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Abstract

This paper defines risk-on risk-off (RORO), an elusive terminology in pervasive use, as the variation in global investor risk taking behavior. Our high-frequency RORO index captures time-varying investor risk appetite across multiple dimensions: advanced economy credit risk, equity market volatility, funding conditions, and currency dynamics. The index exhibits risk-off skewness and pronounced fat tails, suggesting its amplifying potential for extreme, destabilizing events. Compared with the ubiquitous VIX measure, the RORO index reflects the multifaceted nature of risk, underscoring the diverse provenance of investor behavior. Practical applications of the RORO index highlight its valuable role in understanding international portfolio reallocation and return predictability.

Keywords: Risk-on Risk-off, Global Investor Risk Aversion, Extreme Events, Tail Risk, Portfolio Reallocation, Return Predictability.

JEL Codes: F21, F36, F65, G11, G12, G15, G23.

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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.

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1 Introduction

Since the global financial crisis, the term ”risk-on risk-off” has become a pervasive part of the vernacular in the financial press, as well as among academics, policymakers and practitioners. While the phenomenon has tangible effects on risk-taking behavior in financial markets, the exact definition of the term remains unclear. In this paper, we aim to provide a more comprehensive characterization of 'risk-on, risk-off' as different states of the world that reflect variations in global investor risk-taking behavior.

In their handbook chapter, Miranda-Agrippino and Rey (2020a) ask, ”how can we explain the important fluctuations in aggregate risk-taking in world markets?” In response to this query, we build a multi-faceted, yet parsimonious, Risk-on Risk-off (RORO) index to capture realized variation in global investor risk taking.[1] We use daily data from various asset markets in the United States and the Euro area to capture relevant signals about the underlying factors driving aggregate risk bearing capacity. Specifically, our measure presents an aggregation of risk-on risk-off states of the world based on four broad categories reflecting variation in advanced economy credit risk, equity market volatility, funding conditions, and currencies and gold. With an eye to inferring the overall risk bearing capacity of international investors, the RORO index comprises the first principle component of daily changes in these series. The resulting index exhibits significant right-skewness (risk-off) and fat tails. With fat tails, extreme events become both more probable and potentially more destabilizing. To wit, we observe sharp risk-off movements during the global financial crisis, the European debt crisis, the taper tantrum, and the COVID-19 pandemic.

Changes in both risk and risk aversion play a key role in determining asset prices, influencing the willingness of agents to take on risk in financial markets and the premia they command in making portfolio allocations or lending decisions. Critically, changes in risk bearing behavior can change over time both in perceptions over the amount of risk associated with different outcomes, and how that risk is priced (risk aversion). For example, it is well documented in the international capital flows literature that risk asset status or the reach-for-

[1] We are happy to make the the daily and weekly RORO index publicly available at: https://anushachari.weebly.com/roro.html. The data are updated in real time monthly. The website also provides a list of published and working papers that currently use the RORO index, which was first featured in Chari, Dilts Stedman, and Lundblad (2020).

yield phenomenon can generate destabilizing outcomes in either risk-on or risk-off states of the world, attracting capital surges when risk aversion is low (and therefore willingness to bear risk is high) and driving capital flight when risk aversion rises (Chari, Dilts Stedman and Lundblad (2021), (2022), Hofmann, Shim, and Shin (2016)).

The purpose of the RORO index is to serve as a unified summary statistic of risk-seeking/averting behavior that can be used to describe investors' willingness to take on, retain, or offload risky assets, which we call risk-on/risk-off. To be clear, our purpose is not to separate risk from risk aversion. Rather, the RORO index offers a barometer of risk-taking that measures the impetus facing investors, which can emanate from one or many corners of the market. We aim to provide a measure that 1.) reflects the speed with which perceptions of risk can change, and therefore have a bearing on asset prices and volumes (high frequency), 2.) reflects a broad range of agents and their motivations (multifaceted), and 3.) is based on the observed behavior of actual investors (transparent). Currently available measures of risk bearing capacity are *either* available at high frequency, reflect broad conditions, or are based on observed behavior, but not all three. The RORO index represents a novel effort at combining these three facets in summarizing risk-on/risk-off behavior.

High frequency measures of risk appetite almost invariably draw signals from one particular asset market. For example, to proxy for global risk aversion, the literature traditionally documents the sensitivity of portfolio equity flows to the VIX, to such an extent that it has come to be labeled "the fear index" (Avdjiev, Du, Koch, and Shin (2019); Rey (2013)). Yet, recent evidence points to a diminished relationship between the VIX and other key variables after 2008 (Forbes (2020); Miranda-Agrippino and Rey (2020a); Erik, Lombardi, Mihaljek, and Shin (2020)). Avdjiev et al. (2019) attribute the declining role of the VIX to the shifting composition of global capital flows. Cerutti, Claessens, and Rose (2019) suggest that the correlation between the VIX and capital flows is limited to times of crisis and that the role of the global financial cycle may have moderated. Erik et al. (2020) point to a breakdown in the negative relationship between bank leverage and risk appetite since 2009, raising questions about the VIX's reliability as a proxy for the price of bank balance sheets. In a similar fashion, Forbes and Warnock (2021) and Miranda-Agrippino and Rey (2020a) highlight a declining role in the information content of the VIX for explaining credit growth and capital flows.

In contrast, we offer a more holistic approach to characterizing risk bearing capacity, expanding the set of market information employed to more thoroughly represent shifts in aggregate risk bearing. In the course of our analysis, we show that the underlying constituents assert their time-varying relevance by coming to the forefront at different points in time. The usefulness of our proposed measure arises from the notion that the factors impacting risk appetite can emerge from many sources. The universe of investors interested in hedging equity volatility of the S&P 500 may not be the same as global investors focused on fixed-income assets and, hence, susceptible to different sources of risk. It is therefore important to pinpoint what is fundamental about the nature of alternative risks that can drive the aggregate risk-taking behavior of different market participants to ascertain which risks matter, when, and to whom.

It is also important to emphasize as well the interconnections between different types of risks. For example, movements in the VIX impact US broker-dealer leverage, closely mirroring the wholesale funding costs and the intermediation capacity of global banks and thereby generating funding liquidity risk (Adrian and Shin (2010)), Brunnermeier and Pedersen (2009).) In the other direction, a spike in liquidity risk will generally pass through to some degree to option-implied equity volatility. However, this pass-through may be incomplete and its nature can vary across different events. Not every option-implied volatility spike is associated with a liquidity event (and vice versa), and there will be times when multiple risks come to the fore.

It is also clear that the fundamentals that drive different risks differ in their origins. For instance, equity volatility as reflected in advanced economy equity returns and option implied volatility can reflect cash flow growth risk and/or changing discount rates. Credit risk reflected in option-adjusted credit spreads reflects corporate or sovereign default and bankruptcy risk. Currency risk highlights balance sheet mismatches and exposures to changes in exchange rates. Liquidity risk can reflect counterparty risk. For example, banks become more reluctant to lend to one another in the interbank loan market because of the perception that the default risk on loans has increased and/or the market price of taking on such risk has risen (Taylor and Williams (2009)). Liquidity risk can also reflect interest rate risk or constraints on the balance sheet capacity of market makers (for example, dealers in Treasury markets).

Thus, a multivariate approach to summarizing risk-on risk-off states of the world can confer several advantages. Combining credit risk, equity volatility risk, liquidity risk, and currency risk into this holistic measure, we show that different sources of risk become salient at different points of time and contribute in different magnitudes to overall global risk taking behavior at any given point of time. We present two empirical applications to highlight the benefits of using a multi-faceted measure of global investor risk bearing. These exercises examining portfolio rebalancing and return predictability in response to the variations in the composite RORO measure suggest that ignoring alternative sources of risk or the underlying provenance of risk can understate or misrepresent the impact of changes in aggregate risk bearing capacity on the prices and quantities of risk assets in general.

We begin by discussing the construction of the RORO measure and its statistical properties. Next, we decompose the measure into the four categories of risk highlighted above. With these measures in hand, we compare our measure to common asset-price based and survey-based measures of risk and risk sentiment found in the literature. We find that our measures are strongly correlated with other measures of sentiment. While survey-based measures are at a low frequency and asset-price based measures tend to be univariate in nature, our RORO measures have the advantage of being both high-frequency and multivariate.

Turning to our empirical applications, we find that our RORO measure is associated with substantial equity fund outflows in the event of a risk-off shock. Using our sub-indices we see that while all elements of the index have a statistically significant impact, advanced economy credit risk appears to make the biggest impact on equity outflows. In contrast, our equity factor based on option-implied volatility (VIX, VSTOXX) and returns drives the majority of our index's impact on equity returns. Using local projections, we find that the impact of a risk-off shock to our index on equity returns is both substantial and persistent, suggesting substantial return predictability. Critically, our unified index achieves superior explanatory power without sacrificing statistical power.

Decomposing the RORO index into the portion that can be explained by sentiment surveys and an unexplained "residual" shows that the persistent return effects are entirely attributable to the unexplained residual RORO component, while the return effects associated with the sentiment component of RORO dissipate within a month. We interpret this residual to reflect shifting aggregate expectations about fundamentals. That interpretation is informed not simply by the orthogonality to survey sentiment, but by virtue of its persistent impact on returns. Taken together, while common sentiment proxies fail to capture the significant and persistent revisions in expectations among market participants, our comprehensive RORO index does, further highlighting the importance of building a more comprehensive measure.

2 Measuring Risk-on/Risk-off

We construct our Risk-On, Risk-Off (RORO) index as follows.[2] Our RORO index comprises the z-score of the first principal component of daily changes in several standardized variables. First, 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.

Our headline measure encapsulates changes in the price of several assets designed to capture changes in risk expectations. To capture changes related to credit risk, we use the change in the ICE BofA BBB Corporate Index Option-Adjusted Spreads for both the United States and the Euro Area, along with the U.S. BAA corporate - 10Y Treasury spread. To capture risk-on/risk-off signals emanating from advanced economy equity markets, we use the additive inverse of daily total returns on the S&P 500, STOXX 600 and MSCI Advanced Economies Index, along with associated changes in option implied volatilities from the VIX and the VSTOXX indices. 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 the change in the TED spread, the LIBOR-OIS spread, and the bid-ask spread on 3mo Treasuries. Finally, we include the growth rate of the trade-weighted U.S. Dollar Index against advanced foreign economies and the change in the price of gold. Table 1 lists the variables used to construct the index, along with their loadings.

The RORO index features a highly skewed distribution towards downside risk (γ = 1.56) and long, heavy tails (kurtosis κ = 21.98). With heavy tails, extreme outcomes become more probable. The period of the Global Financial Crisis (Fall 2008) and the early days of the COVID

[2]See Cascaldi-Garcia et al. (2020) for a comprehensive survey of existing measures of uncertainty, risk, and volatility.

pandemic (March 2020) display some of the biggest risk-off movements, peaking above 11 standard deviations. The flash crash of the US stock market (5/6/2010), the S&P downgrade of the US credit rating (8/8/2011), and the Brexit vote (6/24/16) also illustrate noteworthy examples of very significant risk-off dates, reaching 5.12, 4.79 and 5.92 standard deviations, respectively.

Agglomerating multiple sources of risk implies that our measure does not rely exclusively on any one basis of risk. Elevating just one source of risk (such as the VIX) in the measurement of risk-on/risk-off suffers from the drawback that the relationship between the measure and asset prices can reflect the preferences of a subset of market participants and may or may not be generalized across time or assets. As mentioned in the introduction, the market participants who take out S&P 500 options to hedge against U.S. equity volatility measured by the VIX index may have characteristics that do not extend to all market participants or risk assets impacted by changing a risk environment.

In contrast, credit spreads represent an alternative candidate measure reflecting risk bearing capacity, capturing default and bankruptcy risk in the context of highly leveraged corporate balance sheets. To see the importance of the distinction, consider US monetary policy. Both sets of asset prices and their underlying drivers take on increased salience in the face of interest rate hikes. In equity prices, the resulting risk-off turn largely reflects revisions to anticipated cash flows and discount rates. On top of this, however, credit spreads reflect the larger impact monetary policy has on leveraged firms via default risk. A broader, multi-market measure reflects this more comprehensive view of the market stance. To wit, the CBOE and S&P recently launched ”credit VIX” indices to track one-month ahead volatility expectations in the US and European investment grade and high-yield markets to capture signals about credit market crises.

Recall that beyond the composite headline index, sub-index groupings 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. With these groupings in hand, we decompose the RORO into contributions from the four categories using variance decomposition.[3] We compute the proportion of RORO's variation explained by subindex $S_{i,t}$ over a rolling window of 520 days as:

$$Prop(S_{i,t}) = \frac{Cov(\widehat{RORO}_t, \hat{\beta}_i S_{i,t})}{Var(\widehat{RORO}_t)} \tag{1}$$

where $\widehat{RORO}_t$ is the fitted value from regressing headline RORO index on the four subcomponents and $S_{i,t}$ represents each of the four subindices individually. Figure 1, Panel (a) shows the proportion of the RORO index's variation that is explained by each of its subindexes.

We then translate daily movements in the RORO index into its constituent parts by multiplying the explained variation by the daily RORO measure: $Prop(S_{i,t}) \times RORO_t$. Note that by construction $\sum_{i=1}^{4} Prop(S_{i,t}) = 1$. Figure 1, Panel (b) displays the daily RORO shocks decomposed into contributions from the subindices.

The analysis in the two panels provides a visual representation of the degree to which distinct sources of risk assert their importance during different episodes. For example, while liquidity risk seldom explains much variation in the RORO measure, it was a pivotal source of risk-off behavior during the Global Financial Crisis. Similarly, credit risk's importance rises in both the GFC and in the onset of the COVID-19 pandemic. In comparatively placid times, the factor comprising equity returns and option implied volatility contributes the bulk of explained variation.[4]

3 RORO and Other Measures of Sentiment

In this section, we analyze the relationship between our risk-on/risk-off measure and alternative sentiment or confidence measures gleaned from a variety of sources. These exercises regress the z-scores of various confidence measures on 1) the RORO measure and 2) the un-

[3] Details of the process are described in Bekaert, Harvey, Lundblad, and Siegel (2011).

[4] Note that constructing the index using a one-year rolling window to extract the first principal component makes little difference either to the variance decomposition or in the analysis described in Sections 3 and 4.

derlying subindices:

$$M_t = \alpha + \beta RORO_t + \epsilon_t \quad (2)$$

$$M_t = \alpha + \sum_i \gamma_i S_{i,t} + \epsilon_t \quad (3)$$

Where M_t refers to one of a number of alternative risk or sentiment measures, $RORO_t$ is the headline RORO index and $S_{i,t}$ contains the four subindices, $S_{i,t}$ = {Spreads$_t$, Equity$_t$, Liquidity$_t$, Currency$_t$}. All measures are expressed in z-scores, so the results which appear in Figure 2(a) can be read as the impact in standard deviations of a one standard deviation RORO shock.[5]

Figure 2 displays the results regressing alternative measures of risk or sentiment on a one standard deviation shock to the daily aggregate RORO index (Panel (a)) and its subcomponents (Panel (b)). Whiskers on the individual bars represent the 95% confidence interval. The Gilchrist-Zakrajšek (2012) excess bond premium, Bekaert, Engstrom, and Xu (2022)'s risk aversion and risk measures (BEX), the real, macro and financial risk measures of Jurado, Ludvigson, and Ng (2015) (JLN), and Miranda-Agrippino and Rey (2020b)'s Global Factor (MAR) are based on asset prices and macro data. We find that a one standard deviation risk-off RORO shock is associated with elevated excess bond premia, increased risk aversion and risk, a large uptick (1.56 - 2.12 standard deviations) in JLN's real, macro and financial uncertainty measures, and a precipitous four standard deviation fall in the Global Factor of Miranda-Agrippino and Rey (2020b).

Among investor-based survey measures of sentiment, we see a risk-off RORO shock is associated with increased bearish-ness and decreased bullish-ness in the American Association of Individual Investors (AAII) survey, and a fall in Sentix's global and US measures. Finally, among consumer surveys, we see that a risk-off RORO shock is associated with a decrease in consumer sentiment as measured by the University of Michigan and Conference Board surveys. In each case, the RORO shock carries the expected sign.

Figure 2, Panel (b) presents the stacked regression coefficients of the individual RORO

[5] While some measures are available at the daily frequency, many are available only at weekly or monthly frequencies. For these cases, our index enters the regression as a weekly or monthly average of the within-period daily shocks.

sub-indices on the sentiment measures. The full regression table is available in an online appendix. In decomposing the impact of a RORO shock into its constituent subindices, the subindices are normalized to a 0.25 standard deviation such that the sum of the total impetus is one standard deviation. We do so to render the results easily comparable to one another. We see that the sizeable response of JLN's real, macro and financial uncertainty measures each reflect, in large part, a response to the credit spreads factor. However, liquidity risk plays on almost equally important role in driving the response of macro and real uncertainty to the headline index, while the equity risk factor plays an almost equally large role in the response of of the financial uncertainty measure. Changes in the excess bond premium result, in large part, from the credit spread factor but also receives some impetus from the liquidity risk factor.

The AAII bullish sentiment (net of bearish) falls with risk-off turns in the equity and credit spread factors. Similarly, the equity and credit risk factors drive much of RORO's relationship to Bekaert et al. (2022)'s risk aversion and risk measures, although risk aversion appears to reflect equity risk more, while physical risk or macro uncertainty reflects credit spreads a bit more.

Unsurprisingly, the equity factor drives the majority of the relationship between our measure of the Global Factor, but the other factors together also play a substantial role. While a one standard deviation risk-off turn in equities is associated with a four standard deviation decrease in the Global Factor, the same magnitude change in our credit risk (spreads) factor or our currency factor are also associated with a one standard deviation drop. Curiously, although the Sentix and consumer survey sentiment measures fall when credit risk rises, they also rise when the other three factors turn risk-off, conditional on credit risk. As a reminder, the equity factor rises when equity returns fall and/or when option-implied volatility rises.

Somewhat less surprising is the sentiment measures' response to the gold and hard currency factor. An increase in the value of the dollar can signal risk-off, but it can also arise from robust US growth or high (relative) US policy rates which may or may not coincide with risk-off behavior. These results highlight the importance of accounting for different sources of risk in measuring sentiment.[6]

[6] We also considered additional measures, which we omit from the main analysis for brevity. These series (with coefficients) include the orthogonalized sentiment index of Baker-Wurgler (0.45), Bloomberg's consumer sentiment indices for the euro area (-0.77) and the UK (-0.01), and the San Francisco Fed's news-based sentiment index

Overall, the most consistent link between alternative measures of sentiment and the RORO index is the credit spread factor. Still, equity volatility, liquidity, currency and gold all play a role, and sometimes constitute the dominant link, thus highlighting the importance of accounting for the underlying provenance of aggregate risk bearing capacity. Next, we turn to two empirical applications that highlight the salience of our multifaceted risk-on risk-off measure.

4 Applications: Capital Flows and Returns

Our applications examine the extent to which global equity mutual funds and ETFs alter their portfolio allocations to emerging markets in response to RORO shocks, and explore the implications of RORO shocks on emerging market aggregate equity returns. We describe the weekly capital flows and daily returns data before turning to the baseline regression specification.

4.1 Capital Flows and Returns

EPFR Global publishes weekly portfolio investment flows by more than 14,000 equity funds and more than 7,000 bond funds, with more than $8 trillion of capital under management. We use their Country Flows dataset to obtain a multilateral, high-frequency proxy of capital flows into and out of emerging markets. The dataset combines EPFR's Fund Flow and Country Weightings data to track the flow of money into world equity and bond markets. The fund flow data report 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 different 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 (i.e., physical flows).

To measure returns on emerging market portfolio assets, we use daily, country-level to-

(-0.06).

tal returns from the Morgan Stanley Capital International (MSCI) local currency and USD indices.[7] The sample of countries comprises emerging markets appearing in each of the flow and return data sets, from May 21, 2003 to Dec. 28, 2022. Of these, we include countries with widespread recognition as emerging market economies.[8] The sample includes Argentina, Brazil, Chile, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, and Turkey.

Our control variables include both global "push" factors associated with external shocks and destination-specific "pull" factors suggested by the international capital flows literature. The capital flow and return regressions thus include advanced market returns and a year fixed effect to control for global financial conditions. Time fixed effects account for slow-moving business cycles and structural changes in the market for ETFs and mutual funds. Country-specific pull factors include local policy rates, average real GDP growth in the previous eight quarters, 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.[9] All control variables enter with a lag to rule out simultaneity, with the exception of the CESI index. Pull, push and domestic macro controls affect capital flows and returns, and also likely react directly to changes in risk-on/risk-off behavior. In fact, our main global "push" variable, advanced economy returns, not only reacts to risk-on/risk-off shocks but likely also drives them.[10]

4.2 Capital Flow Episodes

In the baseline specification, we regress weekly EPFR country-level equity flows onto our RORO measure (and its subcomponents) in a panel with country and time fixed effects, controlling for the "push" and "pull" factors described above. Country-level equity flows, as the

[7] From MSCI, "the local currency series . . . represents the theoretical performance of an index without any impact from foreign exchange fluctuations — a continuously hedged portfolio."

[8] We exclude China due to its unique characteristics, including its size relative to other emerging market economies, measurement issues, and its late entry in the MSCI EM index. EM classifications considered include the IMF, BRICS + Next 11, FTSE, MSCI, S&P, EMBI, Dow Jones, Russell, Columbia University EMPG and BBVA.

[9] The CESI tracks how economic data compare to expectations, rising when economic data exceed consensus forecasts and falling when data come in below forecast estimates.

[10] Note that all daily variables enter as the weekly moving average leading up to the week's EPFR reporting date.

dependent variable, enter as a percent of the previous week's allocation, and weekly changes in the RORO measure (or its subcomponents) are aggregated by a moving average of daily changes.

$$k_{i,t} = \alpha_i + \delta_t + \rho k_{i,t-1} + \beta RORO_t + \gamma_1 PUSH_{t-1} + \gamma_2 PULL_{i,t-1} + \gamma_3 n_{i,t} + \epsilon_{i,t} \tag{4}$$

$$k_{i,t} = \left(\frac{K_{it}}{H_{it-1}} * 100\right)$$

$RORO_t$ is either the overall RORO Index or its nested subcomponents, n_{it} is the news surprise index, and k_{it} is equity fund 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. We include a first-order AR(1) term to account to the autocorrelation induced by scaling.

Columns 1 and 2 of Table 2 display the capital flow responses associated with a shock to the RORO index and the four subcomponents, respectively. In column 1, we show that a one standard deviation risk-off shock to the headline RORO measure yields equity fund outflows (as a percent of the previous week's allocation) of about 11 basis points. This response represents an outcome in the bottom 30 percent of AUM-scaled equity flows across our sample, and, perhaps more importantly, this corresponds to roughly $1.79B per week of total capital outflows from emerging markets, calculated using end-2022 AUM values. In an individual country, take Brazil for example, this would imply a $89.5M outflow in one week.

To highlight the importance of broadening the scope of indicators used to measure risk-on/risk-off, we next explore the impact of the four different subcomponent shocks on emerging market equity flows. Recall that while we document in Section 3 that the equity and option implied volatility component embedded in the RORO construction is important, it is only part of the story. Further, while the literature documents the sensitivity of portfolio equity flows to variation in the VIX index (Avdjiev et al. (2019); Rey (2013)), there is more recent evidence of a potentially diminished role for the VIX (Miranda-Agrippino and Rey (2020a), amongst others). In using a broader, unified measure, we explore the key drivers of risk bearing capacity's impact on equity fund flows beyond the ubiquitous VIX without sacrificing statistical power by over-fitting.

In fact, we find that the impact on equity flows associated with the part of the RORO index most closely linked to the VIX index and the Global Factor of Miranda-Agrippino and Rey (2020b) ('Equity return & OIV') is *dwarfed* by the impact of credit risk in advanced economy debt markets ('Credit spreads'). Specifically, while shocks to the option-implied volatility subcomponent do play a statistically significant role for emerging market equity flows, we find that credit spreads drive the vast majority of the capital flow effect. This result is even more striking when remembering that this exercise focuses solely on equity fund flows as a dependent variable and does not consider fixed income fund flows. Taken together, emerging market equity fund flows are more sensitive to developed market credit shocks than they are to option-implied volatility shocks (VIX). We conclude that while the VIX is clearly an important ingredient, an accurate depiction of risk-on/risk-off requires a more comprehensive index that encompasses a heterogeneous set of shocks across multiple asset markets and geographies such as the RORO index.

Next, we turn to an analysis of RORO shocks on emerging market country-level equity returns. Specifically, Table 3 presents the results of a panel regression of local currency and USD-denominated equity returns (columns 3 and 5, respectively) on the headline RORO index shocks and a host of controls and fixed effects identical to equation 1 above, sans AR(1) term. We find that a one standard deviation risk-off shock to the headline RORO measure yields USD and local currency equity return declines of 80 and 62 basis points, respectively. This magnitude represents 44% and 40%, respectively, of the standard deviation of the daily equity returns across our sample. Realizations of this magnitude would fall in the lower 25th percentile of the unconditional return distribution.

Finally, given the importance of a more comprehensive risk-on/risk-off measure for equity flows documented above relative to any individual subcomponent (including option-implied volatility), we repeat this disaggregation for equity returns. Columns 4 and 6 show the impact on local currency and USD equity returns associated with the part of the RORO index most closely linked to advanced economy equities (and thereby to the VIX index and the Global Factor) is a major, but not the sole, driver. The sub-indices related to developed market credit spreads and currencies also play a substantial role in driving returns.

4.3 Return Predictability

Given that we see significant equity return responses associated with a RORO shock, a natural next question is the extent to which these shock effects are transitory. Specifically, there is also longstanding literature on return predictability (see Keim and Stambaugh (1986) and Fama and French (1989), amongst many, many others) that explores whether shocks engender long-lived return responses consistent with persistent revisions in market expectations about fundamentals, i.e., cash flow growth or discount rates.

We undertake a series of local projections to offer some insights into the dynamic nature of these return reactions to RORO shocks.

$$
\begin{aligned}
r_{i,t-1:t+h} = \alpha_i + \delta_t + \beta_0 RORO_t + \sum_{l=1}^{L} \beta_l RORO_t + \dots \\
+ \sum_{l=1}^{L} \rho_l r_{i,t-l} + \sum_{l=1}^{L} \gamma_l^{(1)} PUSH_{t-l} + \sum_{l=1}^{L} \gamma_l^{(2)} PULL_{i,t-l} + \sum_{l=0}^{L} \gamma_l^{(3)} n_{i,t-l} + \epsilon_{i,t} \quad (5)
\end{aligned}
$$

where $h = \{0, \dots, 260\}$ is the horizon for the impulse response, $RORO_t$ is the RORO Index, n_{it} is the news surprise index, and $r_{i,t:t+h}$ is the cumulative return on either the MSCI USD or the local currency indices between time $t-1$ and $t+h$. We cluster bootstrapped standard errors by country to account for serially correlated error terms. To smooth the excess variability of the estimator, we apply a compound moving median smoother to the estimated series $\hat{\beta}_0 = \{\hat{\beta}_{0,0} \dots \hat{\beta}_{0,H}\}$.[11]

Figure 3, panels (a) and (b) display the results. We find that return responses are not temporary; in fact, the point estimates (regardless of currency denomination) persist for more than a year. Even a more conservative focus on statistical significance, as represented by the reported confidence intervals, shows that these effects linger for at least 150 days. Given that we do not observe price reversals, we conclude that these results are not tied to transitory market microstructure/liquidity issues. Instead, we observe emerging market equity return effects consistent with the notion that RORO shocks, on average, engender a significant and persistent revision in expectations about deeper fundamentals.

[11] Specifically, we first apply a 3-spline moving median smoother with repetition to convergence, followed by a Hanning linear binomial smoother. Smoothed values are obtained by taking the medians of each point in the estimated horizon and the two points around it. Thus, the IRFs pictured show the medians of β_{h-1}, β_h, and β_{h+1}. We then repeat the process with binomial weights.

Finally, to dig more deeply into the nature of this persistence, we decompose the RORO index into the portion that can be explained by the sentiment surveys presented above and a residual. First, we regress our RORO index on the investor survey measures of sentiment from Sentix and AAII to obtain the element of the RORO index that can be explained by survey sentiment. That is, how much of what we are observing is tied to observed measures of risk-on/risk-off that are in the literature? To examine this, we repeat our local projection exercise with the RORO decomposed into the fitted component (Proj(RORO|Sentiment)) and a "residual" (RORO - Proj(RORO|Sentiment)).

$$\begin{aligned} RORO_t &= \alpha + \sum_i \omega n_{i,t} + e_t \\ \widehat{RORO}_t &= \hat{\alpha} + \sum_i \hat{\omega} n_{i,t} \\ \hat{e}_t &= RORO_t - \widehat{RORO}_t \end{aligned}$$

With these two separate measures in hand, we then re-run our main regressions:

$$\begin{aligned} r_{i,t-1:t+h} = \alpha_i + \delta_t + \beta_0^1 \widehat{RORO}_t + \sum_{l=1}^{L} \beta_l^1 \widehat{RORO}_t + \beta_0^2 \hat{e}_t + \sum_{l=1}^{L} \beta_l^2 \hat{e}_t + \dots \\ + \sum_{l=1}^{L} \rho_l r_{i,t-l} + \sum_{l=1}^{L} \gamma_l^{(1)} PUSH_{t-l} + \sum_{l=1}^{L} \gamma_l^{(2)} PULL_{i,t-l} + \sum_{l=0}^{L} \gamma_l^{(3)} n_{i,t-l} + \epsilon_{i,t} \quad (6) \end{aligned}$$

Panels (c) and (d) of Figure 3 provides the decomposed return results. We find that the return effects associated with the component of the RORO index most closely tied to observed survey sentiment dissipate within a month. In sharp contrast, the residual RORO component (i.e., RORO stripped of observed sentiment variation) maintains a very persistent impact on future emerging market equity returns. At some deeper level, the comprehensive RORO index that we build captures more than just the observed variation in other off-the-shelf sentiment proxies. Further, this additional information permits the detection of a risk off shock's implications for persistent revisions in expectations among market participants about emerging markets.

4.4 Comparison with Other Measures

How does the RORO index compare with other measures of sentiment in terms of explaining and predicting emerging market outcomes? In this subsection, we undertake a simple forecasting exercise which highlights the RORO index's utility in predicting both typical and outsized realizations of flows and returns. To do so, we compare the fit of a parsimonious forecast model using only changes in measured sentiment to predict emerging market asset prices and quantities:

$$Y_{i,t-1:t+h} = \alpha_i + \beta_0 RS_t + \sum_{l=1}^{2} \beta_l RS_{t-l} + \epsilon_{i,t} \tag{7}$$

Where RS_t is the measure of risk sentiment under consideration and $Y_{i,t-1:t+h}$ is either the cumulative fund flow from week 0 to week h or the cumulative aggregate return from day $t-1$ to day $t+h$. To show the versatility of our measure, we include forecasts for fixed income fund flows and returns in addition to equity funds and returns. Given the importance of large risk-off events in emerging markets, we show (in addition to the R^2 of a fixed effects panel regression) the fit of a quantile regression on the left tail ($q = 5$), calculated as

$$R^{q=5} = 1 - \frac{\hat{V}^{q=5}}{\tilde{V}^{q=5}} \frac{T-1}{T-k} \tag{8}$$

Where $\hat{V}^{q=5}$ is the sum of weighted absolute deviations of a quantile version of the parsimonious model in equation (7), $\tilde{V}^{q=5}$ is the sum of weighted absolute deviations of a model regressing only on a constant, T is the sample length and k is the number of coefficients.

Figure 4 displays the predictive power of our measure compared with MAR, BEX, Shapiro's sentiment index, the VIX, and the Excess Bond Premium. The results clearly demonstrate that the RORO measure (in red) performs significantly better in predicting both capital flows and returns across different settings when compared to other measures. Panels (a) and (b) focus on capital flows, where the RORO index exhibits stronger predictive power in both the ordinary least squares (OLS) regression and the extreme left tail (Q5) quantile regression. Specifically, the R-squared values are consistently higher for the RORO measure, especially at high frequencies (short horizons). This is evident for both equity and fixed income fund flows, with the RORO measure showing notable outperformance even under extreme risk-off conditions captured in the left tail of the distribution. This result highlights the ability of our multifaceted index to better capture shifts in global risk appetite, offering valuable insights into high-frequency investor behavior.

A similar pattern emerges in Panels (c) and (d), where we analyze the predictability of equity and fixed income returns. Once again, the RORO measure dominates across both the OLS and Q5 regressions, with the highest predictive accuracy observed in the shorter-term (high-frequency) settings. Notably, the RORO measure's strength is particularly pronounced in the extreme left tail (Q5), indicating its ability to capture risk-off shocks that lead to sharp declines in asset returns. This predictive advantage is evident both in equity and fixed income returns, further highlighting the comprehensive nature of the RORO index in comparison to traditional measures like the VIX. In summary, the RORO measure demonstrates comparatively strong predictive performance across both flow and return settings, especially under extreme market conditions, highlighting its utility as a multifaceted indicator of risk-on risk-off behavior in global financial markets.

5 Conclusion

To conclude, the financial world has widely adopted the 'risk-on/risk-off' terminology to describe fluctuations in global investor risk aversion. This paper explores the intricacies of defining and measuring risk-on/risk-off states to provide a more comprehensive understanding of the dynamics at play in global financial markets. The development of the Risk-on Risk-off (RORO) index, which incorporates signals from various asset markets in the United States and the Euro area, offers a more holistic representation of risk appetite rooted in four fundamental categories: advanced economy credit risk, equity market volatility, funding conditions, and currencies and gold.

The statistical properties of the RORO index and its associated sub-indices reveal significant right-skewness and fat-tailed distribution of risk events, with notable risk-off episodes. Furthermore, the analysis emphasizes the evolving nature of global risk factors across different crises, highlighting the need for a flexible and dynamic approach to risk assessment. The paper shows that traditional measures like the VIX are no longer sufficient proxies for global risk bearing, as the composition of capital flows and the interconnectedness of various risk sources have evolved over time. Instead, a multifaceted approach to measuring risk-on/risk-off states proves more stable and informative, capturing the complex interplay of different risks and their impact on market behavior.

The significance of this research lies in its ability to address the multifaceted nature of risk, acknowledging that risks can originate from various sources and affect different classes of investors in distinct ways. By comprehensively considering alternative risk sources, the paper offers a nuanced view of risk-on risk-off dynamics and their implications. This comprehensive approach offers insights into market behavior during crises and highlights the relevance of the RORO index in examining global portfolio reallocation and predicting asset returns. In a world where risk factors are continually evolving, a multifaceted approach like the RORO index offers a timely and comprehensive gauge of global risk appetite, contributing to a better understanding of the complexities of the international financial landscape.

References

Adrian, T., & Shin, H. S. (2010). Liquidity and Leverage. *Journal of Financial Intermediation*, *19*(3), 418–437.

Avdjiev, S., Du, W., Koch, C., & Shin, H. S. (2019). The Dollar, Bank Leverage, and Deviations from Covered Interest Parity. *American Economic Review: Insights*, *1*(2), 193-208.

Baker, M., & Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance*, *61*(4), 1645–1680.

Bekaert, G., Engstrom, E. C., & Xu, N. R. (2022). The Time Variation in Risk Appetite and Uncertainty. *Management Science*, *68*(6), 3975–4004.

Bekaert, G., Harvey, C., Lundblad, C. T., & Siegel, S. (2011). What Segments Equity Markets? *Review of Financial Studies*, *24*(12), 3847–3890.

Brunnermeier, M. K., & Pedersen, L. H. (2009). Market Liquidity and Funding Liquidity. *The Review of Financial Studies*, *22*(6), 2201–2238.

Bruno, V., & Shin, H. S. (2015a). Capital flows and the risk-taking channel of monetary policy. *Journal of Monetary Economics*, *71*, 119-132.

Bruno, V., & Shin, H. S. (2015b). Cross-border banking and global liquidity. *Review of Economic Studies*, *82*(2), 535-564.

Cascaldi-Garcia, D., Sarisoy, C., Londono, J. M., Rogers, J. H., Datta, D., RT Ferreira, T., ... others (2020). What is Certain about Uncertainty? *International Finance Discussion Paper*(1294).

Cerutti, E., Claessens, S., & Rose, A. K. (2019). How Important is the Global Financial Cycle? Evidence from Capital Flows. *IMF Economic Review*, *67*(1), 24–60.

Chari, A., Dilts Stedman, K., & Lundblad, C. (2020, October). *Capital Flows in Risky Times: Risk-on/Risk-off and Emerging Market Tail Risk* (Working Paper No. 27927). National Bureau of Economic Research. doi: 10.3386/w27927.

Chari, A., Dilts Stedman, K., & Lundblad, C. (2021). Taper Tantrums: Quantitative Easing, its Aftermath, and Emerging Market Capital Flows. *The Review of Financial Studies*, *34*(3), 1445–1508.

Chari, A., Dilts Stedman, K., & Lundblad, C. (2022, October). *Global Fund Flows and Emerging Market Tail Risk* (Working Paper No. 30577). National Bureau of Economic Research.

Chari, A., Dilts Stedman, K., & Lundblad, C. (2023, November). *Risk-on risk-off: A multifaceted approach to measuring global investor risk aversion* (Working Paper No. 31907). National Bureau of Economic Research. doi: 10.3386/w31907

Erik, B., Lombardi, M. J., Mihaljek, D., & Shin, H. S. (2020). The Dollar, Bank Leverage, and Real Economic Activity: An Evolving Relationship. *AEA Papers and Proceedings*, *110*, 529-34.

Fama, E., & French, K. (1989). Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics*, *25*(1), 23–49.

Forbes, K. J. (2020). Do Sounder Banks Make Calmer Waters? The Link between Bank Regulations and Capital Flow Waves. *AEA Papers and Proceedings*, *110*, 516-22.

Forbes, K. J., & Warnock, F. E. (2021). Capital flow waves—or ripples? Extreme capital flow movements since the crisis. *Journal of International Money and Finance*, *116*(C).

Gilchrist, S., & Zakrajšek, E. (2012). Credit Spreads and Business Cycle Fluctuations. *American Economic Review*, *102*(4), 1692–1720.

He, Z., & Krishnamurthy, A. (2013). Intermediary asset pricing. *American Economic Review*, *103*(2), 732–770.

Hofmann, B., Shim, I., & Shin, H. S. (2016). Sovereign yields and the risk-taking channel of currency appreciation.

Jotikasthira, C., Lundblad, C., & Ramadorai, T. (2012). Asset Fire Sales and Purchases and the International Transmission of Funding Shocks. *The Journal of Finance*, *67*(6), 2015–2050.

Jurado, K., Ludvigson, S. C., & Ng, S. (2015). Measuring Uncertainty. *American Economic Review*, *105*(3), 1177–1216.

Keim, D., & Stambaugh, R. (1986). Predicting returns in the stock and bond markets. *Journal of Financial Economics*, *17*(2), 357–390.

Miranda-Agrippino, S., & Rey, H. (2020a). The Global Financial Cycle after Lehman. *AEA Papers and Proceedings*, *110*, 523-28.

Miranda-Agrippino, S., & Rey, H. (2020b). US Monetary Policy and the Global Financial Cycle. *The Review of Economic Studies*, *87*(6), 2754–2776.

Miranda-Agrippino, S., & Rey, H. (2022). Chapter 1-The Global Financial Cycle. In G. Gopinath, E. Helpman, & K. Rogoff (Eds.), *Handbook of international economics: International macroeconomics, volume 6* (Vol. 6, p. 1-43). Elsevier.

Rey, H. (2013). Dilemma not trilemma: The global financial cycle and monetary policy independence. *Federal Reserve Bank of Kansas City Economic Policy Symposium*.

Taylor, J., & Williams, J. (2009). A Black Swan in the Money Market. *American Economic Journal: Macroeconomics*, *1*(1), 58-83.

Tukey, J. W. (1977). Smoothing sequences. *Exploratory data analysis*, *2*, 205–236.

Table 1: Data Description and Risk-On Risk-Off (RORO) Loadings

(1) Category	(2) Variable	(3) Treatment	(4) Increase is risk-off	(5) RORO Loading	(6) Primary source	(7) Secondary source	(8) Ticker
Liquidity	G-spread	Diff.	✓	0.02	Wall Street Journal	Haver	F10JON@DAILY, F10JOF@DAILY F05JON@DAILY, F05JOF@DAILY F02JON@DAILY, F02JOF@DAILY
	Ted spread	Diff.	✓	0.12	Intercontinental Exchange, FRB	Haver	FLOD3@DAILY - FTBS3@DAILY
	Libor - 3mo OIS	Diff.	✓	0.15	Intercontinental Exchange	Bloomberg, Haver	FLOD3@DAILY - USSOC Curncy
	Bid-ask spread	Diff.	✓	-0.01	Bloomberg	Bloomberg	USGG3M INDEX
Equity & Option Implied volatility	AE MSCI return	%		0.22	MSCI	Bloomberg	MSDLEAFE Index
	S&P 500 return	%		0.37	S&P Global	Bloomberg	SPX Index
	STOXX 600 return	%		0.42	STOXX Limited	Bloomberg	S100XTD@INTDAILY
	VIX	Diff.	✓	0.35	CBOE	Bloomberg	VIX Index
	VSTOXX	Diff.	✓	0.39	Eurex	Bloomberg	V2X Index
Gold & Currency	Gold price	%	✓	-0.04	Bloomberg	Bloomberg	XAU Curncy
	Dollar vs. AE currencies	%	✓	0.18	Federal Reserve Board	Haver	DTWEXBGS
Credit Spreads	US High Yield Index Option-Adjusted Spread	Diff.	✓	0.39	ICE/BoA	FRED	BAMLH0A0HYM2
	Euro High Yield Index Option-Adjusted Spread	Diff.	✓	0.31	ICE/BoA	FRED	BAMLHE00EHYIOAS
	US BAA - 10Y	Diff.	✓	0.22	Moody's	FRED	BAA10Y

Table 1 lists the variables included in the RORO index. Column (1) lists the four sub-index categories. Column (2) lists the financial variables that enter the index. The RORO index is stationary by construction and requires individual variables to be transformed before inclusion. Column (3) describes how the variable is transformed before inclusion (in percent returns or first differences). In the construction of the index, variables are normalized so that an increase denotes a risk-off state of the world. Column (4) provides an indicator for whether an increase in the variable signals risk-off before normalization and standardized into z-scores. Column (5) shows the regression coefficient (which is the eigenvector of the principal component analysis) of the RORO index on each variable's normalized z-score. Columns (6) and (7) list the primary and secondary sources for the data, and column (8) lists the ticker symbol from the secondary source.

Table 2: Risk-off Shocks, Emerging Market Equity Fund Flows, and Aggregate Returns

	(1) Flows(t)/AUM(t-1)	(2) Flows(t)/AUM(t-1)	(3) MSCI USD (%)	(4) MSCI USD (%)	(5) MSCI LC (%)	(6) MSCI LC (%)
RORO	-0.106***		-0.780***		-0.602***	
	(0.00336)		(0.0197)		(0.0163)	
Credit spreads		-0.0983***		-0.287***		-0.232***
		(0.00339)		(0.0253)		(0.0202)
Equity returns & OIV		-0.0207***		-0.533***		-0.432***
		(0.00371)		(0.0178)		(0.0154)
Liquidity		-0.00246		-0.00174		-0.000992
		(0.00262)		(0.0199)		(0.0164)
Gold & Currency		-0.0121***		-0.242***		-0.105***
		(0.00205)		(0.0132)		(0.0108)
Observations	19818	19818	105058	105058	105058	105058

Standard errors in parentheses

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

Table 2 shows the relationship between a one standard deviation risk-off shock to the aggregate RORO index or its sub-components and equity fund flows and returns. Equity flows are scaled by lagged assets under management. Columns 1-2 show the results for equity fund flows. The flow regressions include one lag of the flows to account for autocorrelated standard errors induced by scaling. Columns 3-6 show the results for MSCI USD and Local Currency total returns, respectively. All specifications include the full set of control variables, country fixed effects, and year fixed effects. The macro controls include advanced economy controls (industrial production, GDP-weighted shadow rates and weekly aggregate bond returns) and emerging market destination controls (domestic interest rates, real effective exchange rates, real GDP growth, and Citibank macro news surprises, the CESI index). Robust standard errors are clustered by country and shown in parentheses. The full regression table is available in an online appendix.

Figure 1: Decomposing the RORO Index into its Sub-Components

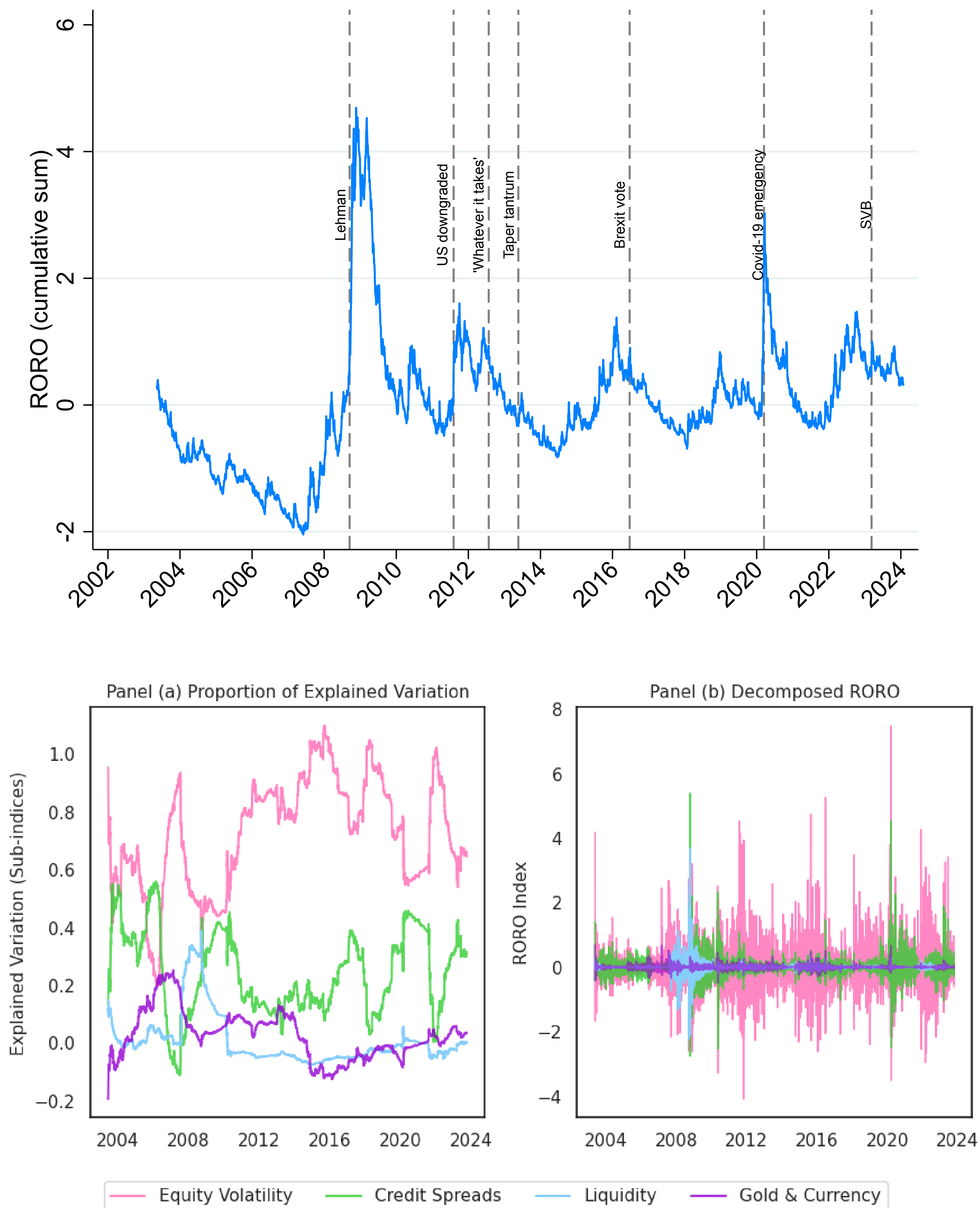

Figure 1 displays the RORO index in levels, summing cumulatively from the start of the index. Below, panel (a) shows the proportion of the RORO index's variation that is explained by each of its subindices, calculated over a rolling sample of 520 business days. Panel (b) decomposes the daily RORO shocks into contributions from the subindices by multiplying the explained variation in Panel (a) by the daily RORO measure. Section 2 outlines the decomposition method in detail.

Figure 2: Risk-off Shocks and Sentiment Measures

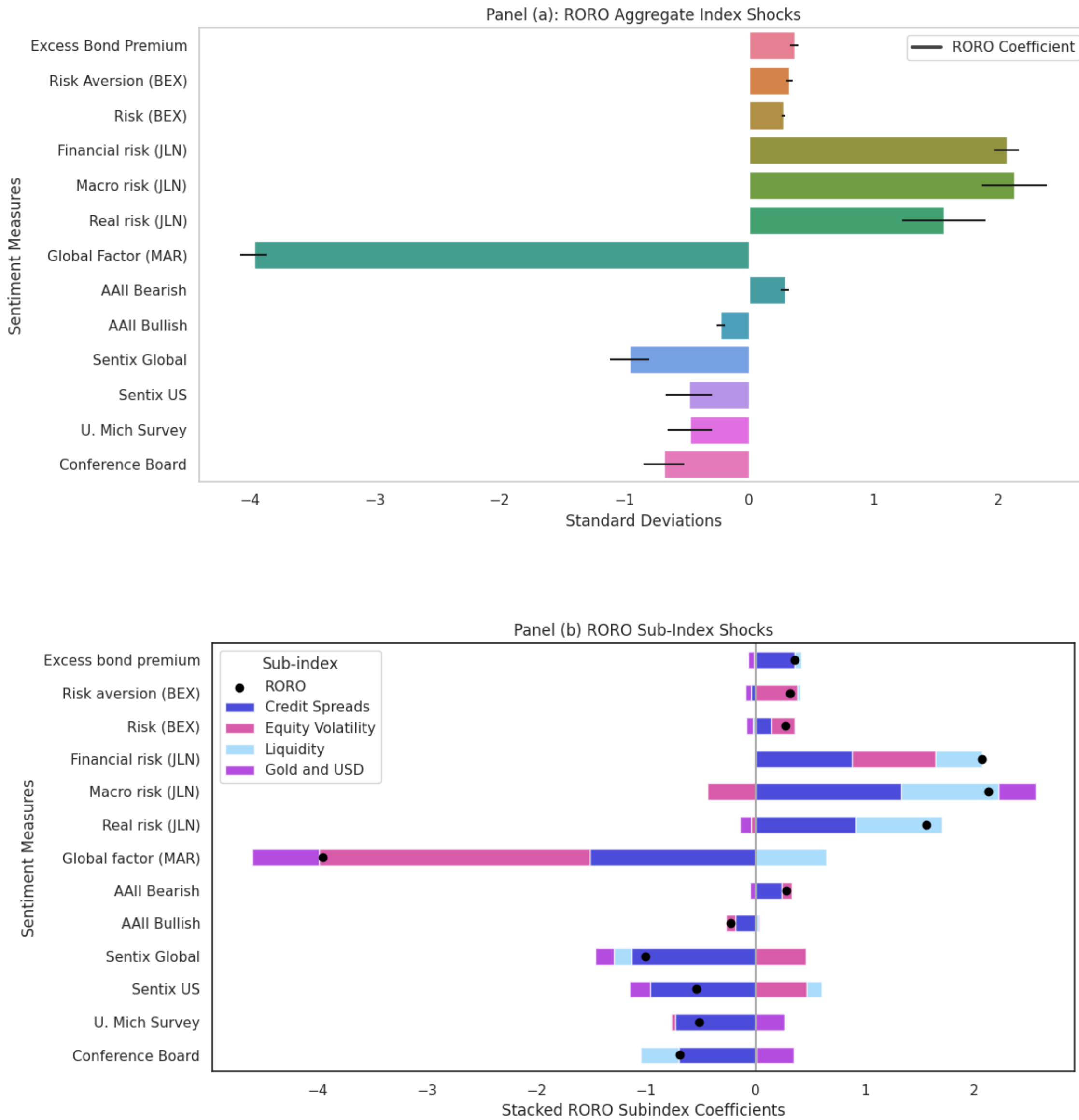

Figure 2 displays the results regressing alternative measures of sentiment on a one standard deviation shock to the daily aggregate RORO index (Panel (a)) and its subcomponents (Panel (b)). The Gilchrist-Zakrajšek excess bond premium, Risk Aversion (BEX), Risk (BEX), and Global Factor (MAR) are based on asset prices and macro variables as are the Jurado, Ludvigson, and Ng (JLN) financial, macro and risk measures. AAII Bullish and Bearish indicators, the Sentix Global and Sentix US are based on investor sentiment surveys. The University of Michigan and Conference Board are consumer sentiment survey-based measures. Sentiment measures are expressed as z-scores. The whiskers on the individual bars represent the 95% confidence interval. Panel (b) presents the stacked regression coefficients of the individual RORO sub-indices on the sentiment measures normalized to 0.25 standard deviations (such that a 1:1 impact would add up to one standard deviation—the size of an aggregate RORO shock). The full regression table is available in an online appendix.

Figure 3: Cumulative equity return following a one standard deviation risk-off RORO shock

Figure 3 Panel (a) displays the results of local projections regressing the cumulative returns of the MSCI local currency and USD indices on the aggregate daily RORO index. Panel (b) displays the results of local projections regressing the returns on the RORO index decomposed into the portion of the RORO index explained by measures of survey sentiment (Proj(RORO|Sentiment)) and the residual (RORO - Proj(RORO|Sentiment)). The former proxies for risk aversion and the residual proxies for physical macro risk. The error bands correspond to the 90th and 95th percent confidence intervals. To smooth the excess variability of the local projection estimates, we apply a compound moving median smoother to the estimated series.

Figure 4: Predictive power of the RORO index (R^2)

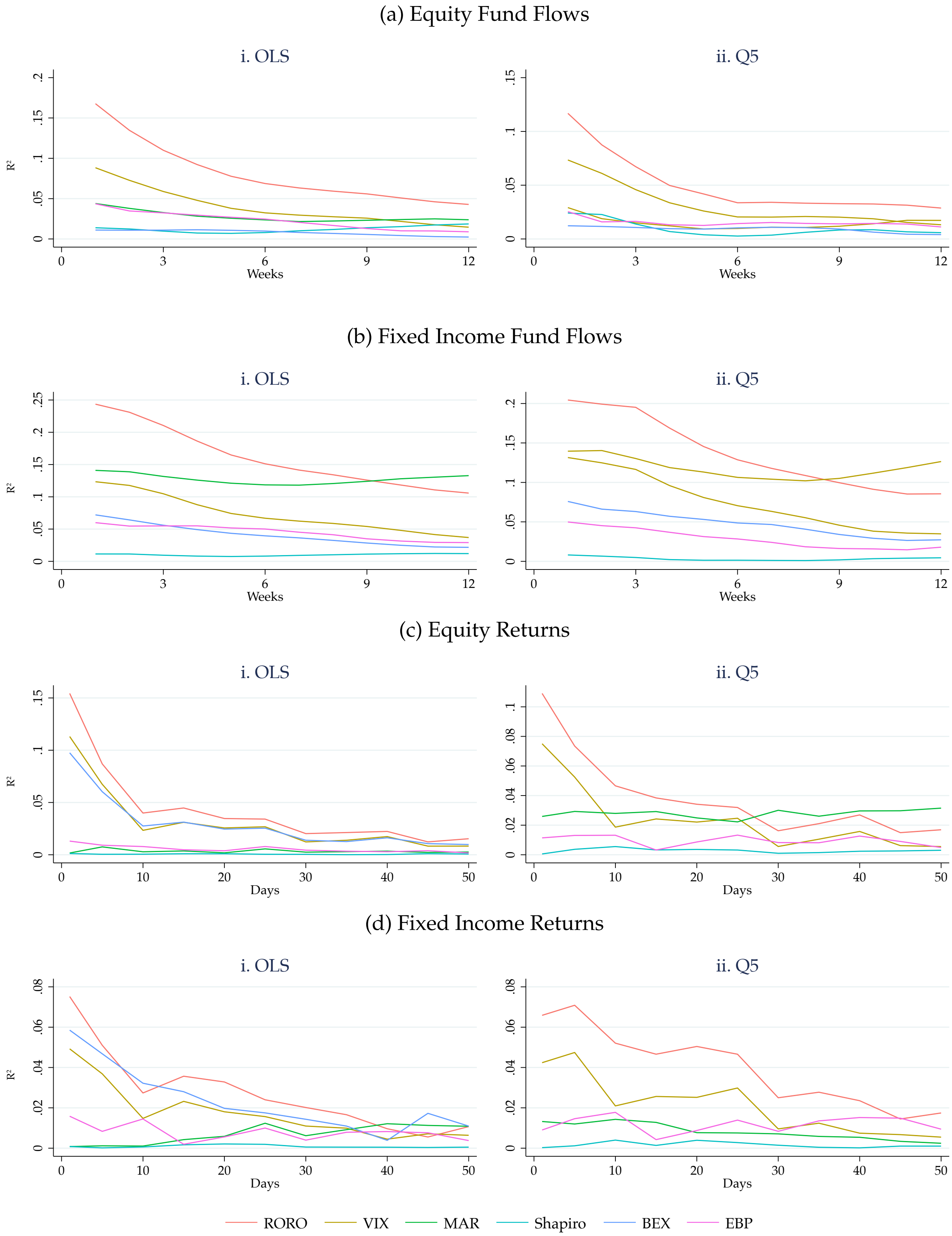

Figure 4 panel (a) displays the results of a parsimonious forecast regression of equity and bond flows and returns on the RORO index and various other measures of sentiment, along with two lags of the same.