DISCUSSION PAPER SERIES

DP17697

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INTERNATIONAL MACROECONOMICS AND FINANCE AND ASSET PRICING

ISSN 0265-8003

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Discussion Paper DP17697
Published 25 November 2022
Submitted 11 November 2022

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Abstract

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JEL Classification: F3, F32, G11, G15

Keywords: Non-bank financial intermediation, Tail risk, Mutual funds, Exchange traded funds, Emerging markets

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Acknowledgements
We thank the numerous seminar and conference participants at the IMF's IEO group, IMF's 2020 Annual Research Conference, the 2022 CEPR International Macroeconomics and Finance Programme Meeting, the LSE-FMG conference, the AEA IEFS meeting, Fordham University, Virginia Tech, UCSC, WE-Are ECB CEPR Conference, IADB, MMF, FMA, the Federal Reserve Bank of Kansas City, Fudan University, Wake Forest University, Boston University, CFE, PIIE, NTU SG, Georgetown, Penn State, European Central Bank, Swiss National Bank, Johns Hopkins, University of Washington, UC Davis, and the IMF Capital Flows group for helpful comments and suggestions. Gaston Gelos, Kathy Yuan, and Mahavash Quereshi provided thoughtful discussions.

Global Fund Flows and Emerging Market Tail Risk*

Anusha Chari† Karlye Dilts Stedman‡ Christian Lundblad§

This Version: October 10, 2022

ABSTRACT

Global risk and risk aversion shocks have distinct distributional impacts on emerging market capital flows and returns. In particular, we find salient consequences of these different global shocks for tail risk in emerging markets. Open-end mutual fund trading provides a key mechanism linking shocks facing global investors to extreme capital flow and return 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 and returns.

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1 Introduction

While portfolio flows to emerging markets offer well-documented benefits (Bekaert, Harvey, and Lundblad (2005); Chari and Henry (2004), Chari and Henry (2008); Henry (2007)), a large literature suggests that global shocks can destabilize both capital flows and asset returns.[1] In particular, tail events, such as sudden stops, capital flow surges and capital flight, present significant challenges for investors and policymakers (Forbes and Warnock (2012), Forbes and Warnock (2021)); Rey (2013); Miranda-Agrippino and Rey (2020b)).

Although we observe large swings in capital flows, evidence on the transmission of global shocks into *extreme* realizations in emerging market flows and returns remains limited. Instead, existing practice largely focuses on expected values and variances as sufficient summary statistics, potentially masking more nuanced distributional impacts, including, critically, the most destabilizing realizations located in the tails. In contrast, our paper employs an 'at-risk' framework (Gelos et al. (2019); Eguren-Martin et al. (2020)) to formalize the measurement of tail risk and characterize the full distribution of emerging market capital flows and returns in the face of important global shocks.[2]

This paper makes three contributions to the literature. First, we emphasize the importance of looking at the implications of global shocks on the full distributions, beyond the mean, of emerging market flows and returns linked to mutual fund activity. Second, we recognize that, analytically, the price and quantity of risk are distinct economic concepts, and we treat them as such. In contrast, many commonly employed measures of global risk in the literature ignore this distinction and its impact on international capital flows and returns. Importantly, we find that shocks to global risk (macro uncertainty) are often more important than global risk aversion shocks for extreme downside risk or the left tails of relevant emerging market quantities. Finally, we emphasize the role of open-end funds and exchange-traded funds (ETFs) as important conduits for global shock transmission, and our results suggest that the growth in passive asset management has significant unintended consequences for emerging market flows and returns.

[1]See for example a non-exhaustive list of papers in Section 1 of the online appendix.

[2]The approach is similar to that taken in Adrian et al. (2019), characterizing "GDP-at-Risk" effects that vary across quantiles.

Underscoring the importance of our agenda, the International Monetary Fund warned in October 2022 that non-bank financial intermediaries with illiquid assets pose a risk to the stability of the global financial system. In particular, liquidity mismatches between withdrawals from open-end mutual funds and illiquid assets (such as those in emerging markets) are a 'major potential vulnerability' (IMF (2022)).[3] These pressures can amplify market volatility and capital flows at risk when investors move to sell in unison.

As professionally managed portfolios (mutual funds and ETFs) increasingly represent important conduits for cross-border capital flows to emerging markets, a reasonable question is whether this evolution in emerging market access carries implications for tail risk. For context, assets under management in global funds investing in the emerging markets included in our sample rose from $69 billion to $1.15 trillion between 2004 and 2020.[4] Fund services range from delivering low-cost vehicles for emerging market exposure to potentially delivering positive risk-adjusted returns. Given the open-end structure of most emerging market funds, financial stability concerns arise if liquidations by asset managers in the face of funding pressures amplify the effects of relevant global shocks.[5]

A key mechanism linking global risk to extreme capital flow realizations resides in the liquidity services that open-end mutual fund managers provide to their investors. Unlike banks, open-end mutual funds do not have much by way of a liquidity backstop, so fund managers generally liquidate or increase their investment positions to meet investor redemptions or subscriptions (see Coval and Stafford (2007)).[6] Redemption requests from investors can occur daily, implying that open-end fund liabilities are very liquid. In contrast, underlying emerging market assets range from moderately illiquid (many equity positions) to very

[3]"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

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

[5]Financial Stability Board (2017), "Policy Recommendations to Address Structural Vulnerabilities from Asset Management Activities."

[6]To avoid selling their illiquid assets in the face of significant redemption pressures, funds maintain a cash buffer. While useful for risk management purposes, cash reserves nevertheless drag on performance, and emerging market fund managers face a tradeoff. They balance how much cash to hold to satisfy potential redemption requests that lock in underperformance against the risk of liquidating their illiquid positions in response to funding shocks from their investor base at a significant discount.

illiquid (many bond positions). If the redemption requests are significant enough to swamp fund cash reserves, liquidating emerging market holdings can generate negative price impacts (see Jotikasthira et al. (2012)). While there is, relative to these theoretical open-end fund redemption pressures, an added layer underlying ETFs that may provide a transmission buffer, ETFs can still be associated with important pass-through effects as well (see, for example, Ben-David et al. (2018) and Da and Shive (2018)).

In particular, index-benchmarked passive fund investments (mutual funds or ETFs), with little managerial discretion, provide a conduit through which global shocks could manifest with consequential price effects, spillovers, and elevated correlations.[7] Sizable investor reactions to consequential global shocks force, to some degree, liquidity-motivated selling by professional fund managers in otherwise illiquid markets. Significant price dislocations potentially follow to the extent that these pressures are correlated across multiple funds. At the extreme, spillover or contagion effects can occur if lower prices, in turn, force other emerging market funds to sell. Given our focus on emerging market tail risk, we ask whether the pressures that mutual funds face exacerbate global shock impacts.

In this paper, we consider global shocks salient for emerging market fund investors, i.e., those tied to the variation in both global risk and risk aversion. 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, Stedman, and Lundblad (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 co-movement tied to its variation.

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

[7] Feedback loops can generate price-liquidity spirals if the investor base responds by increasing redemption requests, leading to further liquidity-motivated sales, generating further price effects, and so on. Poor returns may induce investor redemptions in funds with similar holdings, given the well-known fund flow-performance relation of Sirri and Tufano (1998).

this perceived effect emanates from risk aversion or physical risk. To circumvent this limitation, we instead use the structural model of Bekaert et al. (2022) that explicitly separates the quantity from the price of risk.[8][9]

With distinct risk and risk aversion shocks in hand, we then characterize their *separate* distributional implications for capital flows and returns using the panel quantile regression approach of Machado and Santos Silva (2019). To do so, we obtain a multilateral, high-frequency proxy of capital flows into and out of emerging markets using the country flows dataset 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) separately. Further, these funds primarily represent investors (clients) domiciled in the U.S. and Europe, whereas the equity and fixed income investments are located in the relevant emerging markets. We also collect data on equity and fixed income emerging market returns to analyze price impacts. We use country-level USD and local currency equity return indices from MSCI. Our fixed income returns come from Bloomberg local currency bond indices and the USD Emerging Market Bond Indices from JP Morgan (these primarily represent sovereign bonds).

Our approach confers several sources of plausible exogeneity that facilitate identification. In our setting, (i) the shocks are global, originating in developed markets such as the U.S. or Europe, (ii) the investors are domiciled in advanced economies, and (iii) benchmark investing via both active and passive open-end funds and ETFs closely track the weights in benchmark indices such as the MSCI emerging markets index for equities or JP Morgan's EMBI index for bonds.

Our main findings are as follows. Shocks to both the quantity and price of risk have important but distinct implications for the median emerging market flow and return and the tails of the distributions. We show 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. In particular, we find that the effects associated with the worst realizations, the fifth quantile or extreme downside risk, are often more heav-

[8] Thanks to Nancy Xu for posting these daily series. `https://www.nancyxu.net/risk-aversion-index`

[9] Given 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 demonstrate the robustness of our main findings using two alternative statistical measures of global risk appetite (including the VIX).

ily affected by shocks to the quantity of risk than are the median realizations.

Across asset classes, while adverse shocks engender negative median flow responses for both bonds and equities, we uncover important variation in the measured shock responses in the tails of the distribution. For bond fund flows, adverse global shocks (both risk and risk aversion) increase the probability of the worst portfolio outflow realizations more than they decrease median flows. The result is a significant lengthening of the tails of the portfolio flow distribution in the direction of extreme downside risk. It is further striking that the left tail implications (capital flight) are more pronounced in response to adverse shocks to physical risk or macro uncertainty.

However, we uncover very different distributional responses to global risk and risk aversion shocks for equities. Interestingly, risk aversion shocks elicit a slowdown of both capital inflows and outflows (i.e., a tails-in reaction). While the equity flow distribution shifts leftward in the face of an adverse global risk aversion shock, it also significantly narrows. In sharp contrast, a negative shock to global risk elicits large tails-out responses, considerably elevating the probability of more extreme equity outflow responses (capital flight).[10] To illustrate the implications of different tail reactions to risk aversion and risk shocks, we complement our regression results with a quantitative example. Through the lens of a representative emerging market, we provide the U.S. dollar flow reactions to various high-risk episodes.[11]

In documenting these heterogeneous responses, the advantage of employing a structural model to separate risk shocks from risk aversion shocks becomes clear. The reactions that we observe, while relatively uniform from a directional standpoint (i.e., median flows respond negatively to both types of shocks), show that the tail responses are markedly different. 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. Empirical measures that conflate risk and risk aversion, like the VIX, mask this observation.[12]

[10] 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. In most cases, we show that the worst outflow realizations deteriorate for longer than the median or the highest inflow realizations.

[11] We conduct a quantitative exercise that highlights the economic significance of our approach using the case of Brazil, a significant emerging market. Similar exercises can be done for the full sample, on a country-by-country basis, for different crisis episodes and so on.

[12] We also test the degree to which shocks to global risk or risk aversion elicit flight-to-safety responses by examining the growth rate of assets held in U.S. money market mutual funds. In a manner that complements what we observe for risky emerging market assets, we detect the opposite flow responses to safe assets. However, these

With the baseline results in hand, we turn to the role of managerial discretion in driving 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. Does the sizable role of passive funds matter for the distributional questions at the center of the paper? While low-cost passive investing facilitates emerging market access, an unexpected consequence is that passive fund investors appear far more responsive to global risk shocks across both equities and bonds. 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. We find that passive fund flows react much more (in some cases as much as an order of magnitude) than active fund flows to global shocks. Specifically, passive fixed-income and equity funds show much larger net outflow responses to risk aversion and physical risk shocks across their distributions.

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 to ETFs.

Last, we also examine the distributional implications for emerging market returns. Global risk shocks negatively affect the worst return realizations more than they affect the median return realization, however, this is considerably less true for risk aversion shocks. We find significant differences across asset classes in conjunction with currency denominations for different risk measures. Equity returns are more sensitive to global risk shocks than bond returns. Within asset classes, U.S. dollar indices are more sensitive than local currency indices, suggesting a vital role for currency effects. Further, we also document flows into Treasury money market funds in response to global risk shocks, consistent with a flight to safety. We conclude that the focus in the literature on measures of central tendency is incomplete and that a separation of global risk and risk aversion is required to fully appreciate these nuanced effects.

effects are strongest in the face of risk shocks (as opposed to risk aversion) and for institutional money market funds.

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 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. We turn next to a brief review of the related literature and theoretical background to motivate our empirical analysis.

2 Related Literature and Brief Theoretical Background

Related Literature: Our findings align with the previous literature on mutual fund outflows in times of financial stress. Several studies highlight financial fragility implications of mutual fund outflows, mainly if funds hold illiquid assets while guaranteeing high levels of liquidity to their investor base (Chen, Goldstein, and Jiang (2010), Goldstein, Jiang, and Ng (2017)). Pointing to the illiquidity of fund assets and the vulnerability to fire sales as sources of financial fragility, Falato, Goldstein, and Hortaçsu (2021) document significant outflows from corporate bond funds during the COVID-19 crisis. The pandemic tail shock also triggered a wave of portfolio rebalancing by global mutual funds (Affinito and Santioni (2021)). Evidence suggests that the open-end organizational structure can make asset fire sales and price volatility more likely (see Stein (2009), Manconi, Massa, and Yasuda (2012), Financial Stability Board (2017)), suggesting an intrinsic fragility of mutual fund investments. Mutual fund funding structures, trading strategies, and managerial compensation incentives provide potential mechanisms through which investors' horizons can impact trading and prices during periods of market turmoil (Cella, Ellul, and Giannetti (2013)). We suggest that the volume of liquidity-motivated trading by emerging-market funds arising in response to variation in global investor risk appetite can drive tail risk in emerging market capital flows (like surges or retrenchments) along with attendant asset price dislocations.

The increase in benchmark-driven investors may explain the increased sensitivity of open-end mutual fund flows to global financial conditions (Financial Stability Board (2022)).

Evidence suggests that 70% of country allocations of mutual funds benchmark to indices (Raddatz et al. (2017)) and that fund investors consider emerging market bonds as a single, risky asset class that is more sensitive to global shocks and less sensitive to country factors (Arslanalp and Tsuda (2015)). A recent report finds that the share of active investing in emerging markets has steadily declined over the last decade. Further, given that active fund holdings closely align with asset weights in the benchmark indices, tracking errors that comprise the difference between fund performance and that of the benchmark index have declined significantly (Financial Stability Board (2022)).

The growth of exchange-traded funds (ETFs) further amplifies the sensitivity of international capital flows to the global financial cycle (Converse, Yeyati, and Williams (2020)).[13] Benchmark-driven bond flows are three to five times more sensitive to changes in global risk aversion than the balance of payments measures of portfolio flows (Arslanalp et al. (2020)). In comparison to banks and other financial intermediaries, investment funds tend to reduce their exposure to emerging markets more during periods of financial upheaval, such as the pandemic (Moro and Schiavone (2022)).

Brief Theoretical Background: This subsection briefly outlines an application of the standard rational expectations model of asset trading to emerging market fund flows and returns. The objective is to motivate the empirical analysis and outline the assumptions necessary to connect relevant global shocks with open-end mutual fund subscriptions and redemptions that manifest as emerging market fund flows with attendant asset price impacts.

Consider an open-end emerging market fund manager who initially holds some desired target portfolio. Like Edelen (1999), suppose that the manager experiences an order flow shock (a random number of redemptions and new subscriptions) from her investor base and, assuming she is an active manager, receives signals about the value of emerging-market assets.[14] Suppose also that the order flow shocks are related to the variation in global investor risk aversion. Following the shock, there is a single round of trade that reveals the asset pay-

[13] Previous emerging market crisis-focused literature finds greater investor-induced return co-movement during high volatility periods and suggests that crises spread through the asset holdings of international investors (Kodres and Pritsker (2002); Boyer et al. (2006); Jotikasthira et al. (2012)).

[14] An passive fund manager simply delivers a low-cost vehicle to her clients to facilitate emerging market exposures. Nevertheless, she also provides a liquidity service to her clients via an open-end fund invested in illiquid emerging markets.

offs. This simplified setting captures the essence of the informed performance and liquidity services that open-end fund managers provide while consistent with standard rational expectations models of trade, such as Grossman and Stiglitz (1980).

The order flow shock (redemption or subscription) that the fund experiences moves it away from the target portfolio. Getting back to the desired portfolio allocation requires trading in some or all assets. Further, the larger the flow shock, the greater the motivation to trade to avoid fluctuations in the fund's cash position (Edelen (1999)). A significant cash position acts as a drag on performance, especially if fund manager compensation depends on their ability to track a benchmark portfolio (e.g., Chevalier and Ellison (1997), a feature that is particularly salient for passive funds that are designed to deliver the benchmark index. Fund managers counteract significant investor redemptions or subscriptions by engaging in liquidity-motivated trades with attendant consequences for relatively illiquid emerging markets. This liquidity component of fund managers' trading plays the role of the exogenous supply / noise trading in standard rational expectations trade models (Edelen (1999)). Further, conformity in fund portfolios benchmarked to an index, a potential issue for many actively managed funds and a locked-in reality for passively managed funds with little to no discretion, suggests that these funds are likely to unwind their emerging market positions simultaneously in the face of global risk shocks.

As mentioned in the introduction, passive investment vehicles now play a substantial role in emerging market investing. While traditional open-end index funds face the theoretical redemption pressures outlined above, passive ownership in the emerging market space is increasingly tied to ETFs, for which the theoretical pressures differ in important ways. Specifically, there is an added layer (an arbitrage process) underlying ETFs that may provide a transmission buffer against shock spillovers relative to the inflexibility of open-end index funds.

Unlike open-end funds where investors enter into direct transactions with the fund at the fund's asset value, ETFs are instead traded on exchanges, allowing investors to buy or sell shares at any time at a market-determined price (which may deviate from the underlying asset value). If the market price of the ETF differs from the value of the underlying portfolio, there is an arbitrage opportunity for the fund's authorized participants (large financial institutions that may create or redeem fund shares). For example, if the ETF shares are more expensive than the underlying portfolio, authorized participants can buy the underlying assets, exchange them for fund shares, and sell those shares at a profit. The opposite is, of course, also true. Taken together, to the extent that heavy buying or selling of the ETF affects its market price, the resulting authorized participant activity will eventually engender a transnational pass through to the underlying assets. While this is clearly similar to the open–end redemption pressures outlined above, some "slippage" (tracking error) between the ETF price and the value of the underlying shares does create the potential to buffer shocks, particularly in extreme times. Having said that, Ben-David et al. (2018) show that ETF ownership is associated with elevated volatility in the ETFs' underlying assets. Further, Da and Shive (2018) document significant pass-through effects associated with ETF trading and return correlations. Hence, the importance of the more nuanced ETF machinery in an emerging market setting is largely an empirical question. To examine this further, we consider ETFs as part of aggregate emerging market fund activity and, in Section 4.1, in isolation.

3 The Data

3.1 Separating Global Risk and Risk Aversion

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 et al., 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 2 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).[15] 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 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).[16] 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.[17]

Figure 3 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

[15]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.

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

[17]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)).

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 Capital Flows and Returns

To obtain a multilateral, high frequency proxy of capital flows into and out of emerging markets, 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.

Figure 4 plots the distribution of the EPFR flows summed across the sample countries on a weekly basis, which we produce using the algorithm of Azzalini (2019). As in Adrian et al. (2019), we use the empirical quantiles of the data in each week to fit a skewed-t distribution (proposed by Azzalini and Capitanio (2003)). Visualizing the data in this way underscores the importance of our approach—while the mean clearly shifts from week to week, so does the *shape* of the distribution. The colors in the figure correspond to the financial distress measure of Romer and Romer (2017), which allows us to see that the weekly distribution looks more normal during tranquil times, pictured in blue/violet.

To measure returns on emerging market portfolio assets, we collect daily total returns from a number of well-known indices. Individual country returns on USD and local currency bonds come from J.P. Morgan's Emerging Market Bond Index (EMBI) and the Bloomberg Barclay's Local Bond Index, while we measure country-level equity returns using the Morgan

Stanley Capital International (MSCI) local currency and USD indices. Table 1 displays summary statistics for return and flow measures.

Reflecting the availability of EPFR data, the sample runs from January 7, 2004 to Apr. 15, 2020.[18] 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.[19] 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.[20]

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, shortciteACalvo1993; Fratzscher (2012); Fratzscher et al. (2016); Passari and Rey (2015); Milesi-Ferretti and Tille (2011); Forbes and Warnock (2012)), the capital flow and return regressions include a measure of advanced market returns (obtained from Kenneth French's website), the monetary policy stance of advanced economies as measured by the shadow rate, and the advanced economy industrial production growth.[21] 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

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

[19]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

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

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

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.[22]

With the exception of emerging market news surprises, all control variables enter with a lag to rule out simultaneity.[23] 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

We regress weekly EPFR country-level flows and daily returns 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 effects and control for previously described "push" and "pull" factors. Country-level flows enter as a percent of the previous week's allocation. Daily percentage changes express total returns. As stated in the data description, in the EPFR flow regressions, changes in the risk measures are aggregated by a moving average.

$$R_{it}^{(q)} = \alpha_i^{(q)} + \delta_t^{(q)} + \beta_1^{(q)} Risk_t + \beta_2^{(q)} RA_t + \gamma_1^{(q)} PUSH_t^R + \gamma_2^{(q)} PULL_{it}^R + \epsilon_{i,t} \quad (1)$$

$$k_{it}^{(q)} = \alpha_i^{(q)} + \delta_t^{(q)} + \rho k_{it-1}^{(q)} + \beta_1^{(q)} Risk_t + \beta_2^{(q)} RA_t + \gamma_1^{(q)} PUSH_t^k + \gamma_2^{(q)} PULL_{it}^k + \epsilon_{i,t} \quad (2)$$

where $k_{it}^{(q)} = \left(\frac{K_{it}}{H_{it-1}} * 100\right)$. R_{it} is the EMBI, LC Bond index, MSCI LC or MSCI USD daily total return. $Risk_t$ and RA_t are the risk and risk aversion shocks from Bekaert et al. (2021), 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

[22] 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.

[23] 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.

account for serially correlated error terms.[24][25]

In general, global risk and risk aversion shocks have important implications not only for the median emerging market flow and return but also for 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, ($|\beta^{(.05)}| > |\beta^{(.5)}| > |\beta^{(.95)}|$). We refer to the lengthening of the tails as a "tails out" response which signifies capital flight or retrenchments captured by the left tail and capital inflow slowdowns on the right tail. These patterns come with subtle caveats, highlighting the importance of separating risk from risk aversion and the implications for tail responses.

Figure 5 summarizes the changes in the capital flow distributions when we employ a structural approach. Specifically, the approach reveals an interesting pattern underlying the heterogeneous reactions of the equity and fixed income distributions. Within the structural decomposition, we find that risk and risk aversion shocks shift the distribution to the left and lengthen the tails relative to the median (left panels, Figure 5). Interestingly, variation in the quantity of risk or macro uncertainty has a larger impact across the distribution and adds more weight to the left tail compared to risk aversion itself; this is the case across asset classes and is consistent with a negative shock triggering retrenchment or flight. Where bonds and equity flow (and also return) distributional changes differ is in the dispersive impact of risk aversion shocks. This distinction offers a window into the workings of common measures such as the VIX and enables us to consider risk measurement and co-movement more generally.

In the face of a physical risk shock, the equity flow distribution reacts in step with the distribution of bond flows in that we observe a leftward shift towards net outflows, with tails lengthening relative to the median. In contrast, the equity flow distribution becomes compressed in the face of a risk aversion shock, with the range of the distribution shrinking as it shifts left. The pattern implies that capital outflows (the left tail response) slow down, and

[24] We draw bootstrapped standard errors from 5,000 replications.

[25] We 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.

inflows also slow down (the right tail response). The net result is a compressed equity flow distribution conditioning on a risk aversion shock. Positive coefficients in the left tail indicate that realizations below the 25th percentile are relative to the median and in absolute terms. To reiterate, a positive parameter value in the lower quantiles does not imply an inflow but rather that gross outflows have slowed. This "tails-in" reaction suggests that risk aversion shocks drive net equity outflows primarily by setting off a sudden stop rather than capital flight.

The right panels of Figure 5 plot the quantile regression coefficients for both bonds and equities. The distance from zero captures the magnitude of the negative impact of a risk-off shock for bond and equity flows. The slope of the quantile coefficient curve captures the dispersive effect of the shock. The steep, positively inclined risk aversion coefficient curve for bonds is consistent with elongating tails, capital flight, and an inflow slowdown.

However, the distance of the quantile coefficient curve for uncertainty shocks suggests that the magnitude of the impact of physical risk shocks is, on balance, greater. The flatter, downward sloping quantile risk aversion coefficient curve for equities signals that capital outflows decline by less than the median, but capital inflows slow down significantly more. For equities, the coefficient curve for uncertainty shocks is positive and steep, counterbalancing the impact of the risk aversion shock on the left tail. 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 both equities and bonds. Focusing on the distributional consequences illustrates the differential responses of outflows and inflows captured by the tails, as well as highlights differential responses across important asset classes.[26]

Figure 7 visualizes the changes to the fund flow distribution brought on by shocks to risk and risk aversion, fitting a skewed-t distribution as in Adrian et al. (2019) and others. Starting with fixed income in panel (a), the baseline results suggest two key patterns. First, risk shocks shift the distribution in its entirety, with some additional impact on the left tail, while risk aversion leaves the right tail of the distribution anchored and widens the distribution by exac-

[26]Full results that include the parameter values and standard errors for controls can be found in the online appendix.

erbating the worst outflow realizations. 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 impact of physical risk-off shocks. In this instance, some mass is removed from the right tail (indicating a decrease in total inflow realizations) while a larger mass is added to the left tail (indicating 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, reflecting the "tails-out" features summarized in Figure 5. The black dotted line contemplates the combined impact of the two shocks, which shifts the distribution to the left and removes mass from the right tail of the distribution while placing more mass in the left tail. Overall, the combined effect shows net outflows resulting in part from diminished gross inflows, but in larger part from exacerbated gross outflows, consistent with flight or retrenchment. Visualizing the results in this way helps to contextualize the "tails-out" label—although the tails move out relative to the median, both tails change 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 which pulls out the tails relative to the median and a smaller role for risk aversion which brings the tails closer to the median. 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 lay in large part 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. 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 still clearly represents a severe gross outflow. In contrast, a risk shock takes some mass out of the right tail, while adding substantial mass to the left tail. The net effect is shown with a dotted line, where we see some mass taken out of the right tail, but more mass added to the left tail, reflecting the stronger reaction of the flow density to physical risk shocks.

4.1 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 3 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 tails-in, tails-out distinction. To see this, consider the impact of the Covid-19 risk aversion peak on bonds versus equity fund flows. The bottom row of Table 3, 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 tails-out 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 tails-out 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. Table 4 repeats the exercise in Table 3, 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.[27]

4.2 Passive versus Active Flows

Figure 1 presents the 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 funds from those attributed to passive funds.

Figure 6 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

[27] 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.

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.

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 6). In fixed income, where active management remains more common, this strong tails-in response to adverse risk aversion shocks that we see in Figure 6 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.

4.3 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 Table 6, we present the full decomposition of the effect of global risk and risk aversion shocks on emerging market country flows associated with all passive funds (Columns 1-3, consistent with the left half of Figure 6 discussed above), open-end index funds (columns 4-6), and ETFs (columns 7-9). Panel A shows this disaggregation for fixed income flows, and panel B shows the same for equity 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.[28]

[28] 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.

4.4 Persistence of risk shocks

Thus far, we have provided evidence on the impact of risk and risk aversion in the week immediately following a shock. Given that capital reallocations may not react immediately to shocks, they likely display a lagged response. To shed light on the dynamic reaction of fund flows to the risk and risk aversion shocks, we repeat our baseline exercise as a series of local projections:

$$k_{it+h}^{(q)} = \alpha_i^{(q)} + \delta_t^{(q)} + \rho k_{it-1}^{(q)} + \beta_{1,h}^{(q)} Risk_t + \beta_{2,h}^{(q)} RA_t + \gamma_1^{(q)} PUSH_t^k + \gamma_2^{(q)} PULL_{it}^k + \epsilon_{i,t} \quad (3)$$

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 $\hat{\beta}_j = \{\hat{\beta}_{j,0} \ldots \hat{\beta}_{j,H}\}$.[29]

Figure 8 displays the results. Some common patterns stand out. In each case, the impact of the shock dissipates between weeks 10 and 12, and the effect peaks between 2 to 10 weeks after the impact, indicating that these high-frequency shocks can have long-lasting effects. In terms of the distribution, in most cases, the worst outflow realizations deteriorate for longer than the median or the highest inflow realizations. That is, over 12 weeks, the 5^{th} quantile falls more (and for longer) than the 95^{th}. Across asset classes, risk aversion worsens the tail of the distribution for longer than the median or the right tail, ultimately resulting in a larger cumulative impact. The worsening left tail response is also the case for uncertainty's impact 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's response, the reactions in each case are tails-out on a cumulative basis.

4.5 Returns

The patterns we observe in the reaction of the equity flow distribution to the risk decomposition extend to both bond and equity returns regardless of currency. Both components de-

[29] In particular, we first apply a 3-spline moving median smoother with repetition to convergence, followed by a Hanning linear binomial smoother.

crease returns across the distribution, but physical risk pulls the tails out relative to the median, while risk aversion compresses the distribution. Overall, we find that equity returns react more than fixed income returns, and dollar-denominated returns react more than local currency.

Notably, physical risk does not appear to uniformly shift the fixed income return distribution as it does the equity return distribution. In the face of a physical risk shock, the highest return realizations increase relative to the median and in absolute terms. At the same time, the worst return realizations worsen. On net, the movement in the tails would be consistent with mean returns unaffected by physical risk shocks, again underscoring the importance of modeling the entire distribution.

Figure 9b summarizes the impact of a one standard deviation global shock on the distribution of fixed income and equity returns. Across all return types, a global risk shock shifts the distribution to the left and lengthens the tails, worsening the most negative return realizations more than the median. However, the magnitude and dispersion of the impact differ between fixed income and equity and between the local currency and US$-denominated indices.

In particular, a global risk shock impacts the total return on the equity indices at a rate more than five times the impact on fixed income returns. Within each asset class, dollar returns react more than local currency returns. Fixed income bears this relationship out strikingly, decreasing three to six times the rate of the local currency index in the face of the global risk shock.[30] MSCI USD total returns decrease 28 - 32% more than the local currency equity returns in the face of risk shocks. Given the nature of equity issuance, we attribute this difference to currency effects.

4.6 Flight to Safety

A question that naturally arises when examining the relationship between risk appetite and the allocation to or pricing of risky assets relates to the complementary implication for so-called ”safe” assets. A safe asset is a simple debt instrument expected to preserve its value

[30] While the impact on the local currency index is statistically insignificant, the comparison is still a useful one given that US$-denominated bonds do react in a statistically significant manner.

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 G. B. Gorton (2016) and Caballero et al. (2017b) as examples, among many, 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 monetary stance as measured by the shadow rate as controls in this exercise. We also retain year-fixed effects, and we run the following regression:

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

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 8 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 8 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.[31]. 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

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

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 9 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 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 9, 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 9, 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 counter-balancing 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.[32] 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 uncer-

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

tainty 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:

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

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 6, we report here that we do indeed observe a bigger flow impact associated with large risk-off shocks as 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 and local asset returns. We document that global shocks to the price and quantity of risk have important distributional implications for emerging market portfolio flows and returns. In particular, we find that the worst realizations are often disproportionately affected by risk or macro-uncertainty shocks. Specifically, while some differences exist in the impact across bond versus equity markets and flows versus asset returns, the effects associated with the left tail are generally larger than that on the median realization. Fund flows thus exhibit flight or retrenchment in response to global macro uncertainty or physical risk shocks, but the reaction to risk aversion manifests as a sudden stop.

When mapping from global shocks to investment management funding pressures to emerging market capital flows and asset returns, 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, may face different redemption pressures and benchmarking mandates. In contrast, actively managed funds may possess greater flexibility and discretion when facing relevant pressures. In particular, the amplification effects of higher conformity in global fund investments via passive fund benchmarking can drive herd behavior and elevated correlations in response to global shocks. We expect trading by (passive) emerging market funds to have amplification effects, manifesting as tail risk in emerging market capital flows and returns distributions.

Surprisingly, we see that the actual portfolio allocations and benchmark MSCI weight correlations are very similar for both active and passive funds. However, we find that passive fund flows are significantly more responsive to risk aversion and uncertainty shocks than active fund flows. Further, the passive and active flows show distinctive distributional and granular patterns. For example, for both fixed income and equity markets, passive risk aversion shocks appear to drive a sudden stop response in capital flows. In contrast, the physical quantity of risk drives a capital flight response. Results separating ETFs from active and passive mutual funds also suggest that the ETFs appear to play a critical role in driving the baseline results.

Our results imply that significant fractions of emerging market capital flows associated with mutual funds are linked to passive funds with little to no discretion. Tail risk in emerging markets appears heavily influenced by passive investor mechanical rebalancing in response to global risk shocks. 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 fund flows as a proportion of assets under management

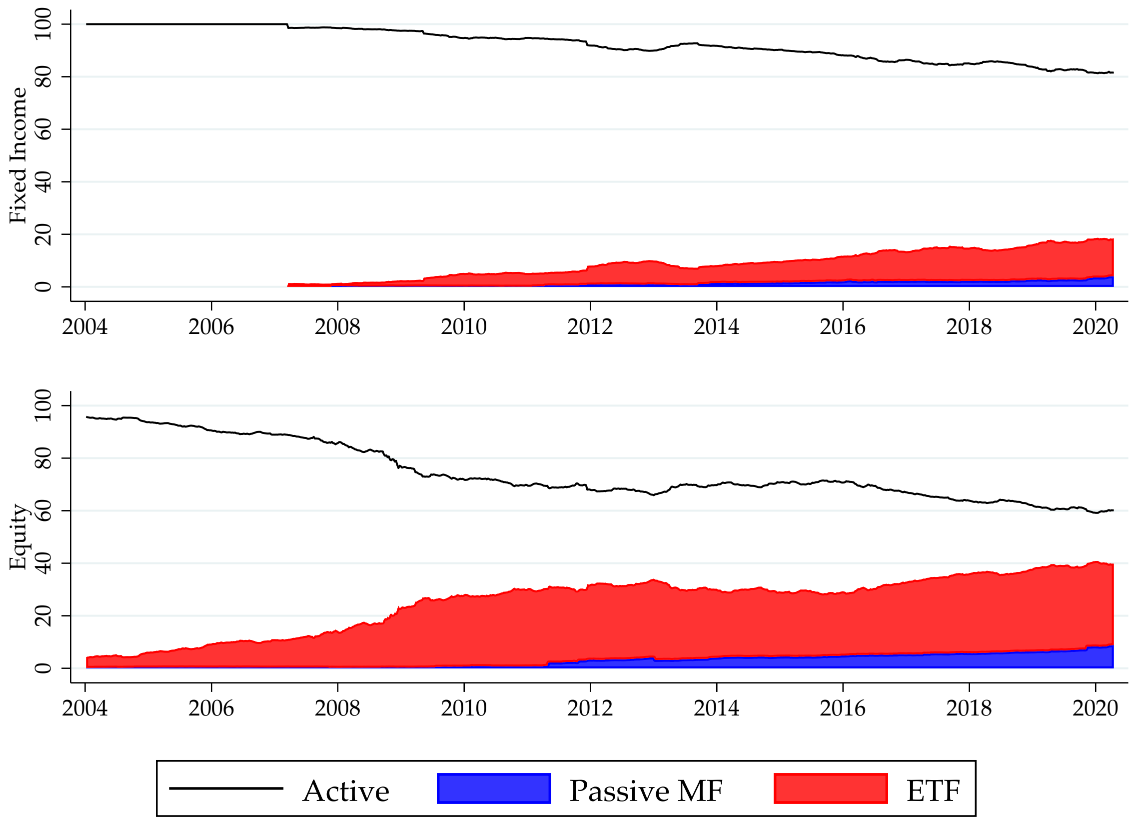


Figure 1 shows the proportion of equity and fixed income assets under management attributable to passive fund flows (decomposed into ETFs and passive mutual funds) and active fund flows.

Figure 2: VIX Decomposition

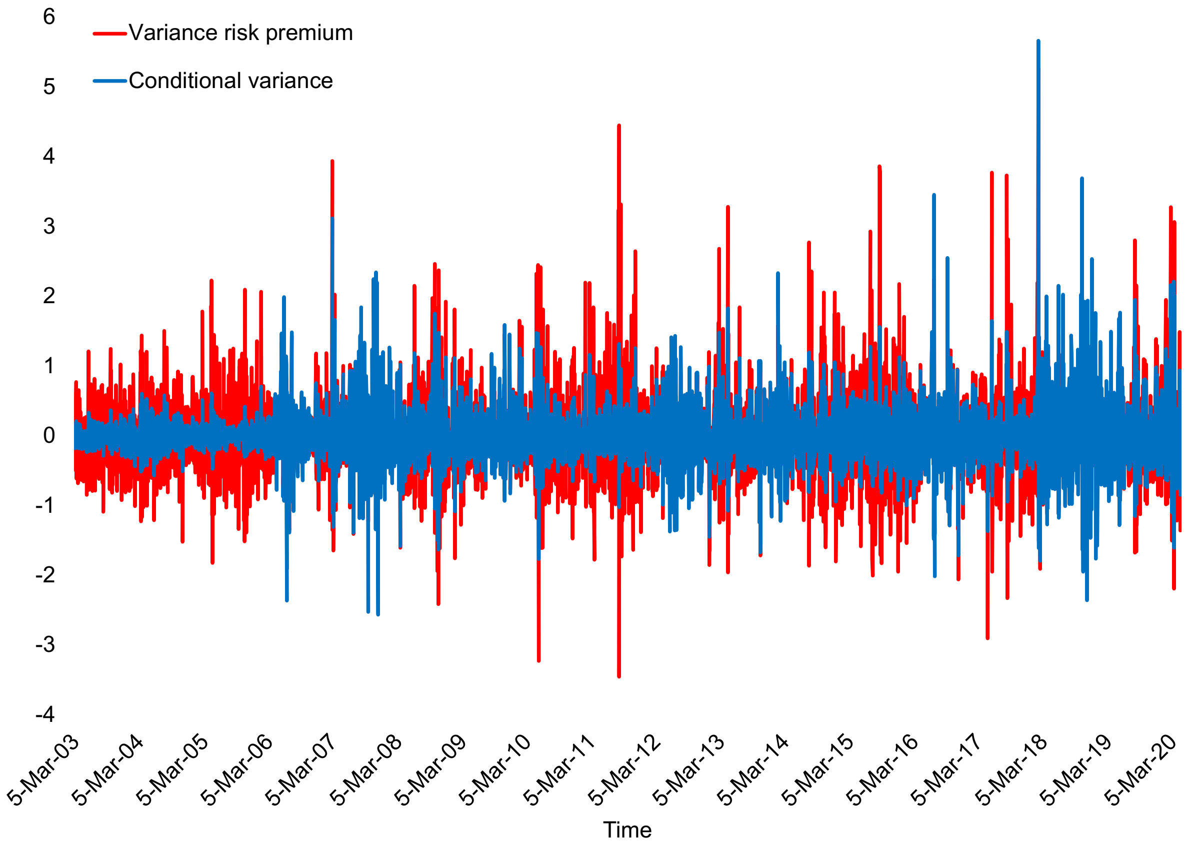
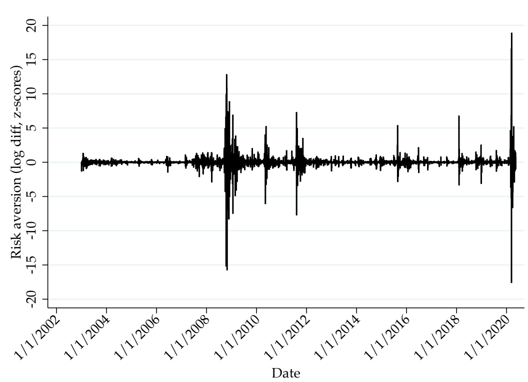
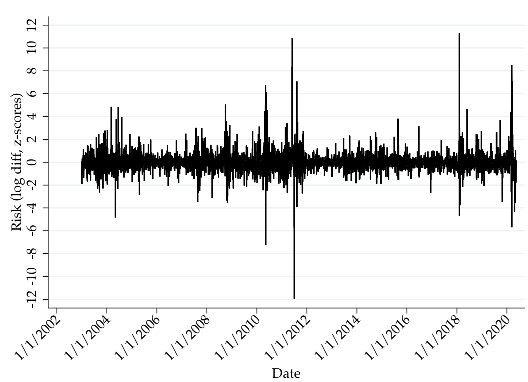


Figure 2 provides a decomposition of the daily log changes in the VIX index into daily log changes in physical volatility (following Bekaert and Hoerova (2014)) and in the variance risk premium (reflecting variation in risk prices).

Figure 3: Risk and Risk Aversion Shocks

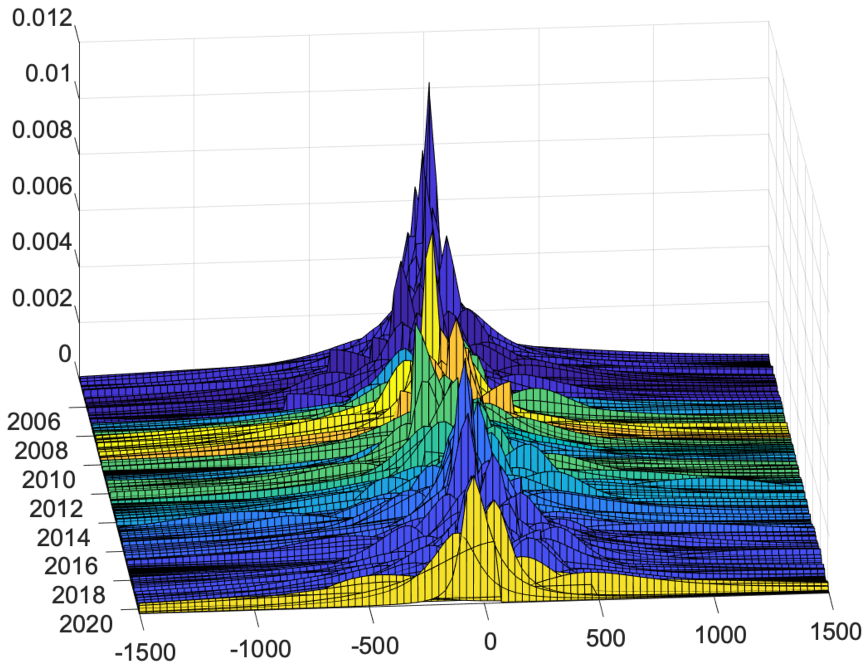


(a) Time Series (log difference): Risk Aversion

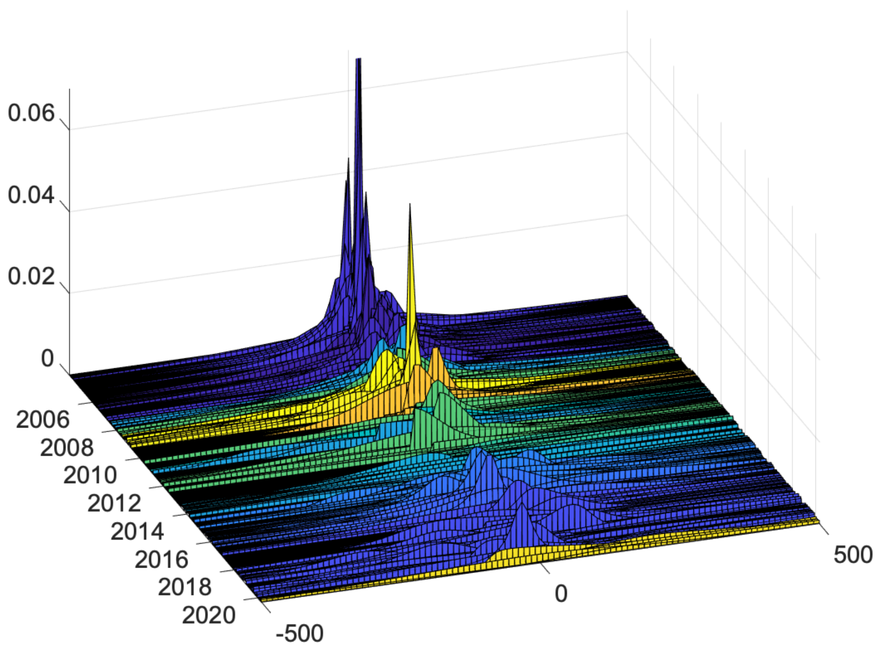


(b) Time Series (log difference): Risk

Figure 4: Distributions

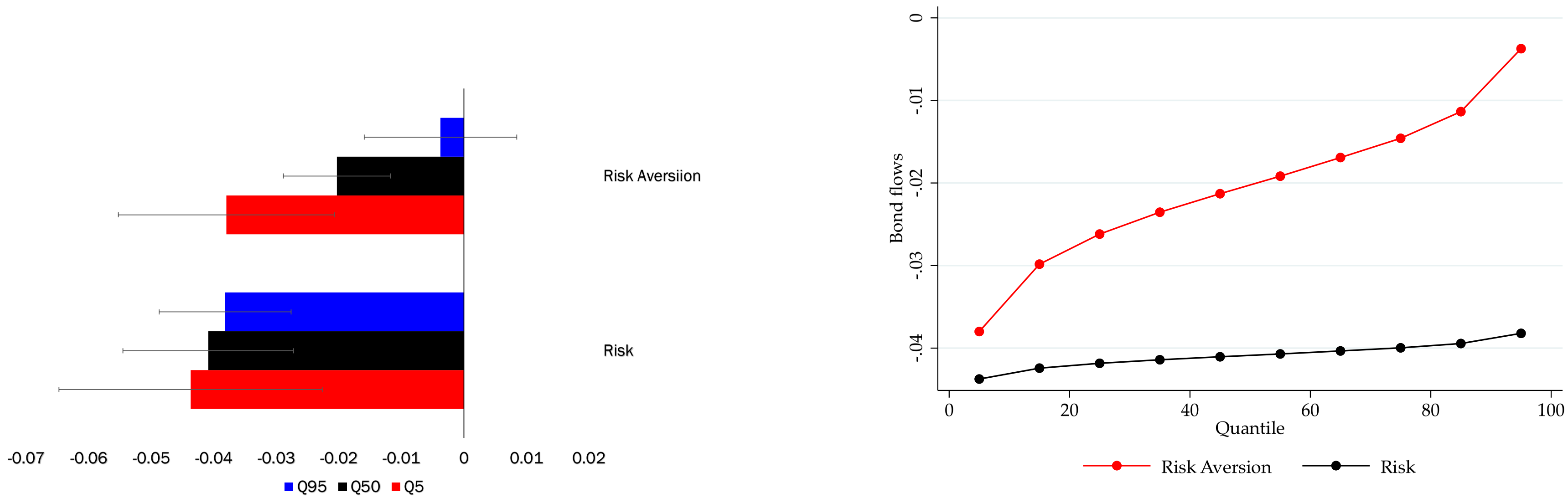


(a) Equity

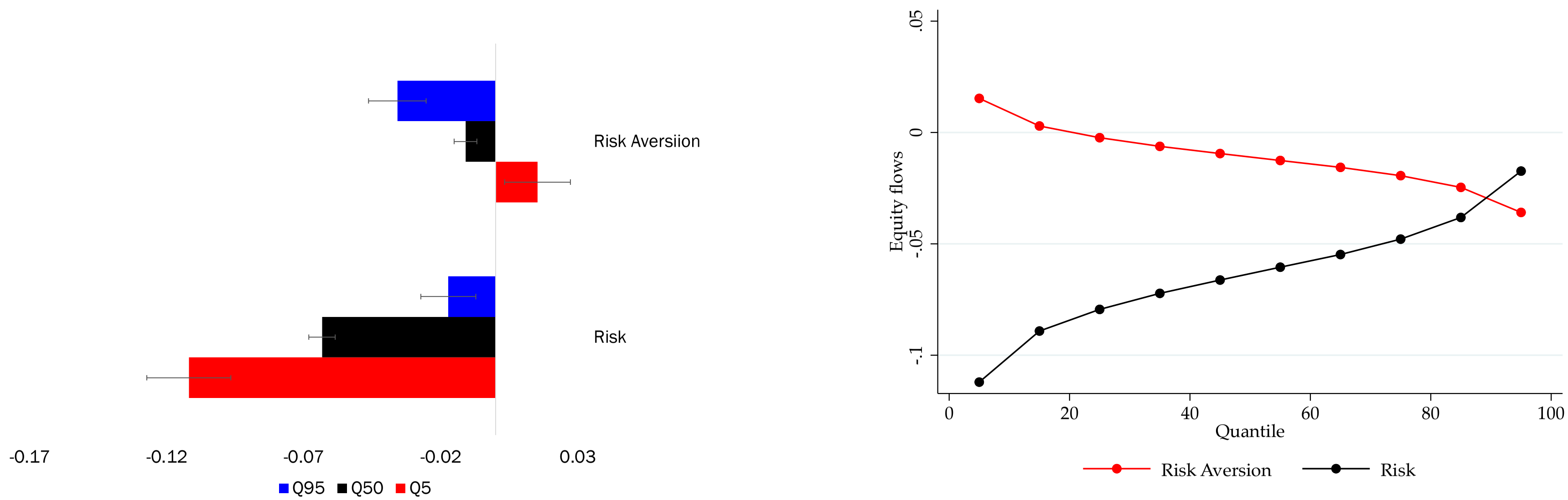


(b) Fixed Income

Figure 4 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).



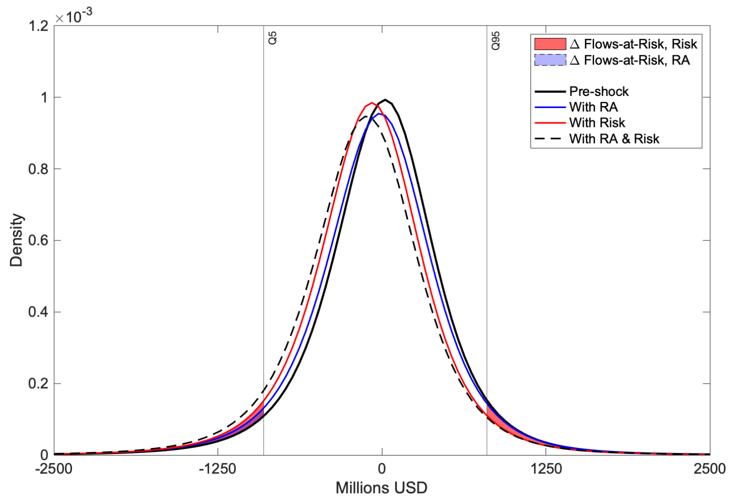
(a) Bond flows (% of AUM_{t-1})



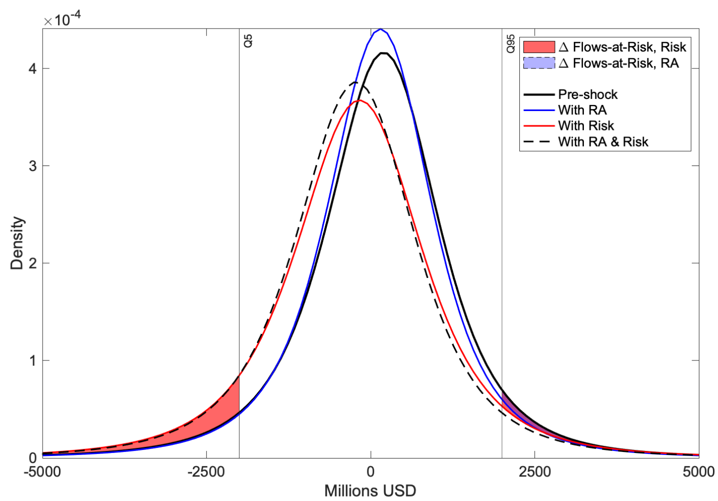
(b) Equity flows (% of AUM_{t-1})

Figure 5: The distributional impact of risk and risk aversion shocks on EPFR bond and equity flows (% of AUM)
Notes: Panels (a) and (b) summarize 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 (2021) and enter the regressions as a weekly moving average. The left panels plot the quantile coefficients for Q5, Q50 and Q95, the left tail, median and right tail responses. Error bars represent 90% confidence intervals. The right panels plot the quantile coefficient curves. 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: Predicted Flow Distributions Conditional on Risk Shocks

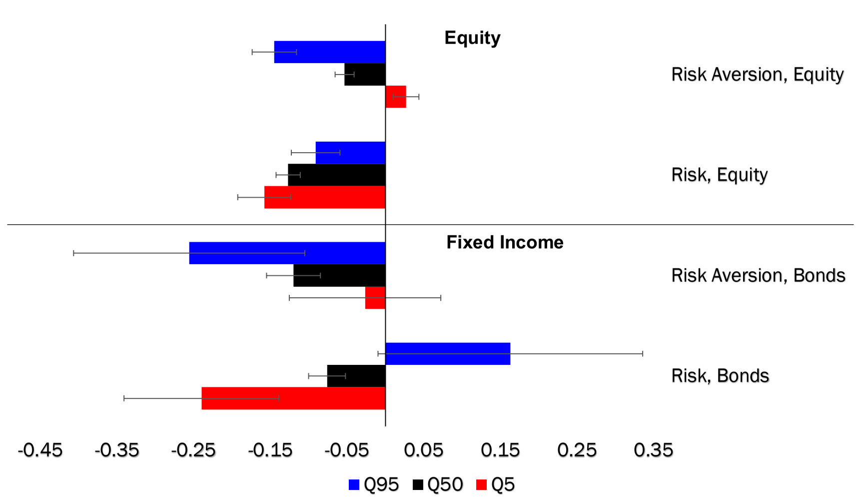


(a) Fixed Income

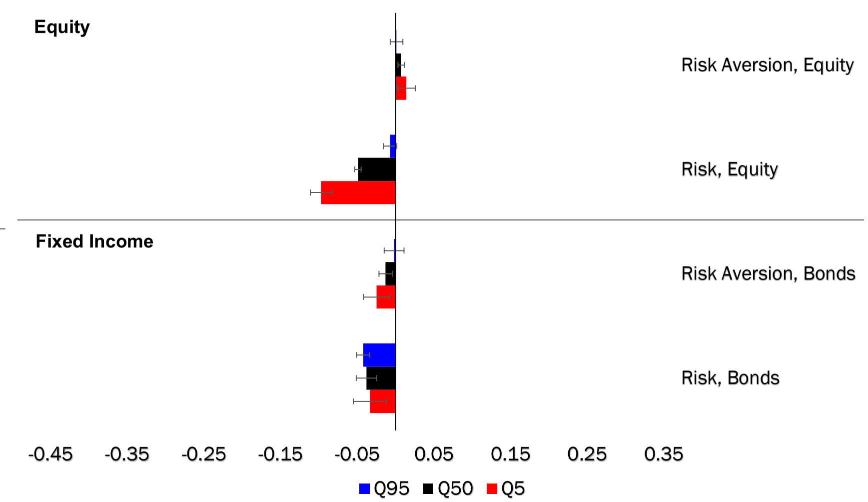


(b) Equity

Figure 7 Plots the results from fitting the distribution of emerging market fixed income (panel a) and equity (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).



(a) Passive



(b) Active

Figure 6: The distributional impact of risk and risk aversion shocks on active and passive EPFR bond and equity flows (% of AUM)
Notes: Panels (a) and (b) summarize 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.

Figure 8: Dynamic Effects using local projections

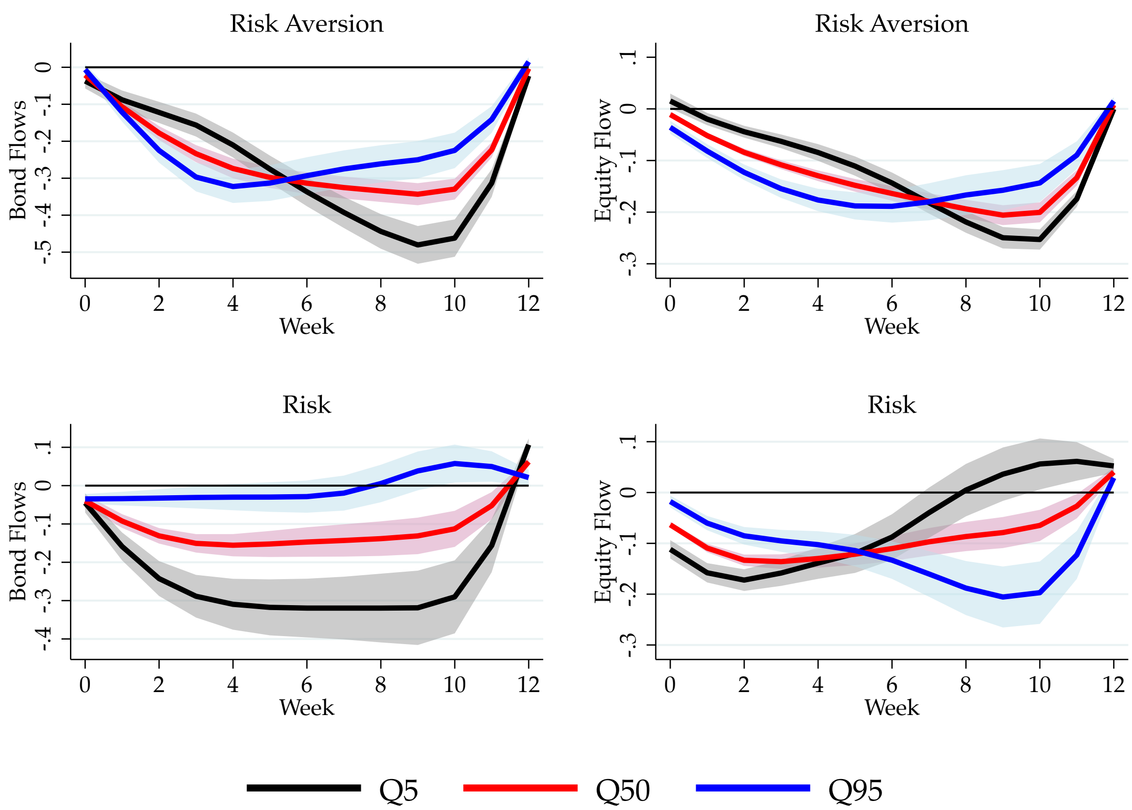
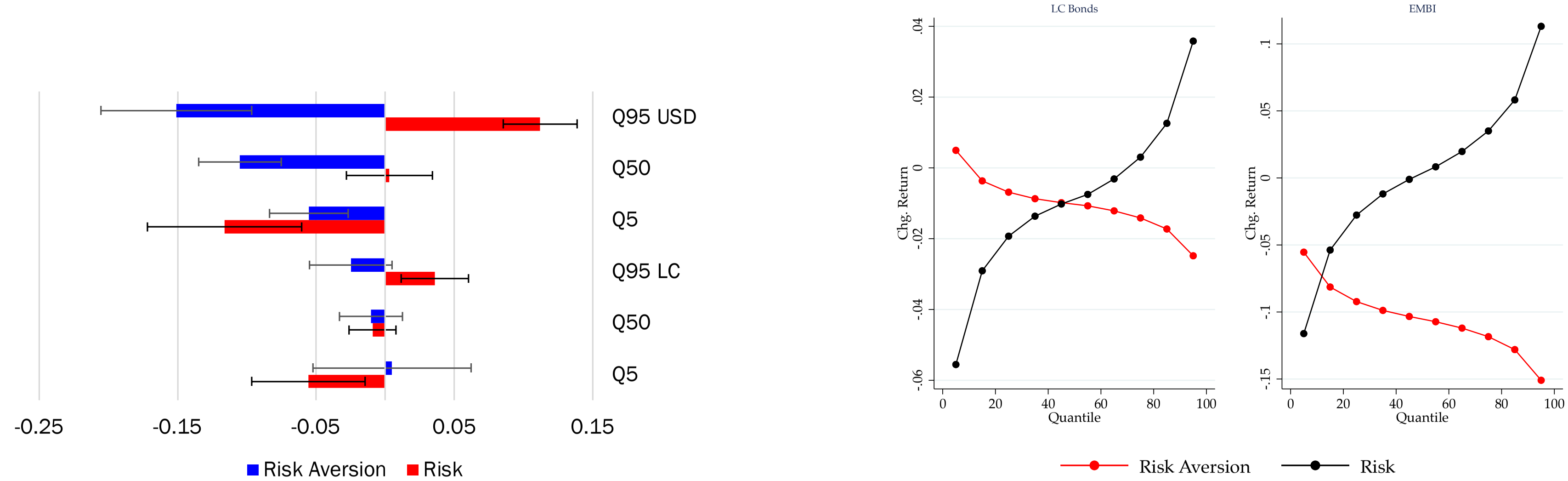
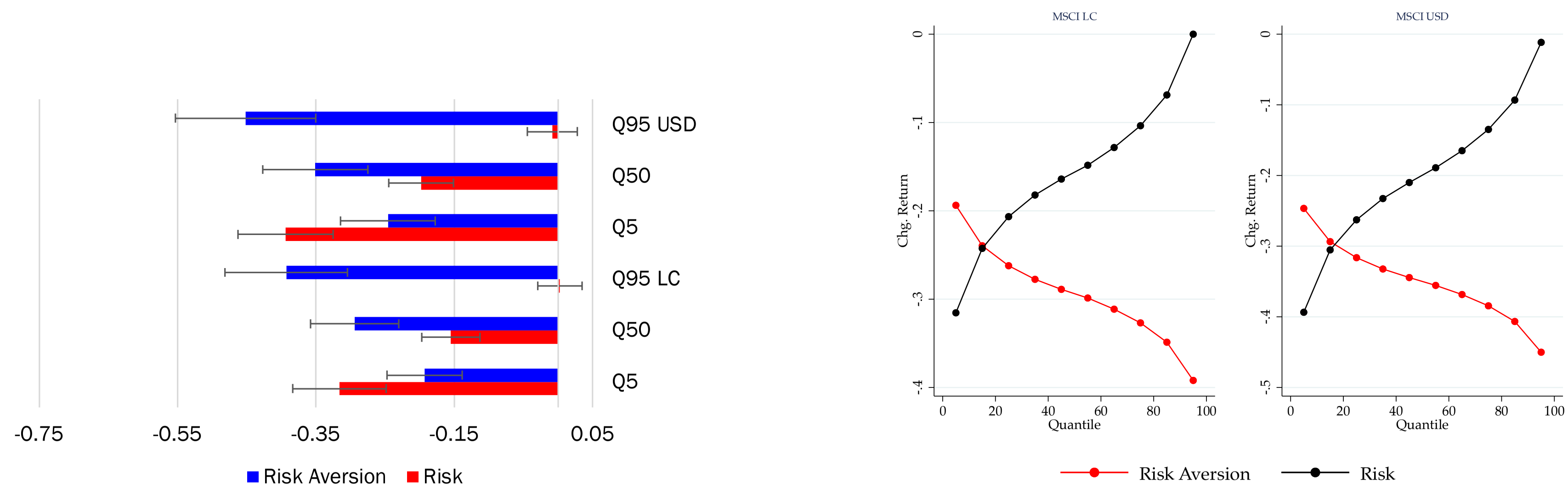


Figure 8 summarizes the impact of a one-standard deviation shock to risk and risk aversion on emerging market bond and equity flows, respectively, over a 12 week-horizon. Risk and risk aversion are the log differences of the estimated series from Bekaert et al (2021) and enter the regressions as a weekly 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.



(a) Bond Returns



(b) Equity Returns

Figure 9b: The distributional impact risk and risk aversion shock on bond and equity returns
Notes: Panels (a) and (b) summarize the impact of a one standard deviation shock to risk and risk aversion on emerging market bond and equity returns, respectively. Risk and risk aversion are the log differences of the estimated series from Bekaert et al (2021). The left panels plot the quantile coefficients for Q5, Q50 and Q95, the left tail, median and right tail responses. Error bars represent 90% confidence intervals. The right panels plot the quantile coefficient curves. 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: % of Lagged AUM	0.05	0.49	-0.71	0.04	0.81	0.76	22.03
Equity Flows (Millions USD)	6.47	117.68	-125.19	1.19	160.83	0.23	38.51
Equity AUM (Billions USD)	18.67	27.16	0.39	6.43	82.88	2.23	7.86
Bond Flow: % of Lagged AUM	0.13	0.69	-0.85	0.17	1.07	-1.01	20.43
Bonds Flows (Millions USD)	6.25	85.81	-63.19	1.96	93.53	-18.35	855.28
Bonds AUM (Billions USD)	8.18	10.77	0.09	3.94	35.22	2.03	7.02
Observations	18584						

(c) Returns

	Mean	St. Dev.	Q5	Q50	Q95	Skewness	Kurtosis
MSCI LC Return	0.04	1.53	-2.23	0.00	2.26	-0.39	21.13
MSCI USD Return	0.04	1.78	-2.67	0.00	2.62	-0.37	17.88
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	92828						

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: 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: 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 3 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 4: 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 4 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 5: The Effect of Benchmarks

(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 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 on aggregate, as in Figure 6. 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: Impact of a one standard deviation risk or risk aversion shock on returns

(a) MSCI USD

	Q5	Q25	Q50	Q75	Q95
Risk Aversion	-0.265***	-0.325***	-0.354***	-0.384***	-0.442***
	(-5.83)	(-7.39)	(-7.74)	(-7.87)	(-7.87)
Risk	-0.378***	-0.255***	-0.195***	-0.134***	-0.0171
	(-10.14)	(-8.65)	(-7.80)	(-6.20)	(-0.85)
Observations	85325	85325	85325	85325	85325

(b) MSCI Local currency

Risk Aversion	-0.209***	-0.267***	-0.295***	-0.324***	-0.380***
	(-5.60)	(-7.24)	(-7.56)	(-7.71)	(-7.74)
Risk	-0.301***	-0.200***	-0.153***	-0.104***	-0.00804
	(-8.15)	(-7.32)	(-6.80)	(-5.49)	(-0.43)
Observations	85346	85346	85346	85346	85346

(c) EMBI

Risk Aversion	-0.0628***	-0.0929***	-0.104***	-0.115***	-0.142***
	(-3.61)	(-5.49)	(-5.26)	(-4.93)	(-4.22)
Risk	-0.108***	-0.0265	0.00287	0.0330*	0.107***
	(-3.34)	(-1.33)	(0.17)	(2.11)	(7.14)
Observations	72648	72648	72648	72648	72648

(d) Local currency bond index

Risk Aversion	0.00420	-0.00731	-0.0106	-0.0145	-0.0249
	(0.12)	(-0.44)	(-0.76)	(-1.29)	(-1.51)
Risk	-0.0534*	-0.0188	-0.00885	0.00282	0.0342*
	(-2.44)	(-1.85)	(-0.89)	(0.29)	(2.43)
Observations	49538	49538	49538	49538	49538

Table 7 summarizes the results of quantile regressions of a) USD MSCI equity returns, b) local currency MSCI equity returns, c) EMBI USD bond returns, and d) local currency daily total returns 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. t-statistics are shown in parentheses. *, **, and *** signify a statistically significant effect at the 10%, 5%, and 1% levels, respectively.

Table 8: 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 8 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 9: 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 9 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.

Global Fund Flows and Emerging Market Tail Risk

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This Version: October 10, 2022

ONLINE APPENDIX

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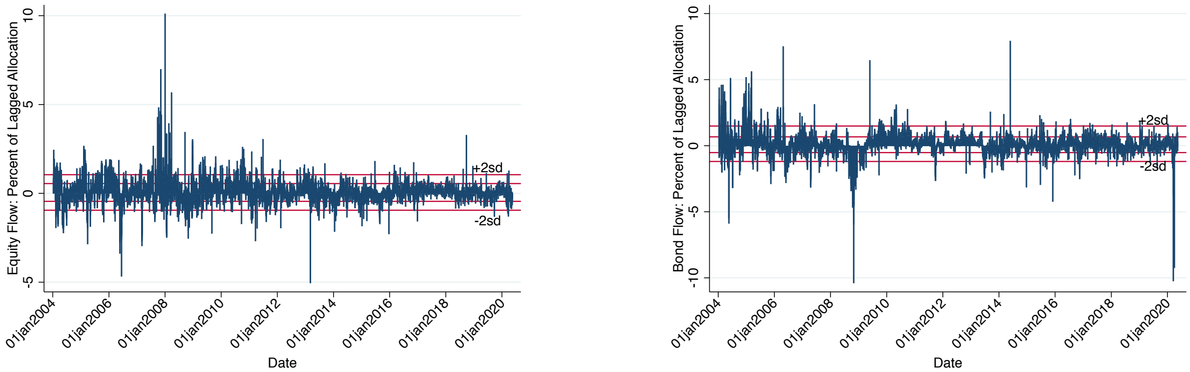
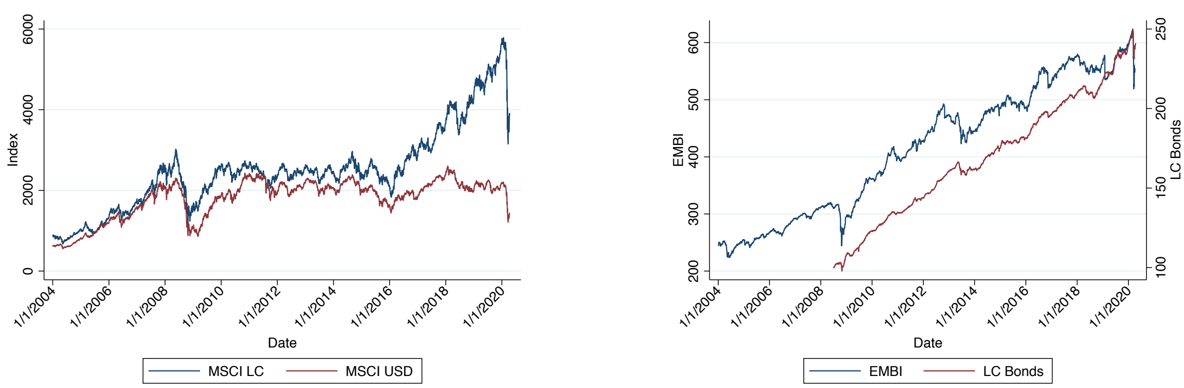
2 Figures

Figure 1: Emerging Market Flows and Returns



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



(b) Total Return Indices

3 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)	6.42	6.66	1.00	5.00	15.00
Adv. Market Return	0.02	0.31	-0.52	0.02	0.50
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	1.56	-0.87	0.00	0.93
REER Growth	0.05	2.12	-3.10	0.13	2.88
Observations	92844				

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)
lbond_perc	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)
lequity_perc	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 4c: A one standard deviation risk-off shock & the distribution of USD equity returns

	(1) Q5	(2) Q25	(3) Q50	(4) Q75	(5) Q95
Risk Aversion	-0.265***	-0.325***	-0.354***	-0.384***	-0.442***
	(-5.83)	(-7.39)	(-7.74)	(-7.87)	(-7.87)
Risk	-0.378***	-0.255***	-0.195***	-0.134***	-0.0171
	(-10.14)	(-8.65)	(-7.80)	(-6.20)	(-0.85)
REER (t-1)	0.00303	-0.000390	-0.00206***	-0.00378*	-0.00704
	(0.62)	(-0.25)	(-3.47)	(-1.83)	(-1.34)
BIS Policy Rate (t-1)	-0.0294*	-0.00975**	-0.000160	0.00967	0.0283
	(-1.81)	(-2.51)	(-0.05)	(1.04)	(1.34)
Real GDP Growth (prev. Q)	1.916***	0.694***	0.0973	-0.515***	-1.676***
	(3.92)	(2.99)	(0.64)	(-2.65)	(-3.89)
Emerging Mkt. News	0.00121	-0.00241	-0.00417**	-0.00598**	-0.00942*
	(0.36)	(-1.41)	(-2.12)	(-2.08)	(-1.84)
Adv. market index (t-1)	-0.0250***	-0.00816***	0.0000834	0.00854***	0.0246***
	(-4.79)	(-3.46)	(0.05)	(4.04)	(5.48)
AE IP Growth (prev. M)	22.46***	9.369***	2.971***	-3.590***	-16.04***
	(9.38)	(8.52)	(4.54)	(-4.24)	(-7.87)
AE Monetary Stance (t-1)	-0.141***	-0.0529**	-0.0100	0.0339**	0.117***
	(-2.60)	(-2.07)	(-0.63)	(2.20)	(3.16)
Observations	85325	85325	85325	85325	85325

t statistics in parentheses

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4c summarizes the results of quantile regressions of MSCI USD daily total returns 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 4d: A one standard deviation risk-off shock & the distribution of local currency equity returns

	(1) Q5	(2) Q25	(3) Q50	(4) Q75	(5) Q95
Risk Aversion	-0.209***	-0.267***	-0.295***	-0.324***	-0.380***
	(-5.60)	(-7.24)	(-7.56)	(-7.71)	(-7.74)
Risk	-0.301***	-0.200***	-0.153***	-0.104***	-0.00804
	(-8.15)	(-7.32)	(-6.80)	(-5.49)	(-0.43)
REER (t-1)	0.000890	-0.000374	-0.000960+	-0.00158	-0.00279
	(0.21)	(-0.29)	(-1.62)	(-0.89)	(-0.61)
BIS Policy Rate (t-1)	-0.0277***	-0.00926***	-0.000714	0.00834**	0.0259***
	(-3.07)	(-2.81)	(-0.39)	(2.34)	(2.85)
Real GDP Growth (prev. Q)	0.876*	0.302+	0.0359	-0.246*	-0.793**
	(1.90)	(1.46)	(0.29)	(-1.65)	(-2.11)
Emerging Mkt. News	0.00104	-0.00224+	-0.00377**	-0.00538**	-0.00851*
	(0.32)	(-1.47)	(-2.27)	(-2.19)	(-1.86)
Adv. market index (t-1)	-0.0203***	-0.00607***	0.000538	0.00753***	0.0211***
	(-5.15)	(-3.11)	(0.33)	(3.90)	(6.02)
AE IP Growth (prev. M)	16.60***	6.963***	2.491***	-2.241***	-11.44***
	(8.39)	(8.66)	(4.78)	(-3.00)	(-6.15)
AE Monetary Stance (t-1)	-0.140***	-0.0508**	-0.00937	0.0345**	0.120***
	(-3.24)	(-2.56)	(-0.67)	(2.18)	(3.50)
Observations	85346	85346	85346	85346	85346

t statistics in parentheses

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4d summarizes the results of quantile regressions of MSCI LC daily total returns 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 4e: A one standard deviation risk-off shock & the distribution of USD bond returns

	(1) Q5	(2) Q25	(3) Q50	(4) Q75	(5) Q95
Risk Aversion	-0.0628***	-0.0929***	-0.104***	-0.115***	-0.142***
	(-3.61)	(-5.49)	(-5.26)	(-4.93)	(-4.22)
Risk	-0.108***	-0.0265	0.00287	0.0330**	0.107***
	(-3.34)	(-1.33)	(0.17)	(2.11)	(7.14)
REER (t-1)	0.00375	0.000577	-0.000564**	-0.00173*	-0.00460+
	(1.17)	(0.70)	(-2.30)	(-1.72)	(-1.46)
BIS Policy Rate (t-1)	-0.0122	-0.00433*	-0.00151	0.00138	0.00845
	(-1.00)	(-1.94)	(-0.74)	(0.25)	(0.57)
Real GDP Growth (prev. Q)	0.872**	0.161+	-0.0946	-0.356+	-0.998*
	(2.14)	(1.57)	(-0.80)	(-1.62)	(-1.92)
Emerging Mkt. News	0.00583***	0.00136**	-0.000242	-0.00189*	-0.00592***
	(4.37)	(2.26)	(-0.32)	(-1.69)	(-2.77)
Adv. market index (t-1)	-0.0101***	-0.00274**	-0.000107	0.00259**	0.00921***
	(-2.73)	(-2.51)	(-0.18)	(2.53)	(2.80)
AE IP Growth (prev. M)	8.671***	1.942***	-0.474	-2.949***	-9.016***
	(4.46)	(3.14)	(-1.16)	(-4.69)	(-4.98)
AE Monetary Stance (t-1)	0.120***	0.0456***	0.0188***	-0.00871	-0.0761***
	(4.36)	(4.62)	(3.19)	(-0.98)	(-3.25)
Observations	72648	72648	72648	72648	72648

t statistics in parentheses

+ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4e summarizes the results of quantile regressions of EMBI daily total returns 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 4f: A one standard deviation risk-off shock & the distribution of local currency bond returns

	(1) Q5	(2) Q25	(3) Q50	(4) Q75	(5) Q95
Risk Aversion	0.00420	-0.00731	-0.0106	-0.0145	-0.0249^{+}
	(0.12)	(-0.44)	(-0.76)	(-1.29)	(-1.51)
Risk	-0.0534**	-0.0188*	-0.00885	0.00282	0.0342**
	(-2.44)	(-1.85)	(-0.89)	(0.29)	(2.43)
REER (t-1)	-0.00512	-0.00147	-0.000422	0.000808	0.00411
	(-0.49)	(-0.76)	(-1.11)	(0.43)	(0.39)
BIS Policy Rate (t-1)	-0.0441***	-0.0111***	-0.00167	0.00943*	0.0393***
	(-2.79)	(-3.16)	(-0.47)	(1.83)	(2.58)
Real GDP Growth (prev. Q)	0.510	-0.00892	-0.158*	-0.332^{+}	-0.802
	(0.73)	(-0.07)	(-1.96)	(-1.59)	(-1.06)
Emerging Mkt. News	0.000347	-0.00280**	-0.00370***	-0.00476***	-0.00761**
	(0.15)	(-2.17)	(-2.81)	(-3.04)	(-2.15)
Adv. market index (t-1)	-0.00747**	-0.00181*	-0.000184	0.00172***	0.00685***
	(-2.34)	(-1.94)	(-0.28)	(2.95)	(2.93)
AE IP Growth (prev. M)	5.735	1.722**	0.574**	-0.777	-4.409
	(1.36)	(2.04)	(2.01)	(-1.12)	(-1.09)
AE Monetary Stance (t-1)	0.0280	-0.00232	-0.0110	-0.0212	-0.0487
	(0.64)	(-0.28)	(-0.99)	(-1.09)	(-0.78)
Observations	49538	49538	49538	49538	49538

t statistics in parentheses

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4f summarizes the results of quantile regressions of local currency daily total returns 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: 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 5 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 6: 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 6b 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.