

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

Anusha Chari* Karlye Dilts Stedman[†] Christian Lundblad[‡]

This Version: April 20, 2021

ABSTRACT

This paper characterizes the implications of risk-on/risk-off shocks for emerging market capital flows and returns. We document that these shocks have important implications not only for the median of emerging markets flows and returns but also for the tails of the distribution. Further, while there are some differences in the effects across bond vs. equity markets and flows vs. asset returns, the effects associated with the worst realizations are generally larger than that on the median realization. We apply our methodology to the COVID-19 shock to examine the pattern of flow and return realizations: the sizable risk-off nature of this shock engenders reactions that reside deep in the left tail of most relevant emerging market quantities.

*Professor of Economics, Department of Economics & Professor of Finance, Kenan-Flagler Business School, University of North Carolina at Chapel Hill & NBER. Email: achari@unc.edu.

[†]Economist, Research Department, Federal Reserve Bank of Kansas City. Email: karlye.stedman@kc.frb.org. The views expressed are those of the authors and do not necessarily reflect those of the Federal Reserve Bank of Kansas City or the Federal Reserve System.

[‡]Richard "Dick" Levin Distinguished Professor of Finance, Kenan-Flagler Business School, University of North Carolina at Chapel Hill. Email:Christian.Lundblad@kenan-flagler.unc.edu.

1 Introduction

While portfolio flows to emerging markets offer well-documented benefits (Bekaert, Harvey and Lundblad (2005); Chari and Henry (2004, 2008); Henry (2007)), tail events such as sudden stops present challenges that prove particularly pressing for investors and policy makers (Forbes and Warnock (2012, 2019); Rey (2013); Miranda-Agrippino and Rey (2020)). There is, of course, a large literature on cross-border capital flows and their implications for financial market returns.¹ However, extant research has largely focused on the first moment of the relevant distributions of these important quantities. In sharp contrast, building on Gelos et al. (2019), we focus on the full distributions of emerging market capital flows and returns; most important, we characterize the manner in which extreme capital flow and return realizations are tied to global risk appetite (“risk-on/risk-off” or RORO).

Despite continuing to be somewhat imprecisely defined, the RORO terminology has come into pervasive use in the financial press and among policy makers in the years since the global financial crisis. In this paper, we focus on RORO shocks as a reflection of variation in global investor risk aversion. As investors rebalance their portfolios away from risk assets and toward safe assets in the face of risk aversion shocks, RORO variation has important implications for asset price determination, particularly for so-called “risk assets”. Jotikasthira, Lundblad, and Ramadorai (2012), for example, document this shock transmission mechanism to emerging market capital flows and asset prices. In response to funding shocks from their investor base (possibly linked to RORO), global funds substantially alter their portfolio alloca-

¹See for example a non-exhaustive list of papers in Section 1 of the online appendix, Alfaro, L., S. Kalemli-Ozcan, and V. Volosovych (2008, 2014); Avdjiev, S., L. Gambacorta, L. S. Goldberg, and S. Schiaffi (2017); Ammer, J., M. De Pooter, C. J. Erceg, and S. B. Kamin (2016); Baskaya, Y. S., J. di Giovanni, S. Kalemli-Ozcan, J.-L. Peydro, and M. F. Ulu (2017); Bauer, M. D., & Neely, C. J. (2014); Broner, F., Didier, T., Erce, A., & Schmukler, S. L. (2013); Bruning, F. and V. Ivashina (2019); Bruno, V. and H. S. Shin (2014, 2015); Calvo, G. A., L. Leiderman, and C. M. Reinhart (1993, 1996).; Cerutti, E., S. Claessens, and D. Puy (2019); Chari, A., K. Dilts Stedman, and C. Lundblad (2020); Chen, J., Mancini Griffoli, T., & Sahay, R. (2014); Clark, John, Nathan Converse, Brahim Coulibaly, and Steve Kamin (2016); Dedola, L., G. Rivolta, and L. Stracca (2017); Dilts Stedman, K. (2019); Eichengreen, B. and P. Gupta (2017); Forbes, K. J. and F. E. Warnock (2012, 2019); Fratzscher, M. (2012); Fratzscher, M., Duca, M. L., & Straub, R. (2016, 2018); Georgiadis, G., & Grab, J. (2015); Ghosh, A. R., Kim, J., Qureshi, M., and Zalduendo, J. (2012); Gilchrist, S., Yue, V., & Zakrajsek, E. (2014, November); Gourinchas, P. O., & Obstfeld, M. (2012); Karolyi, G. A., & McLaren, K. J. (2016); Kim, S. (2001); Kroencke, T. A., Schmeling, M., & Schrimpf, A. (2015); Jotikasthira, P., C. Lundblad, and T. Ramadorai (2012); McCauley, R. N., McGuire, P., & Sushko, V. (2015); Miranda-Agrippino, S. and H. Rey (2019); Milesi-Ferretti, G., & Tille, C. (2011); Mishra, P., Moriyama, K., N’Diaye, P. M. B., & Nguyen, L. (2014); Moore, J., Nam, S., Suh, M., & Tepper, A. (2013); Neely, C. J. (2010); Obstfeld, M. (2015); Obstfeld, M., J. D. Ostry, and M. S. Qureshi (2018); Rogers, J.H., Scotti, C., & Wright, J.H. (2014); Reinhart, C. and V. Reinhart (2009); Rey, H. (2013).

tions to emerging markets with important implications for local asset prices.

Understanding the implications of variation in RORO for emerging market capital flow and return distributions is the focus of our paper. We focus on the extent to which RORO shocks alter the range of the distribution versus shift the distribution. As an example, an adverse, risk-off shock can make the whole emerging market capital flow or return distribution wider by pulling out both of the tails. Alternatively, a risk-off shock could simply fatten the left tail. These differences have important implications for how investors and policy makers should consider downside risk.

To capture realized variation in global investor risk appetite, we use a structural model to measure risk aversion that separates the price of risk (or risk aversion) from the quantity of risk. The approach is based on Bekaert et al (2020). Inference about this separation may, of course, be contaminated by any model mis-specification. Given this concern, we turn to an alternative empirical measure, a RORO index that we build using the first principle component of daily data from asset markets in the United States and the Euro area. This approach has the advantage of incorporating a multi-faceted set of signals from relevant asset markets, but may conflate information about variation in risk appetite with variation in physical risk. Taken together, the model-based and empirical approaches allow us to draw relatively robust conclusions about the effect of RORO shocks on emerging market flows and returns.

The structural model-based decomposition reveals that the distribution of RORO shocks is highly right-skewed (toward risk-off) and fat tailed, spiking during the global financial and COVID-19 crises. With fat tails, extreme events become both more probable and potentially more destabilizing. As examples, we observe sharp risk-off movements during the global financial crisis, the European debt crisis, the taper tantrum, and the COVID-19 crisis. Our alternative, largely statistical measure employs an aggregation of RORO states of the world based on four broad categories that reflect variation in advanced economy credit risk, equity market volatility, funding conditions, and currencies and gold. With an eye to inferring the risk bearing capacity of international investors, our alternative RORO index comprises the first principle component of daily changes in these series. This statistical index, along with several associated sub-indices reflecting these four constituent groups, exhibits interesting distributional features in the sense that it is also well characterized by significant skewness and fat

tails. Reassuringly, the two approaches complement one another in characterizing the distribution of RORO shocks as measures of changing international investor risk-appetite.

Using the panel quantile regression approach of Machado and Santos Silva (2019), we characterize the distributional implications of RORO shocks for emerging market capital flows and returns. In order 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, collectively with more than 8 trillion USD of capital under management. To measure returns on emerging market assets, we use country level USD and local currency equity return indices from MSCI, and our fixed income returns come from Bloomberg local currency bond indices and the USD Emerging Market Bond Indices from JP Morgan. Due to the availability of EPFR data, the sample runs from January 7, 2004 to Apr. 9, 2020.

The novel contribution of our paper is to characterize the impact of shifts in the distributions of global risk on flows and returns as well as the dispersion in outcomes. In other words, our methodology allows us to model both shifts and changes in the shapes of the distributions of global push factors and capital flow and return outcomes. We conclude that with a few exceptions, the emphasis on measures of central tendency in the existing literature on capital flows masks important underlying heterogeneity in the full distribution of global risk. The weight placed on means and variances as sufficient summary statistics precludes the data from speaking to the underlying distributional granularity of global risk – a challenge we overcome by turning to heterogeneous effects across quantiles.²

In addition to our focus on the distribution of global risk, our risk measures illustrate that the underlying factors that constitute global risk can differ across crises and evolve over time. For example, a structural decomposition reveals that the risk-aversion factor was more prominent in the global financial crisis relative to the quantity of risk, while the opposite prevails during the Covid crisis. We also find that while advanced economy equity returns and volatility along with corporate spreads proxying for credit risk were the most significant risk factors during the global financial crisis, movement in corporate spreads and stoppages in funding

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

liquidity predominantly explain capital flows and returns in the aftermath of Covid-19 shock. The corporate spreads factor during the Covid-era are an order of magnitude compared to the global financial crisis.

Regardless of whether we use the structural or statistical method to measure RORO, we find that RORO shocks have important implications, not only for the median of emerging market flows and returns, but also for the tails. We conclude that the focus in the literature on measures of central tendency is incomplete. In particular, we find that the effects associated with the worst realizations, say the fifth quantile, are often more heavily affected by risk-off shocks, compared to the median realization.

The estimates derived from the structural model-based version of RORO suggest that the reactions that we observe, while robust from a directional standpoint vary depending upon whether one separates out variation in risk aversion from variation in risk. Perhaps not surprisingly, variation in global risk is more important for emerging market mutual fund flows. Next, we consider the distributional implications for cross-border flows associated with EPFR bond and equity mutual funds and ETFs. For bond funds, risk-off shocks (however measured) increase the worst portfolio outflow realizations more than they decrease median flows, and therefore risk-off shocks significantly fatten the tails of the portfolio flow distribution. The net effect on bond flows from a risk-off event is that the entire distribution moves to the left. In the equity fund space, in contrast, while we observe that a risk-off shock negatively affects the overall distribution, we also observe that a risk-off shock modestly brings in both the tails.

Next, we turn to the distributional implications for emerging market returns. We find that risk-off shocks negatively affect the worst return realizations more than they affect the median return realization. Further, we find that are important differences across asset class and currency denomination which are consistent across risk measures. Equity returns are more sensitive than bond returns, and within asset classes, U.S. dollar indices are more sensitive than local currency indices.

Finally, we apply our framework to the COVID-19 shock. We examine the distributional pattern of the flow and returns realizations in the face of the sizable risk-off nature of this shock. In the COVID-19 era, a one standard deviation RORO shock expands (compresses)

the tail realizations of the weekly bond (equity) distribution by \$45 (\$6.8) million. A shock equal in magnitude to the largest observation in the COVID-19 sample expands (compresses) the tails realizations of the weekly bond (equity) distribution by \$170.2 (\$25.4) million. Using the structural measure of risk aversion and risk from Bekaert et al (2020), our results suggest that a one standard deviation shock composed of equal parts risk aversion and physical risk separates the tails of the weekly bond (equity) distribution by \$15.8 (\$10.8) million.

Related Literature: Our paper is related to several strands of the literature on capital flows to emerging markets. There is a vast literature on the role of global financial market conditions and boom-bust cycles in emerging market capital flows and returns.³ This literature emphasizes the role of global push factors to explain the ebbs and flows in foreign investment allocations to emerging markets.

Global financial conditions that serve as push factors include advanced economy monetary policy, foreign investor risk aversion, international financial market liquidity, and exchange rate configurations. Forbes and Warnock (2012, 2019) show that global risk factors drive emerging market capital flow surges, sudden stops and retrenchments. Jotikasthira et al. (2012) report that "global funds substantially alter portfolio allocations in emerging markets in response to funding shocks from their investor base."⁴ Our paper contributes to the literature on extreme capital flow movements by focusing on the distributions of capital flows and returns conditional on the distribution of global risk factors.

There are different views in the literature about what constitutes or summarizes changes to global risk sentiment. At the same time, the provenance of risk can differ over time. Focusing on market risk and investor sentiment, Bekaert et al. (2013), Miranda-Agrippino and Rey (2019) and many others use the VIX as a proxy to measure the risk appetite of global investors. Fratzscher (2012) includes the TED spread as a measure of credit risk and liquidity in international capital markets. Chari et al. (2020) use of high-frequency identification to extract U.S. monetary policy shocks using Treasury derivatives data to show that capital flows

³A non-exhaustive list includes Tornell and Schneider, 2007; Mendoza and Terrones, 2008; Mendoza 2010; Obstfeld 2012; Diaz-Alejandro 1983; Calvo et al. 1993; Calvo et al. 1996; Eichengreen and Portes 1987; Reinhart and Reinhart 2009; Reinhart and Rogoff 2009.

⁴Evidence suggests that spillovers from the U.S. to the rest of the world operate through changes in risk premia that drive foreign investor risk tolerance (Borio and Zhu 2012). Caballero and Simsek (2019) provide a model for analyzing capital flow retrenchments to highlight their fickleness, possibly related to asymmetric information or Knightian uncertainty.

to emerging markets are sensitive to term premium shocks in the U.S. yield curve. In this paper, we examine an amalgam of global shocks that collectively comprise global “risk-on” or risk-off environments in international financial markets to investigate the distributional implications of emerging market capital flows and returns. To do so, our aim is also to arrive at a measure of risk encapsulating the multi-faceted nature of global risk-on and risk-off states of the world.

In doing so, our paper draws upon existing evidence documenting the relationship between unitary risk sources and risk appetite. One strand of the literature examines the impact of U.S. monetary policy on global investor risk appetite (Bruno and Shin, 2015 a,b; Chari et al., 2020; Gourinchas and Obstfeld, 2012). Bekaert et al., 2013; Miranda-Agrippino and Rey, 2019; and Bruno and Shin, 2015a) show that U.S. monetary policy changes impact global risk. Expansionary monetary policy corresponds to global “risk-on” while tightening monetary policy shocks correlate with “risk-off” states of the world. Risk-on and risk-off states correspond to changes in risk aversion holding fixed the quantity of risk. Our approach has the advantage of measuring risk aversion using a structural model from Bekaert et. al. (2020) that disentangles the price of risk (or risk aversion) from the quantity of risk.⁵ This literature emphasizes the role risk premia as drivers of capital flows to emerging markets. Chari et al. (2020) disentangle the channels through which U.S. monetary policy shocks can alter expectations hypothesis-driven yields and risk premia in the term structure of U.S. interest rates. Via portfolio rebalancing and signaling, changes in domestic yields and risk premia can have a significant impact on equity prices and bond yields in emerging markets. Bruno and Shin (2015 a, b) propose an international risk-taking channel that underscores the role of liquidity in dollar funding markets—phases of expansionary monetary policy increase the risk-bearing capacity of financial intermediaries and drives international banking flows to emerging markets.

To proxy for global risk aversion, the literature documents the sensitivity of portfolio equity flows to the VIX (Avdjiev et al. 2019; Rey 2015). Recent evidence draws attention to the diminished relationship between the VIX and other key variables after 2008 (Forbes, 2020;

⁵However, inference about this decomposition could suffer from the drawback that the model is incorrectly specified.

Miranda-Agrippino and Rey, 2020, Burcu et. al 2020). Avdjiev et al. (2017) attribute the declining role of the VIX to the shifting composition of global capital flows. Cerutti et al. (2019) suggest that correlation between the VIX and capital flows is limited to times of crisis and that the role for the global financial cycle may have moderated. Burcu et. al (2020) point to a breakdown in the negative relationship between bank leverage and risk appetite since 2009 suggesting that the VIX is no longer a reliable proxy for the price of bank balance sheets. Forbes and Warnock (2020) and Miranda-Agrippino et al. (2020) highlight a declining role in the information content of the VIX for explaining credit growth and capital flows. In contrast, the parameter values using our composite risk-on risk-off measure are remarkably stable (if not stronger) over time given that the measure captures alternative sources of risk. The underlying constituent sources of risk assert their importance or come to the forefront at different points in time.

Our nearest neighbors in the literature are Gelos et. al (2019) who examine a “capital flows-at-risk” model using a quantile regression framework, and Eguren-Martin et al (2020), who examine the probability distribution of emerging market capital flows conditional on information contained in financial asset prices. Both papers propose to characterize the full distribution of capital flows in the face of shocks. Our paper differs from these in several ways. First, using weekly data on flows and returns and daily risk measures, the frequency of our outcome variables matches more closely to the risk measures. We thereby establish a tighter link between the risk measure and our variables of interest, with less potential for confounding influences between the measure of the flow or return, and the event(s) driving changes in risk or risk aversion.

Second, we focus our attention on global risk in particular, rather than taking a broader look at “push” and “pull” factors, which Gelos et al (2019) consider individually and which Eguren-Martin et al (2020) consider in a consolidated manner. Considering the former, a multifaceted measure of risk confers the advantages discussed previously compared to a unitary risk measure like the BBB corporate spread used in Gelos et al (2019); namely, variable sources of risk, geographic diversity, and plausible exogeneity. Eguren-Martin et al (2020) take an approach more in line ours by putting forward the degree to which capital flows respond to many types and sources of shocks, but their single-dimensional measure of global risk (in

additional to a local risk factor calculated as a residual) does not allow for a decomposition into global risk drivers. Likewise, our paper acknowledges, and attempts to characterize, the distinction between risk and risk aversion in shaping outcomes within the distribution by appealing to a structural decomposition.

The paper proceeds as follows. Section 2 outlines the data and methodology for computing our risk-on risk off measures. Section 3 presents our baseline specification and the results from our quantile regression analysis. Section 4 presents a quantitative exercise which demonstrates the distributional implications of our findings applied to the the Covid-19 crisis. Section 5 concludes.

2 The Data

2.1 Computing Risk-on/Risk-off

To capture realized variation in global investor risk appetite, we consider two complementary measures of Risk-On, Risk-Off (RORO). We first turn to the method employed in Bekaert, Engstrom, and Xu (2020; BEX) for a model-based RORO measure to structurally distinguish the price of risk (risk aversion) from the quantity of risk (economic uncertainty). Employing a wide set of macro and financial market data, BEX build on the family of habit-based asset pricing models (see, for example, Campbell and Cochrane (1999)) to separately identify variation in risk and risk aversion. We collect their daily measures of each, using variation in risk aversion as our second RORO measure.⁶ The approach has the advantage of measuring risk aversion using a structural model specifically designed to separate the price of risk (or risk aversion) from the quantity of risk. However, inference about this separation may, of course, be contaminated by any model mis-specification.

In recognition that the model-based approach used to deriving our first measure of variation in investor risk-appetite may suffer from model mis-specification, we build an alternative model-free measure from the first principle component of a multi-faceted set of daily data across several relevant asset markets. We construct a largely statistical RORO index in a manner similar to that described in Datta et al (2017). Our RORO index comprises the z-score of

⁶Thanks to Nancy Xu for making these data available. <https://www.nancyxu.net/risk-aversion-index>

the first principal component of daily changes in several standardized asset market variables. We normalize components 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, however, is that while definitely linked to variation in risk aversion, this measure may nevertheless confound information about variation in risk appetite with variation in physical risk.

Our empirical measure 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 for 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 daily total returns on the S&P 500, STOXX 50 and MSCI Advanced Economies Index, along with associated changes in option implied volatilities from the VIX and the VSTOXX. To account for changes to funding liquidity, we include the daily average change in the G-spread on 2-, 5-, and 10-year Treasuries, along with changes in the TED spread, the 3-month LIBOR-OIS spread, and the bid-ask spread on 3-month Treasuries. Finally, we include growth in the trade-weighted U.S. Dollar Index against advanced foreign economies and the change in the price of gold. Figure 1 displays the time series and histogram of the statistical measure.

To shed light on different components of risk or risk aversion, we also construct four sub-indices. These groupings, chosen to maximize the total explained variation of the components, fall into the four categories above: (1) spreads (credit risk), (2) advanced economy equity returns and implied volatility, (3) funding liquidity, and (4) currency and gold. As in the headline index, the subindices comprise the first principal component of the normalized series. Table 1.1 displays summary statistics for the headline measure and subindices. Since they are expressed as z-scores, we omit their means and standard deviations from the table.

Defining a risk measure comprising multiple sources of risk confers several advantages. First, agglomerating multiple sources of risk allows us to abstract from any one source of risk-off behavior in our baseline analysis. Elevating any particular asset price in the measurement of risk sentiment hazards the possibility that the relationship between the measure-asset and the risk-affected-asset of interest arises from a particular set of market participants, the actions

of whom may not be generalizable across time and across assets. The group of market participants who take out, for example, S&P 500 options to hedge against U.S. equity volatility have characteristics that may not extend equally to all other risk assets we might want to measure in the face of a risk-off shock. Second, our multivariate measure of risk-on/risk-off further permits the decomposition of baseline results into underlying drivers, offering insights into the source of a given risk-on or risk-off event, which itself may differentially drive emerging market capital flows and returns. Third, our measure recognizes sources outside of the United States which may drive risk-on/risk-off changes. Finally, because we measure the relationship of our index to assets in emerging markets, we can appeal to the small open economy character of the recipient markets to strengthen the plausibility of the index's exogeneity to local market fundamentals.

Figure 1 presents our model-based structural decomposition into changes in risk aversion or the price of risk (Panel C) and the quantity risk (D), and in the statistical RORO measure (Panels A and B). Both RORO measures exhibit (risk-off) skewness, excess kurtosis, and time varying volatility (see, also Table 1.1). Further, both measures show large spikes during the global financial, the European debt, and the COVID-19 crises.

Delving into the relationship between our chosen measures, Table 2 shows that, over the full sample, each is correlated with the others, above 0.55. Of note, albeit not unexpectedly, this includes the two model-based components, reflecting the interdependence of risk sentiment and physical risk. To provide a sense of the degree to which the statistical index reflects either or both of risk sentiment or physical risk, we undertake two related exercises which more fully decompose the measures.

First, we orthogonalize the BEX measures to one another, and regress the statistical RORO index on the orthogonalized components. We see in Table 3 that our statistical measure takes more of a signal from changes to risk sentiment compared to changes in physical risk by a factor of two to one. The R^2 of these simple regressions also makes clear that risk aversion explains more variation in the RORO Index compared to physical risk. Second, to explore how this relationship may vary over time, we show in Figure 4 the explained variation in the RORO index over a two year rolling window, plotted alongside the RORO index. With few exceptions, risk aversion explains more variation. Notably, the explanatory power of risk

aversion appears to rise when the variance of RORO increases.

2.2 Capital Flows and Returns

In order 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 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, Lundblad, and Ramadorai (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.

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 Barclays Local Bond Index, while we measure country-level equity returns using the Morgan Stanley Capital International (MSCI) local currency and USD indices. Figure 2 and Table 1.2 display the times series and summary statistics for return and flow measures.

Reflecting the availability of EPFR data, the sample runs from January 7, 2004 to Apr. 15, 2020.⁷ 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.⁸ 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

⁷The exception is local currency bond returns, which only become available in 2008.

⁸We exclude China due to its unique characteristics, including its size relative to other emerging market economies and measurement issues.

Arab Emirates.⁹

2.2.1 Control variables

The literature on patterns of international capital flows separates determinants into common, global “push” factors associated with external shocks, and “pull” country-specific factors. Our control variables include both “push” and “pull” variables suggested by the literature on capital flows.

Following the literature on capital flow determinants (see, for example, Calvo, Leiderman, and Reinhart 1993; Fratzscher 2012; Fratzscher, Lo Duca, and Straub 2014; Passari and Rey 2015; Milesi Ferretti and Tille 2011; Broner et al. 2013; 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.¹⁰ We use year fixed effect 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 (see, for example, Ahmed and Zlate 2014; Forbes and Warnock 2012; Fratzscher 2012; Fratzscher, Lo Duca, and Straub 2013; Eichengreen and Gupta 2014; Moore et al. 2013; Chen, Mancini Griffoli, and Sahay 2014) include local policy rates, real GDP growth, and the broad real effective exchange rate (REER). To control for the influence of local macroeconomic news in the intervening week or day, we include the Citigroup Economic Surprise Index (CESI) for emerging markets. The CESI tracks how economic data compare to expectations, rising when economic data exceed economists’ consensus forecasts and falling when data come in below forecast estimates.¹¹

⁹EM classifications considered include the IMF, BRICS + Next 11, FTSE, MSCI, S&P, EMBI, Dow Jones, Russell, Columbia University EMPG and BBVA.

¹⁰All advanced economy variables comprise a USD real GDP-weighted average of the United States, the UK, the euro area and Japan.

¹¹Indices 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.

With the exception of emerging market news surprises, all control variables enter with a lag to rule out simultaneity.¹² 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 risk-on/risk-off 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.

3 Estimation and Results

We regress weekly EPFR country-level flows and daily returns onto our risk appetite measures using the panel quantile regression approach of Machado and Santos Silva (2019) with country and time fixed effects, controlling for the “push” and “pull” factors described previously. Country level flows enter as a percent of the previous week’s allocation, while total returns are expressed as a daily percentage change. As stated in the data description, in the EPFR flow regressions, changes in the risk measures are aggregated by a moving average.

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

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

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. RA_t is one of (i) the vector of risk/risk aversion measures from Bekaert et al (2020) or (ii) the RORO index in the next subsection. k_{it} is either equity or debt flows (K_{it}) scaled by holdings of the same, H_{it-1} . We cluster bootstrapped standard errors by country to account for serially correlated error terms.¹³

In general, risk-on, risk-off shocks have important implications not only for the median of emerging market flows and returns, but also for the tails of the distribution. In each case,

¹²While 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.

¹³We use bootstrap replications to test that the quantile-specific parameter values are statistically different than one another and find in each case that they are. These results are readily available on request.

a risk-off shock decreases flows and returns across the distribution. Further, in nearly every case we consider, 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 ($|\beta^{(.05)}| > |\beta^{(.5)}| > |\beta^{(.95)}|$). These patterns, as we show in the next subsection, come with some subtle but important caveats.

3.1 Risk-off Shocks and BEX (2020)

We turn first to the structural decomposition of Bekaert et al 2020, which facilitates a separation of risk aversion from physical risk. Figures 6a and 6b summarize the changes in the capital flow distributions when we employ Bekaert et al’s (2020) risk aversion. Specifically, in this instance RA_t is a vector consisting of the change in the risk aversion and physical risk components from that model. This approach reveals an interesting pattern underlying the heterogeneous reactions of the equity and fixed income distributions, which will have implications for the results we find using the statistical approach.

Within the structural decomposition, we find that the impact of risk aversion (and risk itself) on the distribution of fixed income flows follows the general pattern above; that is, a risk-off shock either to sentiment or physical risk measured in this way shifts the distribution to the left and lengthens the tails relative to the median. Interestingly, variation in the quantity of risk has a larger impact across the distribution and puts more weight in the left tail compared to risk aversion itself; this is the case across asset classes and is consistent with a risk-off shock triggering retrenchment or flight.¹⁴ Where bonds and equity funds (and also returns) differ is in their reactions in the dispersive impact of risk aversion shocks. This distinction offers a window into the workings of our statistical measure and enables us to consider risk measurement and co-movement more generally.

In the face of a physical risk shock, the distribution of equity flows reacts in step with the distribution of bond flows in that we observe a leftward shift (toward net outflows), with tails lengthening relative to the median. In contrast, a risk-off shock (as measured by changes in risk aversion) causes the equity flow distribution to become compressed, with the range of

¹⁴In the baseline specification, we constrain risk shocks to impact flows and returns symmetrically—an assumption we will relax in later sections. This implies that physical (as opposed to sentiment) risk-on shocks are associated with surges.

the distribution shrinking as it shifts left. In fact, positive coefficients in the left tail indicate that realizations below the 25th percentile do not just improve relative to the median, they improve in absolute terms as well. Harkening back to the decomposition of our statistical index with respect to sentiment and physical risk and previewing our findings using our statistical index, this will suggest that the distributional reaction that we observe with a statistical RORO shock evinces substantial sensitivity to changing risk aversion. This “tails-in” reaction suggests that risk-off shocks to sentiment drive net equity outflows primarily by setting off a sudden-stop, rather than flight.

3.2 Risk-off Shocks and RORO

Given the aforementioned limitations related to model mis-specification, we turn now to the reacts of EPFR flows and returns to our statistical RORO index, summarized in in Figures 5a - 6d, while Tables 5a - 6.2d isolate the risk-off regression coefficients for each case. As a reminder, each regression includes controls and various fixed effects; full results with all control variable coefficients are available in the Internet Appendix (Tables 4 - 6).¹⁵

Using our statistical RORO index. Figure 5a summarizes the impact of a one standard deviation risk-off RORO shock on the distribution of our EPFR flow measures and cements the importance of measuring the impact across the distribution. While the risk-off shock affects the median of the distribution in a similar manner across asset classes, the tails again behave differently. As in the case of physical risk from BEX 2020, we observe that the risk-off shock decreases bond outflow realizations in the left tail more than it decreases the median realization, and in turn decreases the highest inflow realizations less than the median. The net result is a leftward shift in the distribution, with a lengthening of the tails.

Notably, as we will see in a later exercise, the lengthening in the left tail causes “large” outflow realizations in the unconditional distribution to appear more common in the post-shock distribution. Second, the equity flow distribution also shifts to the left in the face of a risk-off shock; however, the dispersive impact differs by asset class, with the tails extending on the order of 1.5 times the median change in bonds but only 1.04 times the median in equity

¹⁵In order to better understand the role for the various subcomponents that constitute our empirical RORO measure, we also consider a version of the panel quantile regression where RA_t is a vector of the constituent subindices.

flows. The net result is a leftward shift in the distribution, with a modest lengthening of the tails. We observed using the structural decomposition that, while physical risk-off shocks are associated with a “tails-out” reaction of equity flows, risk-off shocks to sentiment compress the distribution. While we saw in the previous subsection that the effect of physical risk on the tail equity flows is larger, risk aversion plays a larger role driving our statistical measure of risk. On net, these countervailing forces nearly cancel each other out in the statistical measure’s impact on the tails of the equity flow distribution.

3.3 Risk-on Risk-off Constituents

Figures 7a and 7b provide a more nuanced picture of our statistical RORO index using a nested panel regression that includes the constituent sub-components (i.e., RA_t becomes the vector of statistical sub-indices).¹⁶ Including the constituent measures together suggests that much of the RORO baseline’s “shifting” impetus emanates in large part from corporate spreads for both equity and bond funds. The nested model also reveals funding liquidity as a prime source of the bond funds’ “tails-out” behavior relative to equity funds. Interestingly, once we include credit risk in the estimation with the advanced economy equity and volatility factor, the latter evinces less impact on equity funds. Interestingly, risk-off in the advanced economy equity factor drives bond inflows, which may reflect the risk-off behavior of rotating out of equities and into bonds.

Undertaking the same decomposition exercise from section 2, we regress the statistical sub-components on the BEX 2020 decomposition to get a sense of the headline index’s inner drivers. We see in figures 4 and table 4 that the credit risk factor (from corporate spreads) is nearly always explained largely by variation in physical risk. By contrast, the advanced economy return and volatility factor draws most of its variation from changes in risk aversion. In contrast, variation in the currency and funding liquidity factors draw fairly evenly from risk aversion and physical risk, leaning slightly toward the latter.

¹⁶The full regression results for each case are available in the Internet Appendix (Table 6).

3.4 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 decrease returns across the distribution, but physical risk pulls the tails out relative to the median, while risk aversion brings 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-off shock, the highest return realizations increase not only relative to the median, but 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, which again underscores the importance of modeling the full distribution.

Figure 5b summarizes the impact of a one standard deviation risk-off RORO shock on the distribution of fixed income and equity *returns*. Across all return types, a risk-off shock shifts the distribution to the left and lengthens the tails, worsening the most negative return realizations more than the median. The magnitude and dispersion of the impact, however, differs between fixed income and equity, and between local currency and USD denominated indices. In particular, a risk-off shock impacts the total return on the equity indices at a rate more than five times the impact on fixed income returns. As with the structural measures, 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 risk off shock.¹⁷ MSCI USD total returns decrease 28 - 32% more than the local currency equity returns in the face of a risk-off shock.

Figure 7c shows how emerging market returns react to the various elements of our RORO index, considered together. Here, advanced economy returns and volatilities, along with corporate spreads, drive the much of the overall magnitude of the distributional shift. This is more so the case for equity returns compared to fixed income returns, reflecting comovements

¹⁷While the impact on the local currency index is statistically insignificant, the comparison is still a useful one given that USD denominated bonds do react in a statistically significant manner.

in global equity returns documented elsewhere in the literature. However, asset classes and currencies all share increased distributional dispersion emanating primarily from credit risk as measured by corporate spreads. In the case of equity returns, the “tails-out” impetus from a risk-off credit risk shock counteracts the “tails-in” impetus from advanced economy equity return shocks. Here again we see a mapping to our chosen structural measures—Figure 6d suggests that risk shocks lengthen the tails enough to outweigh risk aversion’s distributional compression. The net result of both the structural and statistical measures, then, is to increase the incidence of extreme realizations. Taking into account the composition of the shocks, while risk aversion elicits a tails-in response from all returns, and the index draws more signal from risk aversion, the effect of the RORO index is tails-out because these prices vary strongly with the credit risk factor, which draws most of its variation from physical risk.

Comparatively smaller reactions stem from the other two component indices. Currency risk acts as a shift factor which, while always smaller in size than returns or spreads, contributes more to risk-off reactions in dollar denominated returns. Finally, across asset classes and currency denominations, the impact of funding liquidity barely registers, contributing little in the way of shifts or dispersion and almost always statistically insignificant.

3.5 Flight to Safety

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

Accordingly, we test the degree to which our various risk aversion measures reflect a flight-to-safety by repeating the above exercise replacing EPFR emerging market (risky asset) flows with the growth rate of assets held in U.S. money market mutual funds. These data are published by the Investment Company Institute, which reports money market fund assets

to the Federal Reserve each week. To isolate safe assets, we focus on the subset of funds that invest in U.S. government debt.

In this exercise, we 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. We also retain year fixed effects. We run the following regression:

$$g_t^{(q)} = \alpha^{(q)} + \delta_t^{(q)} + \beta^{(q)} RA_t + \gamma_1^{(q)} PUSH_t^k + \epsilon_t \quad (3)$$

Where $g_t^{(q)}$ is the weekly growth rate of government money market assets in quantile q , and RA_t , exactly as above, is either our RORO index or the risk/risk aversion decomposition from Bekaert et al. (2020).

Table 7 summarizes the results. In columns (1)-(4), we observe that risk-off RORO shocks drive *inflows* into Treasury-focused money market funds across the distribution of fund flows; this appear to be particularly true for the right tail, where larger inflows becomes more likely in the face of a risk-off shock. In columns (5)-(8), we show complementary results for the BEX decomposition. A shock to physical risk has some positive effect on government money market fund flows (although this effect is not consistent across the distribution). Risk aversion (risk-off) shocks drive the left tail of the distribution toward the median, but we do not observe statistically significant impacts elsewhere in the distribution. To examine these effects further, we separate these fund flows (in Internet Appendix Table 7) into two subsets of government money market funds, those available to institutions vs. those available to retail investors. We find that the largest effects documented in Table 7 are associated with institutional money market fund flows. Retail flows are considerably less sensitive to risk-off shocks. Taken together, we do detect across our various specifications some reaction to risk-off shocks in the allocation to safe assets in a manner that complements what we observe for risky assets.

4 Quantitative Exercise: An Application to the COVID-19 Crisis

The market turmoil surrounding the global transmission of COVID-19 in early 2020 generated movements in both emerging market portfolio assets and measures of risk that match or exceed the magnitude of other widely recognized risk-off events. Our approach allows us to quantify how the distribution of capital flow realizations changed in the face of COVID-19 shocks and how the sources of risk therein generated patterns distinct from other risk-off events. To quantify the impact of COVID-19 and other large risk-off periods, we undertake two exercises using fitted values from our analysis. First, we show counterfactual quantiles of the post-shock distribution of flows and compare them to the recent history of the data as follows. We define predicted capital flows \hat{k}^q as

$$\hat{k}^q = k^q + \hat{\beta}^q * shock * H \quad (4)$$

where \hat{k}^q is the estimated flow calculated from fitted values, k^q is the q th percentile observed country flow per week in the data since Jan. 2020, H is the average assets under management, and $shock$ is the 10th percentile shock realization in the COVID era (3.1 units). Table 8 reveals the economic magnitudes underlying the parameter values reported in the results.

Starting with bond flows, in the face of a unit shock, the median reallocation is an outflow of \$14.09 million, compared to a pre-shock 2020 median weekly inflow of \$3.7 million. This size shock increases outflow realizations in the 5th quantile by \$22 million per week, compared to \$17.8 million per week at the median. Inflow realizations at the 95th quantile decrease by \$14.8 million. A one standard deviation shock, 3.1 units, increases outflow realization by \$68.03 million, compared to a change of \$55.2 million at the median and \$43.5 million at the 95th quantile. In the peak observation of the COVID-19 crisis, the index reached 11.56 standard deviations, suggesting that Q5, Q50 and Q95 would fall by \$256.7 million, \$205.9 million, and \$162.14 million respectively. A shock of this size pulls the tail realizations apart by \$92 million.

As aforementioned, equity flows show a shrinking of the tails in the event of a risk-off shock. After a one unit shock, the median reallocation is an outflow of \$18.84, compared to a pre-shock 2020 median outflow of \$5.8 million. This size shock increases outflow realizations

in the 5th quantile by \$16.28 million per week, compared to \$18.8 million per week at the median. Inflow realizations at the 95th quantile decrease by \$21.4 million. A one standard deviation shock, 3.1 units, increases outflow realization by \$50.5 million, compared to a change of \$58.4 million at the median and \$66.3 million at the 95th quantile. In the peak observation of the COVID-19 crisis, the index reached 11.56 standard deviations, suggesting that Q5, Q50 and Q95 would fall by \$188.2 million, \$217.7 million, and \$247.3 million respectively. A shock of this size pulls the tail realizations in by \$59 million. Under the peak shock, even the “best” realizations manifest as equity fund outflows.

Second, we fit a kernel density to the predicted values to visualize changes in the flow or return distribution from a 3-unit risk-off shock, displayed in Figure 9. We show 3-unit shocks because this magnitude represents the threshold of the 10th percentile among risk-off shocks in 2020. The fitted distribution of fixed income flows has longer tails and is more highly skewed toward outflows compared to the unconditional distribution (-.61 vs. -1.01). In terms of magnitude, in the face of a 3-unit shock, what would be a tail event in the unconditional distribution looks more like a 10th quantile shock, and therefore more probable. The post-shock median now falls in the bottom 25% of pre-shock realizations. The equity flow distribution appears unchanged in terms of skewness, although here as well the post-shock median falls in the bottom 25% of pre-shock realizations.

The return distributions show more dramatic changes still, although the skewness of the distributions show little change. What the unconditional equity distribution would label a tail outcome lay near the median in the post-shock distribution. While our RORO shock affects EMBI returns to a comparatively smaller degree, the pre-shock tail event still falls within the interquartile range of the unconditional distribution.

Figure 10 repeats this exercise for the subcomponents of Bekaert et al (2020). The conditional distributions attributed to each subcomponent in these figures represents the response of the distribution to a three standard deviation shock to one factor, controlling for the other. We see that, for bond flows, risk aversion and risk contribute in roughly equal measure to the increased mass of value under the left tail, while risk represents the greater force in pushing equity outcomes past the 5th quantile of the unconditional equity flow distribution. In contrast, risk aversion plays a larger role in worsening negative return distributions, particularly

in bond returns.

5 Conclusion and Future Directions

Risk-on/risk-off shocks have important distributional implications for emerging market portfolio flows and returns. In particular, we find that the effects associated with the worst realizations are often disproportionately affected by risk-off shocks. Specifically, while there are some differences in the effects across bond vs. equity markets and flows vs. asset returns, the effects associated with the left tail are generally larger than that on the median realization. We conclude that the focus in the literature on measures of central tendency is incomplete.

A natural next question for our research agenda: do the implications of a RORO shock differ across recipient countries? Given that the mutual fund business exhibits significant variation in manager discretion, the heterogeneity question has two dimensions. The first is country-level heterogeneity, meaning are the effects of an external RORO shock disproportionately experienced across countries along important dimensions. Gelos et al. (2019) show that variation in recipient country economic policy and business fundamentals affect capital flows. In the context of our setting, the question arises whether recipient country conditions impact fund reallocation in the face of risk-off shocks. In particular, we want to be able to address the extent to which fund managers view emerging markets as a single asset class or whether country fundamentals matter for fund allocations.

An important caveat, however, is that the level of discretion fund managers possess varies considerably across fund type. Representing about half of the emerging market fund space towards the end of the sample, passive index funds and ETFs have very little manager discretion. As a consequence, passive index fund and ETF re-allocation in the face of a risk-off shock may induce elevated correlations among countries and minimize the effect of cross-country heterogeneity. Actively managed mutual funds, however, enjoy considerable discretion. Country fundamentals may be central to their allocation decision. Preliminary results separating ETFs from active and passive mutual funds suggest that the ETFs appear to play a critical role in driving the baseline results. Going forward, we will assess the complete effect of tail events on capital flows by closely examining these actual vehicles that investors use to

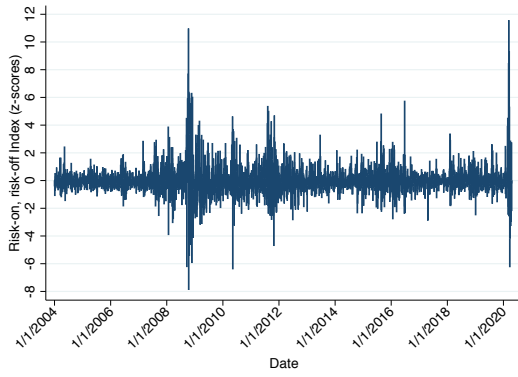
access emerging markets.

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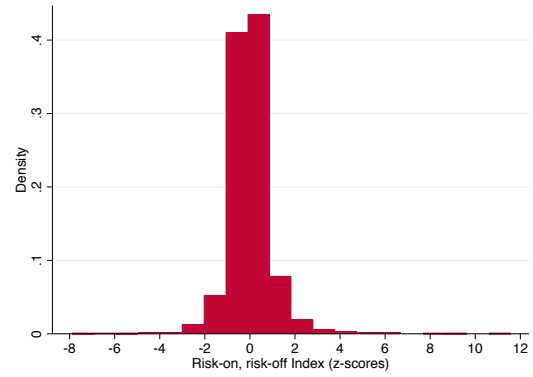
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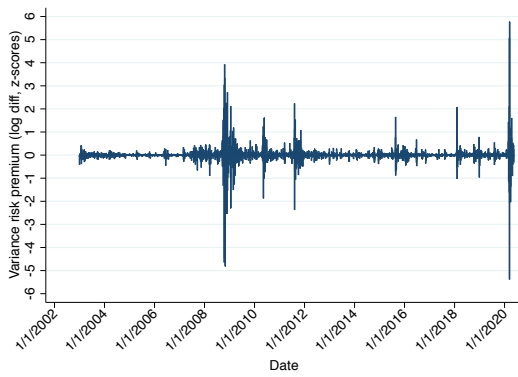
Figure 1: Risk-on/Risk-off Measures



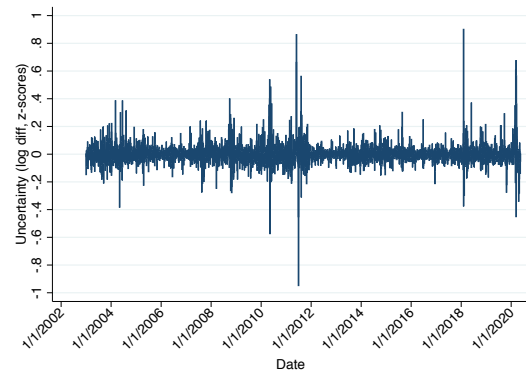
(a) Time series: RORO



(b) Histogram: RORO

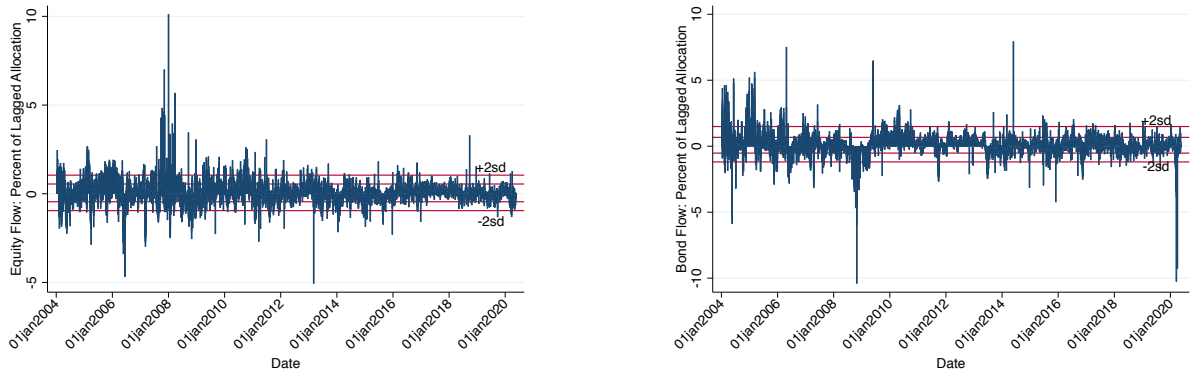


(c) Time Series (log difference): Risk Aversion (Bekaert et al 2020)

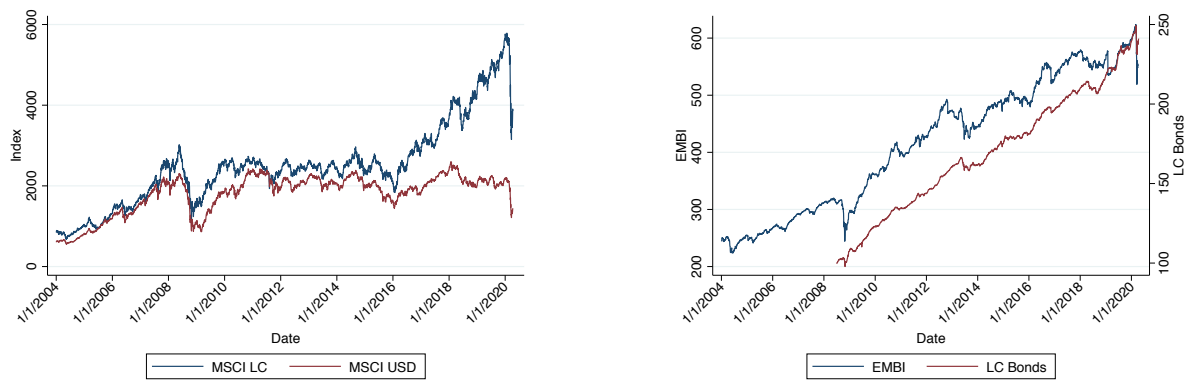


(d) Time Series (log difference): Risk (Bekaert et al 2020)

Figure 2: Emerging Market Flows and Returns



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



(b) Total Return Indices

Figure 3: Explained Variation

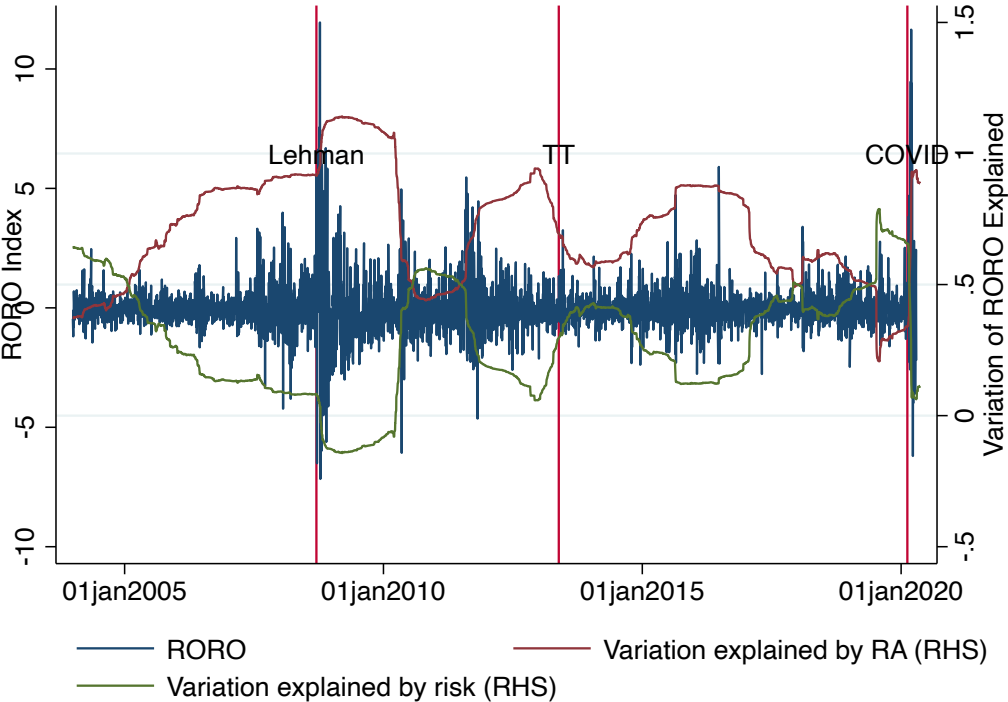
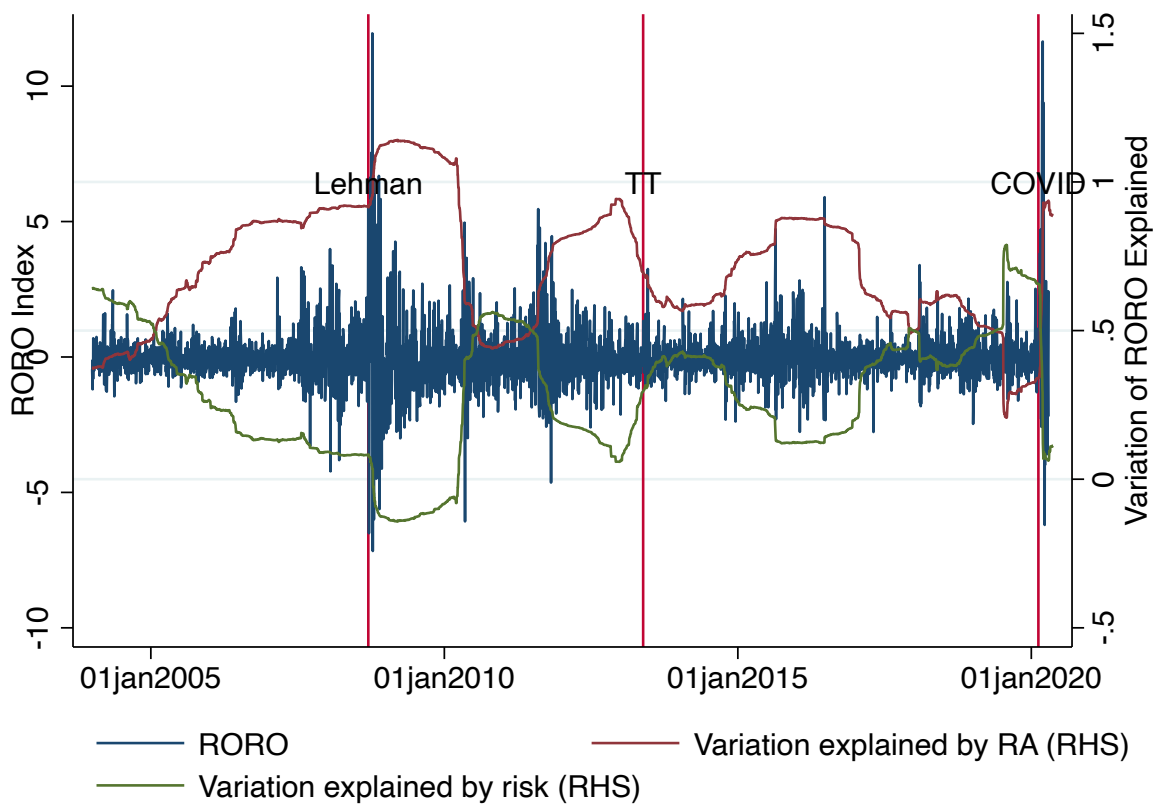
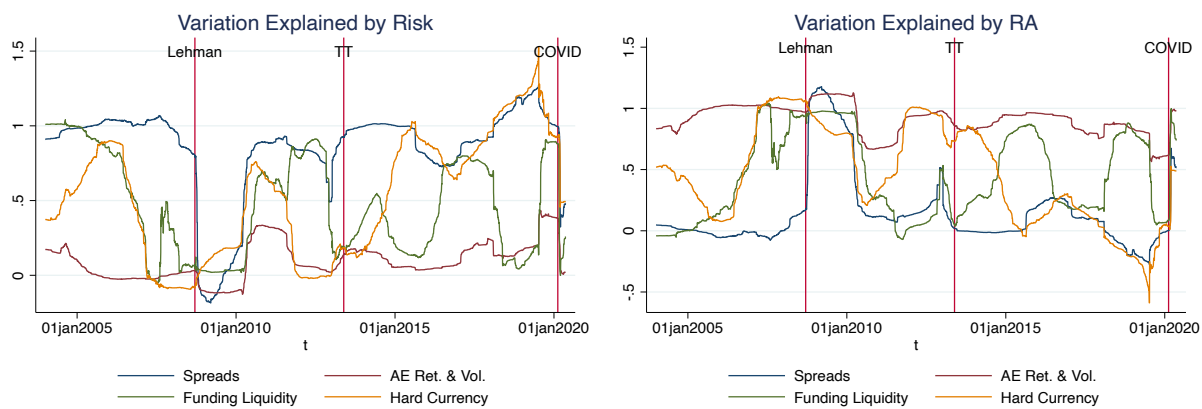


Figure 4: Explained Variation



(a) Headline RORO Index



(b) Constituent Sub-indices

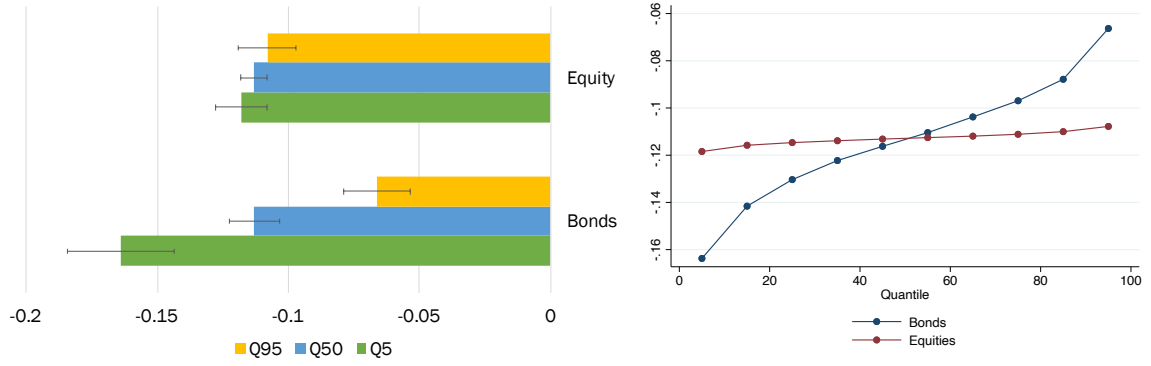


Figure 5a: A one standard deviation risk-off (RORO) shock & the distribution of EPFR flows (% of AUM)
 Notes: This figure summarizes the impact of a one-standard deviation risk-off shock as measured by our RORO Index. Error bars represent 90% confidence intervals.

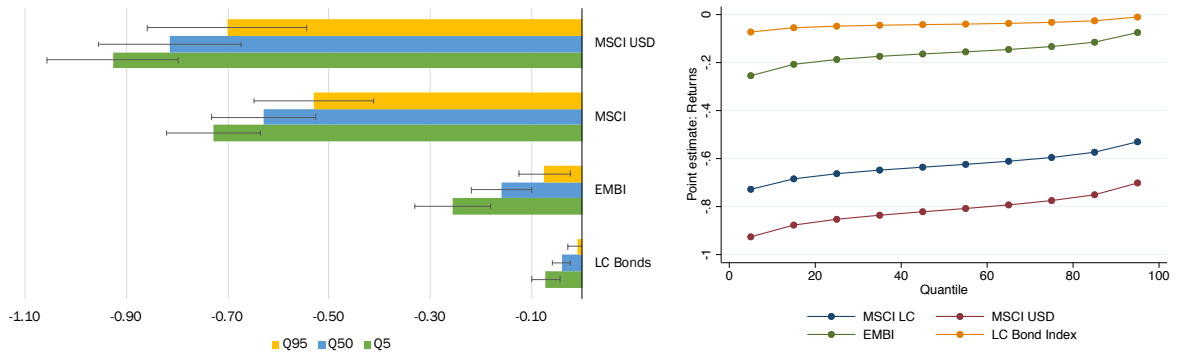
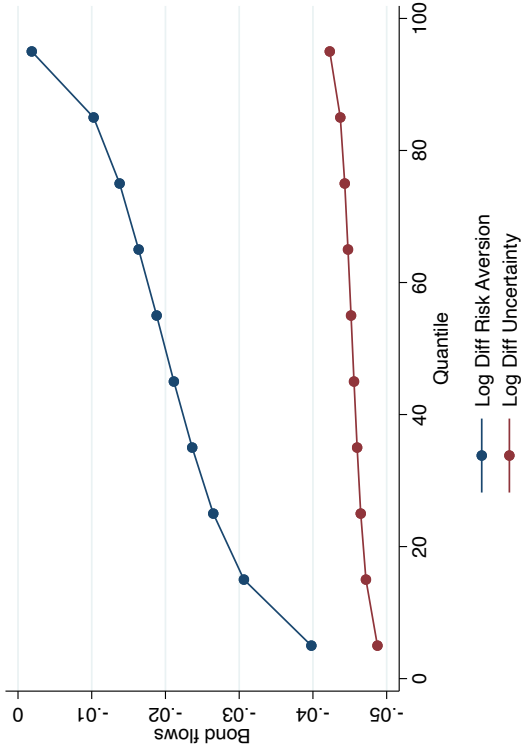
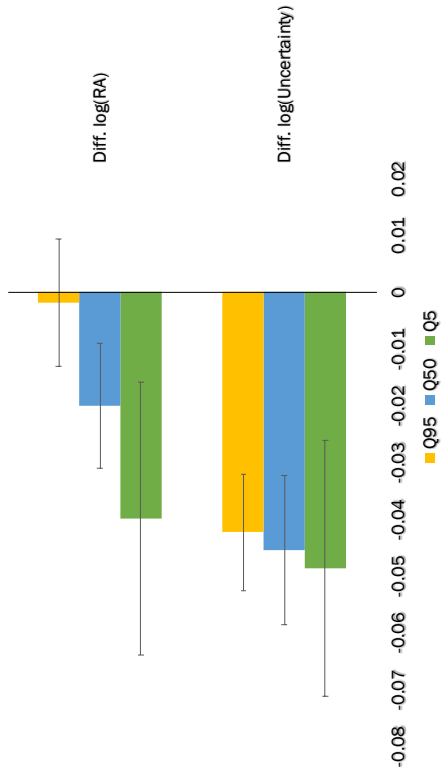
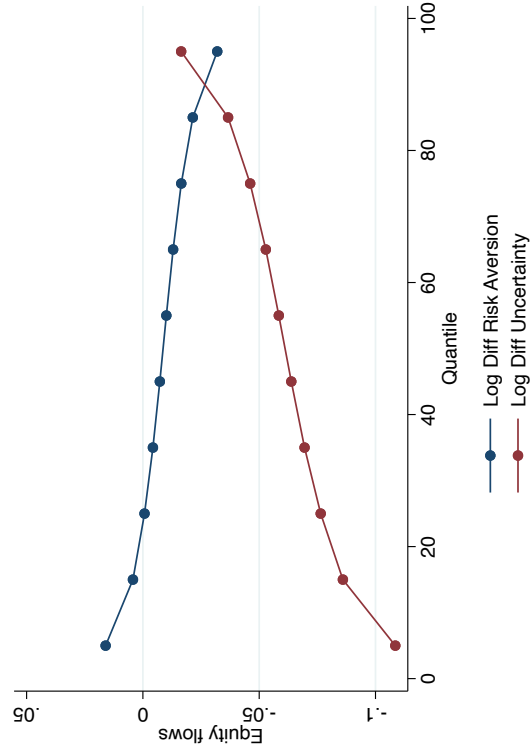
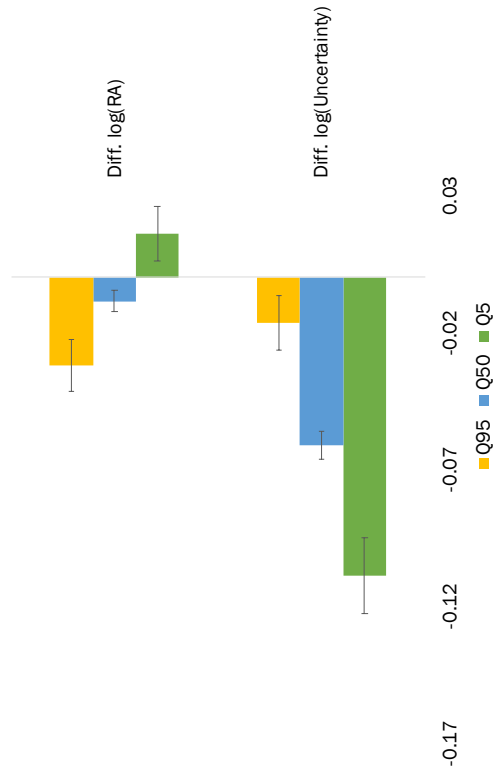


Figure 5b: Impact of a one standard deviation risk-off (RORO) shock on the distribution of returns
 Notes: This figure summarizes the impact of a one-standard deviation risk-off shock as measured by our RORO Index. Error bars represent 90% confidence intervals.



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



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

Figure 6a: Impact of a one standard deviation risk-off (BEX) shock on the distribution of EPFR flows (% of AUM)
 Notes: This figure summarizes the impact of a one-standard deviation risk-off shock as measured by Bekaert et al (2020). Error bars represent 90% confidence intervals.

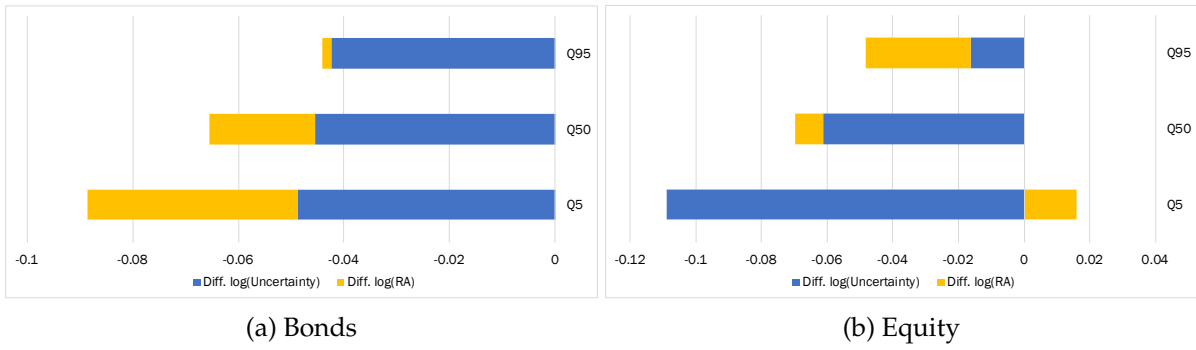
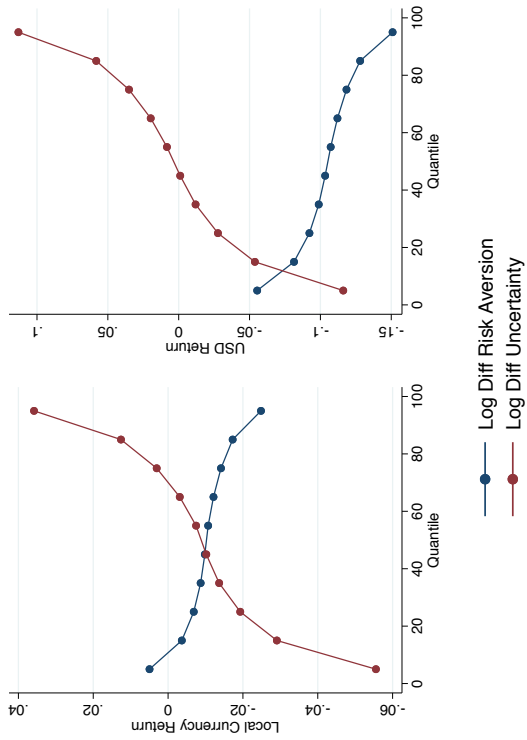
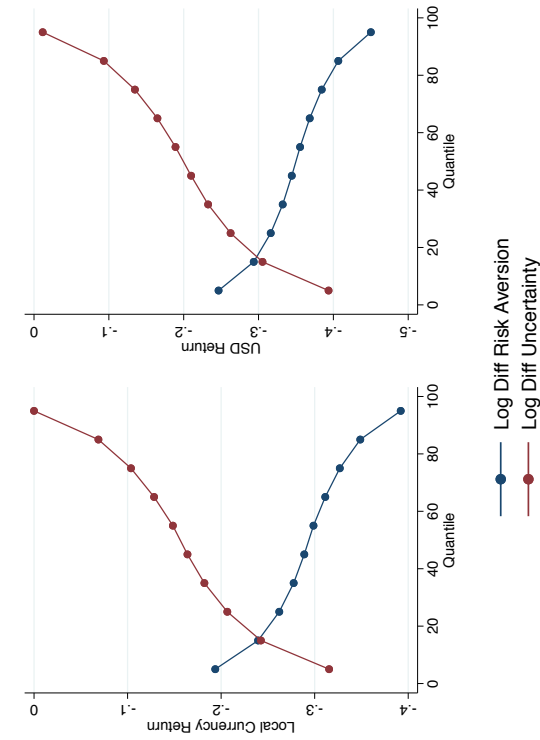


Figure 6b: A one standard deviation constituent risk-off (BEX) shock & the distribution of EPFR flows (% of AUM)
 Notes: This figure summarizes the impact of a one-standard deviation risk-off shock as measured by Bekaert et al (2020).



(a) Bond Returns



(b) Equity Returns

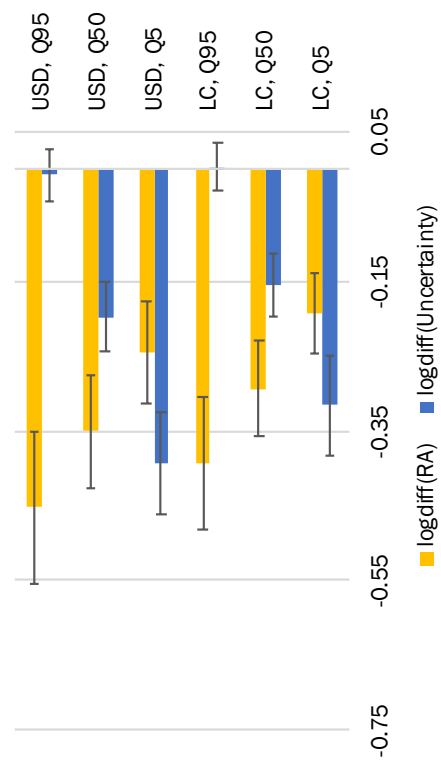
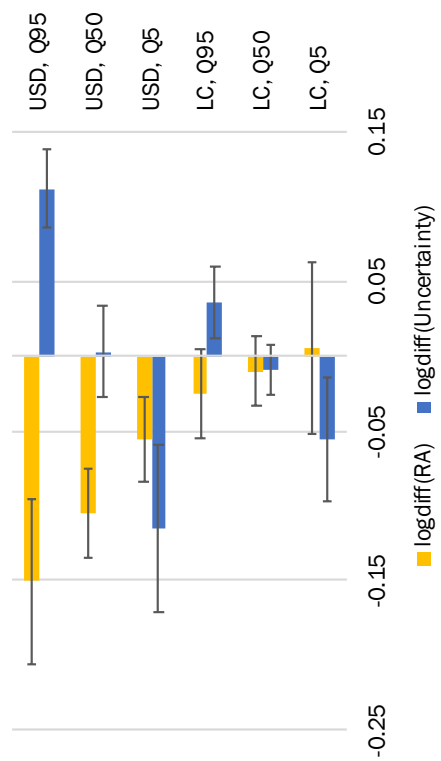


Figure 6c: Impact of a one standard deviation risk-off shock on the distribution of EPFR flows (% of AUM)
 Notes: This figure summarizes the impact of a one-standard deviation risk-off shock as measured by Bekaert et al (2020). Error bars represent 90% confidence intervals.

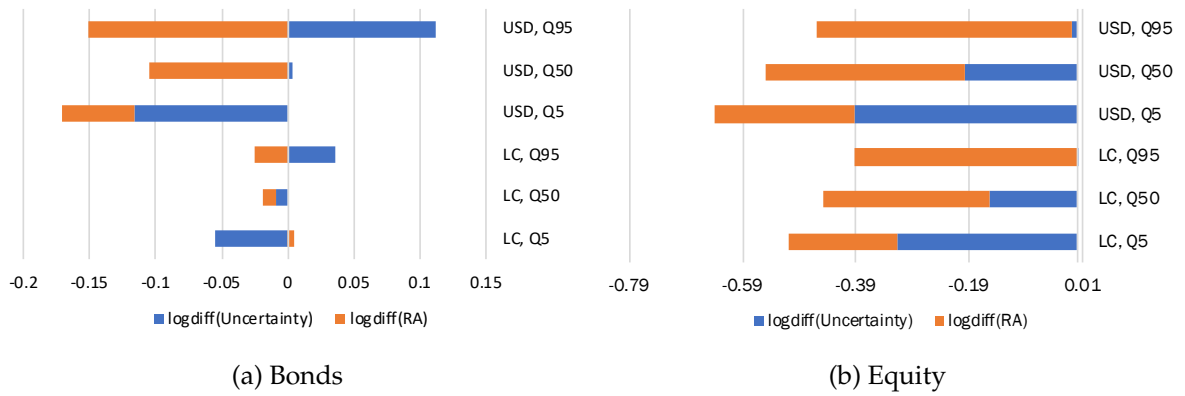


Figure 6d: A one standard deviation constituent risk-off (BEX) shock & the distribution of returns

Notes: This figure summarizes the impact of a one-standard deviation risk-off shock as measured by Bekaert et al (2020).

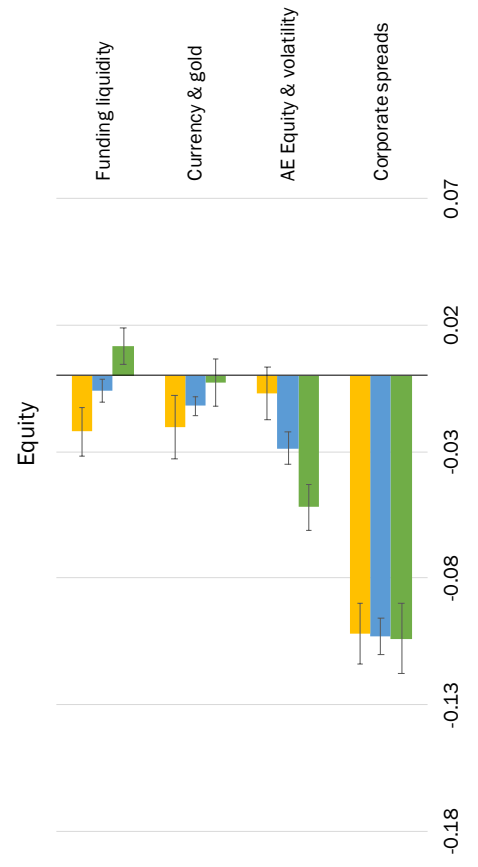
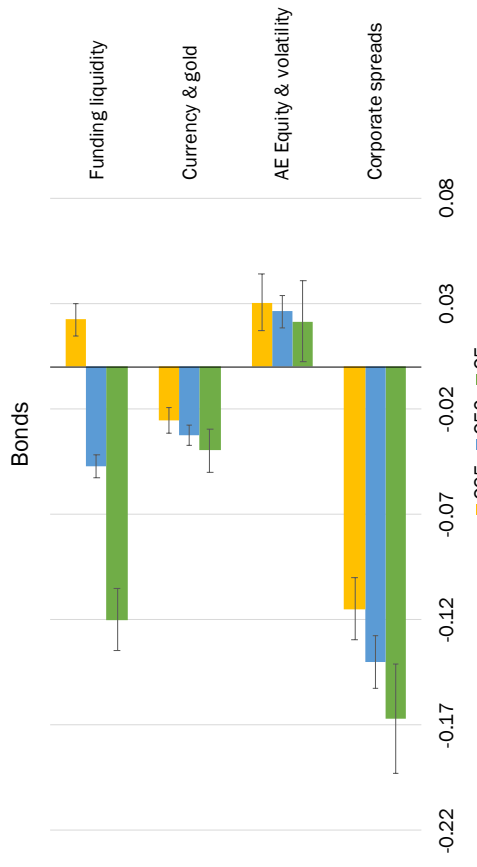
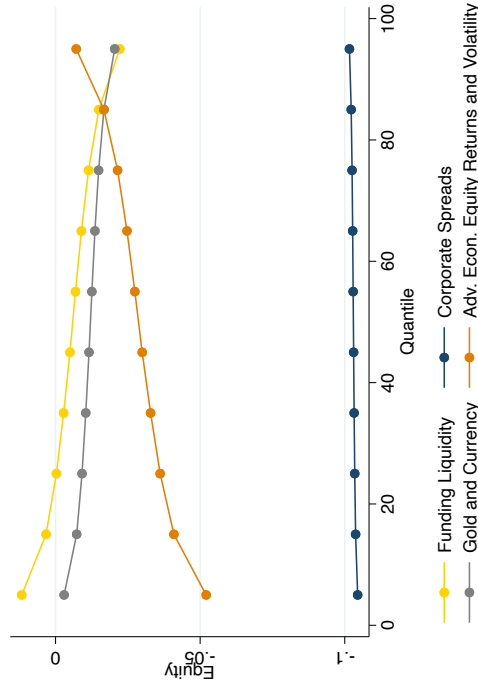


Figure 7a: Impact of a one standard deviation risk-off shock on the distribution of EPFR flows (% of AUM)
 Notes: This figure summarizes the impact of a one-standard deviation risk-off shock as measured by our constituent sub-indices index. Error bars represent 90% confidence intervals.

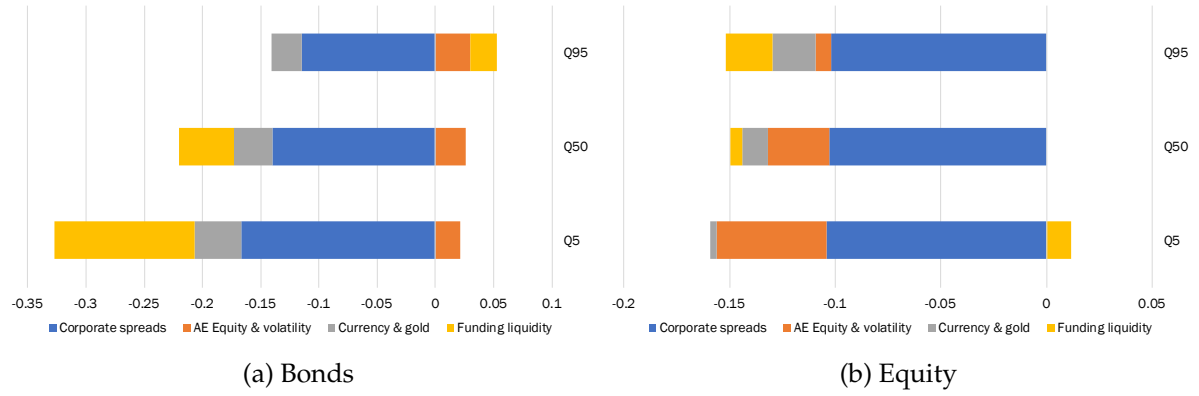


Figure 7b: A one standard deviation constituent risk-off (RORO) shock & the distribution of EPFR flows (% of AUM)

Notes: This figure summarizes the impact of a one-standard deviation risk-off shock as measured by our RORO subindices.

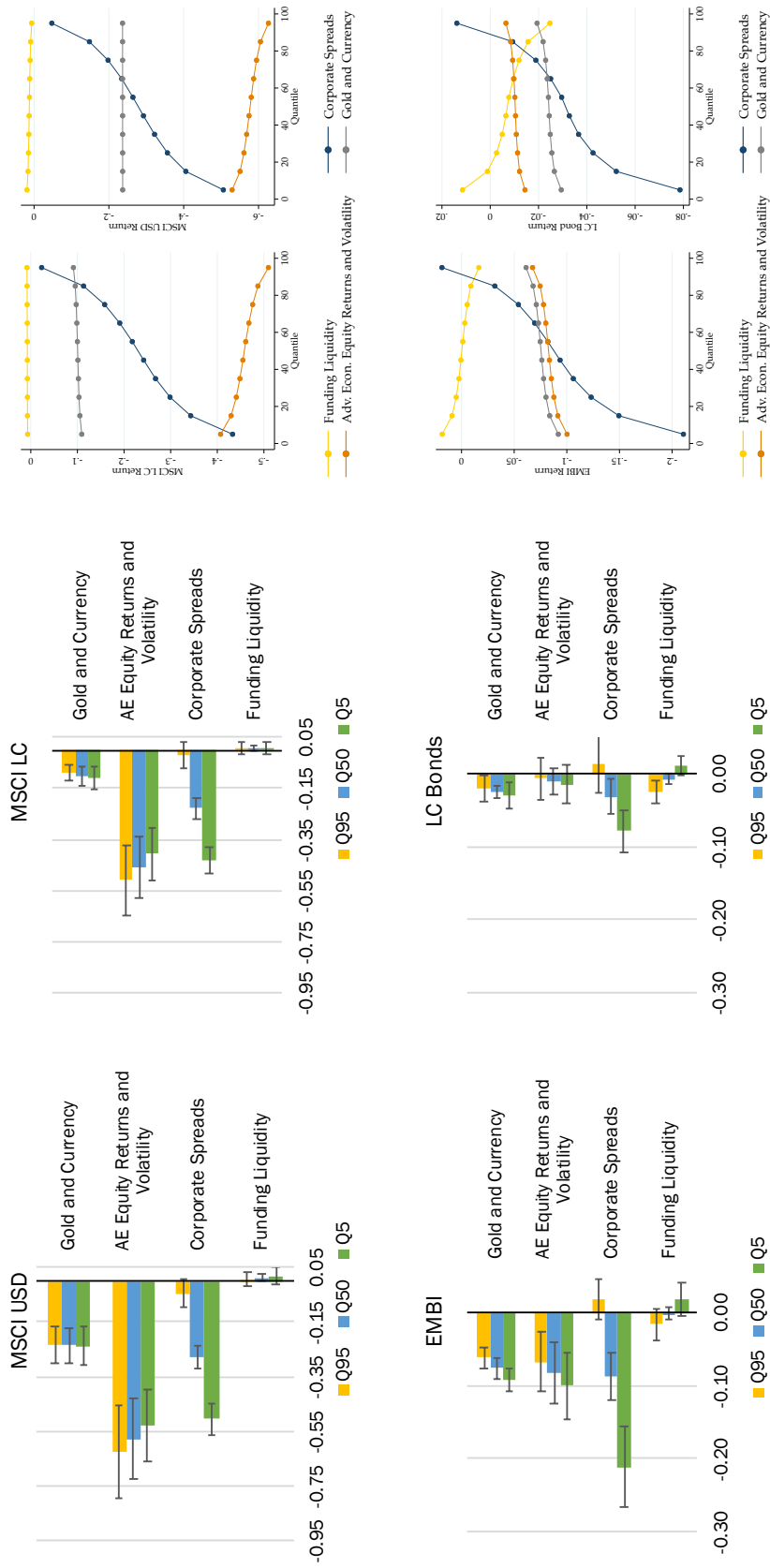


Figure 7c: Impact of a one standard deviation risk-off shock on the distribution of returns

Notes: This figure summarizes the impact of a one-standard deviation risk-off shock as measured by our constituent sub-indices. Error bars represent 90% confidence intervals.

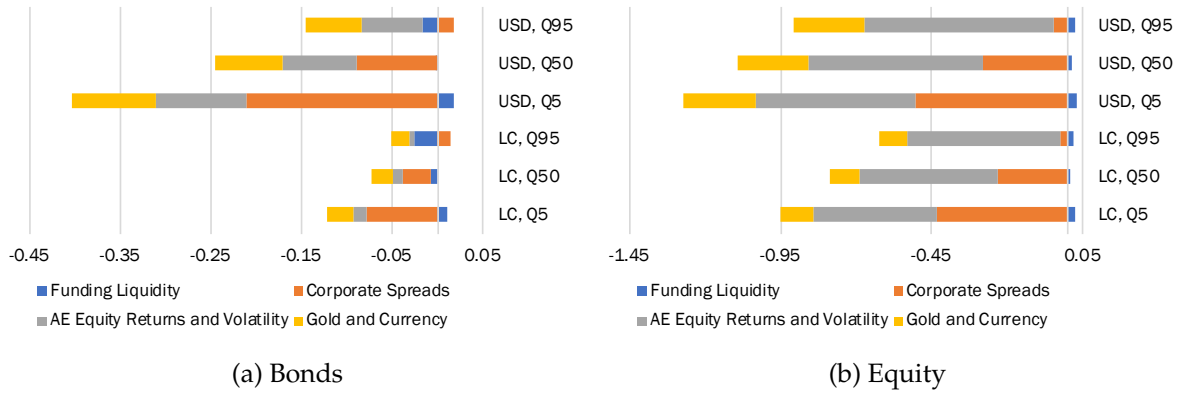
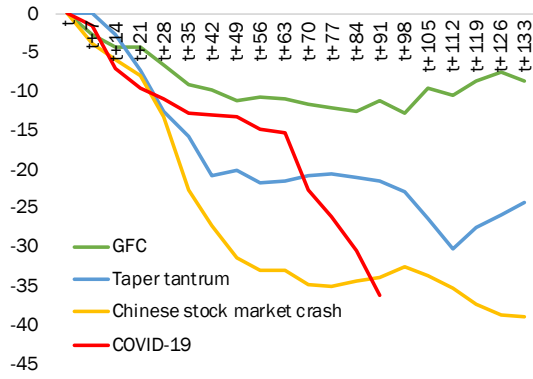


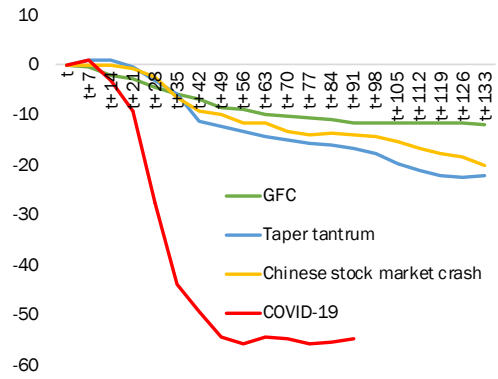
Figure 7d: A one standard deviation constituent risk-off (RORO) shock & the distribution of returns

Notes: This figure summarizes the impact of a one-standard deviation risk-off shock as measured by our RORO subindices.

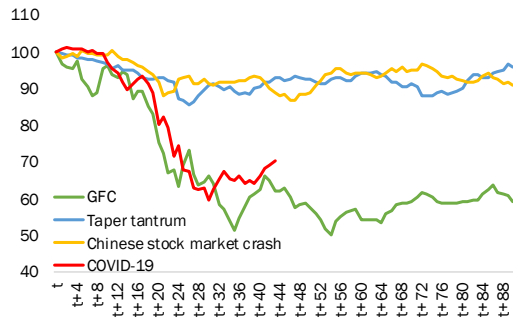
Figure 8: Emerging market capital flows and returns in recent risk-off episodes



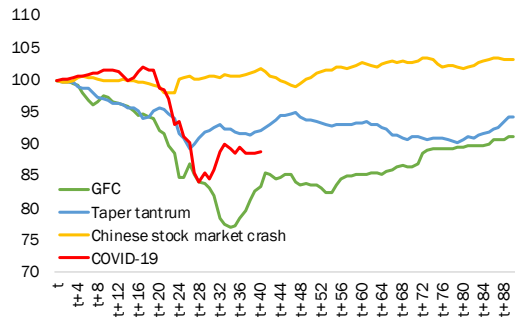
(a) Equity flows (USD Billions)



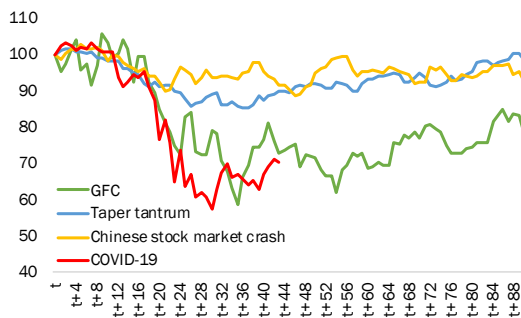
(b) Bond flows (USD Billions)



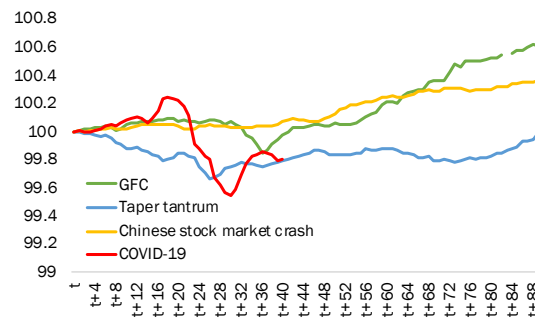
(c) MSCI USD



(d) EMBI

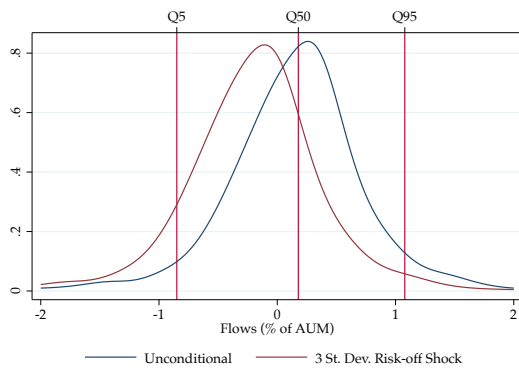


(e) MSCI LC

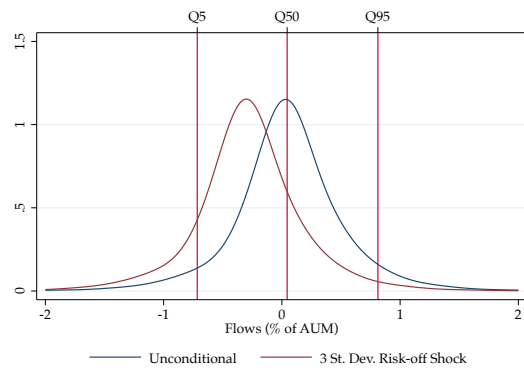


(f) Local currency Bond Index

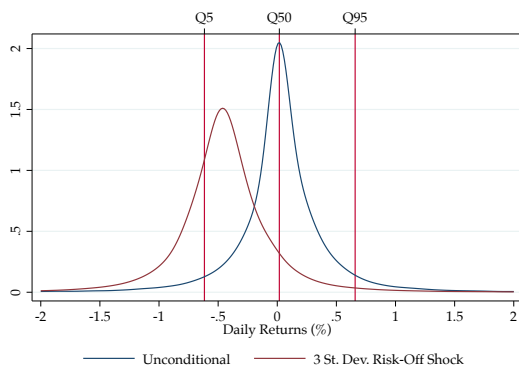
Figure 9: Effect of a three standard deviation risk-off shock on the distribution of returns and EPFR flows



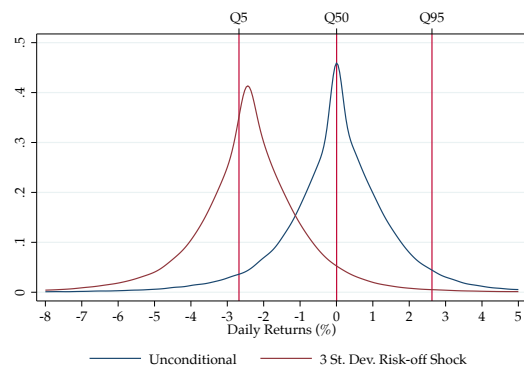
(a) Bond flows



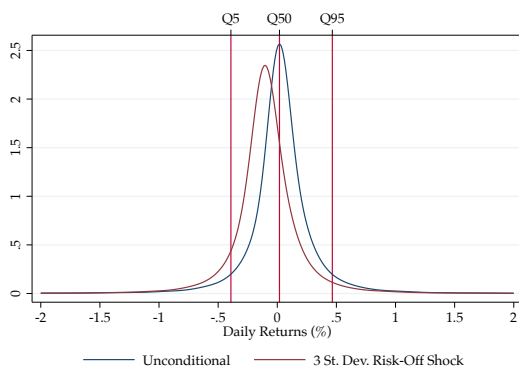
(b) Equity flows



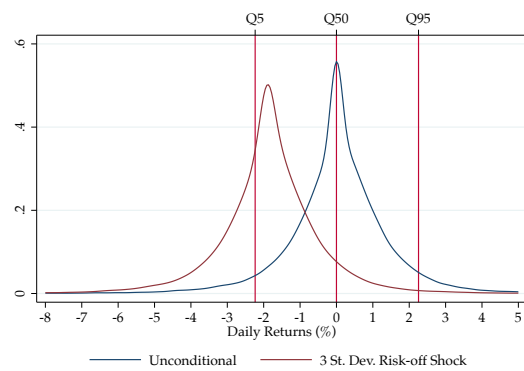
(c) EMBI



(d) MSCI USD

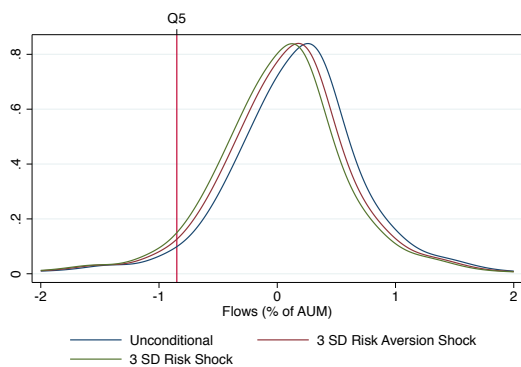


(e) LC Bond Index

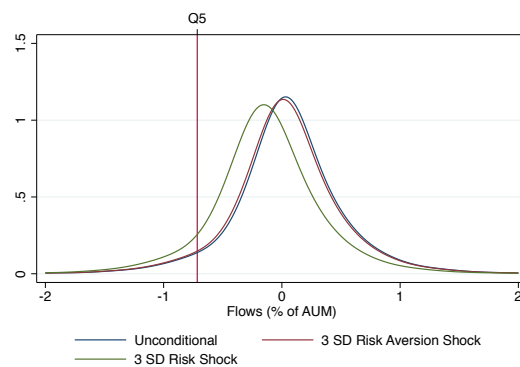


(f) MSCI LC

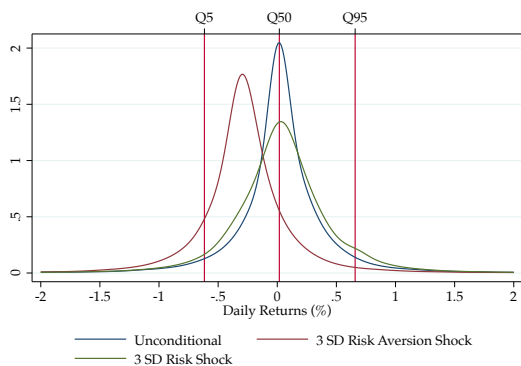
Figure 10: Effect of a three standard deviation risk-off BEX shock on the distribution of returns and EPFR flows



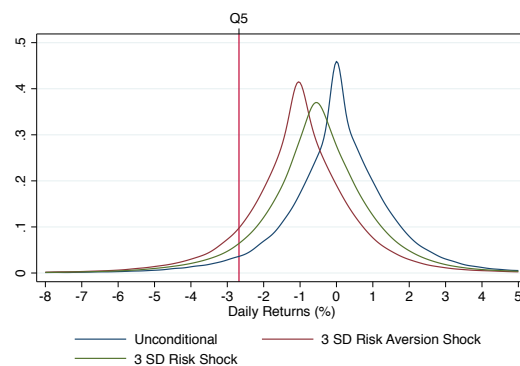
(a) Bond flows



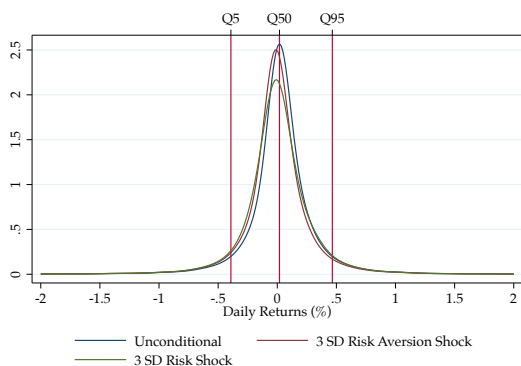
(b) Equity flows



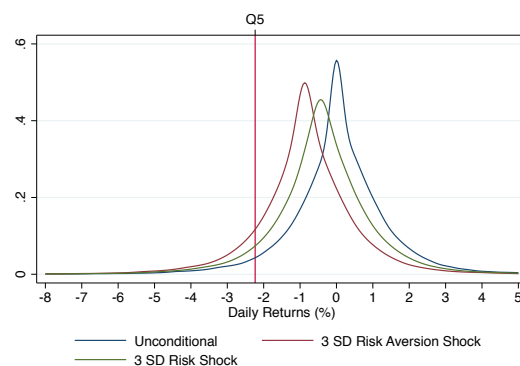
(c) EMBI



(d) MSCI USD



(e) LC Bond Index



(f) MSCI LC

Table 1.1: Risk-on/Risk-off Summary Statistics

	Q5	Q50	Q95	Skewness	Kurtosis
RORO Index	-1.32	-0.08	1.54	1.91	22.84
Funding Liquidity	-0.90	0.01	0.86	1.15	80.71
AE Equity Returns/Volatility	-1.36	-0.07	1.55	1.25	20.03
Gold and Currencies	-1.70	-0.01	1.77	0.14	5.77
Corporate Spreads	-1.30	-0.07	1.31	2.43	34.93
Log Diff. Risk Aversion	-0.72	-0.00	0.74	0.03	112.09
Log Diff. Uncertainty	-1.12	-0.06	1.27	1.36	30.86
Observations	4517				

Table 1.2: Emerging Market Summary Statistics

(a) 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						

(b) 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 2: Correlations

	RORO Index	Log Diff. Risk Aversion	Log Diff. Uncertainty
RORO Index	1		
Log Diff. Risk Aversion	0.607***	1	
Log Diff. Uncertainty	0.584***	0.560***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Regressions

	(1) RORO Index	(2) RORO Index	(3) RORO Index
Risk Aversion \perp Risk	0.609*** (11.75)		0.610*** (14.17)
Risk \perp Risk Aversion		0.296*** (8.11)	0.297*** (9.72)
Constant	0.00132 (0.11)	-0.000628 (-0.04)	-0.000685 (-0.06)
Observations	4270	4270	4270
R^2	0.368	0.086	0.455

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Average Explained Variation

	Risk Aversion	Risk
RORO	0.701 (0.217)	0.300 (0.220)
Funding Liquidity	0.419 (0.360)	0.494 (0.351)
Credit Risk	0.138 (0.294)	0.848 (0.296)
AE Returns and Volatility	0.906 (0.121)	0.0945 (0.124)
Currency	0.457 (0.395)	0.513 (0.398)

Table 5: Impact of a one standard deviation risk-off (RORO) shock

(a) Bond flows					
	(1)	(2)	(3)	(4)	(5)
	Q5	Q25	Q50	Q75	Q95
RORO Index	-0.164*** (-13.27)	-0.130*** (-16.97)	-0.113*** (-19.40)	-0.0969*** (-17.50)	-0.0663*** (-8.52)
Observations	17607	17607	17607	17607	17607
(b) Equity flows					
RORO Index	-0.118*** (-19.62)	-0.115*** (-35.52)	-0.113*** (-37.53)	-0.111*** (-29.14)	-0.108*** (-16.24)
Observations	17659	17659	17659	17659	17659
(c) USD equity returns					
RORO Index	-0.926*** (-11.78)	-0.853*** (-10.20)	-0.815*** (-9.51)	-0.775*** (-8.77)	-0.701*** (-7.34)
Observations	84794	84794	84794	84794	84794
(d) Local currency equity returns					
RORO Index	-0.926*** (-11.78)	-0.853*** (-10.20)	-0.815*** (-9.51)	-0.775*** (-8.77)	-0.701*** (-7.34)
Observations	84794	84794	84794	84794	84794
(e) USD bond returns					
RORO Index	-0.255*** (-5.57)	-0.187*** (-4.87)	-0.160*** (-4.40)	-0.133*** (-3.89)	-0.0740* (-2.42)
Observations	72192	72192	72192	72192	72192
(f) Local currency bond returns					
RORO Index	-0.0731*** (-4.32)	-0.0484*** (-4.14)	-0.0408*** (-3.86)	-0.0322** (-3.15)	-0.00961 (-0.81)
Observations	49045	49045	49045	49045	49045

Table 5 summarizes the results of quantile regressions of a) bond flows, b) equity flows, c) USD MSCI equity returns, d) local currency MSCI equity returns, e) EMBI USD bond returns, and f) local currency daily total returns on our headline RORO index. 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 of RORO at the 10%, 5%, and 1% levels, respectively.

Table 6.1: Impact of a one standard deviation risk-off (BEX) shock on EPFR flows (% of AUM)

(a) Bond flows					
	(1)	(2)	(3)	(4)	(5)
	Q5	Q25	Q50	Q75	Q95
Log Diff. Risk Aversion	-0.0398** (-2.72)	-0.0265** (-2.97)	-0.0200** (-3.00)	-0.0138* (-2.57)	-0.00186 (-0.27)
Log Diff. Risk	-0.0487*** (-3.56)	-0.0465*** (-4.83)	-0.0454*** (-5.71)	-0.0443*** (-6.57)	-0.0423*** (-6.77)
Observations	17436	17436	17436	17436	17436
(b) Equity flows					
Log Diff. Risk Aversion	0.0160** (2.59)	-0.000685 (-0.22)	-0.00870*** (-3.65)	-0.0165*** (-5.70)	-0.0320*** (-5.60)
Log Diff. Risk	-0.109*** (-12.86)	-0.0764*** (-16.70)	-0.0611*** (-19.58)	-0.0461*** (-15.49)	-0.0164** (-2.72)
Observations	17487	17487	17487	17487	17487

Table 6.1 summarizes the results of quantile regressions of a) bond flows and b) equity flows on our chosen structural shocks from Bekaert et al 2019. 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 of RORO at the 10%, 5%, and 1% levels, respectively.

Table 6.2: Impact of a one standard deviation risk-off (BEX) shock on returns

(a) MSCI USD					
	Q5	Q25	Q50	Q75	Q95
Log Diff. Risk Aversion	-0.247*** (-5.89)	-0.318*** (-7.45)	-0.351*** (-7.59)	-0.386*** (-7.54)	-0.453*** (-7.35)
Log Diff. Risk	-0.395*** (-9.38)	-0.262*** (-7.79)	-0.198*** (-6.99)	-0.133*** (-5.53)	-0.00830 (-0.38)
Observations	84730	84730	84730	84730	84730
(b) MSCI Local currency					
Log Diff. Risk Aversion	-0.195*** (-5.83)	-0.263*** (-7.55)	-0.295*** (-7.61)	-0.328*** (-7.53)	-0.394*** (-7.32)
Log Diff. Risk	-0.316*** (-7.68)	-0.206*** (-6.63)	-0.156*** (-6.11)	-0.102*** (-4.89)	0.00235 (0.12)
Observations	84751	84751	84751	84751	84751
(c) EMBI					
Log Diff. Risk Aversion	-0.0558** (-3.24)	-0.0924*** (-6.06)	-0.105*** (-5.80)	-0.119*** (-5.39)	-0.151*** (-4.53)
Log Diff. Risk	-0.116*** (-3.40)	-0.0282 (-1.34)	0.00299 (0.16)	0.0348* (1.98)	0.114*** (7.03)
Observations	72131	72131	72131	72131	72131
(d) Local currency bond index					
Log Diff. Risk Aversion	0.00487 (0.14)	-0.00683 (-0.42)	-0.0102 (-0.73)	-0.0141 (-1.22)	-0.0245 (-1.37)
Log Diff. Risk	-0.0565* (-2.23)	-0.0195 (-1.80)	-0.00904 (-0.87)	0.00330 (0.34)	0.0364* (2.46)
Observations	49079	49079	49079	49079	49079

Table 6.2 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 2019. 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 of RORO at the 10%, 5%, and 1% levels, respectively.

Table 7: A one standard deviation risk-off shock & the distribution of government money market fund assets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Q5	Q50	OLS	Q95	Q5	Q50	OLS	Q95
RORO Index	0.167** (2.87)	0.217*** (5.43)	0.275** (2.88)	0.432* (2.14)				
AE Mkt. Return	0.0914*** (6.95)	0.0658*** (6.67)	0.100*** (6.74)	0.110*** (3.85)	0.0946*** (6.53)	0.0621*** (6.75)	0.0965*** (6.71)	0.104** (2.62)
AE Real GDP Growth (t-1)	-10.36 (-1.76)	0.749 (0.09)	-8.561 (-0.96)	-41.37 (-1.35)	-5.779 (-0.79)	-4.893 (-0.83)	-9.549 (-1.10)	-28.84 (-0.85)
AE Monetary Stance (t-1)	0.494*** (3.59)	0.360* (2.42)	0.812*** (3.33)	1.112** (2.75)	0.533* (2.49)	0.387** (2.90)	0.773** (3.26)	0.754 (1.34)
Log Diff. Risk Aversion					0.182* (2.33)	-0.0821 (-1.36)	-0.0979 (-0.62)	-0.346 (-0.92)
Log Diff. Risk					-0.0160 (-0.19)	0.309*** (5.46)	0.298 (1.91)	0.410 (1.45)
Constant	-15.69*** (-8.58)	-10.51*** (-5.96)	-16.47*** (-5.74)	-16.41* (-2.51)	-16.38*** (-6.59)	-10.02*** (-5.88)	-15.74*** (-5.74)	-14.93 (-1.69)
Observations	628	628	628	628	656	656	656	656

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7 summarizes the results of quantile regressions of changes in government money market funds on our RORO and BEX indices. Bootstrapped standard errors are clustered by country.

Table 8: Effect of a COVID-era risk-off shock on the distribution of country EPFR flows

(a) RORO Index

	Panel A: Bonds	Q5	Q50	Q95	Panel B: Equity	Q5	Q50	Q95
	Observed flows	-473.56	3.73	178.13	Observed flows	-258.62	-5.79	109.69
β (unconditional) $\sigma = 1$	% of AUM/week	-0.16	-0.11	-0.07	% of AUM/week	-0.12	-0.11	-0.11
	Millions USD	-503.55	-16.94	166.01	Millions USD	-280.20	-26.45	89.94
$\beta^* \text{Covid1Stdev}$ $\sigma = 3.1$	% of AUM/week	-0.51	-0.35	-0.21	% of AUM/week	-0.37	-0.35	-0.33
	Millions USD	-566.53	-60.33	140.55	Millions USD	-325.52	-69.85	48.47
$\beta^* \text{CovidPeak}$ $\sigma = 11.56$	% of AUM/week	-1.90	-1.31	-0.77	% of AUM/week	-1.36	-1.31	-1.25
	Millions USD	-820.26	-235.16	37.97	Millions USD	-508.08	-244.67	-118.62

(b) Risk Aversion (BEX 2020)

	Panel A: Bonds	Q5	Q50	Q95	Panel B: Equity	Q5	Q50	Q95
	Observed flows	-473.56	3.73	178.13	Observed flows	-258.62	-5.79	109.69
β (unconditional) $\sigma = 1$	% of AUM/week	-0.04	-0.02	0.00	% of AUM/week	0.02	-0.01	-0.03
	Millions USD	-480.84	0.07	177.79	Millions USD	-255.70	-7.38	103.84
$\beta^* \text{Covid1Stdev}$ $\sigma = 3.1$	% of AUM/week	-0.12	-0.06	-0.01	% of AUM/week	0.05	-0.03	-0.10
	Millions USD	-496.12	-7.61	177.08	Millions USD	-249.55	-10.72	91.55
$\beta^* \text{CovidPeak}$ $\sigma = 11.56$	% of AUM/week	-0.46	-0.23	-0.02	% of AUM/week	0.18	-0.10	-0.37
	Millions USD	-557.70	-38.55	174.20	Millions USD	-224.80	-24.18	42.04

(c) Risk (BEX 2020)

	Panel A: Bonds	Q5	Q50	Q95	Panel B: Equity	Q5	Q50	Q95
	Observed flows	-473.56	3.73	178.13	Observed flows	-258.62	-5.79	109.69
β (unconditional) $\sigma = 1$	% of AUM/week	-0.05	-0.05	-0.04	% of AUM/week	-0.11	-0.06	-0.02
	Millions USD	-482.46	-4.58	170.40	Millions USD	-278.56	-16.96	106.69
$\beta^* \text{Covid1Stdev}$ $\sigma = 3.1$	% of AUM/week	-0.15	-0.14	-0.13	% of AUM/week	-0.34	-0.19	-0.05
	Millions USD	-501.17	-22.01	154.15	Millions USD	-320.42	-40.43	100.40
$\beta^* \text{CovidPeak}$ $\sigma = 11.56$	% of AUM/week	-0.56	-0.52	-0.49	% of AUM/week	-1.26	-0.71	-0.19
	Millions USD	-576.51	-92.25	88.71	Millions USD	-489.05	-134.96	75.02