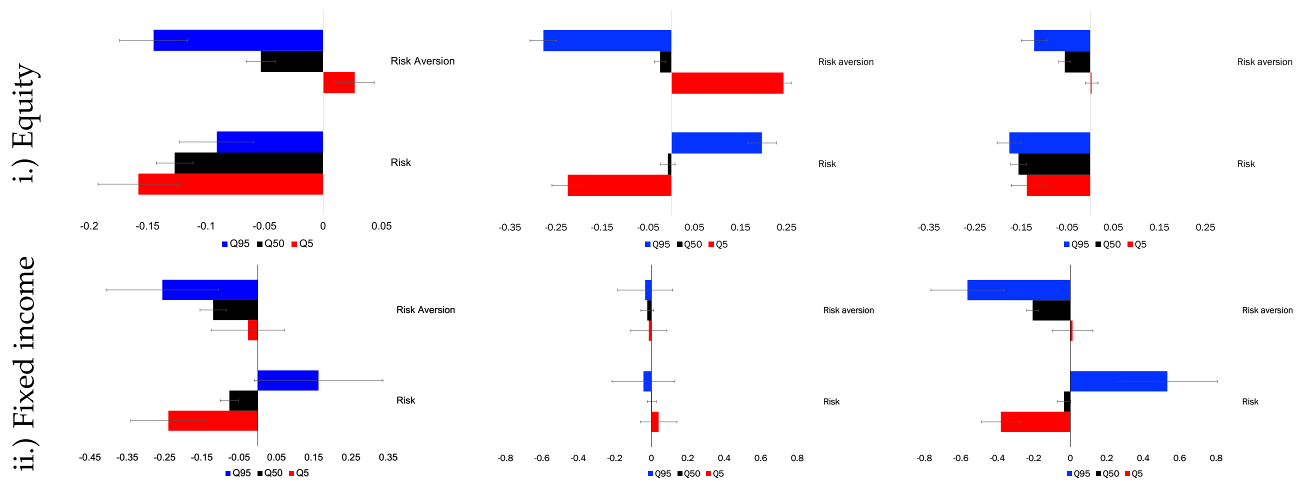


(b) Fixed Income

Figure 8 Plots the results from fitting the distribution of emerging market equity (panel a) and fixed income (panel b) fund flows conditional on a shock to risk aversion or risk to a skewed-t probability distribution using the algorithm of Azzalini (2019).

Figure 9: The distributional impact of risk and risk aversion shocks on mutual fund and ETF EPFR bond and equity flows (% of AUM)

(a.) Passive (b.) Mutual Funds (c.) ETFs



Notes: Figure 9 summarizes the impact of a one standard deviation shock to risk and risk aversion on emerging market passive and active fund flows, respectively. Risk and risk aversion are the log differences of the estimated series from Bekaert et al (2021) and enter the regressions as a weekly moving average. 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.

Table 1: Summary Statistics

(a) Risk- and Risk Aversion Summary Statistics

	Mean	St. Dev	Q5	Q50	Q95	Skewness	Kurtosis
Risk Aversion	0.00	1.05	-0.72	-0.00	0.74	0.03	112.09
Risk	-0.01	0.91	-1.12	-0.06	1.27	1.36	30.86
Observations	4330						

(b) EPFR Country Flows

	Mean	St. Dev.	Q5	Q50	Q95	Skewness	Kurtosis
Equity Flow: Equity Flows (Millions USD)	7.80	112.59	-113.49	1.32	158.16	0.09	31.85
Equity AUM (Billions USD)	18.66	28.03	0.42	6.64	83.49	2.54	10.26
Bond Flow: Bonds Flows (Millions USD)	7.89	56.06	-52.35	2.39	86.02	-4.80	96.37
Bonds AUM (Billions USD)	7.91	9.80	0.10	4.35	32.35	1.98	7.07
Observations	19690						

(c) Returns

	Mean	St. Dev.	Q5	Q50	Q95	Skewness	Kurtosis
Exchange rate return	0.01	0.69	-0.87	0.00	0.93	14.96	1382.07
MSCI LC Return	0.04	1.53	-2.23	0.00	2.26	-0.40	21.05
MSCI USD Return	0.04	1.79	-2.68	0.00	2.62	-0.38	17.81
EMBI Return	0.02	0.62	-0.61	0.02	0.66	-5.12	317.62
LC Bond Return	0.03	0.57	-0.39	0.02	0.46	0.55	1396.99
Observations	93385						

Table 1 displays summary statistics of (a) our chosen risk and risk aversion measures from Bekaert et al (2021), (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.

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

(a) Bond flows

	Q5	Q25	Q50	Q75	Q95
Risk aversion	-0.0380***	-0.0262***	-0.0203***	-0.0146**	-0.00373
	(0.0105)	(0.00646)	(0.00522)	(0.00502)	(0.00742)
Risk	-0.0437***	-0.0418***	-0.0409***	-0.0400***	-0.0382***
	(0.0128)	(0.00962)	(0.00829)	(0.00728)	(0.00642)

(b) Equity flows

	Q5	Q25	Q50	Q75	Q95
Risk aversion	0.0153*	-0.00233	-0.0110***	-0.0194***	-0.0359***
	(0.00730)	(0.00355)	(0.00251)	(0.00301)	(0.00639)
Risk	-0.112***	-0.0794***	-0.0634***	-0.0479***	-0.0173**
	(0.00932)	(0.00478)	(0.00293)	(0.00256)	(0.00608)

Table 2 summarizes the results of quantile regressions of a) bond flows and b) equity flows on our chosen structural shocks from Bekaert et al (2021). 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.

Table 3: The impact of a 0.5% fund-driven liquidation on asset returns

	(1) FX Return	(2) MSCI LC	(3) MSCI USD	(4) FX Return	(5) EMBI	(6) LC Bonds
% Δ equity mkt.	10.07***	-31.03***	-38.36***			
	(2.113)	(4.622)	(6.014)			
% Δ bond mkt.				3.787*	-8.006***	-6.759***
				(1.986)	(1.773)	(1.352)
Policy Rate (t-1)	0.0113***	-0.00663*	-0.00502	0.0118***	-0.00827***	-0.00903*
	(0.00374)	(0.00377)	(0.00523)	(0.00352)	(0.00260)	(0.00482)
REER (t-1)	0.00506***	-0.00609	-0.0112***	0.00607***	-0.00232	-0.000417
	(0.00156)	(0.00356)	(0.00356)	(0.00152)	(0.00190)	(0.00214)
Real GDP Growth (t-1)	-0.479	0.434	0.817	-0.415	-0.623	-0.790***
	(0.442)	(0.384)	(0.483)	(0.479)	(0.693)	(0.268)
Emerging Mkt. News	-0.0108	-0.0898***	-0.0786***	-0.0137	0.00585	-0.00470
	(0.0125)	(0.0169)	(0.0158)	(0.0141)	(0.00791)	(0.0134)
Adv. Mkt. Index (t-1)	0.00756**	0.00686	0.00340	0.0129***	-0.0118***	-0.00470*
	(0.00299)	(0.00553)	(0.00540)	(0.00367)	(0.00229)	(0.00260)
Observations	17511	17515	17515	15822	13550	10230

Standard errors in parentheses

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

Table 3 shows the impact of a 0.5% 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. All specifications include country and year fixed effects, with standard errors clustered by country.

Table 4: The effect of risk and risk aversion shocks on the distribution of Brazilian EPFR flows

(a) Risk Aversion

Risk Aversion	**Panel i: Bonds**	Q5	Q50	Q95	**Panel ii: Equity**	Q5	Q50	Q95
β*Normalization								
$\sigma = 1.91$	Flow Quantiles: 2012	-216.05	58.97	466.24	Flow Quantiles: 2012	-74.21	65.58	180.17
	% of AUM/week	-0.04	-0.02	0.00	% of AUM/week	0.03	-0.02	-0.06
	Est. Change	-16.25	-8.17	-0.76	Est. Change	12.48	-6.78	-24.95
	Est. Flow Quantiles	-232.3	50.8	465.5	Est. Flow Quantiles	-61.7	58.8	155.2
β*GFC								
$\sigma = 7.5$	Flow Quantiles: 2006	-30.94	19.24	99.73	Flow Quantiles: 2006	-248.03	44.50	637.82
	% of AUM/week	-0.30	-0.08	-0.01	% of AUM/week	0.07	-0.04	-0.13
	Est. Change	-29.084	-7.990	-0.743	Est. Change	35.37	-19.23	-70.74
	Est. Flow Quantiles	-60.0	11.2	99.0	Est. Flow Quantiles	-212.7	25.3	567.1
β*CovidPeak								
$\sigma = 8.5$	Flow Quantiles: 2019	-48.81	84.15	184.38	Flow Quantiles: 2019	-357.96	-38.15	396.77
	% of AUM/week	-0.34	-0.17	-0.02	% of AUM/week	0.14	-0.07	-0.27
	Est. Change	-146.43	-73.58	-6.84	Est. Change	121.44	-66.03	-242.87
	Est. Flow Quantiles	-195.2	10.6	177.5	Est. Flow Quantiles	-236.5	-104.2	153.9

(b) Risk

Risk	**Panel i: Bonds**	Q5	Q50	Q95	**Panel ii: Equity**	Q5	Q50	Q95
β*Normalization								
$\sigma = 2.56$	Flow Quantiles: 2012	-216.05	58.97	466.24	Flow Quantiles: 2012	-74.21	65.58	180.17
	% of AUM/week	-0.125	-0.116	-0.108	% of AUM/week	-0.279	-0.156	-0.042
	Est. Change	-50.90	-47.45	-44.21	Est. Change	-255.40	-143.17	-38.43
	Est. Flow Quantiles	-266.9	11.5	422.0	Est. Flow Quantiles	-329.6	-77.6	141.7
β*GFC								
$\sigma = 4.04$	Flow Quantiles: 2006	-30.94	19.24	99.73	Flow Quantiles: 2006	-248.03	44.50	637.82
	% of AUM/week	-0.20	-0.10	-0.09	% of AUM/week	-0.44	-0.25	-0.07
	Est. Change	-19.17	-9.55	-8.90	Est. Change	-237.43	-133.09	-35.72
	Est. Flow Quantiles	-50.1	9.7	90.8	Est. Flow Quantiles	-485.5	-88.6	602.1
β*CovidPeak								
$\sigma = 6.7$	Flow Quantiles: 2019	-48.81	84.15	184.38	Flow Quantiles: 2019	-357.96	-38.15	396.77
	% of AUM/week	-0.33	-0.30	-0.28	% of AUM/week	-0.73	-0.41	-0.11
	Est. Change	-141.23	-131.66	-122.67	Est. Change	-668.44	-374.69	-100.57
	Est. Flow Quantiles	-190.0	-47.5	61.7	Est. Flow Quantiles	-1026.4	-412.8	296.2

Table 4 shows the counterfactual quantiles of the post-shock distribution of flows and compare them to the distribution from the year preceding the shock (shown in the first row of each section). In the second row, we take the maximum Risk or RA shock from each of US monetary policy normalization, the GFC, and the initial Covid period and multiply it by our estimated parameter values. The estimated change in the third row is the value in row 2 multiplied a a three-month average of AUM preceding the shock to generate a dollar value for the flow, $\hat{k}^q = k^q + \hat{\beta}^q * shock * H$. Row 4 sums rows 1 and 3 to show a sample conditional distribution prevailing as a result of the risk shock.

Table 5: Benchmark Weights

(a) Benchmark Weights

	MSCI Weight	EPFR Passive Weight	GDP Weight	Market Cap Weight
Taiwan	18.9	17.8	3.5	11.2
South Africa	12.2	9.1	3.2	11.1
Malaysia	4.7	3.3	2.3	5.1
Chile	2.3	1.5	1.8	2.8
Thailand	3.3	4.4	2.7	4.4
Brazil	16.6	18.4	16.1	12.1
Mexico	7.2	7.4	8.4	5.0
India	11.7	13.3	14.1	17.7
Hungary	0.9	0.9	1.1	0.4
Philippines	1.3	1.6	1.8	2.4
Russia	8.7	9.2	12.5	9.0
Peru	0.8	0.8	1.2	0.9
Poland	2.3	1.5	3.8	2.0
Qatar	0.6	0.2	1.0	2.0
Indonesia	3.4	4.0	6.5	4.4
Czech Republic	0.6	0.7	1.6	0.5
Colombia	0.9	0.5	2.4	1.7
Egypt	0.6	0.8	1.8	0.8
Turkey	2.2	3.0	7.1	2.6
United Arab Emirates	0.5	0.4	2.4	2.3
Argentina	0.3	1.1	3.1	0.7
Pakistan	0.1	0.4	1.7	0.7

(b) Actual Allocation Percentage vs. MSCI Weights

	MSCI Weight	Passive Equity Allocations	Active Equity Allocations
MSCI Weight	1		
Passive Equity Allocations	0.9618	1	
Active Equity Allocations	0.9525	0.9869	1

Table 5, Panel (a) shows the correlation between the proportion of each country's assets in the sample total AUM and MSCI EM weights. Panel (b) shows the average weight of each sample country in the MSCI, as well as the the proportion of passive fund AUM, GDP, and market capitalization in the data set attributable to each country.

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

(a) All Funds

	(1) Q5	(2) Q50	(3) OLS	(4) Q95
Risk Aversion	0.182**	-0.0821	-0.0979	-0.346
	(0.0779)	(0.0603)	(0.157)	(0.377)
Risk	-0.0160	0.309***	0.298*	0.410
	(0.0824)	(0.0566)	(0.156)	(0.282)

(b) Institutional Funds

	(1) Q5	(2) Q50	(3) OLS	(4) Q95
Risk Aversion	0.248***	-0.0123	-0.0903	-0.419
	(0.0886)	(0.0665)	(0.177)	(0.345)
Risk	-0.00334	0.332***	0.342*	0.465*
	(0.0913)	(0.0633)	(0.177)	(0.260)

(c) Retail Funds

	(1) Q5	(2) Q50	(3) OLS	(4) Q95
Risk Aversion	-0.0199	-0.0817	-0.122	-0.161
	(0.0520)	(0.0501)	(0.128)	(0.209)
Risk	0.0549	0.105***	0.184*	0.235***
	(0.0561)	(0.0380)	(0.109)	(0.0888)
Observations	656	656	656	656

Standard errors in parentheses

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

Table 6 summarizes the results of OLS and quantile regressions of changes in government money market funds on risk and risk aversion shocks from Bekaert et al (2021). Specifications include year fixed effects, 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 the advanced economy industrial production growth. Standard errors are shown in parentheses. *, **, and *** signify a statistically significant effect at the 10%, 5%, and 1% levels, respectively.

Table 7: The impact of a one standard deviation shock on fund flows: VIX, RORO, and BEX (2021)

(a) Bonds

	Q5	Q25	Q50	Q75	Q95
VIX Index	-0.0449***	-0.0348***	-0.0298***	-0.0251***	-0.0159**
	(0.00264)	(0.00148)	(0.00229)	(0.00343)	(0.00581)

	Q5	Q25	Q50	Q75	Q95
RORO index	-0.155***	-0.127***	-0.112***	-0.0974***	-0.0707***
	(0.00294)	(0.00287)	(0.00354)	(0.00473)	(0.00695)

	Q5	Q25	Q50	Q75	Q95
Risk aversion	-0.0380***	-0.0262***	-0.0203***	-0.0146**	-0.00373
	(0.0105)	(0.00646)	(0.00522)	(0.00502)	(0.00742)
Risk	-0.0437***	-0.0418***	-0.0409***	-0.0400***	-0.0382***
	(0.0128)	(0.00962)	(0.00829)	(0.00728)	(0.00642)

	Q5	Q25	Q50	Q75	Q95
VIX Index	-0.0496***	-0.0507***	-0.0513***	-0.0518***	-0.0529***
	(0.00379)	(0.00267)	(0.00261)	(0.00291)	(0.00412)

(b) Equity

	Q5	Q25	Q50	Q75	Q95
RORO index	-0.123***	-0.119***	-0.117***	-0.115***	-0.112***
	(0.00567)	(0.00352)	(0.00360)	(0.00446)	(0.00708)

	Q5	Q25	Q50	Q75	Q95
Risk aversion	0.0153*	-0.00233	-0.0110***	-0.0194***	-0.0359***
	(0.00730)	(0.00355)	(0.00251)	(0.00301)	(0.00639)
Risk	-0.112***	-0.0794***	-0.0634***	-0.0479***	-0.0173**
	(0.00932)	(0.00478)	(0.00293)	(0.00256)	(0.00608)

Table 7 summarizes the results of quantile regressions of a) bond flows and b) equity flows on the VIX (in log differences), on the RORO index, and on our chosen structural shocks from Bekaert et al (2021). 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 shown in parentheses. *, **, and *** signify a statistically significant effect at the 10%, 5%, and 1% levels, respectively.

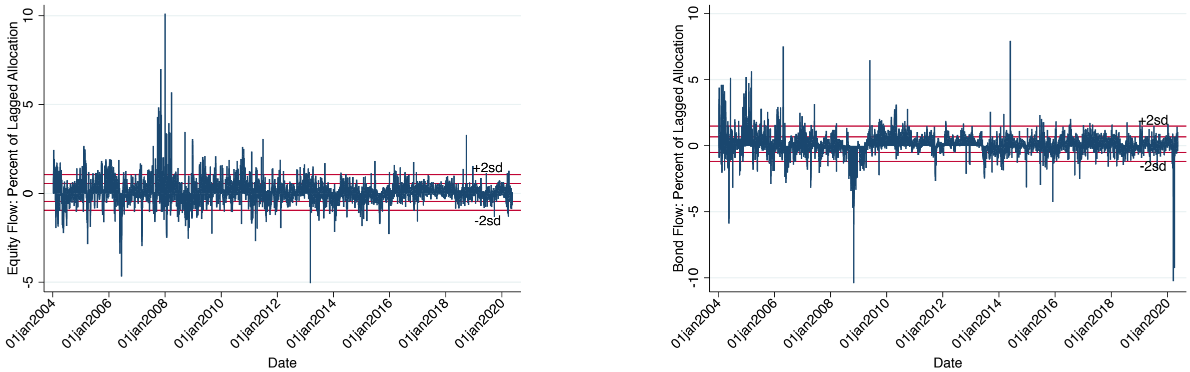
Online Appendix

(Not for publication)

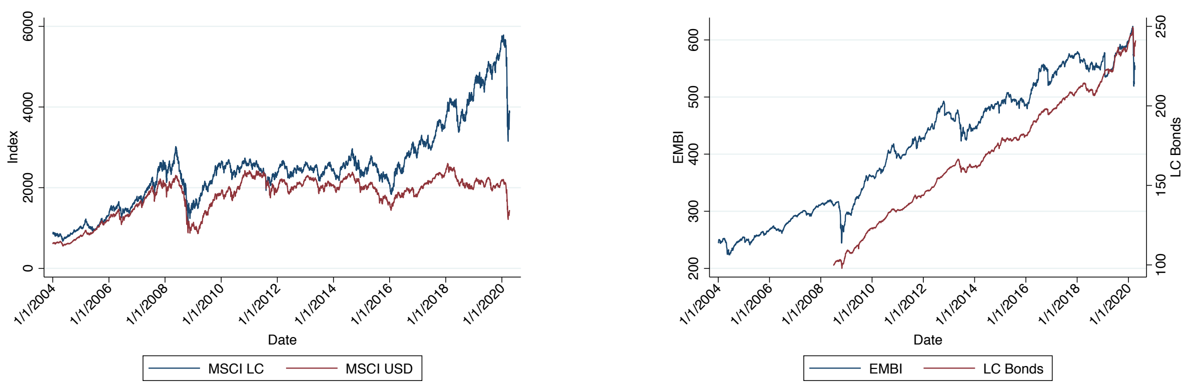
Global Fund Flows and Emerging Market Tail Risk

Online Appendix Figures

Figure 1: Emerging Market Flows and Returns

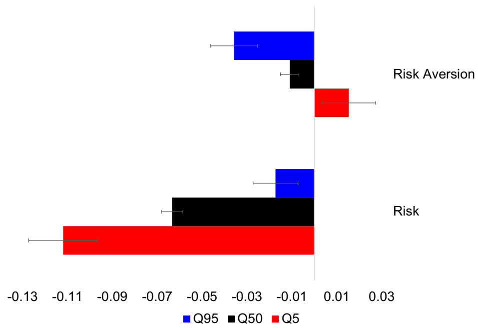


(a) EPFR Country Flows (% of Lagged AUM)

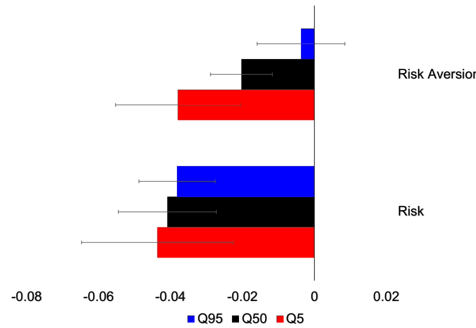


(b) Total Return Indices

Figure 2: The distributional impact of risk and risk aversion shocks on EPFR bond and equity flows (% of AUM)



(a) Equity



(b) Fixed Income

Figure 2 summarizes the impact of a one standard deviation shock to risk and risk aversion on emerging market bond and equity flows, respectively. Risk and risk aversion are the log differences of the estimated series from Bekaert et al (2022) and enter the regressions as a weekly moving average. The bars plot the quantile coefficients for quantiles $q = \{5, 50, 95\}$. Error bands represent 90% bootstrapped confidence intervals clustered by country. 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.

Online Appendix Tables

Table 1: Sample Countries

Argentina	Pakistan
Brazil	Peru
Chile	Philippines
Colombia	Poland
Czech Republic	Qatar
Egypt	Russia
Hungary	South Africa
India	Taiwan*
Indonesia	Thailand**
Malaysia	Turkey
Mexico	United Arab Emirates

* Indicates eventual exclusion from EMBI, returns extended using S&P Bond Index.

Table 2: Control Variables Summary Statistics

	Mean	St. Dev.	Q5	Q50	Q95
BIS Policy Rate (t-1)	6.45	6.93	1.00	5.12	15.25
Adv. Market Return	0.02	0.31	-0.52	0.02	0.49
Avg. RGDP Growth (8Q)	0.04	0.03	-0.00	0.04	0.08
Emerging Mkt. News	-0.01	2.82	-4.10	0.00	4.10
Exchange rate return	0.01	0.69	-0.87	0.00	0.93
REER Growth	0.05	2.12	-3.10	0.13	2.88
Observations	93384				

Table 3: Risk-on/Risk-off Correlations Matrix

	RORO	Risk aversion	Risk	VIX
RORO	1			
Risk aversion	0.6078	1		
Risk	0.5902	0.5679	1	
VIX	0.7013	0.8534	0.6681	1

Table 4a: A one standard deviation risk-off shock & the distribution of bond flows

	Q5	Q25	Q50	Q75	Q95
Risk aversion	-0.0380***	-0.0262***	-0.0203***	-0.0146**	-0.00373
	(0.0105)	(0.00646)	(0.00522)	(0.00502)	(0.00742)
Risk	-0.0437***	-0.0418***	-0.0409***	-0.0400***	-0.0382***
	(0.0128)	(0.00962)	(0.00829)	(0.00728)	(0.00642)
Policy Rate (t-1)	-0.00251	-0.00114	-0.000452	0.000210	0.00147
	(0.0104)	(0.00418)	(0.00164)	(0.00266)	(0.00812)
REER (t-1)	-0.00133	-0.000683	-0.000358	-0.0000441	0.000554
	(0.00175)	(0.000549)	(0.000359)	(0.000838)	(0.00195)
Real GDP Growth (t-1)	0.240	0.168	0.132	0.0978	0.0318
	(0.414)	(0.215)	(0.144)	(0.137)	(0.277)
Emerging Mkt. News	0.00332	-0.0123***	-0.0200***	-0.0276***	-0.0419***
	(0.00348)	(0.00142)	(0.00129)	(0.00221)	(0.00438)
Adv. Mkt. Index (t-1)	-0.00301	-0.00601***	-0.00751***	-0.00896***	-0.0117***
	(0.00157)	(0.000542)	(0.000671)	(0.00116)	(0.00223)
AE IP Growth (t-1)	5.216***	6.033***	6.443***	6.837***	7.589***
	(0.623)	(0.315)	(0.273)	(0.360)	(0.665)
AE Average Shadow Rate (t-1)	0.0692***	-0.0574***	-0.121***	-0.182***	-0.298***
	(0.0126)	(0.00887)	(0.0117)	(0.0156)	(0.0242)
AR(1)	0.643***	0.552***	0.506***	0.463***	0.379***
	(0.0409)	(0.0232)	(0.0182)	(0.0192)	(0.0333)

Table 4a summarizes the results of quantile regressions of EPFR country bond flows on risk and risk aversion shocks. Bootstrapped standard errors are clustered by country. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4b: A one standard deviation risk-off shock & the distribution of equity flows

	Q5	Q25	Q50	Q75	Q95
Risk aversion	0.0153*	-0.00233	-0.0110***	-0.0194***	-0.0359***
	(0.00730)	(0.00355)	(0.00251)	(0.00301)	(0.00639)
Risk	-0.112***	-0.0794***	-0.0634***	-0.0479***	-0.0173**
	(0.00932)	(0.00478)	(0.00293)	(0.00256)	(0.00608)
Policy Rate (t-1)	-0.000378	0.0000926	0.000323	0.000547	0.000987
	(0.00188)	(0.00130)	(0.00128)	(0.00146)	(0.00214)
REER (t-1)	-0.000878	-0.000749*	-0.000686	-0.000624	-0.000504
	(0.000786)	(0.000348)	(0.000376)	(0.000575)	(0.00108)
Real GDP Growth (t-1)	-0.285	-0.0200	0.110	0.236	0.484
	(0.318)	(0.101)	(0.0811)	(0.172)	(0.385)
Emerging Mkt. News	-0.0207***	-0.0208***	-0.0208***	-0.0209***	-0.0209***
	(0.00250)	(0.00146)	(0.00129)	(0.00151)	(0.00251)
Adv. Mkt. Index (t-1)	0.00470***	0.00217**	0.000929	-0.000278	-0.00265
	(0.00106)	(0.000823)	(0.000921)	(0.00112)	(0.00167)
AE IP Growth (t-1)	6.416***	2.881***	1.149*	-0.535	-3.842***
	(0.772)	(0.509)	(0.478)	(0.536)	(0.803)
AE Average Shadow Rate (t-1)	0.100***	-0.0244**	-0.0854***	-0.145***	-0.261***
	(0.0146)	(0.00871)	(0.00912)	(0.0119)	(0.0200)
AR(1)	0.430***	0.417***	0.411***	0.404***	0.392***
	(0.0295)	(0.0199)	(0.0213)	(0.0263)	(0.0407)

Table 4b summarizes the results of quantile regressions of EPFR country equity flows on risk and risk aversion shocks. Bootstrapped standard errors are clustered by country. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: The effect of hypothetical risk and risk aversion shocks on the distribution of Brazilian EPFR flows

	Panel i: Bonds	Q5	Q50	Q95	Panel ii: Equity	Q5	Q50	Q95
Flow Quantiles: 2019		-48.81	84.15	184.38	Flow Quantiles: 2019	-357.96	-38.15	396.77
Risk = 3	% AUM	-0.15	-0.14	-0.13	% AUM	-0.33	-0.18	-0.05
	USD Millions	-63.24	-58.95	-54.93	USD Millions	-291.98	-163.67	-43.93
	Est. Flow Quantiles	-112.05	25.20	129.45	Est. Flow Quantiles	-649.94	-201.82	352.84
Risk aversion = 1	% AUM	-0.04	-0.02	0.00	% AUM	0.02	-0.01	-0.03
	USD Millions	-17.23	-8.66	-0.81	USD Millions	14.29	-7.77	-28.57
	Est. Flow Quantiles	-66.03	75.50	183.57	Est. Flow Quantiles	-343.67	-45.92	368.20
Quantile change: Risk-dominant		-80.47	-67.61	-55.73		-277.69	-171.44	-72.50
Total Est. Flow Quantiles		-129.27	16.54	128.65		-635.65	-209.59	324.27
Risk = 1	% AUM	-0.05	-0.05	-0.04	% AUM	-0.11	-0.06	-0.02
	USD Millions	-21.08	-19.65	-18.31	USD Millions	-97.33	-54.56	-14.64
	Est. Flow Quantiles	-69.89	64.50	166.07	Est. Flow Quantiles	-455.29	-92.70	382.13
Risk aversion = 3	% AUM	-0.12	-0.06	-0.01	% AUM	0.05	-0.03	-0.10
	USD Millions	-51.68	-25.97	-2.42	USD Millions	42.86	-23.30	-85.72
	Est. Flow Quantiles	-100.49	58.18	181.96	Est. Flow Quantiles	-315.10	-61.45	311.06
Quantile change: Risk aversion-dominant		-72.76	-45.62	-20.72		-54.47	-77.86	-100.36
Total Est. Flow Quantiles		-121.57	38.53	163.65		-412.43	-116.01	296.41

Table 5 shows the counterfactual quantiles of the post-shock distribution of flows and compare them to the distribution from 2019 (shown in the first row of the table). In the first row of each subsection, we take a hypothetical Risk or RA shock and multiply it by our estimated parameter values. The estimated change in the second row is the value in row 2 multiplied by Brazilian AUM in 2019 to generate a dollar value for the flow, $\hat{k}^q = k^q + \hat{\beta}^q * \sigma * H$. Row 3 sums rows 1 and 3 to show a sample conditional distribution prevailing as a result of the risk shock. The row labeled "Total" shows the sum of estimated quantile changes conditional on risk and risk aversion shocks.

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

(a) Passive Bonds

	Q5	Q50	Q95	MF Q5	MF Q50	MF Q95	ETF Q5	ETF Q50	ETF Q95
Risk aversion	-0.0265	-0.120***	-0.256**	-0.0140	-0.0230**	-0.0342	0.0124	-0.207***	-0.564***
	(-0.44)	(-5.63)	(-2.80)	(-1.27)	(-3.15)	(-1.87)	(0.18)	(-10.52)	(-4.62)
Risk	-0.240***	-0.0762***	0.163	0.0395**	0.00245	-0.0441	-0.381***	-0.0341	0.532**
	(-3.91)	(-5.17)	(1.55)	(2.86)	(0.17)	(-0.94)	(-5.90)	(-1.55)	(3.19)
Observations	13270	13270	13270	11556	11556	11556	13274	13274	13274

(b) Passive Equity

	Q5	Q50	Q95	MF Q5	MF Q50	MF Q95	ETF Q5	ETF Q50	ETF Q95
Risk aversion	0.0269**	-0.0534***	-0.145***	0.243***	-0.0247***	-0.278***	0.00254	-0.0556***	-0.122***
	(2.66)	(-7.06)	(-8.24)	(6.84)	(-4.48)	(-6.99)	(0.30)	(-6.98)	(-7.08)
Risk	-0.158***	-0.127***	-0.0910***	-0.225***	-0.00798	0.196***	-0.138***	-0.156***	-0.176***
	(-7.52)	(-13.21)	(-4.73)	(-4.90)	(-1.00)	(3.70)	(-6.79)	(-14.95)	(-10.95)
Observations	17459	17459	17459	17493	17493	17493	17493	17493	17493

Table 6 summarizes the results of quantile regressions of a) bond flows and b) equity flows on risk and risk aversion shocks from Bekaert et al (2021). Columns 1 - 3 correspond to passive fund flows (mutual funds and ETFs together). Columns 4 - 6 correspond to the response of passive mutual fund flows, and columns 7 - 9 correspond to the respond of ETF flows. Bootstrapped standard errors are clustered by country. Controls, country fixed effects, and year fixed effects are included in the regressions. t-statistics are shown in parentheses. *, **, and *** signify a statistically significant effect at the 10%, 5%, and 1% levels, respectively.

Table 7: Asymmetric Impacts of Risk Shocks

	Fixed Income			Equity		
	Q5	Q50	Q95	Q5	Q50	Q95
1[RA > Q75]	0.145***	0.081***	0.019	-0.079***	-0.020*	0.036
	(0.034)	(0.014)	(0.032)	(0.030)	(0.011)	(0.025)
1[Risk > Q75]	-0.131***	-0.099***	-0.068**	-0.053	-0.034**	-0.016
	(0.036)	(0.015)	(0.034)	(0.036)	(0.014)	(0.031)
Risk Aversion	0.177***	0.094***	0.015	0.064***	0.041***	0.019
	(0.037)	(0.015)	(0.036)	(0.024)	(0.009)	(0.021)
Risk	0.055**	0.013	-0.028	-0.015	-0.063***	-0.110***
	(0.028)	(0.011)	(0.027)	(0.026)	(0.010)	(0.022)
RA x 1[RA > Q75]	-0.486***	-0.287***	-0.096*	-0.076**	-0.122***	-0.166***
	(0.059)	(0.024)	(0.056)	(0.035)	(0.013)	(0.030)
Risk x 1[Risk > Q75]	-0.046	-0.007	0.031	-0.082*	0.049***	0.174***
	(0.043)	(0.017)	(0.041)	(0.042)	(0.016)	(0.036)
N	17,490	17,490	17,490	17,506	17,506	17,506

Table 7 summarizes the results of quantile regressions of EPFR country equity flows on risk and risk aversion measures, interacting the shocks with an indicator variable equal to one when the shock is above the 75th percentile of its distribution. Bootstrapped standard errors are clustered by country. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: The distributional impact of Risk or Risk aversion shocks on EPFR flows (% of AUM), Ex-Covid period

(a) Bond flows

	Q5	Q25	Q50	Q75	Q95
Risk aversion	-0.0397*	-0.0266**	-0.0201*	-0.0138	-0.00172
	(0.0194)	(0.00965)	(0.00865)	(0.0116)	(0.0215)
Risk	-0.0344*	-0.0368***	-0.0380***	-0.0392***	-0.0415*
	(0.0163)	(0.00814)	(0.00730)	(0.00979)	(0.0181)

(b) Equity flows

	Q5	Q25	Q50	Q75	Q95
Risk aversion	0.0140	-0.00273	-0.0109	-0.0189**	-0.0346**
	(0.0150)	(0.00757)	(0.00564)	(0.00655)	(0.0129)
Risk	-0.109***	-0.0780***	-0.0625***	-0.0475***	-0.0180
	(0.0141)	(0.00711)	(0.00530)	(0.00616)	(0.0122)

Table 8b summarizes the results of quantile regressions of a) bond flows and b) equity flows on our chosen structural shocks from Bekaert et al (2021), controlling for the early covid period with a dummy equal to one after January 20, 2020. The table presents the impact of a one standard deviation shock on bond and equity flows. 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. t-statistics are shown in parentheses. *, **, and *** signify a statistically significant difference in the effect at the 10%, 5%, and 1% levels, respectively.