Rare Disaster Concerns Everywhere*

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Abstract

We show that rare disaster concerns strongly drive cross-sectional return variation both within and across asset classes, including international equity indices, currencies, global government bonds, and commodities. Using a large set of out-of-the-money options on these assets, we measure the global financial market's rare disaster concerns under only no-arbitrage conditions. Assets that have low (high) return covariations with such concerns earn high (low) excess returns in the future. Such return patterns are not attributed to effects of global value and momentum, and are robust to various long/short positions of average investors. Our results are not explained by consumption and macroeconomic disaster risk, financial market disaster risk, and funding and liquidity constraints of financial intermediaries. The evidence suggests time-varying disaster fear/aversion as a potential venue to reconcile return dynamics across asset classes.

Keywords: Bond; Currency; Commodity; Equity; Rare disaster concerns; Options

JEL classifications: G12, G13, F37

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"Expected returns vary over time. How correlated is such variation across assets and asset classes? How discount rates vary over time and across assets?"

John Cochrane, American Finance Association Presidential Address, January 8, 2011

"Large-scale asset purchases ... can signal that the central bank intends to pursue a persistently more accommodative policy stance than previously thought. Such signaling can also increase household and business confidence by helping to diminish concerns about 'tail' risks ..."

Ben Bernanke, Chairman of the Federal Reserve, at the FRB Kansas City Economic Symposium, Jackson Hole, August 31, 2012

1 Introduction

The *ex ante* concerns of rare disasters on financial markets (hereafter rare disaster concerns) often deviate from the disaster risk measured using (limited) historical observations of *ex post* disaster shocks.[1] In this paper, we uncover a strong return pattern driven by rare disaster concerns: assets that deliver contemporaneously low returns amid high market rare disaster concerns are unfavorable securities, and hence require high expected returns. Such a return pattern is pervasive across asset classes including international equity indices, currencies, global government bonds, and commodities, echoing the importance of "concerns about 'tail' risks" emphasized by Ben Bernanke in designing the U.S. monetary policies.[2] It makes a step forward on the path of understanding "how discount rates vary over time and across assets", the research agenda outlined by John Cochrane in 2011 Presidential Address to the American Finance Association.

To capture such *ex ante* disaster concerns, we construct a rare disaster concern index ($\mathbb{RIX}$) based on out-of-the-money (OTM) put options that contain rich information about the *ex ante*

[1] Our focus is on disasters of financial markets (the extreme downside movements of financial asset prices), different from Rietz (1988), Veronesi (2004), Barro (2006), Gabaix (2012), Gourio (2012), and Wachter (2013) who study the disaster risk of consumptions and macroeconomic fundamentals. Though our results do not directly speak to the macroeconomic driver of the finanical market's disasters, we conduct analysis on whether return dynamics driven by rare disaster cocnerns can be explained by disaster risk of fundamentals (see Section 5 for details). For comparisons of disaster distribution estimates from macroeconomic data and those from S&P 500 index options, see Backus, Chernov, and Martin (2011) and Seo and Wachter (2013).

[2] The meaning of rare disaster concerns in our framework is also related to "the perception of tail risk" pointed out by Olivier Blanchard (the chief economist of IMF) in an influential article published in The Economist, January 31, 2009: "so what are policymakers to do? First and foremost, reduce uncertainty. Do so by removing tail risks, and the perception of tail risks."

market's expectations on future rare disasters.[3] Assuming only no-arbitrage conditions, our $\mathbb{RIX}$ measure equals to a disaster insurance price that will spike whenever investors become concerned about disasters in the future, though it does not separate preference and belief about disaster risk. Empirical estimates using options on 30 international equity indices, 32 currencies, 14 government bond futures, and 28 commodity futures from 1996 to 2012 show that $\mathbb{RIX}$s are rather informative about the market's perception of future disaster events in different markets and asset classes. $\mathbb{RIX}$s spike up not only when disasters happened such as the Asian financial crisis in 1997, the collapse of Long-Term Capital Management in 1998, the 9/11 terrorist attack in 2001, the stock market downturn in 2002, the global bond market sell-off in 2003, and the 2007-2008 global financial crisis, but also during periods of high disaster concerns with no subsequent realized disaster shocks such as the Flash Crash in May 2010, and the stock market rally in October 2011.

Our basic premise of asset return dynamics driven by rare disaster concerns is that low $\mathbb{RIX}$-covariation assets are unfavorable securities (they deliver contemporaneously low returns when the market's rare disaster concerns spike) and hence require high expected returns. Consistent with this hypothesis, we find systematic patterns that low $\mathbb{RIX}$-covariation assets on average earn higher excess returns than high $\mathbb{RIX}$-covariation assets in each asset class we study. For example, when portfolios are monthly formed, the low-minus-high $\mathbb{RIX}$-covariation portfolios on average significantly earn 0.76%, 0.37%, 0.21% and 0.90% per month in equity indices, currencies, bonds, and commodities, respectively. Moreover, this $\mathbb{RIX}$-covariation effect is not short-lived. At the semi-annual frequency of portfolio formation, return spreads of these low-minus-high $\mathbb{RIX}$-covariation portfolios are even larger, 0.97%, 0.54%, 0.28%, and 1.45%, respectively, and all are close to three standard errors from zero.

We further show that rare disaster concerns are strongly correlated across assets. As a result, in order to capture the common variations of assets' rare disaster concerns, we construct a global rare disaster concern index ($\mathbb{GRIX}$) as the first principal component (PC) of the correlation matrix of three asset-class-specific rare disaster concern indices (this PC explains 70% of the covariations).[4] We show the $\mathbb{GRIX}$ is important in explaining cross-sectional return variation across markets and

[3] In a recent study about risk-neutral moments and expected stock returns, Conrad, Dittmar, and Ghysels (2013) argue that "options reflect a true *ex ante* measure of expectations" (p.3)

[4] Asness, Moskowitz, and Pedersen (2013) use a similar approach in constructing global value and momentum factors.

asset classes. In particular, we rank all 104 global investment assets into five $\mathbb{GRIX}$-covariation quintiles. On the monthly and quarterly frequencies of portfolio formation, the low-minus-high $\mathbb{GRIX}$-covariation portfolios on average significantly earn 1.00% and 0.72% per month, with t-statistics of 3.6 and 2.5, respectively. These cross-sectional return variations associated with $\mathbb{GRIX}$ are not attributed to effects of global market, value, and momentum, and leverage and margin constraints – the alphas benchmarked on various global factor models range from 0.76% to 0.96% per month with t-statistics larger than three most of time. More importantly, both low and high $\mathbb{GRIX}$-covariation portfolios contain assets from multiple asset classes, and the asset composition varies over time in response to time-varying rare disaster concerns of the global financial market, implying that return dynamics driven by the $\mathbb{GRIX}$ are indeed pervasive across all asset classes including equity, currency, bond, and commodity. Moreover, we show that alternative measures of rare disaster concerns such as a global volatility index ($\mathbb{GVIX}$) and volatility skew deliver similar return patterns, though less significant due to larger noises of these measures than $\mathbb{GRIX}$ in capturing disaster concerns. Overall, we show that rare disaster concerns are an important determinant of securities' expected returns in the cross section of global markets and asset classes.

Asset return dynamics across markets and asset classes incur involved issues such as perspectives of average investors and the global vs local nature of disaster concerns. We conduct further analysis to investigate these issues. First, our baseline results discussed above take the perspective of an average U.S. investor who have long positions in international equity indices, foreign currencies, and global government bond futures considering the funds of various types holding such positions in practice, but have short positions in commodity futures following the long-standing hedging pressure theory that commodity hedgers are net short in commodity futures to hedge the physical commodity price risk (Keynes, 1923; Bessembinder, 1992; Hirshleifer, 1988; Cheng, Kirilenko, and Xiong, 2014; Cheng and Xiong, 2014). In consequence, the $\mathbb{GRIX}$ measure in our baseline results use OTM put options on equity indices, foreign currencies, and bond futures, but OTM call options on commodity futures, in capturing the global market disaster concerns. However, alternative perspectives exist. For example, an average investor with a global market portfolio positively related to the global macroeconomy or financial market may view the surging prices of bonds as signaling disasters because of flight-to-safety and flight-to-quality (Longstaff, 2004; Beber, Brandt, and Kavajecz, 2009; Campbell, Pflueger, and Viceira, 2013, 2014). As a result, OTM calls on bonds should be used to capture the global rare disaster concerns. Moreover, investors are known to take carry trades in the currency market and hence long (short) currencies with a high (low) interest rate. For such investors, OTM puts on high carry currencies should be used to capture their disaster concerns. We re-compute the $\mathbb{GRIX}$ measure with such alternative perspectives and find that the strong return pattern driven by rare disaster concerns still persist. For example, with both alternative perspectives in bonds and currencies, the low-minus-high $\mathbb{GRIX}$-covariation portfolios on average significantly earn 0.82% with a t-statistic of 2.8. Therefore, return dynamics driven by rare disaster concerns are robust to alternative perspectives of average investors across markets and asset classes.

Second, we investigate the return dynamics driven by global vs local, in the sense of across asset classes, rare disaster concerns to understand the global and local nature of disaster concerns. We orthogonalize the $\mathbb{RIX}$ for each of the four asset classes by regressing it on the $\mathbb{RIX}$s of the other three, and take the residuals as the asset-class-local $\mathbb{RIX}$. We then form portfolios of unfavorable and favorable assets using an asset's covariation with respect to this asset-class-local $\mathbb{RIX}$ both in asset class it belongs to and in the other three asset classes. We find marginally significant return spreads driven by such asset-class-local $\mathbb{RIX}$s in equity and commodity markets, but not in currency and bond markets. Such results suggest that disaster concerns of currencies and bonds are "completely global", whereas those of equities and commodities have components that drive "local" return dynamics but not the whole global financial market.

So far, our empirical results show that the economic mechanism associated with disaster concerns is critically important to understand return dynamics across asset classes. However, as mentioned above, the rare disaster concern measures based on option prices do not separate preference and belief. An increase in $\mathbb{RIX}$ can be due to increasing disaster risk of economic fundamentals and financial markets (Barro, 2006; Gabaix (2012), Martin (2013c), and Wachter (2013)), increasing funding and capital constraints of institutional investors (Brunnermeier and Pedersen, 2009; Garleanu, Pedersen, and Poteshman, 2009; Garleanu and Pedersen, 2011; He and Krishnamurthy, 2012, 2013), and increasing disaster fear/perception (Liu, Pan, and Wang, 2005; Bates, 2008; Drechsler, 2013; Bollerslev and Todorov, 2011; Barberis, 2013; Chen, Dou, and Kogan, 2013; Weitzman, 2007). We hence conduct a comprehensive analysis to further investigate implications of our results for various economic channels (all associated with disaster risk) driving asset prices.

We collect variables for three economic channels, consumption and macro disaster risk, financial market disaster risk, and liquidity and funding constraints of financial intermediates. To measure the consumption and macro disaster risk, we collect a large set of variables of consumption and macroeconomic risk for both U.S. and global economies (U.S., U.K., Japan, and Europe). To measure the financial market disaster risk, we collect series of financial market liquidity and stock market tail risk, and construct series of high-order risk-neutral moments using options on various asset classes. Finally, to capture the liquidity and funding constraints of financial intermediaries, we collect series of funding liquidity and leverage shocks of financial dealers.

We perform both correlation analyses and time-series regressions of low-minus-high $\mathbb{GRIX}$-covariation portfolio returns on these measures. Our results strongly indicate that the global asset return predictability driven by ex-ante disaster concerns cannot be explained by the exposure to disaster risk of consumption and macro fundamentals and disaster risk of financial markets. Moreover, it is not simply phantom of liquidity/capital constraints of financial intermediaries. Overall, our results suggest time-varying disaster fear/aversion, which is shown to drive asset prices only in U.S. stock markets by Bates (2008), Drechsler (2013), and Bollerslev and Todorov (2011), might be the potential channel to reconcile security returns across asset classes. We stress that our empirical evidence does not imply that standard disaster risk models are unimportant. Alternatively, the $\mathbb{RIX}$ can be interpreted as a better measure of ex-ante disaster risk than other empirical proxies, and hence our results can simply be evidence supporting disaster risk theory. Though plausible, this interpretation faces an obstruction that the return spread of high-minus-low $\mathbb{RIX}$-covariation portfolios is significantly positive during most crisis periods, including the recent financial crisis that is fairly extreme in the history of the global economies; it is expected to be negative should we go with a disaster risk interpretation.[5]

Our study contributes to the growing literature that document return patterns across markets and asset classes, including Asness, Moskowitz, and Pedersen (2013), Koijen, Moskowitz, Pedersen, and Vrugt (2012), Moskowitz, Ooi, and Pedersen (2012), Fama and French (2012), and Hou, Karolyi, and Kho (2011). Our work complement these studies by uncovering a strong and per-

[5]In the appendix, we show that rare disaster concerns as assets' characteristics cannot explain cross-sectional average returns, and indeed it is the $\mathbb{RIX}$ (and $\mathbb{GRIX}$) covariations that explain returns. We also perform checks on using various data of global asset returns such as the U.S. exchange trade funds and our results are robust to different return specifications.

vasive return pattern across asset classes that are closely associated with an important economic mechanism, i.e., rare disaster concerns. As discussed above, the $\mathbb{RIX}$-covariation return patterns cannot be attributed to characteristic effects documented in these studies. Other recent studies on global asset pricing include Frazzini and Pedersen (2012) who propose betting-against-beta (BAB) factors motivated by leverage constraints and Lettau, Maggiori, and Weber (2013) who use the downside risk CAPM (DR-CAPM) beta, originally proposed by Ang, Chen, and Xing (2006) for the U.S. equity market, to explain expected returns across asset classes. We show that our results associated with rare disaster concerns cannot be attributed to these factors.

Our study also contributes to the disaster risk literature by documenting the explanatory power of rare disaster concerns on security returns across asset classes, whereas existing studies largely focus on the U.S. equity market or different asset classes in isolation (Jurek, 2009; Bollerslev and Todorov, 2011; Burnside et al., 2011; Farhi and Gabaix, 2011; Gabaix, 2012; Julliard and Ghosh, 2012; Longstaff and Piazzesi, 2004; Bali, Cakici, and Whitelaw, 2011; Kelly, 2012).[6] Furthermore, as discussed above, our joint approach of studying multiple asset classes sheds light on merits of different channels related to disaster risk, suggesting time-varying disaster fear/perception as a potential framework to unify "*how* discount rates vary over time and across assets" (Cochrane, 2011).[7] We leave this for future work.

The rest of the paper is organized as follows. Section 2 discusses the option data and measures of rare disaster concerns. Section 3 systematically examines rare disaster concerns and asset returns. Section 4 investigate issues related to portfolios across asset classes. Section 5 studies implications of our results for different economic channels of disaster risk. Section 5 concludes. The appendix provides robustness checks, and a separate online appendix provides additional empirical results and detailed information on options data.

[6] Other related asset pricing models with jump risk include Benzoni, Collin-Dufresne, and Goldstein (2011), Du (2011), Naik and Lee (1990), Eraker and Shaliastovich (2008), Shaliastovich (2009), Santa-Clara and Yan (2010), Drechsler and Yaron (2011), with a focus on option pricing.

[7] Two recent studies, Martin (2013b) and Ross (2013), characterize the empirical patterns of expected returns extracted exclusively from option prices.

2 Option Data and Rare Disaster Concern Measures

Out-of-the-money options are most informative about ex-ante expectations of extreme movements of security prices and hence disaster risk of financial markets. In this section, we introduce our large panel of options data on international equity indices, currencies, global government bond futures, and commodity futures, and discuss the measures of rare disaster concerns. Before delving into details, we first lay down the framework to unify various asset classes, in particular the perspective of the average investor and correspondingly whether increasing or declining security prices poses risk to her. Our baseline framework will take the perspective of an average U.S. investor who have long positions in international equity indices, foreign currencies, and global government bond futures considering the funds of various types holding such positions in practice, but have short positions in commodity futures following the long-standing hedging pressure theory that commodity hedgers are net short in commodity futures to hedge the physical commodity price risk (Keynes, 1923; Bessembinder, 1992; Hirshleifer, 1988; Cheng, Kirilenko, and Xiong, 2014; Cheng and Xiong, 2014). In consequence, the $\mathbb{RIX}$ measure in our baseline framework will use OTM put options on equity indices, foreign currencies, and bond futures, but OTM call options on commodity futures to capture the global market disaster concerns. We check robustness of our results to alternative perspectives of average investors in Section 4.

2.1 Option data

International Equity Indices. We obtain daily index option prices from Thomson Reuters Tick History (TRTH) for 30 international equity markets (index abbreviations are in parentheses): Australia (ASX 200), Austria (ATX), Belgium (BEL 20), Canada (TSX 60), Denmark (OMX C20), Europe (ESTX 50), Finland (OMX H25), France (CAC 40), Germany (DAX), Greece (ASE 20), Hong Kong (HSI), India (CNX Nifty), Israel (TA 25), Italy (FTSE MIB), Japan (Nikkei 225), Mexico (IPC), Netherlands (AEX), Nordic Countries (VINX 30), Norway (OBX), Poland (WIG 20), Russia (RTS), Singapore (SGX), South Korea (KOSPI 200), Spain (IBEX 35), Sweden (OMX S30), Switzerland (SMI), Taiwan (TAIEX), Thailand (SET 50), United Kingdom (FTSE 100), and United States (S&P 500).[8] The sample period is from January 1996 through October 2012, with

[8] Except the index options of Mexico, Russia, Singapore, and Spain that are written on equity index futures associated with the cash equity indices, all other index options are written on the major cash index of a country or

variations depending on specific indices. Our data cover a large range of maturities, from 7 to 300 calendar days mostly, and a large range of strikes with moneyness (the ratio between spot and strike) from 0.7 to 1.3.

We also collect the data of international equity indices and index futures from TRTH as the underlying security prices of these index options. For the calculation of $\mathbb{RIX}$, we use the interbank borrowing rates corresponding to each equity market as the short-term discount rate for options, following the financial industry standard. In particular, we use the LIBOR, EURIBOR, and zero-coupon curves implied from interest rate swaps that are main global interbank interest rates, along with NIBOR, SIBOR, and WIBOR as local interbank rates for Norway, Singapore, and Poland, respectively. Appendix 1 provides detailed information of these equity index options.

Currencies. We obtain daily prices of over-the-counter (OTC) currency options from J.P. Morgan. These options are written on US-dollar-based exchange rates (i.e., units of foreign currencies per US Dollar). We have the following 32 currencies (currency codes are in parentheses): Argentine Peso (ARS), Australian Dollar (AUD), Brazilian Real (BRL), Canadian Dollar (CAD), Chilean Peso (CLP), Colombian Peso (COP), Czech Koruna (CZK), Danish Krone (DKK), Euro (EUR), Hong Kong Dollar (HKD), Hungarian Forint (HUF), Icelandic Krona (ISK), Indian Rupee (INR), Indonesian Rupiah (IDR), Israeli Shekel (ILS), Japanese Yen (JPY), Malaysian Ringgit (MYR), Mexican Peso (MXN), New Zealand Dollar (NZD), Norwegian Krone (NOK), Peruvian Nuevo Sol (PEN), Philippine Peso (PHP), Polish Zloty (PLN), Russian Federation Rouble (RUB), Singaporean Dollar (SGD), South African Rand (ZAR), South Korean Won (KRW), Swedish Krona (SEK), Swiss Franc (CHF), Taiwanese Dollar (TWD), Thai Baht (THB), and United Kingdom Pound (GBP). The sample period is from January 1996 through May 2012, with variations depending on specific currencies.[9] The market of these currency options is the deepest, largest, and most liquid market for options of any kind.[10] Our data contain implied volatility quotes for options of one-month maturity and five strikes that have standardized Black-Scholes deltas: at the money (ATM), 10-delta call, 10-delta put, 25-delta call, and 25-delta put.[11]

region.

[9] Because our main option samples start from January 1996, we don't consider the currencies of eurozone countries before 1999 and only keep the Euro series starting from January 1999.

[10] According to the Bank for International Settlements (BIS), the notional value outstanding of OTC currency options at the end of June 2012 is 110 trillion US dollars.

[11] The convention in foreign exchange markets is to multiply the put delta by –100 and call delta by 100. Hence, a 10-delta put has a delta of –0.1, while a 10-delta call has a delta of 0.1.

We first convert the deltas into strikes using the implied volatilities based on the extended Black-Scholes formula in Garman and Kohlhagen (1983), and then covert the implied volatilities into prices using the strikes. Here, we use the one-month LIBOR obtained from Datastream as the interest rates of US Dollar (USD) and major interbank borrowing rates as interest rates of other currencies. In addition, we extract daily spot exchange rates of 32 currencies against USD from Barclays and Reuters (via Datastream) for the same time period as the currency option sample. Our spot exchange rates are based on midpoint quotes (i.e., the average of bid and ask rates).

Global Government Bonds. We obtain daily prices of sovereign bond futures and associated futures options from different exchanges (via J.P. Morgan). We collect the following 14 bond futures: Australia 3 and 10 Year Treasury Bonds, Ten-Year Government Bond of Canada, Euro-Bobl, Euro-Schatz, Euro-Bund, Italy 10 Year Government Bond, Japan 10 Year Government Bond, Spain 10 Year Government Bond, Long Gilt (UK 10-Year Bond), U.S. 2, 5, and 10 Year Treasury Notes, and U.S. 30 Year Treasury Bond.[12] The sample period is from January 1996 through December 2012, with variations depending on specific bonds.

As bond futures and futures options are issued usually in a quarterly cycle (March, June, September, and December), we collect data of both the front contract with the nearest expiration date (and time-to-maturity of up to three months) and the back contract with the second nearest expiration date (and time-to-maturity of up to six months). There are around nine strikes, with at-the-money, in-the-money, and out-of-the-money strikes all available, for options of each maturity. Moreover, the futures options are of American style, and we treat them as European options. We expect the impact of early exercise to be negligible for our calculation as we use only out-of-the money options for which the early exercise is most unlikely.[13] The interbank borrowing rates corresponding to each bond market is used as the short-term discount rate for options, including LIBOR, EURIBOR, and zero-coupon curves implied from interest rate swaps. Appendix 1 provides detailed information of these government bond futures options.

[12] For Germany government bonds (their notional contract values are in euros), Schatz has 1.75-2.25 year maturity, Bobl has 4.5-5.5 year maturity, and Bund has 8.5-10.5 year maturity. For brevity, we call them Germany 2YR, 5YR, 10YR bonds, respectively, in figures and tables throughout the paper. Note that in bond futures market, these contracts are subject to the cheapest to deliver restriction, which has a certain range of maturity close to but not necessarily equal to the original maturity underlying these futures contracts.

[13] Jorion (1995) shows that early exercise premium is negligible for short maturity ATM options on futures. Overdahl (1988) also finds that early exercise of options on bond futures happens only about 0.1% of the time, and only for options that are significantly in the money.

Commodities. We collect end-of-day closing prices of liquid exchange-listed options on major commodity futures in the U.S. and international commodity markets from the Commodity Research Bureau (CRB). Our commodity option sample includes Butter (BA), Soybean oil (BO), Corn (C-), Cocoa (CC), Crude oil-WTI (CL), Cotton (CT), Milk (DE), Fedder cattle (FC), Gold (GC), Copper (HG), Heat oil (HO), Unleaded Gasoline (HU), Orange juice (JO), Coffee (KC), Lumber (LB), Live cattle (LC), Lean hogs (LH), Natural gas (NG), Oats (O-), Palladium (PA), Pork bellies (PB), Platinum (PL), Coal (QL), RBOB blendstock gasoline (RB), Rough rice (RR), Soybeans (S-), Sugar (SB), Silver (SI), Soybean meals (SM), and Wheat (W-), in major commodity groups of Agricultural, Energy, Meat, Metal, and Soft. Though many of these commodity futures options can go back before 1990s, we use data from January 1996 to December 2012 mostly, with variations depending on specific commodities, to match the sample of other three asset classes.

We also collect commodity futures data from the CRB. Similar to bond futures and options, we use both the front contract with the nearest expiration date and the back contract with the second nearest expiration date following the literature (Gorton, Hayashi, and Rouwenhorst, 2013; Hong and Yogo, 2012).[14] The grid of strikes is deep. Similar to bond futures options, we treat commodity futures options of American style as European options. All the commodity futures and options are quoted in USD, hence we use the one-month LIBOR as the short-term discount rate. Appendix 1 provides detailed information of these commodity futures options.

2.2 Rare disaster concern measures

The ideal measure of rare disaster concerns should be parsimonious in terms of combining OTM puts of different moneyness, and also rigorous in terms of picking up only the disaster risk and excluding other types of risk like volatility risk in option prices. To construct such a measure, we employ the methodology in Gao, Gao, and Song (2013) to develop a set of $\mathbb{RIX}$s for each asset of equity indices, currencies, bonds and commodities. The construction of these disaster concern measures build on the literature of model-free implied volatility (Carr and Madan, 1998; Bakshi and Madan, 2000; Britten-Jones and Neuberger, 2000; Carr and Wu, 2009; Du and Kapadia, 2012).

In particular, our rare disaster concern index ($\mathbb{RIX}$) is essentially equal to the difference between

[14] Bakshi, Gao, and Rossi (2013) do not use the front contract to avoid the effect of the first notice day falling before the expiration date of the front contact, which makes the investor face physical delivery issues from the counterparty. We have tried this choice of futures contracts and found our results were not changed.

the prices of two different option portfolios,

$$\begin{aligned}
\mathbb{IV}^- &\equiv \frac{2e^{r\tau}}{\tau}\int_{K<S_t}\frac{1}{K^2}P(S_t;K,T)dK,\\
\mathbb{V}^- &\equiv \frac{2e^{r\tau}}{\tau}\int_{K<S_t}\frac{1-\ln\left(K/S_t\right)}{K^2}P(S_t;K,T)dK,
\end{aligned}\tag{1}$$

where only OTM put options that protect investors against negative price jumps are used. We then define the $\mathbb{RIX}$ as

$$\mathbb{RIX} \equiv \mathbb{V}^- - \mathbb{IV}^- = \frac{2e^{r\tau}}{\tau}\int_{K<S_t}\frac{\ln\left(S_t/K\right)}{K^2}P(S_t;K,T)dK. \tag{2}$$

Note that $\mathbb{IV}^-$ contains positions in OTM puts with a weight inversely proportional to their squared strikes, while $\mathbb{V}^-$ differs by assigning larger (smaller) weights to more deeply OTM put options. Since more deeply OTM options protect investors against larger price changes, it is intuitive that the difference between $\mathbb{IV}^-$ and $\mathbb{V}^-$ captures investors' expectation about the distribution of large price variations. We note that rare disaster concern measures can be constructed similarly with OTM calls depending on perspectives of the average investor across markets and asset classes, as discussed above.

Assume the price process follows the Merton (1976) jump-diffusion model with $dS_t/S_t = (r-\lambda\mu_J)\,dt + \sigma dW_t + dJ_t$, where r is the constant risk-free rate, σ is the volatility, W_t is a standard Brownian motion, J_t is a compound Poisson process with jump intensity λ, and the compensator for the Poisson random measure $\omega\,[dx,dt]$ is equal to $\lambda\frac{1}{\sqrt{2\pi}\sigma_J}\exp\left(-\left(x-\mu_J\right)^2/2\right)$. We can show that

$$\mathbb{RIX} \equiv 2\mathbb{E}_t^{\mathbb{Q}}\int_t^T\int_{R_0}\left(1+x+x^2/2-e^x\right)\omega^-\left[dx,dt\right], \tag{3}$$

where $\omega^-\,[dx,dt]$ is the Poisson random measure associated with negative price jumps. Therefore, our $\mathbb{RIX}$ captures all the high-order (≥ 3) moments of the jump distribution with negative sizes given that $e^x-(1+x+x^2/2) = x^3/3+x^4/4+\cdots$.

We observe from (2) and (3) that the $\mathbb{RIX}$ is both parsimonious in combining options with different moneyness and also rigorous in capturing high-order (≥ 3) moments of the jump distribution. Hence, we shall use $\mathbb{RIX}$ as our main measure of ex-ante disaster concerns in empirical analysis.

Nevertheless, alternative measures of rare disaster concerns exist. We consider two such measures to check the robustness of the asset return patterns associated with rare disaster concerns. The first is $\mathbb{IV}^-$, a model-free measure of semi-variance as the downside version of the model-free implied volatility, which underlies the CBOE VIX (using S&P500 options). As $\mathbb{IV}^-$ is also a weighted average of OTM put option prices, we expect it to capture the rare disaster concerns to certain extent, which echoes the role of CBOE VIX as an "investor fear gauge". We dub it as $\mathbb{VIX}^-$. The second is the implied volatility skew, defined as the difference between the Black-Scholes implied volatility of out-of-the-money and at-the-money options. It captures the expensiveness of the OTM options relative to ATM options and hence disaster concerns potentially. Though intuitive and popular in financial industry, these two measures may contain larger noises in terms of capturing disaster concerns than our $\mathbb{RIX}$ measure that captures purges the lower-moment risks according to (3).

2.3 Empirical estimation

Following the literature, we clean option data of the four asset classes as follows: (1) we exclude options with non-standard expiration dates, with missing implied volatility, with zero open interest, with either zero bid price or negative bid–ask spread; (2) we discard observations with bid or ask price less than 0.05 to mitigate the effect of price recording errors; and (3) we remove observations where option prices violate no-arbitrage bounds. Finally, we only consider options with maturity larger than 7 days and less than 180 days for liquidity concerns.

Throughout the paper, we use the 30-day horizon to construct each asset's $\mathbb{RIX}$, i.e., $T - t = 30$. On a daily basis, we choose options with exactly 30 days to expire, if they are available. Otherwise, we choose two contracts that have the nearest maturities of 30 days with one longer and the other shorter than 30 days. We exclude days with fewer than two option quotes of different moneyness levels for each chosen maturity.[15] As observed from (2), the computation of $\mathbb{RIX}$ relies on a continuum of moneyness levels. Following Carr and Wu (2009) and Gao, Gao, and Song (2013), we interpolate implied volatilities across the range of observed moneyness levels. For moneyness levels outside of the available range, we use the implied volatility of the lowest (highest) moneyness contract for moneyness levels below (above) it.

[15] Since the currency options are written on USD-based exchange rates, put options correspond to the depreciation of USD and appreciation of the other currency, and vice versa for calls.

In total, we generate 2,000 implied volatility points equally spaced over a strike range of zero to three times the current spot price for each chosen maturity each date. We then obtain a 30-day implied volatility curve either exactly or by interpolating the two implied volatility curves of the two chosen maturities. Finally, we use the generated 30-day implied volatility curve to compute the OTM option prices by the Black–Scholes formula and then $\mathbb{RIX}$ according to a discretization of equation (2) for each day. After obtaining those daily estimates of each asset, we take the daily average over each month to deliver a monthly time series of this asset's $\mathbb{RIX}$.

Figure 1 visualizes rare disaster concerns by showing time-series mean and standard deviation of monthly $\mathbb{RIX}$ for each of 30 international equity indices, 32 currencies, 14 global government bonds, and 28 commodity futures (Appendix 2 provides detailed summary statistics of these rare disaster concern indices). The sample periods of options data of these assets vary and we list them below each panel. Within the equity class (Panel A), the Russia market has the highest mean of $\mathbb{RIX}$ and the Singapore market has the lowest; South Korean equity market has the highest standard deviation of $\mathbb{RIX}$ and Israel equity market has the lowest. Within the currency class (Panel B), the currency of Iceland has both the highest mean and standard deviation of $\mathbb{RIX}$, most likely due to the recent 2007-08 financial crisis (the currency option data of Icelandic Krona begin in 2006). Within the bond class (Panel C), the U.S. 30-year bond displays the highest mean of $\mathbb{RIX}$ and the Canada 10-year bond displays the highest standard deviation of $\mathbb{RIX}$. We also observe long-term bonds in general have higher $\mathbb{RIX}$ means and standard deviations than short-term bonds. Within the commodity class (Panel D), the natural gas displays the highest mean of $\mathbb{RIX}$ and the RBOB blendstock gasoline displays the highest standard deviation.

After constructing each asset's $\mathbb{RIX}$ at month t and averaging the cross-section of $\mathbb{RIX}$s using all available ones at that time, we aggregate all assets' $\mathbb{RIX}$s within an asset class into an asset-class-specific $\mathbb{RIX}$. Figure 2 presents time-series plots of four asset-class-specific rare disaster concern indices: $\mathbb{EQRIX}$ for equity index, $\mathbb{FXRIX}$ for currency, $\mathbb{BDRIX}$ for bond, and $\mathbb{CMRIX}$ for commodity. Equity-class rare disaster concerns are more volatile, and they spike when the global financial markets *experienced* realized shocks such as the 1997 Asian Financial Crisis and the recent 2007-08 global recession. Importantly, high levels of $\mathbb{EQRIX}$ also correspond to the periods when the financial markets *fear* future global disaster events such as the Flash Crash in May 2010 and market rally in October 2011.[16] Bond-class rare disaster concerns also spike in 2003 when there was a sell-off in global bond markets. One can also observe a commonality pattern among the four asset-class-specific $\mathbb{RIX}$s. We further discuss co-movement of rare disaster concerns in Section 3.

3 Rare Disaster Concerns and Asset Returns

In this section, we present our baseline results on how rare disaster concerns drive global asset returns. After discussing the return data for international equity indices, currencies, bond futures, and commodity futures, we present empirical evidence within each asset class. We then document the strong co-movement of $\mathbb{RIX}$s across asset classes and construct a global rare disaster concern index ($\mathbb{GRIX}$). Finally we show that $\mathbb{GRIX}$-covariation is a key determinants of cross-sectional return variations across markets and asset classes.

3.1 Return data

Our return data on equity indices, currencies, bonds and commodities match the sample of options introduced in Section 2. We describe return calculations as follows.

International Equity Index Returns. We obtain monthly returns of the 30 international equity indices from MSCI and FTSE (via Datastream). These returns are denominated in local currencies, and we convert them into USD-based returns as follows.

Let $r_t^{f,k}$ be the net (and simple) return on equity index k denoted in a local currency for month t, and S_t be the spot exchange rate of currency k against US Dollar (i.e., foreign currency unit (FCU) per USD) at the end of month t. Then the USD-based net return on equity index k for month $t+1$ is

$$r_{t+1}^k = S_t(1 + r_{t+1}^{f,k})/S_{t+1} - 1 \tag{4}$$

We then subtract r_{t+1}^k by $R_{t+1}^{f,US}$, the one-month U.S. T-bill rate, to obtain the excess return rx_{t+1}^k. To ensure our portfolio strategies are implementable for investors, we use spot exchange rates from

[16] Appendix 3 presents an event study of rare disaster concerns during the five-day period surrounding the event of 2010 Flash Crash. The Flash Crash happened on the U.S. equity market on May 6, 2010. Interestingly, we observe increased concerns on international equity markets not only on the event day but also on the day afterwards. Moreover, increased concerns show up not only on equity class, but on currency and bond classes as well. These results are consistent with the *ex ante* nature of $\mathbb{RIX}$s, rare disaster concerns can increase with with no subsequent realized disaster shocks.

J.P. Morgan, one of the largest foreign currency dealers, to make such conversions.

Currency Returns. We use daily spot and one-month forward exchange rates against USD of the 32 currencies obtained from Barclays and Reuters (via Datastream). Our empirical procedures closely follow prior influential studies of currency returns such as Lustig, Roussanov, and Verdelhan (2011).[17] We use both spot and forward exchange rates that correspond to midpoint quotes (i.e., the average of bid and ask rates). Following the tradition in the currency literature, we work with spot and forward rates in logarithms, denoted as s and f, respectively. The change in (log) spot rate is defined as $\Delta s_{t+1} = s_{t+1} - s_t$.

For a U.S. investor who buys a foreign currency k in the forward market and sells it in the spot market one month later, we calculate the monthly (log) excess return as

$$rx_{t+1}^k \equiv f_t^k - s_{t+1}^k,$$

which is equal to the (log) forward discount minus the spot rate change

$$rx_{t+1}^k = R_t^{f,k} - R_t^{f,US} - \Delta s_{t+1}^k,$$

where $R_t^{f,k}$ and $R_t^{f,US}$ are the one-month risk-free rates of the foreign country and U.S., respectively. If covered interest rate parity (CIP) holds, the forward discount is equal to the interest rate differential: $f_t^k - s_t^k \approx R_t^{f,k} - R_t^{f,US}$.[18] Because we will perform portfolio analyses on combined assets from equity, currency, and bond classes, we use simple returns in our empirical analysis to be consistent across asset classes (see the robustness check in Section 5.3 for portfolio results of currency log returns).

Bond Futures Returns. We collect daily prices of 14 bond futures from various exchanges (via J.P. Morgan). For each instrument, we compute monthly rolling excess returns of the most liquid futures contract (typically the nearest or the next nearest to delivery contract). In particular,

[17] Some of these currencies are pegged partly or completely to USD over our sample period (e.g., Argentine Peso (ARS), Hong Kong Dollar (HKD), and Peruvian Nuevo Sol (PEN)). Similar to Lustig, Roussanov, and Verdelhan (2011), we keep them in our sample because forward contracts are easily accessible to investors. Our results remain unchanged if these currencies are excluded.

[18] Based on the large failure of CIP, we delete the following observations from our sample: Malaysia (August 1998 - June 2005) and Indonesia (December 2000 - May 2007). According to Akram, Rime, and Sarno (2008), the CIP holds at daily and lower frequencies. Although this relation breaks down during the recent 2007-2008 financial crisis, including or excluding those observations does not change our empirical results.

at the end of each month, we select the nearest to maturity contract that will not expire during next month (often called the "front" futures contract).[19] We calculate the futures return on a fully collateralized position as follows.

Let $F_{t,T}^{f,k}$ be the futures price (in local currency) for bond k at the end of month t, with expiration date T. Let $R_t^{f,k}$ be the one-month risk-free rate in the same bond market during month t, which is assumed to be the interest earned on collateral. Then the monthly net return on a fully collateralized long position in futures contract k with expiration date T is

$$r_{t+1,T}^{f,k} = \left(\frac{F_{t+1,T}^{f,k}}{F_{t,T}^{f,k}} + R_t^{f,k} \right) - 1.$$

Hence, the monthly excess return of the bond futures k is $rx_{t+1,T}^{f,k} = r_{t+1,T}^{f,k} - R_t^{f,k} = F_{t+1,T}^{f,k}/F_{t,T}^{f,k} - 1$, and then we convert it into USD-based excess return $rx_{t+1,T}^{k}$ using a similar procedure (4).[20]

Commodity Futures Returns. We collect daily prices of 28 commodity futures from the CRB. Similar to bond futures, we compute monthly rolling excess returns of the most liquid futures contract (typically the nearest or the next nearest to delivery contract), on a fully collateralized position. In particular, at the end of each month, we select the nearest to maturity contract that will not expire during next month (often called the "front" futures contract).[21]

Let $F_{t,T}^{M,k}$ be the futures price (in USD) for commodity k at the end of month t, with expiration date T. Let $R_t^{f,US}$ be the one-month risk-free rate for U.S. dollars in month t and hence the interest rate on collateral. Then the monthly excess return on a fully collateralized long position in commodity futures contract k with expiration date T is

$$rx_{t+1,T}^{M,k} = \left(\frac{F_{t+1,T}^{M,k}}{F_{t,T}^{M,k}} + R_t^{USD,k} \right) - 1 - R_t^{USD,k} =_{t+1,T}^{M,k} / F_{t,T}^{M,k} - 1.$$

Table 1 reports summary statistics of global asset monthly excess returns (in excess of the one-month U.S. T-bill rate) in US dollars. On average, equity index earns 0.53% per month with a

[19] As robustness checks, we also consider the "far" futures contract (the next maturity after the most liquid one) and the 30-day constant maturity futures contract interpolated using the nearest and the next nearest to delivery contracts. Results are similar (see Section 5.3 for details).

[20] Asness, Moskowitz, and Pedersen (2013), Bessembinder (1992), de Roon, Nijman, and Veld (2000), Gorton, Hayashi, and Rouwenhorst (2013), Moskowitz, Ooi, and Pedersen (2012), and Koijen, Moskowitz, Pedersen, and Vrugt (2012) compute returns on futures contracts similarly.

[21] The appdendix contains robustness checks with the "far" futures contract and the interpolated 30-day futures contract simlar to bond futures.

standard deviation of 7.6%, currency earns 0.45% per month with a standard deviation of 3.6%, bond futures earns 0.20% per month with a standard deviation of 1.3%, and commodity earns 0.36% per month with a standard deviation of 9.2%. Regarding skewness and kurtosis, equity index return is left skewed whereas currency, bond, and commodity returns are right skewed; and interestingly bond futures have heavier return tails than the other three asset classes. Turning into individual assets within each asset class, the Russia investable market index, the currency of Indonesian Rupiah, the Spain 10-year bond futures, and the unleaded gasoline yield the highest mean excess returns of 2.56%, 3.26%, 0.35%, and 2.46% per month, within the asset classes of equity index, currency, bond, and commodity, respectively. Overall, we observe large cross-sectional return variations both within an asset class and across asset classes, which presents a challenging job for asset-pricing models.

3.2 $\mathbb{RIX}$ covariation and portfolio construction

Starting from December 1997, we perform 24-month rolling-window regression of an asset's monthly excess returns on the factors of market excess return and the rare disaster concern index in computing the asset's $\mathbb{RIX}$ covariation. To ensure we have a reasonable number of observations in the estimation, we require assets to have at least 18 months of returns. Specifically, we estimate $\mathbb{RIX}$ covariation in the following way: in the equity class we regress equity index excess returns (USD-based returns in excess of the one-month U.S. T-bill rate) on the MSCI world equity index excess returns and $\mathbb{EQRIX}$; in the currency class we regress currency returns on the dollar value factor (currency market returns) and $\mathbb{FXRIX}$; in the bond class we regress bond futures returns on the Barclays Capital global government bond index return and $\mathbb{BDRIX}$; and in the commodity class we regress the commodity futures returns on the S&P GSCI index return and $\mathbb{CMRIX}$. Our option sample in measuring rare disaster concerns and return sample in estimating $\mathbb{RIX}$ covariations are unbalanced panel data. We restrict the return sample to match the options sample, i.e., we require the availability of an asset's options (and its associated $\mathbb{RIX}$) when using time-series regressions to estimate its $\mathbb{RIX}$ covariation so that this asset's rare disaster concern contributes to the aggregated rare disaster concern index (within or across asset classes).

We perform standard portfolio analysis on $\mathbb{RIX}$ covariation and examine future asset returns. When analyzing returns within an asset class, we rank assets into four groups based on their

$\mathbb{RIX}$ covariations, and then calculate equal weighted portfolio excess returns and abnormal returns (alphas) based on benchmark models. For the analysis of returns across asset classes, we sort all the assets of the four global asset classes into five quintiles based on their covariation with respect to global rare disaster concern index that we will discuss shortly. We construct the low-minus-high $\mathbb{RIX}$-covariation portfolio that is long low $\mathbb{RIX}$-covariation (unfavorable) assets and short high $\mathbb{RIX}$-covariation (favorable) assets, both within and across asset classes. To study the horizons of $\mathbb{RIX}$ covariation in explaining asset returns, we consider portfolio formation at monthly, quarterly, semi-annual, and annual frequencies. Finally, to measure alphas, we use the Asness-Moskowitz-Pedersen (AMP) value and momentum factors, Frazzini-Pedersen (FP) betting-against-beta factor, and Moskowitz-Ooi-Pedersen (MOP) time series momentum factors, which have beee shown to drive security returns across asset classes.[22]

3.3 $\mathbb{RIX}$ covariation and returns within asset classes

Table 2 presents results of $\mathbb{RIX}$-covariation portfolios in each asset class. In particular, we form four portfolios within each of the four asset classes of equity, currency, bond and commodity, based on assets' covariation with respect to rare disaster concern indices $\mathbb{EQRIX}$, $\mathbb{FXRIX}$, $\mathbb{BDRIX}$, and $\mathbb{CMRIX}$, respectively. On average, there are five equity indices, six currencies, three bond futures, and seven commodity futures in each respective $\mathbb{RIX}$-covariation portfolio. To examine whether diversification benefits exist across asset classes, we also conduct a simple combination strategy that yields equal weighted returns across the four asset classes.

Three main results arise. First, we find consistent patterns that low $\mathbb{RIX}$-covariation assets earn higher returns than high $\mathbb{RIX}$-covariation assets in each asset class. The return differences between low and high $\mathbb{RIX}$-covariation assets are not only statistically significant but also economically large. For example, when we monthly form portfolios, the low-minus-high (LMH) $\mathbb{RIX}$-covariation portfolios on average significantly earn 0.76%, 0.37%, 0.21%, and 0.90% per month within asset classes of equity, currency, bond, and commodity, respectively.

Second, asset return predictability associated with $\mathbb{RIX}$ covariation is not short-lived. For

[22] We also use other benchmark factors to compute alphas in different asset classes. For example, in the class of international equity indicies, we use the Fama-French three factors augmented with the Carhart's momentum factor in the international context (Fama and French, 2012). In the currency class, we use the two common risk factors of Lustig, Roussanov, and Verdelhan (2011). In the commodity class, we use the common risk factors based on commodity basis (Yang (2013)). Our results remain unchanged.

example, at the semi-annual frequency of portfolio formation, these portfolios earn even higher average returns (0.97%, 0.54%, 0.28%, and 1.45% per month), all close to three standard errors from zero. In addition, at various frequencies of portfolio formation, the spreads of LMH $\mathbb{RIX}$-covariation portfolios mainly come from high excess returns earned by low $\mathbb{RIX}$-covariation assets (the long leg).

Third, these return patterns from assets' return covariation with rare disaster concerns are largely unexplained by well-known benchmark factors across asset classes. Specifically, alphas of LMH $\mathbb{EQRIX}$-covariation, $\mathbb{FXRIX}$-covariation, and $\mathbb{CMRIX}$-covariation portfolios are significant at all frequencies of portfolio formation, whereas those of LMH $\mathbb{BDRIX}$-covariation portfolios are significant at all frequencies except quarterly. The alphas are still economically large, only slightly lower than the corresponding raw returns. Furthermore, the LMH $\mathbb{RIX}$-covariation portfolio from the simple combination strategy yields 0.60% to 0.77% (0.56% to 0.81%) mean returns (alphas) per month depending on the portfolio formation frequency, all statistically significant (most of time t-statistics are larger than three). This result of combination strategy illustrates the important diversification effect of $\mathbb{RIX}$-covariation portfolios across asset classes.

Figure 3 shows year-by-year annual returns and Sharpe ratios of the LMH $\mathbb{RIX}$-covariation portfolios within each asset class and through the asset-class combination. The outperformance of low $\mathbb{RIX}$-covariation assets is not restricted to a particular year. Importantly, the return spreads of LMH $\mathbb{RIX}$-covariation portfolios are positive during a few disaster periods such as the 2002 stock market downturn and the 2007-2008 global financial crisis, which suggests that asset returns associated with *ex ante* rare disaster concerns differ from those driven by disaster risk. Should one interpret low $\mathbb{RIX}$-covariation assets as risky because of their high sensitivity to disaster risk, the return spreads of LMH $\mathbb{RIX}$-covariation portfolios are expected to be negative when disaster shocks are realized.

3.4 Co-movement in rare disaster concerns

We perform correlation analysis of rare disaster concerns and report results in Table 3. Panel A presents the summary statistics of all pairwise sample correlations of $\mathbb{RIX}$s in each asset class. The mean correlations are 0.78, 0.61, 0.28, and 0.31 within equity, currency, bond, and commodity markets respectively. We also compute the pairwise correlations of $\mathbb{RIX}$s across assets from different classes. The mean (median) correlations are the following: 0.43 (0.46) between equity and non-equity classes, 0.46 (0.51) between currency and non-currency classes, 0.24 (0.31) between bond and non-bond classes, and 0.27 (0.29) between commodity and non-commodity classes. These results indicate strong co-movements or commonality of rare disaster concerns both within an asset class and across asset classes.

To capture the commonality of disaster concerns across markets and asset classes, we construct a global rare disaster concern index ($\mathbb{GRIX}$) as the first principal component of the correlation matrix of three asset-class-specific rare disaster concern indices ($\mathbb{EQRIX}$ for equity, $\mathbb{FXRIX}$ for currency, $\mathbb{BDRIX}$ for bond, and $\mathbb{CMRIX}$ for commodity). The $\mathbb{GRIX}$, which essentially averages rare disaster concerns across asset classes, accounts for over 70% of the covariations of the rare disaster concern indices for the four asset classes. Panel B of Table 3 presents correlations of the global and asset-class-specific rare disaster concern indices. We observe that (both Pearson and Spearman) correlations between $\mathbb{GRIX}$ and $\mathbb{EQRIX}$, $\mathbb{FXRIX}$, $\mathbb{BDRIX}$ and $\mathbb{CMRIX}$ range between 53% to 92%, with statistical significance at 1% level.

3.5 $\mathbb{GRIX}$ covariation and returns across asset classes

In this section, we present our main results on the relation between $\mathbb{GRIX}$ covariations and security returns across asset classes, i.e., portfolios that potentially consist of different asset classes given the global nature of $\mathbb{GRIX}$.[23] We rank all 104 global investment assets into five $\mathbb{GRIX}$-covariation quintiles and examine their future returns. On average, there are 17 assets in each quintile portfolio. Panel A of Table 4 presents monthly mean excess returns and alphas, whereas Panels B and C present factor loadings of monthly and quarterly formed portfolios.

Panel A of Table 4 shows that global rare disaster concerns (channeled through $\mathbb{GRIX}$ covariation) are a key driver of return variations across markets and asset classes. In particular, when

[23] The appendix contains results on the $\mathbb{GRIX}$ covariation and returns within each asset class. When portfolios are monthly formed, there are significant return spreads between low and high $\mathbb{GRIX}$-covariation portfolios in equity and bond classes (0.79% for equity index with a t-statistic of 2.4, and 0.26% for bond futures with a t-statistic of 2.2), but not in currency class (0.17% with a t-statistic of 1.0). The LMH $\mathbb{GRIX}$-covariation portfolio in the combination strategy earns 0.41% per month that is more than three standard errors from zero, again indicating the diversification benefit across asset classes. Such return spreads within each asset class decrease and become less statistically significant as we move into lower frequencies of portfolio formation. Yet, when averaging across three asset classes, the combination strategy still yields significant return differences between low and high $\mathbb{GRIX}$-covariation portfolios (e.g., at the semi-annual frequency spreads of 0.27% with a t-statistic of 2.1). Overall, these results provide initial evidence on the explanatory power of global rare disaster concerns on cross-sectional asset returns.

portfolios are monthly formed, the return spread between low and high $\mathbb{GRIX}$-covariation portfolios is 1.00% per month with a significant t-statistic of 3.6. This return spread gradually decreases as portfolios are formed at further lower frequencies (0.72%, 0.42%, and 0.02% with t-statistics of 2.5, 1.6, and 0.1 at the quarterly, semi-annual, and annual frequencies, respectively). In addition, these return spreads are mainly driven by assets with low $\mathbb{GRIX}$ covariations – all low $\mathbb{GRIX}$-covariation quintiles earn significant excess returns around 0.70% per month at different portfolio formation frequencies. In contrast, all high $\mathbb{GRIX}$-covariation quintiles do not earn monthly excess returns that are statistically different from zero.

Table 4 also shows that asset returns associated with $\mathbb{GRIX}$ are not attributed to effects of global value and momentum, BAB factors, and time series momentum. In particular, Panel A of Table 4 shows that monthly alphas of LMH $\mathbb{GRIX}$-covariation portfolios are all economically large, especially at monthly and quarterly frequencies of portfolio formation, ranging from 0.76% to 0.96% (with t-statistics from 2.3 to 3.2). Furthermore, Panels B and C show that loadings on the market factor, the VME factors, and the BAB factor have little explanatory power for the return spread between low and high $\mathbb{GRIX}$-covariation quintiles.

Does the low (or high) $\mathbb{GRIX}$-covariation portfolio only contain assets from a single asset class? Moreover, does the asset composition across equity indices, currencies, bond futures, commodity futures vary over time in the low (or high) $\mathbb{GRIX}$-covariation portfolio? Figure 4 presents asset class distributions over time of both low (top panel) and high (bottom panel) $\mathbb{GRIX}$-covariation portfolios.[24] Take the allocation distribution of the equity index as an example. We first count the number of equity indices within the low (or high) $\mathbb{GRIX}$-covariation quintile, and then divide it by the total number of equity indices that are available for investment at the end of each month when we form $\mathbb{GRIX}$-covariation portfolios.

Two main results arise from Figure 4. First, no single asset class fills up the low or high $\mathbb{GRIX}$-covariation portfolio at any time. That is, both low and high $\mathbb{GRIX}$-covariation portfolios contain assets from multiple asset classes in our sample. Second, the composition of low and high $\mathbb{GRIX}$-covariation portfolios varies over time, indicating that asset classes on average have time-varying loadings on $\mathbb{GRIX}$. Overall, our empirical evidence implies that return dynamics driven by

[24] In Appendix, we report the frequency of each asset within one asset class appearing in low and high asset-class-specific $\mathbb{RIX}$-covariation portfolios.

the $\mathbb{GRIX}$ are indeed pervasive across all asset classes (equity, currency, bond, and commodity) in response to time-varying global rare disaster concerns.

3.6 Alternative measures of rare disaster concerns

In this section, we show that the return dynamics driven by rare disaster concerns persist when alternative measures are used, though less significant due to larger noises of these measures than $\mathbb{GRIX}$ in capturing ex-ante disaster concerns. We consider the two alternative measures discussed in Section 2.2, $\mathbb{VIX}^-$ and volatility skew, dubbed as $\mathbb{GVIX}^-$ and $\mathbb{GVS}$ in the setting of global markets and asset classes. To construct $\mathbb{GVIX}^-$ and $\mathbb{GVS}$, we follow the procedures similar to the $\mathbb{GRIX}$ construction. Specifically, we first employ each asset's options data to estimate $\mathbb{VIX}^-$ and volatility skew measures using all available moneyness, average over assets within an asset class to get asset-class $\mathbb{VIX}^-$ and volatility skew measures, and finally take the first principal component of the correlation matrix of the four asset-class-specific measures.

We rank the 104 global investment assets into five quintiles based on their covariation with $\mathbb{GVIX}^-$ and $\mathbb{GVS}$. Table 5 reports monthly mean excess returns and alphas. Similar to results in Table 4 for $\mathbb{GRIX}$-covariation portfolios, unfavorable assets with respect to rare disaster concerns outperform favorable assets by 0.67% and 0.61% each month, with t-statistics of 2.5 and 2.1, respectively, based on $\mathbb{GVIX}^-$ and $\mathbb{GVS}$. The alphas are significant for portfolios based on $\mathbb{GVIX}^-$ (about 0.68% with a t-statistics of 2.4), though not for those based on $\mathbb{GVS}$ (about 0.28% with a t-statistic of 1.0). By contrast, returns of $\mathbb{GRIX}$-covariation portfolio are more significant, with a mean excess return of 1.0% (a t-statistic of 3.6) and an alpha of 0.96% (a t-statistic of 3.2) from Panel A of Table 4. Overall, the strong (but less significant) return patterns based on $\mathbb{GVIX}^-$ and $\mathbb{GVS}$ confirm that rare disaster concerns are a key driver of security returns across markets and asset classes, and that $\mathbb{GRIX}$ captures the global rare disasters better than alternative measures.

4 Additional Analyses on Global Asset Portfolios

Asset return dynamics across markets and asset classes incur involved issues such as perspectives of average investors. Furthermore, the global and local nature of rare disaster concerns is important for understanding the asset allocation in a portfolio across markets and asset classes. In this section, we first conduct analysis to show that the pervasive return pattern associated with rare disaster concerns is robust to alternative perspectives of average investors. We then dissect the global and local nature of rare disaster concerns.

4.1 Alternative positions of average investors

As discussed in Section 2, our baseline results take the perspective of an average U.S. investor who have long positions in international equity indices, foreign currencies, and global government bond futures and short positions in commodity futures. In consequence, the $\mathbb{GRIX}$ measure in our baseline results use OTM put options on equity indices, foreign currencies, and bond futures and OTM call options on commodity futures to capture the global market disaster concerns.

However, alternative perspectives exist. For example, an average investor with a global market portfolio positively related to the global macroeconomy or financial market may view the surging prices of bonds as signaling disasters because of flight-to-safety and flight-to-quality (Longstaff, 2004; Campbell, Pflueger, and Viceira, 2013, 2014), As a result, OTM calls on bonds should be used to capture the global rare disaster concerns. Moreover, investors are known to take carry trade portfolios in the currency market and hence long currencies with a high interest rate. In this case, OTM puts on high carry currencies should be employed to capture the disaster concerns of global markets.

To investigate whether return dynamics driven by rare disaster concerns are robust to alternative perspectives of average investors, we re-compute the $\mathbb{GRIX}$ measure consistent with such alternative perspectives. In particular, the alternative $\mathbb{BDRIX}$ can be computed using OTM calls on bond futures by a formula similar to (2). Furthermore, we compute the alternative $\mathbb{FXRIX}$ using OTM puts (calls) on the foreign currency with a higher (lower) interest rate than US. We then reconstruct the $\mathbb{GRIX}$ with these alternative asset-class-specific $\mathbb{RIX}\sim$, similar to the baseline $\mathbb{GRIX}$. We estimate each asset's return covariation with the alternative $\mathbb{GRIX}$ and then monthly form five quintiles.

Table 6 reports the mean excess returns and alphas when only using the alternative $\mathbb{BDRIX}$, only using the alternative $\mathbb{FXRIX}$, and using both the alternative $\mathbb{BDRIX}$ and $\mathbb{FXRIX}$. We observe that the return dynamics driven by rare disaster concerns are robust to such alternative perspectives of average investors. The return spread between unfavorable assets with low covariation with rare disaster concerns and favorable assets ranges from 0.82% to 0.89% (with t-statistics from 2.8 to 3.1) in different scenarios of alternative perspectives, about the same as the baseline results in Panel A of Table 4. Moreover, the alphas are from 0.61% to 0.84% with t-statistics above 2. Overall, we find that the return dynamics associated with rare disaster concerns across markets and asset classes are robust to alternative perspectives of average investors.

4.2 Global and local disaster concerns

To understand global and local nature of the rare disaster concerns, we orthogonalize an asset-class $\mathbb{RIX}$ by regressing it on the other three asset-class $\mathbb{RIX}$s and take the residuals as the asset-class-local $\mathbb{RIX}$. We then form portfolios according to an asset's covariation with respect to this local $\mathbb{RIX}$, both in the asset classes it belongs to and the other three asset classes together. For example, we perform a time series regression of monthly $\mathbb{EQRIX}$ (equity-class disaster concerns) on $\mathbb{FXRIX}$ (currency), $\mathbb{BDRIX}$ (government bond), and $\mathbb{CMRIX}$ (commodity), and use the residuals as a measure of the local $\mathbb{EQRIX}$. Within the equity class, we monthly form five local-$\mathbb{EQRIX}$-covariation quintiles; and across the currency, bond, and commodity assets classes, we form quintiles in a similar way. We perform similar regression and portfolio analyses for local $\mathbb{FXRIX}$, $\mathbb{BDRIX}$, and $\mathbb{CMRIX}$.

Table 7 reports these portfolio excess returns in Panel A and five-factor alphas in Panel B. We find marginally significant return differences driven by such asset-class-local $\mathbb{RIX}$s in equity and commodity classes, but not in currency and bond markets. Also as expected, none of the asset-class-local $\mathbb{RIX}$s can explain returns in the other three asset classes. Such results suggest that disaster concerns of currencies and bonds are "completely global", whereas those of equities and commodities have components that drive "local" return dynamics but not the whole global financial market.

5 Economic Channels of Rare Disaster Concerns

The rare disaster concern measures based on option prices do not separate preference and belief. Hence, an increase in $\mathbb{RIX}$ can be due to increasing disaster risk of economic fundamentals and financial markets (Barro, 2006; Gabaix (2012), Martin (2013c), and Wachter (2013)), increasing funding and capital constraints of institutional investors (Brunnermeier and Pedersen, 2009; Garleanu, Pedersen, and Poteshman, 2009; Garleanu and Pedersen, 2011; He and Krishnamurthy, 2012, 2013), and increasing disaster fear/perception (Liu, Pan, and Wang, 2005; Bates, 2008; Drechsler, 2013; Bollerslev and Todorov, 2011; Barberis, 2013; Chen, Dou, and Kogan, 2013; Weitzman, 2007). In this section, we conduct a comprehensive analysis to investigate implications of our return patterns driven by rare disaster concerns for various economic channels (all associated with disaster risk) of asset pricing theories. We collect variables for three economic channels, consumption and macro disaster risk, financial market disaster risk, and liquidity and funding constraints of financial intermediates, and study whether return dynamics associated with $\mathbb{GRIX}$ can be explained by them.

5.1 Economic channels and empirical measures

Consumption and Macroeconomic Disaster Risk. We obtain various measures of macroeconomic risk, including GDP growth, inflation, recession indicator, corporate default risk, and term spread of bond yields, for global economies (U.S., U.K., Japan, and Europe). The GDP growth is the real per-capita growth rate of GDP, computed quarterly by the real GDP growth rate obtained from Federal Reserve Economic Data (FRED) of the Federal Reserve Bank of St. Louis and the annual population growth obtained from the World Economic Outlook (WEO) database of International Monetary Fund (IMF). The inflation rate is the monthly year-on-year percentage change of the core CPI in different economies published by their respective central banks. For example, we use the Harmonized Index of Consumer Prices (HICP) for the Euro area. At monthly frequency, we collect the recession indicator for the U.S. economy from the NBER, and that for global economies from the Organization of Economic Development (OECD).[25] To obtain global factors of the GDP growth, the inflation rate, and the recession indicator, we calculate the average of each factor across U.S., U.K., Japan, and Europe, weighted by their respective beginning-of-year GDP obtained from the WEO.

We also proxy the corporate default risk using the difference between the Moody's AAA and BAA corporate bond yield obtained from the FRED for U.S. We use the difference between the AAA and BBB corporate bond yield indices with maturities of 7–10 years for U.K. and Euro zone, and the difference between investment and non-investment grade corporate bond yield indices for

[25] The recession indicator is equal zero (one) if an economy enters into a state of peak (trough) *ex post*.

Japan, both obtained from J.P. Morgan. Finally, we compute the term spread between the 10-year bond yield and 3-month T-bill rate for U.S., U.K., Japan, and Europe (using Germany as a proxy). We use differences (shocks to term spread and default factors) to measure risk exposure. The global term spread and default risk factors are computed as the first principal component of the correlation matrix of corresponding shocks across countries. We use the correlation rather than covariance matrix to accommodate the difference in volatility and scale of factors across various economies (see a similar approach in Asness, Moskowitz, and Pedersen (2013)).

Financial Market Disaster Risk. To measure the financial market disaster risk, we collect series of financial market liquidity and stock market tail risk, and construct series of high-order risk-neutral moments using options on various asset classes. Due to data constraints, we only use the U.S. variables for market liquidity, including the on-the-run minus off-the-run 10-year Treasury yield spread obtained from the Federal Reserve Board and innovations of the liquidity factor in Pastor and Stambaugh (2003) (obtained from Robert Stambaugh's webpage). Using the methodology in Bakshi, Kapadia, and Madan (2012), we also construct high-order risk-neutral moments, including variance, skewness, and kurthosis based on the set of equity indices, currencies, bond futures, and commodity futures options (the aggregation procedures are similar to those of constructing $\mathbb{GRIX}$).

Funding and Liquidity Constraints of Financial Intermediaries. Our variables of funding liquidity and leverage constraints of financial intermediaries include the "noise" measure in Hu, Pan, and Wang (2012) (obtained from Jun Pan's webpage) associated with the abundance of arbitrage capital and the leverage shock to the securities broker-dealers (obtained from Tyler Muir's website) in Adrian, Muir, and Etula (2012). We also collect series of Treasury-Eurodollar (TED) spread (the local 3-month interbank borrowing interest rate minus the local 3-month T-bill rate), the LIBOR-Repo spread (the local 3-month interbank borrowing interest rate minus the local 3-month General Collateral repurchase rate), and the Swap-Treasury spread (the local 10-year interest rate swap rate minus the local 10-year government bond yield) in each of the four markets. We first obtain daily series of the 3-month interbank borrowing interest rates (LIBOR for the U.S., the U.K., and Japan, and EURIBOR for Europe), 3-month T-bill rates, 3-month General Collateral repurchase rate, 10-year government bond yields, and 10-year interest rate swap rates from several datasources (J.P. Morgan, TRTH, and FRED). We then average daily data to construct monthly series. Finally, in order to measure liquidity shocks, we take the first-order difference in each of these monthly series.[26]

5.2 Results

Table 8 reports correlations of rare disaster concern indices with measures of global macroeconomic disaster risk (in Panel A), with measures of financial market disaster risk (in Panel B), and liquidity and funding constraints of finanical intermediaries (in Panel C). We find that $\mathbb{RIX}$s have low correlations with these measures, less than 30% mostly. As exceptions, the recession indicator and leverage shock to dealer-brokers have correlations with rare disaster concners at about 40% and -50%, respectively. Notably, the risk-neutral high-order moments based on the same set of options have low correlations with our $\mathbb{RIX}$ measures, suggesting that the $\mathbb{RIX}$ is not simply repackaing these high-order moments.

Panel A of Table 9 reports regression results of low-minus-high (LMH) $\mathbb{RIX}$-covariation portfolio returns (within and across asset classes) on macroeconomic disaster risk proxies. We observe that macroeconomic risk factors are generally not significant in explaining the return spreads between low and high $\mathbb{RIX}$-covariation portfolios, with the regression adjusted R^2 mostly small and oftentimes negative. Several factors do show certain statistical significance in driving return spreads of $\mathbb{RIX}$-covariation portfolios, such as the global market return. However, their economic significance is contradictory with interpreting the macroeconomic risk as driving our $\mathbb{RIX}$-covariation portfolio returns. Specifically, when the market return is low, low $\mathbb{GRIX}$-covariation assets earn even higher returns than high $\mathbb{GRIX}$-covariation assets. Moreover, though having a correlation of 0.49 with our $\mathbb{GRIX}$, the recession indicator has no power to explain our $\mathbb{GRIX}$-covariation portfolio returns at all. These results suggest that asset return predictability associated with the global market's rare disaster concerns is distinct from the exposure to disaster risk associated with macroeconomic downturns.

Panel B of Table 9 reports regression results for LMH $\mathbb{RIX}$-covariation portfolio returns on disaster risk factors of financial markets. Similar to macroeconomic disaster risk factors, financial market liquidity factors and the risk-neutral moments are hardly significant in explaining the time-series variability of the LMH $\mathbb{RIX}$-covariation portfolio return, with the risk-neutral kurtosis as the

[26] Defining shocks as the residuals from an AR(1) or AR(2) model (e.g., Korajczyk and Sadka, 2008; Moskowitz and Pedersen, 2012; Asness, Moskowitz, and Pedersen, 2013) does not change our results.

only exception for $\mathbb{GRIX}$ portfolios. However, the explanatory power is weak with the regression adjusted R^2 about 1%.

Panel C of Table 9 reports regression results for LMH $\mathbb{RIX}$-covariation portfolio returns on funding and liquidity constraints of finanical intermediaries. We observe that these variables are not significant in explaining the return spreads between low and high $\mathbb{RIX}$-covariation portfolios, including the leverage shock factor that is shown to have a high correlation of -0.6 with $\mathbb{GRIX}$. The regression adjusted R^2 are mostly small.

Overall, our results strongly indicate that the global asset return predictability driven by ex-ante disaster concerns cannot be explained by the exposure to disaster risk of consumption and macro fundamentals and disaster risk of financial markets. Moreover, it is not simply phantom of liquidity/capital constraints of financial intermediaries. Excluding these channels as driving our return patterns associated with rarer disaster concerns, such evidence suggests that time-varying disaster fear/perception, which is shown to drive asset prices in U.S. stock markets by Bates (2008), Drechsler (2013), and Bollerslev and Todorov (2011), might be a potential channel to reconcile security returns across asset classes.

We stress that our empirical evidence does not imply that models with macroeconomic and finanical disaster risk and model with intermediary constraints are unimportant. Alternatively, the $\mathbb{RIX}$ can be interpreted as a better measure of ex-ante disaster risk than other empirical proxies, and hence our results can simply be evidence supporting disaster risk theory. Though plausible, this interpretation faces an obstruction that the return spread of high-minus-low $\mathbb{RIX}$-covariation portfolios is significantly positive during most crisis periods, including the recent financial crisis that is fairly extreme in the history of the global economies; it is expected to be negative should we go with a disaster risk interpretation.

5.3 Fama-MacBeth Regressions

Table 10 reports Fama-MacBeth (1973) regression coefficient estimates and t-statistics from cross-sectional regressions of USD-based excess returns of the 104 global assets on their covariations with respect to the rare disaster concern indices, market return, liquidity risk, GDP growth, inflation, default risk, and term risk. Except for market beta, we estimate each asset's non-market beta in month t from a bivariate regression that always includes the market factor (the MSCI world equity index return in excess of one-month U.S. T-bill rate). For example, to estimate an asset's $\mathbb{GRIX}$ covariation we regress its excess returns on the market factor and the global rare disaster concern index based on the past 18-24 monthly observations. To reduce beta estimation error, we use each asset's beta rankings as regressors when running cross-sectional regressions at each point of time. Specifically, we form four $\mathbb{RIX}$-covariation portfolios within each asset class and use these rankings for "Asset-Class $\mathbb{RIX}$ covariation"; we form 10 $\mathbb{GRIX}$-covariation deciles across all assets and use these rankings for "Global $\mathbb{RIX}$ covariation". For other macro and liquidity betas, we do the same by forming 10 beta deciles and use their rankings. Thus, regression coefficients are comparable across different model specifications.

Results of the first two regression specifications confirm our portfolio results in Section 3, illustrating the asset return predictability driven by rare disaster concerns both within and across asset classes. In the other four specifications (with specifications (3) and (5) controlling for U.S. macroeconomic and liquidity risk factors and specifications (4) and (6) controlling for global risk factors), the coefficients on $\mathbb{RIX}$ beta are negative and statistically significant except for one case. Moreover, the regression coefficients of $\mathbb{RIX}$-covariation and $\mathbb{GRIX}$-covariation do not change much in presence of macroeconomic and liquidity risk betas. Regarding other regression coefficients, inflation beta is significantly negative with a right sign, and global default risk beta is significantly positive with a wrong sign. Overall, the explanatory power of rare disaster concerns on global asset return variations is robust to market beta, liquidity risk beta, real GDP growth beta, inflation beta, default risk beta, or term risk beta.

6 Robustness Checks

In this section, we discuss the robustness of our main findings about assets' covariation with rare disaster concerns and their cross-sectional expected returns. The detailed results are in Appendix.

6.1 Downside risk CAPM betas

Can the downside risk CAPM (DR-CAPM) in Lettau, Maggiori, and Weber (2013) price the cross section of $\mathbb{RIX}$-covariation portfolios? An interpretation of DR-CAPM is that assets having higher covariances with the market during its downturns than its upturns are more risky and hence require higher expected returns in equilibrium. Recall in our analysis low $\mathbb{RIX}$-covariation assets are unfavorable ones delivering low returns during the time of high disaster concerns of the market and we find they earn high excess returns on average. Thus, it seems imperative to ask whether low $\mathbb{RIX}$-covariation assets have high DR-CAPM betas, and particularly, whether the exposure to realized downside return shocks on the market is large enough to explain the return difference between low and high $\mathbb{RIX}$-covariation assets.

Among the set of $\mathbb{RIX}$-covariation portfolios of three asset classes, we estimate each portfolio's DR-CAPM beta by regressing its monthly excess returns on the market excess returns using only downstates that are all months in which the market return is at least one standard deviation below its sample mean (see Table 10 for details about the choice of market factor and the sample period of calculating mean and standard deviation of market returns). Table 10 presents DR-CAPM beta estimates, t-statistics, and regression R-squares. Two results arise. First, a fair amount of time series return variations of $\mathbb{RIX}$-covariation portfolios during market downstates are captured by the corresponding market excess returns.[27] This pattern is especially true for equity indices and currencies. Second, within each asset class, variations in loadings on the DR-CAPM market factor are unable to explain the cross-sectional return differences between low and high $\mathbb{RIX}$-covariation assets. The DR-CAPM betas of low-minus-high $\mathbb{RIX}$-covariation portfolios are both small in general and statistically insignificant. For example, the DR-CAPM beta spreads of the combination portfolios are 0.12 and 0.15, respectively, at frequencies of monthly and semi-annual portfolio formation, and both are less than one standard error from zero.

We also look at downside risk CAPM betas of $\mathbb{GRIX}$-covariation portfolios formed across 104 assets (there are 26 monthly observations in which we use as market downstates to estimate regression). Figure 5 illustrates the failure of DR-CAPM in explaining cross-sectional mean returns of $\mathbb{GRIX}$-covariation portfolios. The downside beta of low $\mathbb{GRIX}$-covariation portfolio (0.87 with a t-statistic of 4.6), if anything, is lower than that of high $\mathbb{GRIX}$-covariation portfolio (0.98 with a t-statistic of 4.6), which goes in a wrong direction to explaining the monthly return spreads of low-minus-high $\mathbb{GRIX}$-covariation portfolio 0.62% (see Panel A of Table 5).[28] Although our analy-

[27] Our definition of market downstate assigns 24, 21, and 29 monthly observations in asset classes of equity, currency, and bond, respectively.

[28] In an (unreported) analysis, we also follow Ang, Chen, and Xing (2006) to estimate assets' downside risk CAPM betas on a rolling-window basis. We find no systematic and significant return variations associated with these downside betas. In the asset class of equity indices, for example, the monthly return difference between low and high

sis suggests that the downside risk CAPM cannot explain global asset returns associated with rare disaster concerns, we interpret these results with caution given the relatively short sample period in our study (1996-2012) and (potentially) the lack of power in performing DR-CAPM asset pricing tests. In sum, the empirical findings in this section reiterate our earlier point in Section 4 that assets' covariation with the market's rare disaster concerns can be much different from their exposure to realized downside shocks on the market return.

6.2 Asset return data

We evaluate the strength of our main results of asset-class $\mathbb{RIX}$-covariation portfolios by using various data of global asset returns as follows: (1) we use exchange trade funds (ETFs) on the U.S. equity market to track international equity indices in our sample, and then use their monthly returns in the Center for Research in Security Prices (CRSP) to estimate ETFs' $\mathbb{EQRIX}$ betas and calculate equal-weighted index portfolio returns; (2) we use log returns instead of simple returns to estimate currencies' $\mathbb{FXRIX}$ betas and calculate currency portfolio returns; and (3) we use interpolated futures returns of 30-day constant maturity (contracts are based on the nearest and next nearest to delivery) to estimate bonds' $\mathbb{BDRIX}$ betas and calculate bond portfolio returns. Appendix 5 provides details of ETFs that are used to track international equity indices.[29]

We check mean excess returns of $\mathbb{RIX}$-covariation portfolios within each of three asset classes. In Panel A, when U.S. equity ETFs are used as investable assets, we find significant return spreads of low-minus-high $\mathbb{EQRIX}$-beta portfolios, especially when forming portfolios on quarterly, semi-annual, or annual basis. Moreover, these spreads (0.67% to 0.85% per month) are close to those of $\mathbb{EQRIX}$-beta portfolios based on the original Datastream returns of MSCI/FTSE international equity indices (0.86% to 0.97% as shown in Table 2). In Panels B and C, when using log returns on currency and interpolated futures returns on bond, respectively, we find return results very similar to those reported in our baseline analysis (see Table 2 for details). For example, the spreads of low-minus-high $\mathbb{FXRIX}$-beta portfolios vary from 0.36% to 0.46% based on the specification of log returns, and these numbers vary from 0.37% to 0.52% based on the specification of simple returns

downside-beta portfolios is 0.28% (with an insignificant t-statistic of 0.9). These results are available upon request.

[29] Among 30 equity indices, we are able to locate 28 ETFs with available returns in CRSP. Two equity markets, Finland and Denmark, have ETFs lunched on the U.S. equity market in January 2012, for which, however, we are unable to find corresponding monthly return data in CRSP.

7 Conclusion

We show that rare disaster concerns strongly drive cross-sectional return variation both within and across asset classes, including international equity indices, currencies, global government bonds, and commodities. Using a large set of out-of-the-money options on these assets, we measure the global financial market's rare disaster concerns under only no-arbitrage conditions. Assets that have low (high) return covariations with such concerns earn high (low) excess returns in the future. Such return patterns are not attributed to effects of global value and momentum, and are robust to various long/short positions of average investors.

We also find that our results are not explained by consumption and macroeconomic disaster risk, financial market disaster risk, and funding and liquidity constraints of financial intermediaries. The evidence suggests time-varying disaster fear/aversion as a potential venue to reconcile return dynamics across asset classes, making a step forward towards understanding "*how* discount rates vary over time and across assets" (Cochrane, 2011). We leave the exploration of this direction for future work.

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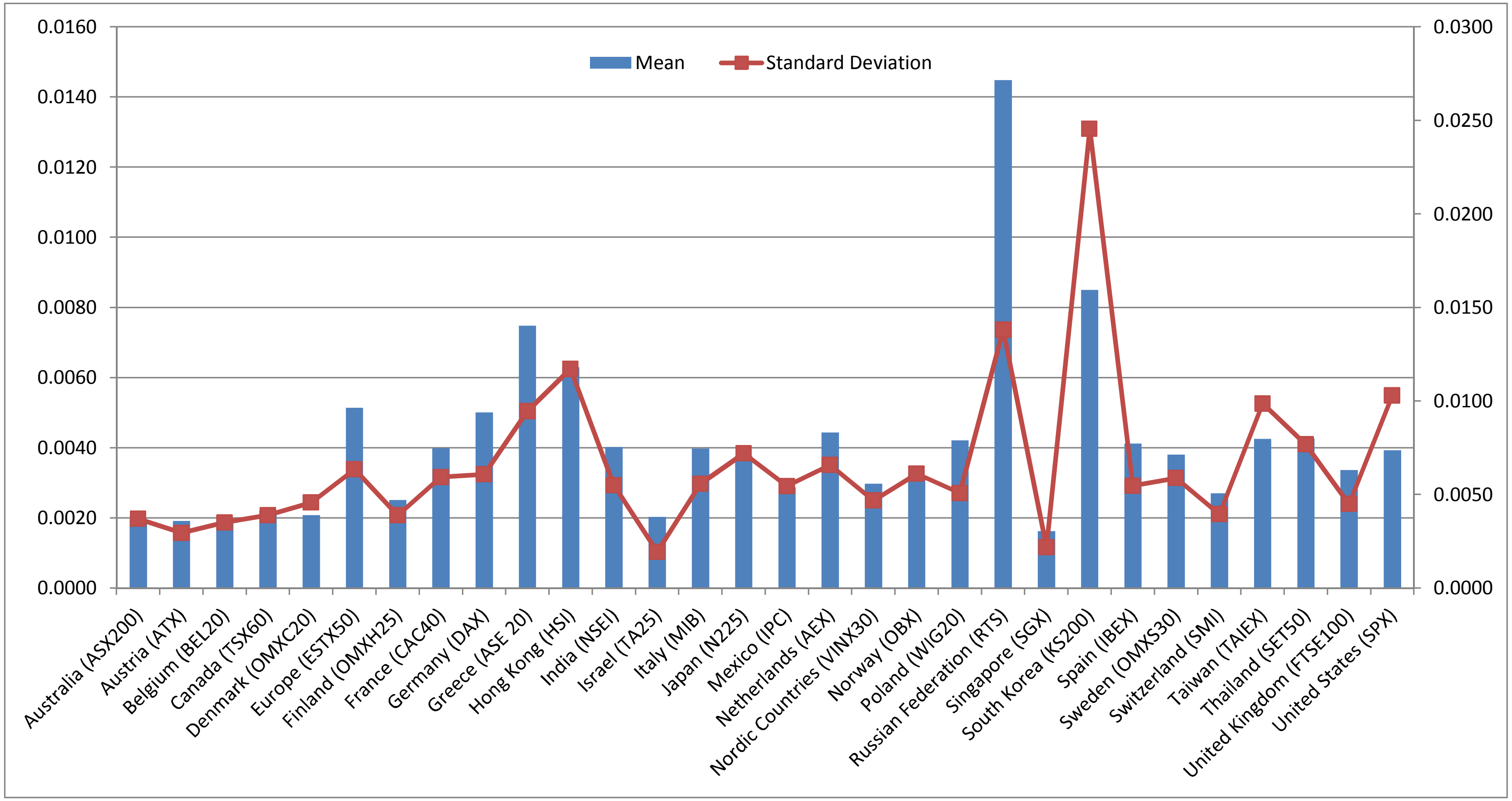
Figure 1: Rare disaster concern index (RIX) for equity index, currency, sovereign bond, and commodity

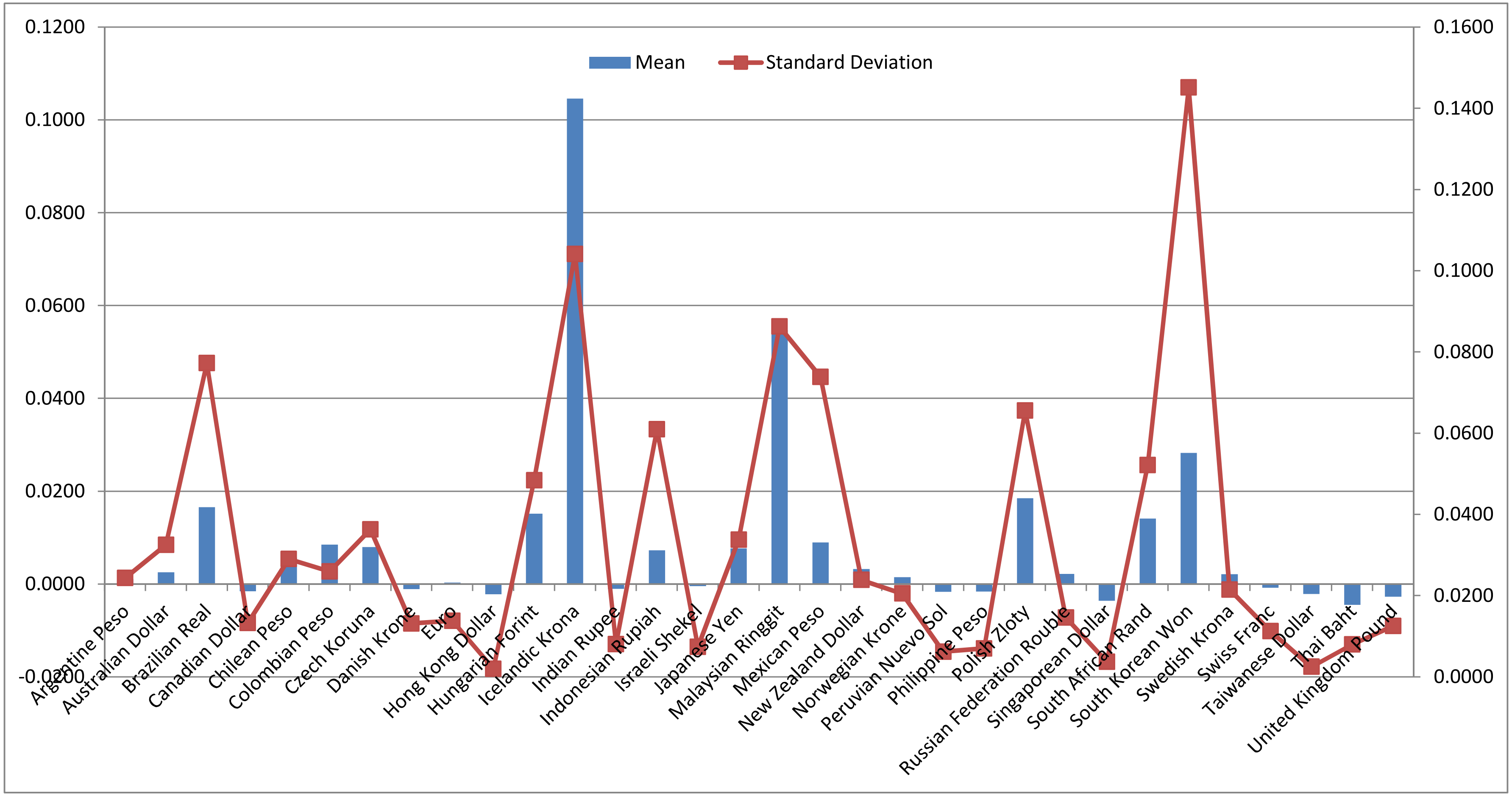
This figure shows time-series mean (left axis) and standard deviation (right axis) of monthly RIX for each of 30 international equity indices (Panel A), 32 foreign currencies (Panel B), 14 global government bonds (Panel C), and 28 commodities (Panel D). We also list option sample period below each panel.

Panel A: International equity index



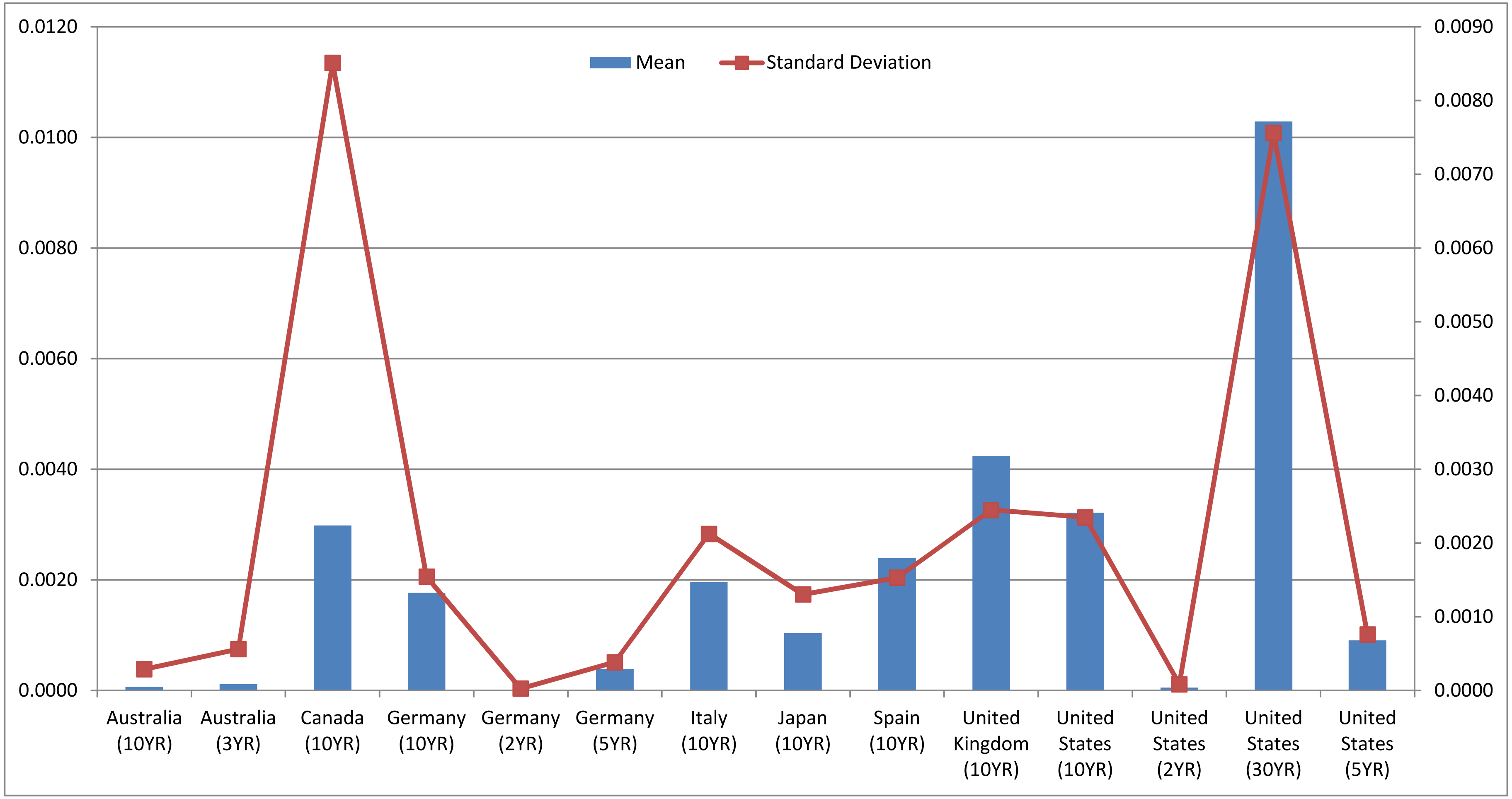
Equity index option sample period: ASX200 (2001:02 - 2012:10), ATX (1996:01 - 2012:10), BEL20 (1996:01 - 2012:10), TSX60 (1999:09- 2012:10), OMXC20 (2005:10 - 2012:01), ESTX50 (2001:07 - 2012:10), OMXH25 (2005:02 - 2012:10), CAC40 (2005:05 - 2012:10), DAX (2001:07 - 2012:10), ASE20 (2000:10 - 2012:10), HSI (1996:01 - 2012:10), NSEI (2001:07 - 2012:10), TA25 (1996:01 - 2012:10), MIB (2004:05 - 2012:10), N225 (1996:01 - 2012:10), IPC (2004:06 - 2012:10), AEX (1997:01 - 2012:10), VINX30 (2006:09 - 2012:10), OBX (1999:02 - 2012:10), WIG20 (2003:09 - 2012:10), RTS (2009:03 - 2012:10), SGX (2009:04 - 2012:10), KS200 (1997:07 - 2012:10), IBEX (2001:11 - 2012:10), OMXS30 (2004:11 - 2012:10), SMI (2001:07 - 2012:10), TAIEX (2001:06 - 2012:10), SET50 (2008:06 - 2012:10), FTSE100 (1996:01 - 2012:10), SPX (1996:01 - 2012:10).

Panel B: Foreign currency



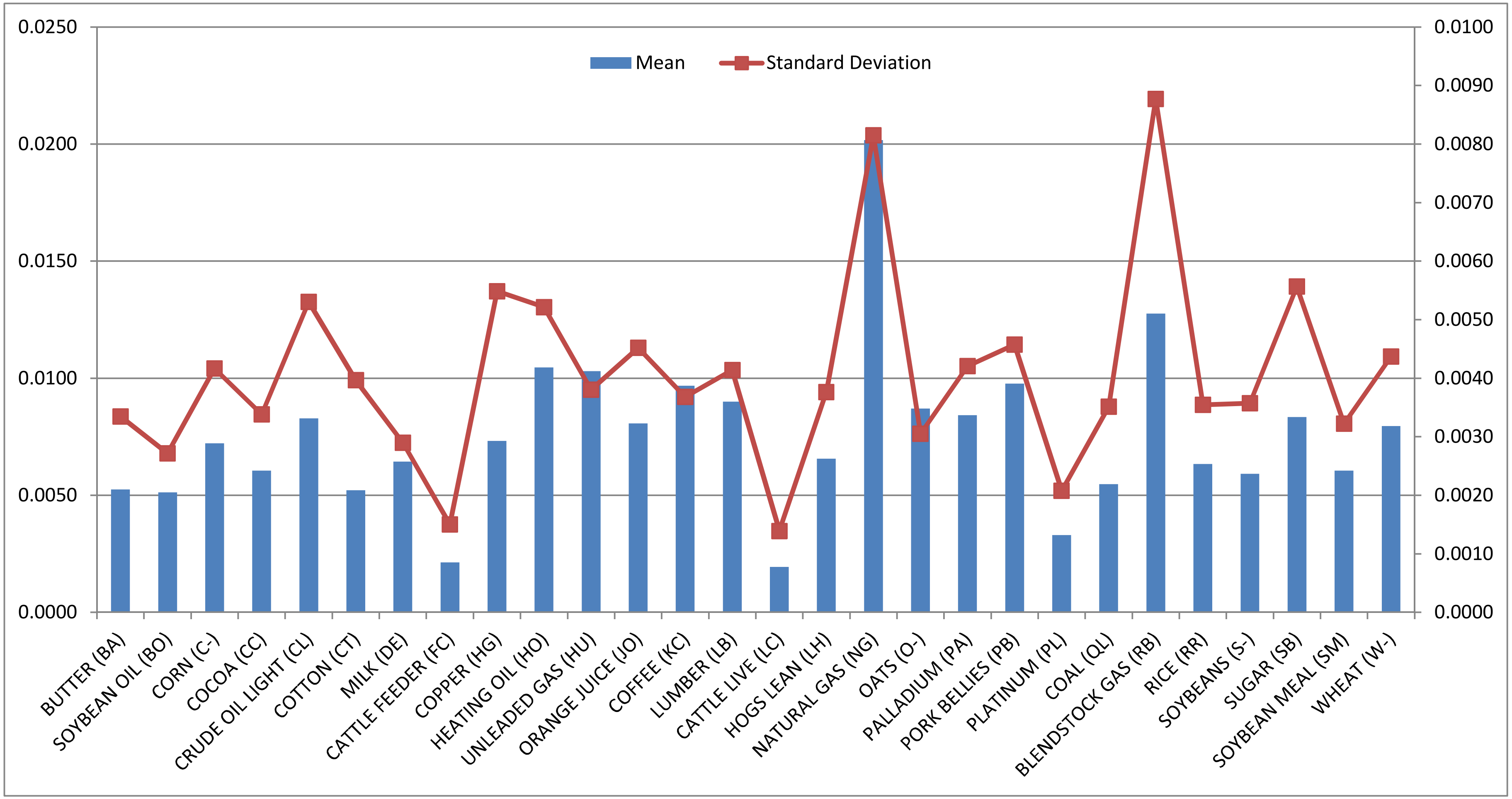
Currency option sample period: ARS (2004:03 - 2012:05), AUD (1996:01 - 2012:05), BRL (2004:03 - 2012:05), CAD (1996:02 - 2012:05), CLP (2004:03 - 2012:05), COP (2004:03 - 2012:05), CZK (2000:11 - 2012:05), DKK (1996:07 - 2012:05), EUR (1999:01 - 2012:05), HKD (1996:01 - 2012:05), HUF (2000:11 - 2012:05), ISK (2006:01 - 2012:05), INR (2004:03 - 2012:05), IDR (2001:03 - 2012:05), ILS (2004:03 - 2012:05), JPY (1996:02 - 2012:05), MYR (2000:11 - 2012:05), MXN (2000:11 - 2012:05), NZD (1996:12 - 2012:05), NOK (1996:02 - 2012:05), PEN (2004:03 - 2012:05), PHP (2003:02 - 2012:05), PLN (2000:11 - 2012:05), RUB (2006:01 - 2012:05), SGD (1997:03 - 2012:05), ZAR (1996:01 - 2012:05), KRW (2002:02 - 2012:05), SEK (1996:01 - 2012:05), CHF (1996:01 - 2012:05), TWD (2004:08 - 2012:05), THB (2000:11 - 2012:05), GBP (1996:01 - 2012:05). Note: The RIX mean and standard deviation of Icelandic Krona (ISK) are divided by 10.

Panel C: Glboal government bond



Bond futures option sample period: AUS 10YR (1996:01 - 2012:12), AUS 3YR (1996:01 - 2012:12), CAN 10YR (1996:01 - 2003:05), DEU 10YR (1996:01 - 2012:12), DEU 2YR (1998:02 - 2012:12), DEU 5YR (1996:01 - 2012:12), ITA 10YR (1996:01 - 2000:06), JPN 10YR (1996:01 - 2012:12), ESP 10YR (1996:01 - 2000:08), GBR 10YR (1996:01 - 2012:12), USA 10YR (1996:01 - 2012:12), USA 2YR (2006:11 - 2012:12), USA 30YR (1996:01 - 2012:12), USA 5YR (1996:01 - 2012:12).

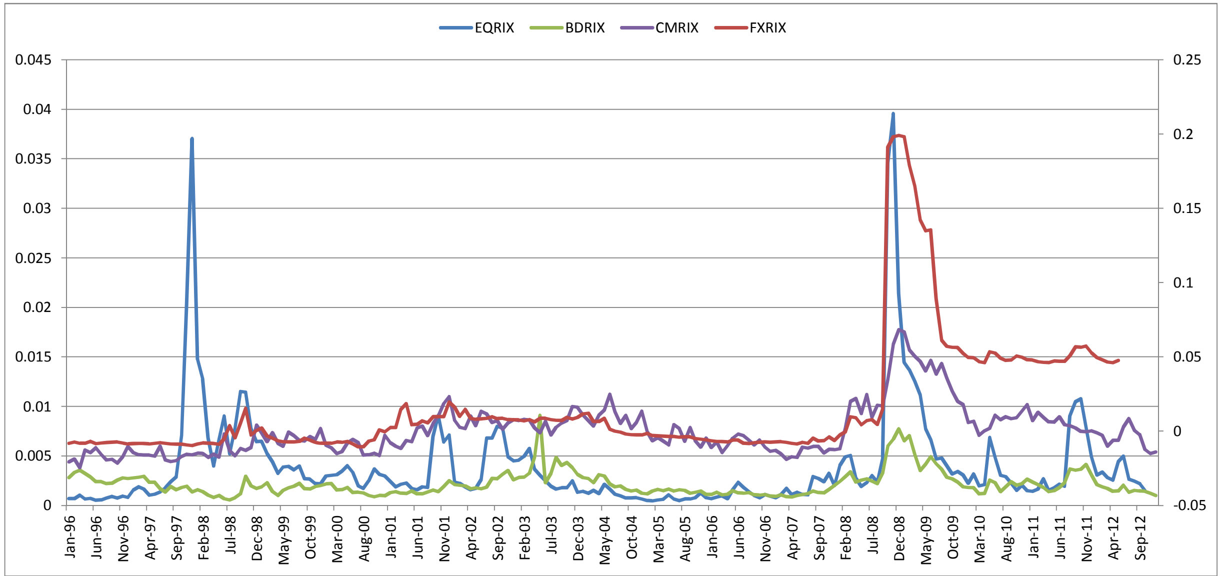
Panel D: Commodity



Commodity futures option sample period 1996:01 - 2012:12 with the following exceptions: BA (2008:07 - 2012:12), HU (1996:01 - 2006:11), LH (1996:11 - 2012:12), PA (2010:11 - 2012:12), PB (1996:01 - 2010:05), QL (2009:07 - 2012:10), RB (2006:05 - 2012:12).

Figure 2: Time series of four asset-class-specific RIXs (equity, currency, bond, and commodity)

Each asset-class-specific rare disaster concern index (RIX) is calculated as the cross-sectional average of available assets' RIXs within that asset class at point of time. The top figure presents monthly time series of RIXs: international equity index (EQRIX), currency (FXRIX), global government bond (BDRIX), and commodity (CMRIX). The values of EQRIX, BDRIX, and CMRIX are on left axis, and the values of FXRIX are on right axis. To facilitate the presentation, we multiply the original values of FXRIX and BDRIX by 100, and those of CMRIX by 10. The bottom figure marks important events associated with EQRIX spikes.



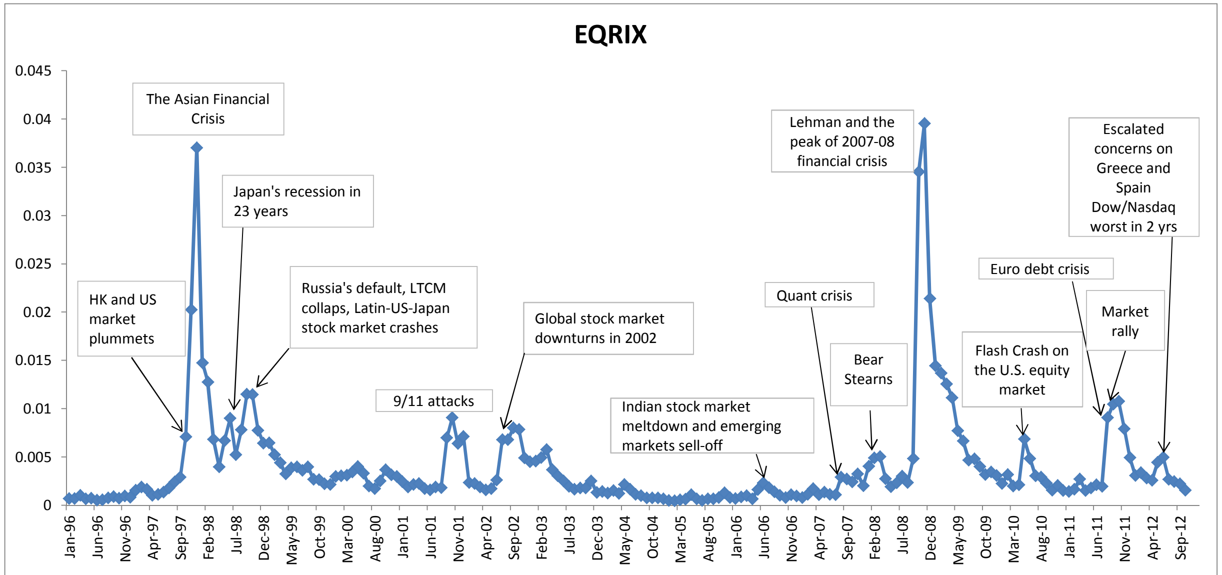
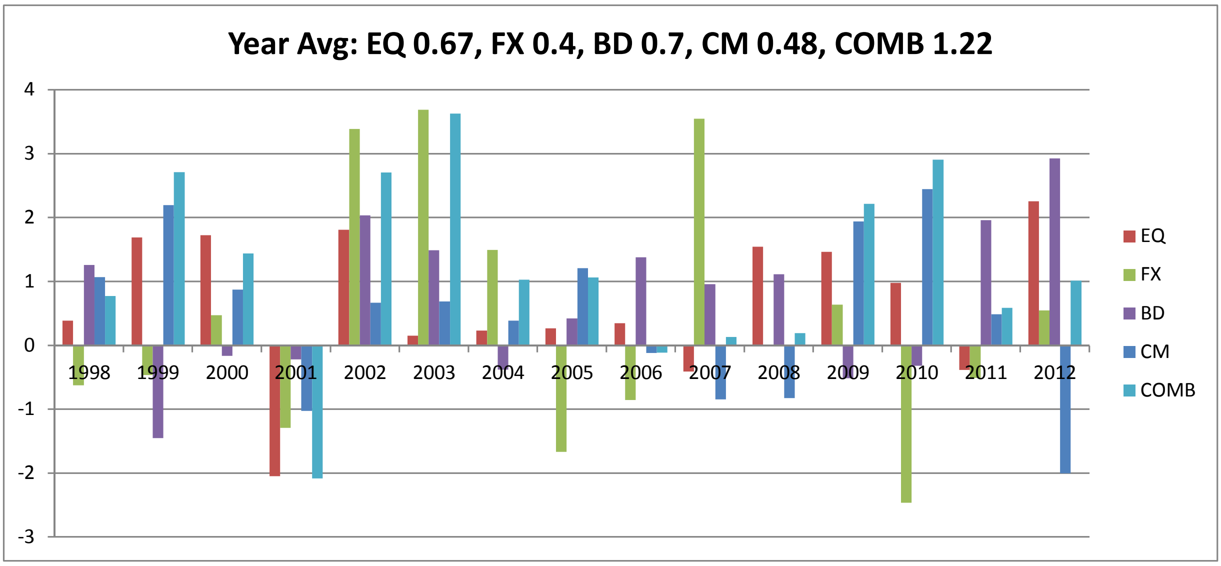


Figure 3: Annual Sharpe ratios of unfavorable-minus-favorable portfolios within asset classes

This figure shows the annual Sharpe ratio each year from the strategy of going long unfavorable assets (low RIX beta) and short favorable assets (high RIX beta). We peform the strategy within each of the following asset classes: international equity index (EQ), currency (FX), government bond futures (BD), and commodity futures (CM). We also consider the strategy that takes the equal weighted combination across these four asset classes (COMB). The top figure present results based on monthly portfolio formation, and the bottom figure present results based on semi-annual portfolio formation. Note: the monthly returns in 2012 are only up to May.



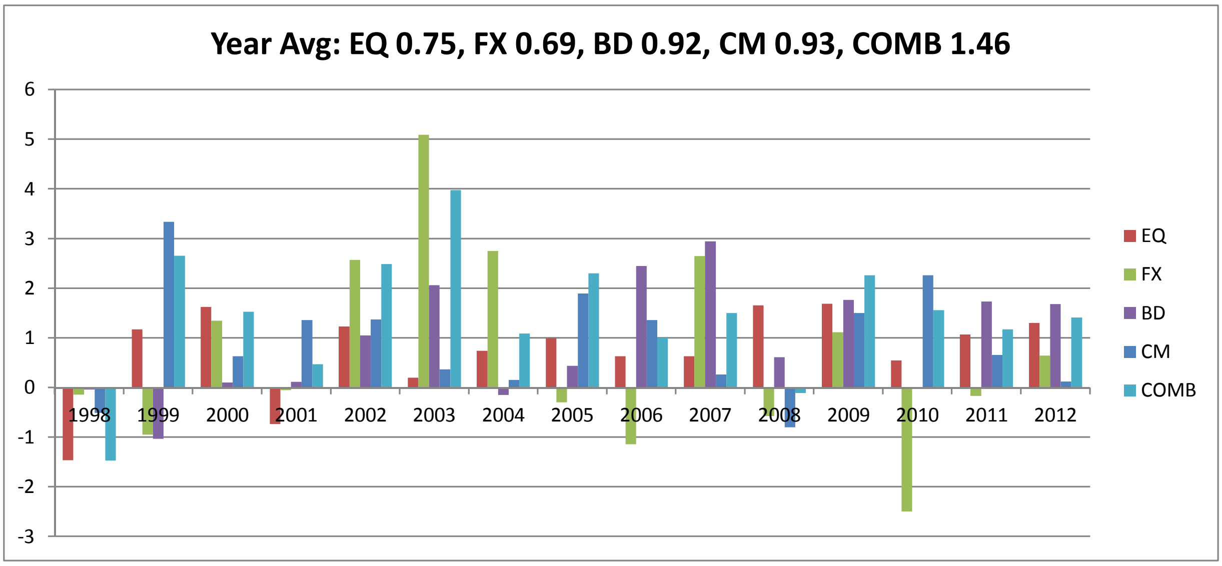
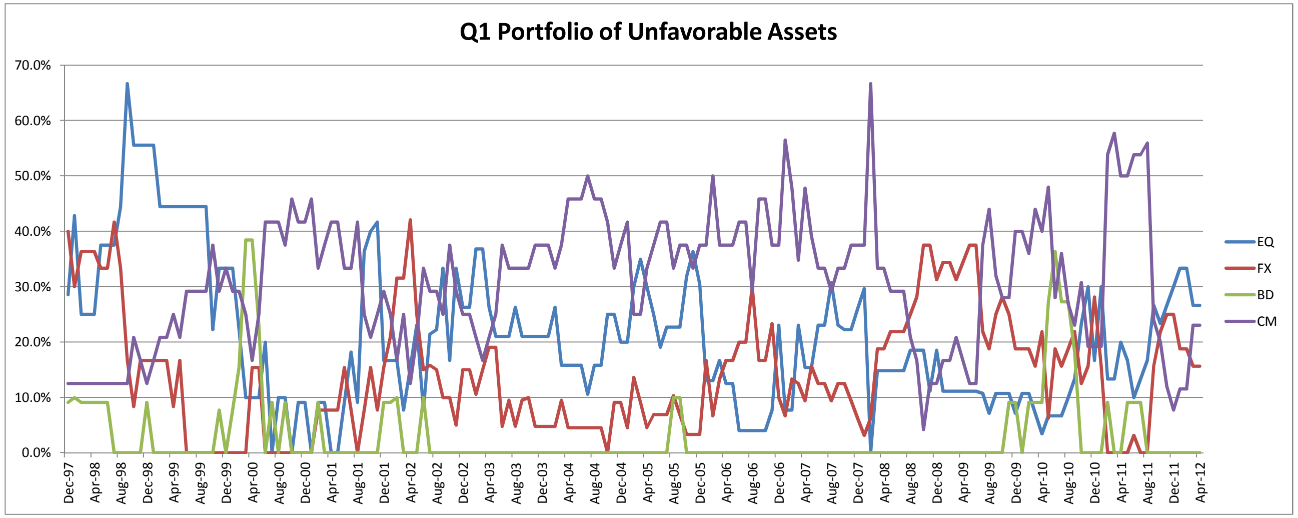


Figure 4: Asset class distribution

This figure shows the time series of asset class distributions across equity index (EQ), currency (FX), bond (BD), and commodity (CM) within the portfolios of unfavorable assets (top panel) and favorable assets (bottom panel). The global rare disaster concern index (GRIX) is estimated as the first principal component of the correlation matrix of three asset-class-specific rare disaster concern indices (EQRIX FXRIX, BDRIX, and CMRIX). At the end of each month from December 1997 to April 2012, we rank global assets (30 equity indices, 32 foreign currencies, 14 bond futures, and 28 commodity futures in total) into quintiles according to their GRIX betas. Assets in the low (high) GRIX-beta portfolio are unfavorable (favorable). We estimate each asset's GRIX beta by regressing its excess returns on the market factor and GRIX based on the past 18-24 monthly observations. To get asset class distribution, we first count the number of assets from an asset class within a GRIX-beta quintile, and then divide it by the total number of assets from that asset class that is available for investment as of portfolio formation. For example, if there are 10 equity indices available at portfolio formation month *t*, and the low GRIX-beta quintile consists of 3 equity indices, then the equity-class distribution is 30%.



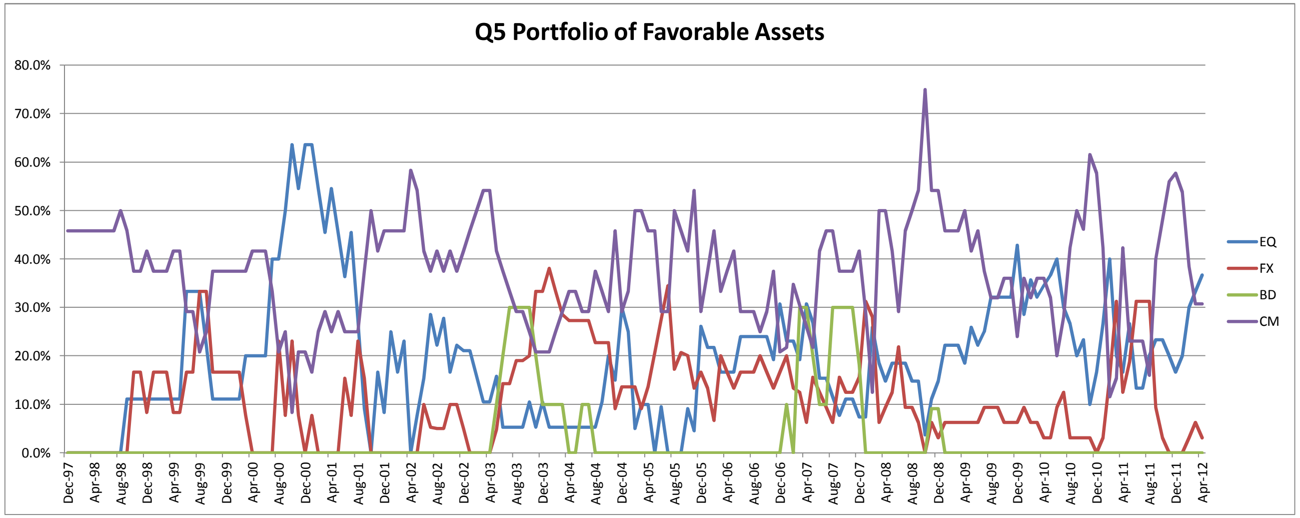


Table 1: Summary statistics of global asset returns by markets and asset classes

This table reports summary statistics of global asset monthly excess returns (in excess of the one-month U.S. T-bill rate). Returns are based on US dollar. Panel A presents returns of international equity index (the 1st column shows the index name from Datastream), Panel B presents returns of foreign currency, Panel C presents returns of global government bond futures (the 1st column shows country name and bond maturity), and Panel D presents returns of commodity futures. For each of these assets, we use out-of-the-money options to measure rare disaster concerns and construct rare disaster concern index (RIX). The months in which we obtain asset excess returns correspond to the sample period in which its rare disaster concern index becomes available (see Figure 1 for underlying options and sample periods).

	Mean	Std	Skew	Kurt	Q1	Median	Q3
Panel A: International equity index							
MSCI Australia Investable Market	0.93%	0.066	-0.629	1.834	-2.28%	1.36%	4.91%
MSCI Austria Investable Market	0.44%	0.071	-0.895	4.205	-3.66%	0.58%	4.84%
MSCI Belgium Investable Market	0.38%	0.064	-1.313	5.379	-2.46%	0.93%	4.32%
MSCI Canada Investable Market	0.77%	0.064	-0.622	2.101	-2.76%	1.03%	5.12%
MSCI Switzerland Investable Market	0.51%	0.051	-0.452	0.387	-2.27%	1.04%	2.95%
MSCI Germany Investable Market	0.53%	0.078	-0.411	1.267	-3.62%	0.80%	4.90%
MSCI Denmark Investable Market	0.64%	0.073	-0.813	2.083	-2.75%	1.96%	5.48%
MSCI Spain Investable Market	0.56%	0.075	-0.480	1.110	-2.83%	1.23%	4.71%
FTSE Eurofirst 300 Eurozone Euro	0.25%	0.069	-0.489	0.867	-3.58%	0.94%	4.84%
MSCI Finland Investable Market	0.12%	0.084	0.006	1.007	-5.34%	0.70%	4.96%
MSCI France Investable Market	0.20%	0.071	-0.482	0.384	-3.64%	0.72%	5.03%
MSCI United Kingdom Investable Market	0.39%	0.048	-0.381	1.479	-2.07%	0.50%	3.29%
MSCI Greece Investable Market	-0.97%	0.103	-0.258	1.383	-7.38%	-0.23%	5.11%
MSCI Hong Kong Investable Market	0.57%	0.076	0.022	2.296	-3.61%	0.81%	4.13%
MSCI India Investable Market	1.48%	0.093	-0.014	1.924	-3.87%	1.66%	7.73%
MSCI Israel Investable Market	0.52%	0.071	-0.188	0.770	-3.01%	0.96%	4.97%
MSCI Italy Investable Market	-0.16%	0.074	-0.351	0.462	-4.06%	0.07%	4.98%
MSCI Japan Investable Market	-0.21%	0.056	0.199	-0.092	-4.30%	-0.26%	3.51%
MSCI Korea Investable Market	0.94%	0.125	0.821	4.386	-5.90%	0.17%	7.10%
MSCI Mexico Investable Market	1.15%	0.074	-1.017	3.308	-2.21%	1.69%	6.17%
MSCI Nordic US Dollar	0.30%	0.085	-0.358	1.149	-4.48%	0.33%	5.39%
MSCI Netherlands Investable Market	0.31%	0.064	-0.638	1.306	-3.43%	0.82%	4.15%
MSCI Norway Investable Market	0.87%	0.082	-0.712	2.162	-4.00%	1.44%	6.47%
MSCI Poland Investable Market	0.83%	0.100	-0.386	0.775	-5.26%	2.20%	7.05%
MSCI Russia Investable Market	2.56%	0.117	0.215	0.541	-4.73%	1.98%	10.51%
MSCI Singapore Investable Market	2.29%	0.082	0.631	1.181	-2.13%	1.93%	5.54%
MSCI Sweden Investable Market	0.84%	0.081	-0.252	1.682	-3.04%	0.50%	6.06%
MSCI Thailand Investable Market	1.43%	0.100	-0.878	1.991	-4.39%	2.11%	8.45%
MSCI Taiwan Investable Market	0.54%	0.080	-0.006	0.063	-4.62%	0.32%	6.39%
MSCI United States Investable Market	0.44%	0.048	-0.656	0.815	-2.31%	1.24%	3.63%
	0.53%	0.076	-0.143	3.575	-3.49%	0.82%	4.93%
Panel B: Foreign currency							
Argentine Peso	0.57%	0.026	6.421	57.077	-0.08%	0.35%	0.91%
Australian Dollar	0.39%	0.037	-0.463	1.647	-1.74%	0.46%	2.63%
Brazilian Real	1.25%	0.044	-0.963	2.108	-0.67%	1.60%	4.01%
Canadian Dollar	0.18%	0.025	-0.292	3.243	-1.20%	0.22%	1.68%
Swiss Franc	0.00%	0.032	0.314	1.297	-2.26%	-0.17%	2.05%
Chilean Peso	0.36%	0.038	-1.335	4.602	-1.50%	0.44%	2.89%
Colombian Peso	0.70%	0.040	-0.219	0.895	-1.49%	0.85%	2.98%
Czech Koruna	0.51%	0.039	-0.365	0.538	-1.67%	0.83%	3.29%
Danish Krone	0.01%	0.030	0.109	0.888	-1.83%	-0.09%	1.79%
Euro	0.08%	0.031	-0.033	0.767	-1.64%	0.04%	2.04%
United Kingdom Pound	0.13%	0.025	-0.274	1.452	-1.39%	0.16%	1.77%
Hong Kong Dollar	-0.01%	0.002	1.206	6.417	-0.08%	-0.01%	0.04%
Hungarian Forint	0.70%	0.046	-0.976	2.255	-1.89%	1.07%	3.85%
Indonesian Rupiah	3.26%	0.064	-0.126	0.586	-0.43%	2.17%	7.21%
Indian Rupee	0.23%	0.025	-0.040	1.233	-1.04%	0.35%	1.68%
Icelandic Krona	-0.25%	0.053	-0.708	4.250	-2.80%	0.07%	2.58%
Israeli Shekel	0.19%	0.027	-0.147	0.284	-1.27%	0.11%	1.94%
Japanese Yen	-0.07%	0.032	0.748	3.590	-2.08%	-0.17%	1.88%

South Korean Won	0.23%	0.037	-0.134	3.909	-1.21%	0.33%	1.90%
Mexican Peso	0.16%	0.029	-1.339	5.168	-1.04%	0.45%	1.91%
Malaysian Ringgit	1.98%	0.026	-0.634	-0.373	0.12%	2.01%	4.47%
Norwegian Krone	0.14%	0.032	-0.215	0.860	-1.73%	0.17%	1.91%
New Zealand Dollar	0.35%	0.039	-0.198	1.410	-2.04%	0.55%	2.68%
Peruvian Nuevo Sol	0.57%	0.024	2.347	11.416	-0.24%	0.30%	1.02%
Philippine Peso	0.56%	0.017	-0.529	-0.109	-0.25%	0.76%	1.90%
Polish Zloty	0.59%	0.044	-0.737	1.431	-1.79%	0.85%	3.53%
Russian Federation Rouble	0.34%	0.035	-0.902	3.032	-0.56%	0.40%	1.73%
Singaporean Dollar	-0.01%	0.019	-0.286	2.027	-0.99%	0.11%	1.05%
Swedish Krona	0.02%	0.033	0.089	0.282	-2.16%	-0.04%	1.79%
Thai Baht	1.10%	0.030	2.006	6.271	-0.46%	0.64%	2.03%
Taiwanese Dollar	0.05%	0.018	0.341	0.779	-1.03%	-0.21%	1.17%
South African Rand	1.20%	0.059	0.664	1.327	-2.14%	0.43%	3.70%
	0.45%	0.036	0.181	4.260	-1.23%	0.26%	2.12%
Panel C: Global government bond futures							
Australia 10YR	0.03%	0.003	0.035	0.064	-0.15%	0.02%	0.20%
Australia 3YR	0.05%	0.003	0.219	0.179	-0.15%	0.02%	0.26%
Canada 10YR	0.20%	0.015	-0.112	-0.062	-0.60%	0.24%	1.01%
Germany Bund 10YR	0.32%	0.014	0.018	0.058	-0.68%	0.47%	1.25%
Germany Schatz 2YR	0.09%	0.004	-0.033	0.488	-0.16%	0.07%	0.34%
Germany Bobl 5YR	0.22%	0.009	-0.020	-0.149	-0.37%	0.23%	0.77%
Spain 10YR	0.35%	0.014	0.101	0.830	-0.39%	0.35%	1.06%
United Kingdom Gilt 10YR	0.25%	0.016	0.025	0.501	-0.75%	0.23%	1.29%
Italy 10YR	0.07%	0.013	-0.389	-0.699	-0.64%	0.19%	1.07%
Japan 10YR	0.22%	0.010	-1.325	6.686	-0.18%	0.33%	0.78%
United States of America 10YR	0.34%	0.016	0.054	2.038	-0.69%	0.36%	1.39%
United States of America 2YR	0.17%	0.004	0.630	0.922	-0.04%	0.12%	0.36%
United States of America 30YR	0.31%	0.026	-0.045	2.869	-1.29%	0.44%	1.95%
United States of America 5YR	0.22%	0.011	0.007	1.028	-0.40%	0.22%	0.88%
	0.20%	0.013	0.096	8.240	-0.32%	0.15%	0.78%
Panel D: Commodity futures							
BUTTER (BA)	0.15%	0.074	-0.036	0.687	-4.76%	0.71%	4.96%
SOYBEAN OIL (BO)	0.10%	0.078	0.011	1.527	-4.01%	0.24%	5.02%
CORN (C-)	-0.25%	0.084	0.139	0.508	-5.05%	-0.97%	5.48%
COCOA (CC)	0.47%	0.094	0.542	1.073	-5.28%	-0.50%	5.00%
CRUDE OIL LIGHT (CL)	1.12%	0.096	-0.039	0.682	-5.04%	1.22%	7.58%
COTTON (CT)	-0.41%	0.087	0.335	0.691	-5.39%	-0.61%	3.64%
MILK (DE)	0.63%	0.079	0.417	1.978	-4.72%	0.99%	4.62%
CATTLE FEEDER (FC)	0.31%	0.041	-0.534	2.755	-2.07%	0.53%	2.98%
COPPER (HG)	0.92%	0.083	0.009	2.783	-4.36%	0.45%	5.82%
HEATING OIL (HO)	1.40%	0.104	0.400	1.752	-4.81%	1.46%	6.74%
UNLEADED GASOLINE (HU)	2.46%	0.124	0.610	1.708	-5.03%	1.71%	10.25%
ORANGE JUICE (JO)	-0.03%	0.088	0.316	0.258	-5.63%	-0.75%	4.70%
COFFEE (KC)	0.28%	0.108	0.758	1.038	-7.88%	-0.81%	5.52%
LUMBER (LB)	-0.73%	0.092	0.341	0.442	-7.23%	-1.33%	4.91%
CATTLE LIVE (LC)	0.17%	0.043	-0.642	3.817	-2.21%	0.05%	2.75%
HOGS LEAN (LH)	-0.46%	0.081	0.020	1.373	-5.33%	-0.45%	4.88%
NATURAL GAS (NG)	-0.55%	0.156	0.618	1.016	-11.59%	-1.10%	8.23%
OATS (O-)	0.24%	0.097	0.672	1.349	-6.17%	-0.65%	5.07%
PALLADIUM (PA)	0.55%	0.078	-0.755	1.647	-4.78%	1.88%	5.94%
PORK BELLIES (PB)	1.10%	0.107	0.654	1.840	-5.87%	0.27%	7.07%
PLATINUM (PL)	0.92%	0.064	-0.805	4.133	-2.36%	1.55%	4.94%
COAL (QL)	-0.34%	0.073	0.350	0.108	-5.24%	-0.93%	3.63%
BLENDSTOCK GASOLINE (RB)	1.59%	0.108	-0.757	2.695	-4.14%	2.74%	8.65%
RICE (RR)	-0.60%	0.076	0.006	0.464	-4.99%	-0.78%	4.26%
SOYBEANS (S-)	0.79%	0.078	-0.282	0.510	-3.56%	0.21%	6.45%
SUGAR (SB)	0.43%	0.113	-0.975	7.405	-6.22%	0.64%	6.50%
SOYBEAN MEAL (SM)	1.43%	0.086	0.077	0.762	-3.81%	1.22%	6.77%
WHEAT (W-)	-0.69%	0.088	0.578	1.766	-6.72%	-1.28%	4.97%
	0.36%	0.092	0.292	2.848	-5.07%	0.03%	5.37%

Table 2: Portfolio returns of unfavorable and favorable assets within asset classes

Within an asset class, we estimate an asset's RIX beta using its asset-class-specific rare disaster concern index and the asset's past 18-24 monthly returns, and then form four RIX-beta portfolios. Assets in the low (high) RIX-beta portfolio are unfavorable (favorable). We also form a hedge portfolio within an asset class by going long in unfavorable assets and short in favorable assets. We consider portfolio formation at monthly/quarterly/semi-annual/annual frequency and calculate equal-weighted returns. This table presents the mean excess returns (monthly raw return in excess of the 1-month U.S. T-bill rate), abnormal returns (alphas) based on various factors, and Newey-West *t*-statistics (in parentheses) of each RIX-beta portfolio in each market and asset class we study: equity index (EQ), currency (FX), sovereign bond futures (BD), and commodity futures (CM). We also report results of each combination RIX-beta portfolio that generates equal weighted return across four asset classes (COMB). To measure alphas, we use the following benchmark factors for different asset classes: Asness-Moskowitz-Pedersen (AMP) value and momentum factors, Frazzini-Pedersen (FP) betting-against-beta factor, and Moskowitz-Ooi-Pedersen (MOP) time series momentum factor. Returns are reported in percent. On average, there are 5 equity indices, 6 currencies, 3 bond futures, and 7 commodities in each portfolio.

	Monthly Portfolio Formation					Quarterly Portfolio Formation				
	EQ	FX	BD	CM	COMBO	EQ	FX	BD	CM	COMBO
Unfavorable	1.023	0.827	0.356	0.807	0.739	1.015	0.873	0.280	0.821	0.730
	(1.80)	(3.40)	(3.12)	(2.05)	(2.80)	(1.83)	(3.16)	(2.71)	(1.88)	(2.69)
2	0.476	0.147	0.181	0.591	0.321	0.599	0.246	0.205	0.352	0.301
	(0.83)	(0.86)	(2.86)	(1.53)	(1.32)	(1.00)	(1.35)	(3.08)	(0.96)	(1.20)
3	0.382	0.327	0.153	0.379	0.279	0.316	0.318	0.165	0.406	0.265
	(0.74)	(1.95)	(2.32)	(0.97)	(1.20)	(0.59)	(1.83)	(2.44)	(1.17)	(1.16)
Favorable	0.260	0.454	0.142	-0.092	0.142	0.156	0.352	0.194	-0.268	0.114
	(0.51)	(2.36)	(1.84)	(-0.25)	(0.59)	(0.29)	(1.75)	(2.41)	(-0.83)	(0.52)
U - F	0.763	0.373	0.213	0.899	0.597	0.859	0.521	0.086	1.088	0.616
	(2.42)	(2.00)	(2.54)	(2.07)	(3.58)	(2.55)	(2.70)	(1.07)	(2.27)	(3.49)
Alpha of unfavorable-minus-favorable portfolio										
AMP alpha	0.672	0.348	0.199	0.901	0.659	0.814	0.469	0.073	0.981	0.650
	(2.34)	(1.82)	(2.69)	(2.12)	(4.17)	(2.60)	(2.38)	(0.94)	(2.15)	(4.02)
FP alpha	0.677	0.347	0.193	0.955	0.614	0.786	0.496	0.055	1.015	0.574
	(2.12)	(1.83)	(2.49)	(2.19)	(3.53)	(2.13)	(2.58)	(0.70)	(2.23)	(3.35)
MOP alpha	0.615	0.332	0.159	0.914	0.563	0.738	0.469	0.043	1.035	0.602
	(2.12)	(1.72)	(2.15)	(2.18)	(3.26)	(2.28)	(2.36)	(0.56)	(2.32)	(3.69)

	Semi-Annual Portfolio Formation					Annual Portfolio Formation				
	EQ	FX	BD	CM	COMBO	EQ	FX	BD	CM	COMBO
Unfavorable	1.072	0.928	0.412	1.047	0.810	1.010	0.836	0.368	0.759	0.722
	(1.93)	(3.34)	(3.92)	(2.58)	(3.06)	(1.68)	(3.45)	(3.32)	(1.89)	(2.70)
2	0.415	0.073	0.176	0.010	0.164	0.478	0.132	0.158	0.177	0.234
	(0.74)	(0.41)	(3.02)	(0.03)	(0.68)	(0.87)	(0.74)	(2.82)	(0.48)	(1.01)
3	0.499	0.367	0.153	0.775	0.409	0.360	0.367	0.128	0.873	0.408
	(0.89)	(2.06)	(2.49)	(2.17)	(1.73)	(0.70)	(2.10)	(1.91)	(2.41)	(1.89)
Favorable	0.104	0.392	0.133	-0.402	0.042	0.080	0.420	0.174	-0.391	0.097
	(0.20)	(1.95)	(1.52)	(-1.24)	(0.19)	(0.16)	(2.27)	(1.98)	(-1.19)	(0.44)
U - F	0.968	0.535	0.279	1.449	0.768	0.930	0.416	0.194	1.149	0.625
	(2.79)	(2.69)	(3.39)	(3.48)	(4.56)	(2.99)	(2.24)	(2.43)	(2.80)	(3.94)
Alpha of unfavorable-minus-favorable portfolio										
AMP alpha	0.928	0.512	0.247	1.304	0.810	0.860	0.422	0.189	1.025	0.592
	(2.84)	(2.53)	(3.11)	(3.21)	(4.97)	(2.80)	(2.21)	(2.52)	(2.45)	(3.45)
FP alpha	0.889	0.516	0.260	1.417	0.758	0.829	0.384	0.174	1.138	0.581
	(2.30)	(2.56)	(3.18)	(3.51)	(4.20)	(2.50)	(1.97)	(2.23)	(2.77)	(3.14)
MOP alpha	0.840	0.497	0.246	1.299	0.742	0.876	0.407	0.114	1.036	0.584
	(2.57)	(2.40)	(3.08)	(3.19)	(4.36)	(2.89)	(2.04)	(1.43)	(2.52)	(3.54)

Table 3: Correlation of rare disaster concerns

This table presents sample correlations of rare disaster concern indices (RIXs) both within and across asset classes. For each asset from four asset classes, we use its OTM options to construct its RIX. Then within an asset class, we average across all assets' RIXs to construct the asset-class-specific RIX: EQRIX for equity index, FXRIX for currency, BDRIX for bond, and CMRIX for commodity. We also develop the global rare disaster concern index (GRIX) that is based on the first principal component of the correlation matrix of EQRIX, FXRIX, BDRIX, and CMRIX. Panel A reports summary statistics of pairwise correlations of RIXs. For example, within the equity class, we estimate all pairwise sample (Pearson) correlations of equity RIXs, and report summary statistics in the first row. In addition, we estimate all pairwise correlations between equity's RIXs and currency's RIXs, between equity's RIXs and bond's RIXs, and between equity's RIXs and commodity's RIXs, and report summary statistics in the second row. We do the same for currency, bond, and commodity classes. We exclude the correlation of each asset's RIX with itself (i.e., remove the 1's). Panel B reports both Pearson correlations (upper diagonal elements) and Spearman correlations (lower diagonal elements) of asset-class-specific RIXs and the global RIX. All of these sample correlations are significant at 1% level.

Panel A: summary statistics of pairwise correlations of rare disaster concern indices

Pairwise correlations of RIX	Mean	Median	25th pctl	75th pctl	# of pairs
Within the class of international equity index	0.78	0.83	0.70	0.93	435
Between equity index and non-equity asset classes	0.43	0.46	0.19	0.72	2166
Within the class of foreign currency	0.61	0.69	0.47	0.83	496
Between foreign currency and non-currency classes	0.46	0.51	0.26	0.71	2256
Within the class of sovereign bond futures	0.28	0.22	-0.01	0.58	88
Between bond futures and non-bond asset classes	0.24	0.31	-0.03	0.53	1150
Within the class of commodity futures	0.31	0.34	0.17	0.48	373
Between commodity futures and non-commodity asset classes	0.27	0.29	0.11	0.47	2110

Panel B: correlations of global rare disaster concern indices across asset classes

	EQRIX	FXRIX	BDRIX	CMIX	GRIX
EQRIX	1	0.55	0.43	0.38	0.68
FXRIX	0.39	1	0.65	0.80	0.92
BDRIX	0.27	0.44	1	0.61	0.82
CMRIX	0.27	0.79	0.46	1	0.86
GRIX	0.53	0.80	0.74	0.81	1

Table 4: Portfolios of unfavorable and favorable assets across markets and asset classes

Our sample consists of 30 equity indices, 32 currencies, 14 government bonds, and 28 commodities. The global rare disaster concern index (GRIX) is based on the first principal component of the correlation matrix of four asset-class rare disaster concern indices (see Table 3 for details). We estimate each asset's GRIX beta using its past 18-24 monthly returns and then form five GRIX-beta quintiles across these 114 global investment assets. Assets in the low (high) GRIX-beta portfolio are unfavorable (favorable). We also form a hedge portfolio by going long in unfavorable assets and short in favorable assets. We consider portfolio formation at monthly/quarterly/semi-annual/annual frequency. Panel A presents mothly mean excess returns and alphas benchmarked on the five-factor global asset pricing model (MSCI global equity market excess return, Frazzini-Pedersen betting-against-beta (BAB), Moskowitz-Ooi-Pedersen time series momentum (TSMOM), and Asness-Moskowtiz-Pedersen value and momentum factors). Panels B and C present factor loadings of monthly and quarterly formed portfolios. Newey-West *t* -statistics are shown in parentheses. On average, there are 17 assets in each quintile portfolio.

Panel A: portfolio excess returns and alphas (in percent)

	Monthly Form.		Quarterly Form.		Semi-Ann. Form.		Annual Form.	
	Excess Return	Alpha	Excess Return	Alpha	Excess Return	Alpha	Excess Return	Alpha
Unfavorable	1.063	0.546	0.877	0.463	0.709	0.267	0.684	0.484
	(3.27)	(2.08)	(2.76)	(1.83)	(2.24)	(1.03)	(1.90)	(1.77)
2	0.380	-0.020	0.399	0.053	0.541	0.267	0.317	0.197
	(1.75)	(-0.11)	(1.84)	(0.29)	(2.19)	(1.22)	(0.96)	(0.71)
3	0.380	-0.057	0.286	-0.092	0.292	-0.090	0.278	0.143
	(1.90)	(-0.47)	(1.31)	(-0.66)	(1.30)	(-0.63)	(1.43)	(1.06)
4	0.241	-0.282	0.300	-0.258	0.106	-0.463	0.104	-0.147
	(0.74)	(-1.24)	(0.93)	(-1.11)	(0.36)	(-2.34)	(0.39)	(-0.79)
Favorable	0.062	-0.416	0.153	-0.297	0.289	-0.192	0.668	0.528
	(0.16)	(-1.60)	(0.43)	(-1.13)	(0.85)	(-0.71)	(1.86)	(1.84)
U-F	1.001	0.962	0.724	0.760	0.420	0.458	0.016	-0.044
	(3.55)	(3.17)	(2.48)	(2.34)	(1.63)	(1.42)	(0.05)	(-0.14)

Panel B: factor loadings of monthly formed portfolios

	MSCI Market	FP BAB	MOP TSMOM	AMP Value	AMP Momentum
Unfavorable	0.563	0.633	0.252	-0.343	-0.228
	(9.46)	(3.31)	(2.36)	(-1.96)	(-1.81)
2	0.386	0.500	0.140	-0.070	-0.122
	(8.79)	(5.17)	(2.63)	(-0.71)	(-1.44)
3	0.392	0.477	0.088	0.074	0.028
	(11.75)	(4.75)	(2.34)	(0.77)	(0.31)
4	0.598	0.756	-0.026	0.260	0.084
	(9.53)	(3.89)	(-0.43)	(1.79)	(0.68)
Favorable	0.591	1.134	-0.067	-0.181	-0.087
	(8.42)	(6.23)	(-0.79)	(-1.10)	(-0.60)
U-F	-0.028	-0.501	0.318	-0.162	-0.141
	(-0.44)	(-2.09)	(2.71)	(-0.77)	(-0.80)

Panel C: factor loadings of quarterly formed portfolios

	MSCI Market	FP BAB	MOP TSMOM	AMP Value	AMP Momentum
Unfavorable	0.524	0.602	0.183	-0.298	-0.192
	(8.14)	(2.88)	(1.95)	(-1.69)	(-1.46)
2	0.365	0.523	0.082	-0.034	-0.068
	(9.16)	(5.06)	(1.30)	(-0.24)	(-0.75)
3	0.394	0.516	0.074	-0.020	-0.027
	(8.75)	(4.99)	(1.78)	(-0.27)	(-0.35)
4	0.595	0.811	0.010	0.191	0.099
	(10.14)	(4.25)	(0.16)	(1.33)	(0.89)
Favorable	0.583	1.101	-0.049	-0.067	-0.123
	(9.23)	(6.60)	(-0.57)	(-0.45)	(-0.81)
U-F	-0.059	-0.500	0.232	-0.231	-0.069
	(-0.87)	(-1.98)	(2.22)	(-1.04)	(-0.37)

Table 5: Alternative measures of global rare disaster concerns

We rank 104 global investment assets into favorable and unfavorable portfolios based on two alternative measures of global rare disaster concerns: (1) "Global VIX" is the model-free implied volatility across markets and asset classes; and (2) "Implied Volatility Skew" is the difference in option implied volatility between OTM puts and ATM calls (across markets and asset classes). To construct these measures, we follow the procedures similar to the GRIX construction. For example, we first employ each asset's options data to estimate implied volatility through all available moneyness, average over assets within an asset class to get asset-class VIX, and finally apply PCA across four asset classes to extract the GVIX. We do the same for implied volatility skewness. Each asset's return covariation with the global rare disaster concerns is used to monthly form five quintiles. Assets with low (high) covariances are unfavorable (favorable). This table presents equal-weighted portfolio mean excess returns and five-factor alphas.

	Global VIX		Implied Volatility Skew	
	Excess Return	Alpha	Excess Return	Alpha
Unfavorable	0.940	0.464	0.851	0.197
	(2.98)	(1.85)	(2.48)	(0.65)
2	0.486	-0.002	0.230	-0.160
	(2.14)	(-0.01)	(1.18)	(-1.02)
3	0.240	-0.119	0.431	0.006
	(1.24)	(-1.10)	(2.67)	(0.05)
4	0.179	-0.362	0.369	-0.103
	(0.54)	(-1.41)	(1.40)	(-0.61)
Favorable	0.274	-0.215	0.237	-0.180
	(0.73)	(-0.88)	(0.70)	(-0.59)
U-F	0.666	0.680	0.614	0.376
	(2.48)	(2.44)	(2.05)	(1.04)

Table 6: Alternative definitions of long/short positions in bonds and currencies

We rank 104 global investment assets into favorable and unfavorable portfolios based on alternative choices of long/short positions in government bonds, foreign currencies, and the combination of these two cases. In the first definition, an investor goes short in bond futures and hence we use the OTM calls of bond futures options to estimate the bond-class RIX. In the second definition, an investor goes short (long) in a foreign currency when the foreign country's interest rate is lower (higher) than the U.S. interest rate and hence we use the OTM calls (puts) of this currency to estimate the currency-class RIX. We reconstruct the global GRIX factor by aggregating over each asset's RIX and then four asset-class-specific RIXs. The methodology is the same one used in our baseline analysis. We estimate each asset's return covariation with the GRIX factor and then monthly form five quintiles (see Table 4 for details). Assets with low (high) covariances are unfavorable (favorable). This table presents equal-weighted portfolio mean excess returns and five-factor alphas.

	Bond (Short)		FX (Long or Short)		Bond (Short) and FX (Long or Short)	
	Excess Return	Alpha	Excess Return	Alpha	Excess Return	Alpha
Unfavorable	0.977	0.437	0.981	0.469	0.960	0.375
	(3.02)	(1.70)	(3.03)	(1.77)	(2.96)	(1.52)
2	0.336	-0.185	0.540	0.011	0.382	-0.157
	(1.33)	(-1.04)	(2.50)	(0.07)	(1.49)	(-0.83)
3	0.292	-0.153	0.400	-0.015	0.330	-0.101
	(1.29)	(-1.14)	(1.81)	(-0.11)	(1.57)	(-0.73)
4	0.433	-0.050	0.078	-0.325	0.320	-0.111
	(1.50)	(-0.24)	(0.26)	(-1.58)	(1.10)	(-0.49)
Favorable	0.091	-0.275	0.127	-0.369	0.136	-0.233
	(0.24)	(-1.02)	(0.33)	(-1.38)	(0.36)	(-0.90)
U-F	0.886	0.712	0.854	0.838	0.824	0.609
	(3.05)	(2.39)	(2.96)	(2.60)	(2.78)	(1.99)

Table 7: Orthognized asset-class RIX and returns of portfolios within and across asset classes

We first orthognize an asset-class RIX by regressing it on the other asset-class RIXs, and then we form portfolios of unfavorable and favorable assets using an asset's beta with respect to this orthognized RIX. For example, we perform a time series regression of monthly EQRIX (equity-class disaster concerns) on FXRIX (currency), BDRIX (government bond), and CMRIX (commodity), and use the residuals as a measure of the orthognized EQRIX. Within the equity class, we monthly form five orthognized-EQRIX-beta quintiles; and across the currency, bond, and commodity assets classes, we form quintiles in a similar way. We perform similar regression and portfolio analyses for FXRIX, BDRIX, and CMRIX. This table presents equal-weighted portfolio mean excess returns and five-factor alphas (in percent).

Panel A: excess returns

	EQRIX residual		FXRIX residual		BDRIX residual		CMRIX residual	
	Within EQ	Across (FX, BD, CM)	Within FX	Across (EQ, BD, CM)	Within BD	Across (EQ, FX, CM)	Within CM	Across (EQ, FX, BD)
Unfavorable	0.715	0.356	0.503	0.208	0.179	0.405	0.795	0.697
	(1.19)	(1.16)	(1.95)	(0.50)	(1.88)	(1.03)	(1.71)	(2.02)
2	0.616	0.383	0.428	0.228	0.134	0.376	0.283	0.392
	(1.09)	(2.94)	(2.11)	(0.76)	(1.85)	(1.20)	(0.60)	(1.84)
3	0.440	0.171	0.267	0.487	0.255	0.507	0.300	0.138
	(0.85)	(0.81)	(1.39)	(1.86)	(3.38)	(1.73)	(0.76)	(0.64)
Favorable	0.161	0.681	0.535	0.672	0.245	0.462	0.288	0.447
	(0.31)	(1.89)	(2.20)	(1.59)	(2.67)	(1.42)	(0.66)	(1.33)
U-F	0.555	-0.324	-0.032	-0.464	-0.067	-0.056	0.507	0.250
	(1.60)	(-1.01)	(-0.20)	(-1.28)	(-0.74)	(-0.21)	(0.97)	(1.26)

Panel B: 5-factor alphas

	EQRIX residual		FXRIX residual		BDRIX residual		CMRIX residual	
	Within EQ	Across (FX, BD, CM)	Within FX	Across (EQ, BD, CM)	Within BD	Across (EQ, FX, CM)	Within CM	Across (EQ, FX, BD)
Unfavorable	0.290	0.262	0.301	-0.394	0.050	-0.156	0.586	0.015
	(0.86)	(0.97)	(1.50)	(-1.19)	(0.51)	(-0.46)	(1.21)	(0.08)
2	0.299	0.295	0.281	-0.281	0.016	-0.097	-0.298	-0.022
	(1.20)	(2.57)	(1.75)	(-1.18)	(0.26)	(-0.43)	(-0.66)	(-0.15)
3	-0.054	0.082	0.136	0.082	0.205	0.065	-0.147	-0.211
	(-0.26)	(0.44)	(0.87)	(0.47)	(2.78)	(0.35)	(-0.38)	(-1.60)
Favorable	-0.482	0.537	0.365	0.226	0.120	-0.107	-0.651	0.018
	(-2.00)	(1.54)	(1.84)	(0.68)	(1.08)	(-0.58)	(-1.60)	(0.11)
U-F	0.772	-0.275	-0.063	-0.620	-0.070	-0.049	1.237	-0.003
	(2.17)	(-0.79)	(-0.40)	(-1.53)	(-0.59)	(-0.16)	(2.13)	(-0.01)

Table 8: RIX correlations with factors of disaster risk

The macroeconomic variables include quarterly real GDP growth per capita, inflation based on the change of CPI, recession dummy based on NBER recession dates, default risk based on the change of default spread (the spread between U.S. corporate bonds and U.S. Treasuries), and term risk based on the change of term spread (the spread between long-term and short-term government bonds). The variables related to finanical market disaster risk include the Pastor-Stambaugh innovation measure, the spread between on-the-run and off-the-run 10-year government Treasury notes, and risk-neutral (RN) moment risks of variance, skewness, and kurtosis based on the set of equity indices, currencies, bond futures, and commodity futures options (the aggregation procedures are similar to those of constructing GRIX). An increase of the Pastor-Stambaugh innovation measure and the spread between on-the-run and off-the-run 10-year government Treasury notes represent higher illiquidity. The variables of funding and liquidity constraints of financial intermediaries include the broker-dealer leverage shock, the Hu-Pan-Wang noise measure, the Treasury-Eurodollar (TED) spread, the spread between interest rate swap and T-bill, the spread between LIBOR and repo, and the aggregated funding liquidity risk based on the principal component analysis (PCA) of the last three types of spreads.

	EQRIX	FXRIX	BDRIX	CMRIX	GRIX
Panel A: Disaster Risk of Consumption and Macro Fundamentals					
Real GDP Growth	-0.34	-0.24	-0.20	-0.18	-0.29
Inflation	0.10	-0.25	-0.05	-0.22	-0.14
Recession	0.39	0.42	0.36	0.41	0.49
Default Risk	0.38	0.07	-0.01	-0.06	0.07
Term Risk	0.18	0.20	0.20	0.17	0.23
Panel B: Disaster Risk of Financial Market					
Pastor-Stambaugh Liq.	0.10	0.06	0.10	0.07	0.10
On-Off Run Spread	0.32	0.09	0.09	-0.02	0.13
RN Moment Risk (Var.)	0.26	0.07	0.13	0.09	0.08
RN Moment Risk (Skew.)	-0.07	0.05	-0.05	0.12	0.12
RN Moment Risk (Kurt.)	0.01	-0.04	-0.05	-0.07	-0.01
Panel C: Funding and Liquidity Constraints of Financial Intermediaries					
Hu-Pan-Wang Noise	0.33	-0.01	0.06	-0.07	0.07
Leverage Shock	-0.49	-0.60	-0.48	-0.49	-0.61
TED Spread	0.10	-0.12	-0.08	-0.18	-0.10
Swap - T-bill	0.13	0.19	0.11	0.16	0.19
Libor - Repo	0.11	-0.09	-0.06	-0.16	-0.07
Funding Liquidity Risk (PCA)	0.16	-0.07	-0.05	-0.16	-0.05

Table 9: RIX Portfolios and Economic Channels of Disaster Risk

This table reports coefficient estimates and Newey-West *t* -statistics (in parentheses) from regressing unfavorable-minus-favorable (UMF) hedge portfolio returns on the macroeconomic disaster risk (Panel A), financial market disaster risk (Panel B), and funding and liquidity constraint (Panel C) factors. Within each of asset classes of equity index (EQ), currency (FX), government bond (BD), and commodity (CM), we construct the hedge portfolio using the asset's RIX beta (see Table 2 in detail). Combining asset-class hedge portfolios together, we construct a hedge portfolio that generates equal weighted return across four asset classes (COMBO). Using all assets from global markets and asset classes (ALL), we construct the hedge portfolio based on the asset's GRIX beta (see Table 4 in detail). The construction of various risk factors is explained in Table 8.

	UMF Return (EQ)	UMF Return (FX)	UMF Return (BD)	UMF Return (CM)	UMF Return (COMBO)	UMF Return (ALL)
Panel A: Disaster Risk of Consumption and Macro Fundamentals						
Market return	-0.018	0.098	0.410	0.144	0.015	-0.058
	(-0.26)	(1.16)	(2.00)	(1.65)	(0.46)	(-1.07)
Real GDP growth	0.002	-0.001	-0.001	0.002	0.001	0.001
	(0.64)	(-0.46)	(-0.66)	(0.36)	(0.50)	(0.28)
Inflation	-0.000	-0.000	-0.001	-0.026	-0.006	-0.005
	(-0.05)	(-0.02)	(-0.27)	(-2.45)	(-1.52)	(-0.77)
Recession	-0.003	-0.005	0.001	-0.006	-0.003	0.002
	(-0.26)	(-0.79)	(0.21)	(-0.33)	(-0.50)	(0.24)
Default risk	-0.004	-0.005	0.001	0.009	-0.001	0.002
	(-0.57)	(-1.47)	(0.28)	(0.86)	(-0.43)	(0.34)
Term risk	-0.002	0.014	0.004	-0.008	0.000	-0.002
	(-0.16)	(2.10)	(0.69)	(-0.60)	(0.10)	(-0.18)
Adj. R-square	-0.03	0.01	0.05	0.04	0.00	-0.03
Panel B: Disaster Risk of Financial Market						
Pastor-Stambaugh Liq.	0.078	0.014	-0.024	0.040	0.030	0.023
	(1.71)	(0.55)	(-1.62)	(0.62)	(1.50)	(0.47)
On-Off Run Spread	-0.002	-0.000	0.000	-0.001	-0.001	-0.001
	(-1.17)	(-0.53)	(1.21)	(-0.89)	(-1.36)	(-0.83)
RN Moment Risk (Var.)	0.144	-1.261	3.598	7.131	0.000	0.002
	(0.10)	(-0.37)	(0.19)	(1.25)	(0.02)	(0.73)
RN Moment Risk (Skew.)	-0.014	-0.006	0.004	-0.306	-0.005	-0.007
	(-0.59)	(-0.39)	(0.84)	(-1.59)	(-1.75)	(-0.98)
RN Moment Risk (Kurt.)	0.003	0.001	-0.001	0.056	-0.004	-0.008
	(0.97)	(0.18)	(-1.07)	(1.37)	(-1.88)	(-2.08)
Adj. R-square	0.03	-0.02	0.07	0.06	0.04	0.01
Panel C: Funding and Liquidity Constraints of Financial Intermediaries						
Hu-Pan-Wang Noise	-0.004	-0.001	0.003	-0.007	-0.003	-0.003
	(-0.96)	(-0.29)	(1.47)	(-1.33)	(-1.33)	(-0.70)
Leverage Shock	-0.000	-0.000	-0.000	0.000	-0.000	-0.000
	(-0.15)	(-1.30)	(-0.31)	(0.20)	(-0.07)	(-0.55)
TED Spread	0.007	-0.002	-0.001	0.005	0.003	-0.003
	(1.51)	(-0.84)	(-0.42)	(0.71)	(1.28)	(-0.71)
Swap - T-bill	-0.001	0.003	0.002	0.000	0.001	0.000
	(-0.43)	(2.17)	(1.25)	(0.11)	(0.52)	(0.20)
Libor - Repo	-0.006	0.002	0.001	-0.003	-0.003	0.003
	(-0.96)	(0.77)	(0.36)	(-0.41)	(-1.01)	(0.78)
Funding Liq. Risk (PCA)	0.001	-0.000	-0.000	0.002	0.000	0.000
	(0.43)	(-0.21)	(-0.15)	(0.86)	(0.24)	(0.32)
Adj. R-square	-0.01	0.00	0.06	0.02	0.00	-0.01

Table 10: Fama-MacBeth cross-sectional regressions of global asset returns

We report Fama-MacBeth (1973) coefficient estimates (in percent) and Newey-West *t* -statistics (in parentheses) of regressing global assets' realized USD-based excess returns in month *t+1* on asset RIXs, global RIX beta, and other betas in month *t* . Our testing assets include 30 international equity indices, 32 currencies, 14 sovereign bond futures, and 28 commodity futures. In addition to GRIX beta, we estimate each asset's betas with respect to the following macroeconomic risk, liqudity risk, investment style, and tail risk factors: (1) MSCI world equity index excess return, (2) U.S. liquidity risk factor that is based on the first principal component of various market liquidity and funding liquidity measures in the U.S., (3) U.S. real GDP growth per capita, (4) U.S. inflation rate, (5) U.S. default risk that is based on the change of U.S. default spread, (6) U.S. term risk that is based on the change of U.S. term spread, (7) the global version of these liquidity and macroeconomic variables, (8) the global investment factors of value and momentum, betting-against-beta (BAB), and time series momentum (TSMOM), and (9) the global tail risk factors of risk-neutral (RN) moment risks of variance, skewness, and kurtosis. To reduce estimation error in regressors, we use each asset's rankings as regressors in performing cross-sectional regressions at each point of time. For example, we form 5 GRIX-beta quintiles across all assets and use these rankings for "Global RIX beta". We do the same for other variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Global RIX beta	-0.212	-0.190	-0.173	-0.156	-0.216	-0.174	-0.156
	(-3.13)	(-2.88)	(-2.32)	(-2.06)	(-2.85)	(-2.30)	(-1.76)
Asset RIXs (characteristics)		0.014					
		(0.24)					
Market beta			0.088	0.124	0.050	0.080	0.135
			(0.73)	(1.17)	(0.35)	(0.67)	(0.93)
U.S. Liquidity risk beta			-0.067				
			(-0.62)				
U.S. Real GDP growth beta			0.029				
			(0.35)				
U.S. Inflation beta			0.098				
			(1.02)				
U.S. Default risk beta			0.130				
			(1.47)				
U.S. Term risk beta			0.109				
			(1.43)				
Global Liquidity risk beta				-0.107			-0.153
				(-1.02)			(-1.65)
Global Real GDP growth beta				-0.082			-0.166
				(-0.90)			(-1.66)
Global Inflation beta				-0.036			-0.080
				(-0.46)			(-0.86)
Global Default risk beta				0.180			0.126
				(1.71)			(1.21)
Global Term risk beta				0.124			0.156
				(1.69)			(1.76)
Global Volatility risk beta				0.155			0.006
				(1.40)			(0.05)
Global Value beta					0.085		0.036
					(0.79)		(0.33)
Global Momentum beta					0.118		0.134
					(0.84)		(1.13)
Global BAB beta					-0.095		-0.109
					(-0.91)		(-1.04)
Global TSMOM beta					-0.086		-0.088
					(-0.62)		(-0.71)
Global RN variance risk beta						0.176	0.178
						(1.75)	(1.33)
Global RN skewness risk beta						-0.178	-0.123
						(-2.10)	(-1.42)
Global RN kurtosis risk beta						-0.126	-0.093
						(-1.36)	(-0.92)
Average R-square	0.02	0.04	0.15	0.16	0.16	0.14	0.26

Figure A-1: Downside risk of portfolios of unfavorable and favorable assets

This figure presents mean excess returns of five GRIX-beta quintiles against their downside risk CAPM (DR-CAPM) betas. These quintile portfolios are monthly formed using 104 global assets of equity indices, currencies, government bonds, and commodities (see Table 4 in detail). Assets in the low (high) GRIX-beta portfolio are unfavorable (favorable). To estimate each portfolio's DR-CAPM beta, we regress its monthly excess returns on the MSCI world equity index excess returns using only downsates that are all months in which the market return is at least one standard deviation below its sample mean over the period from January 1998 through May 2012. The DR-CAPM beta of unfavorable-minus-favorable hedge portfolio is -0.008 (with a *t* -statistic of -0.03).

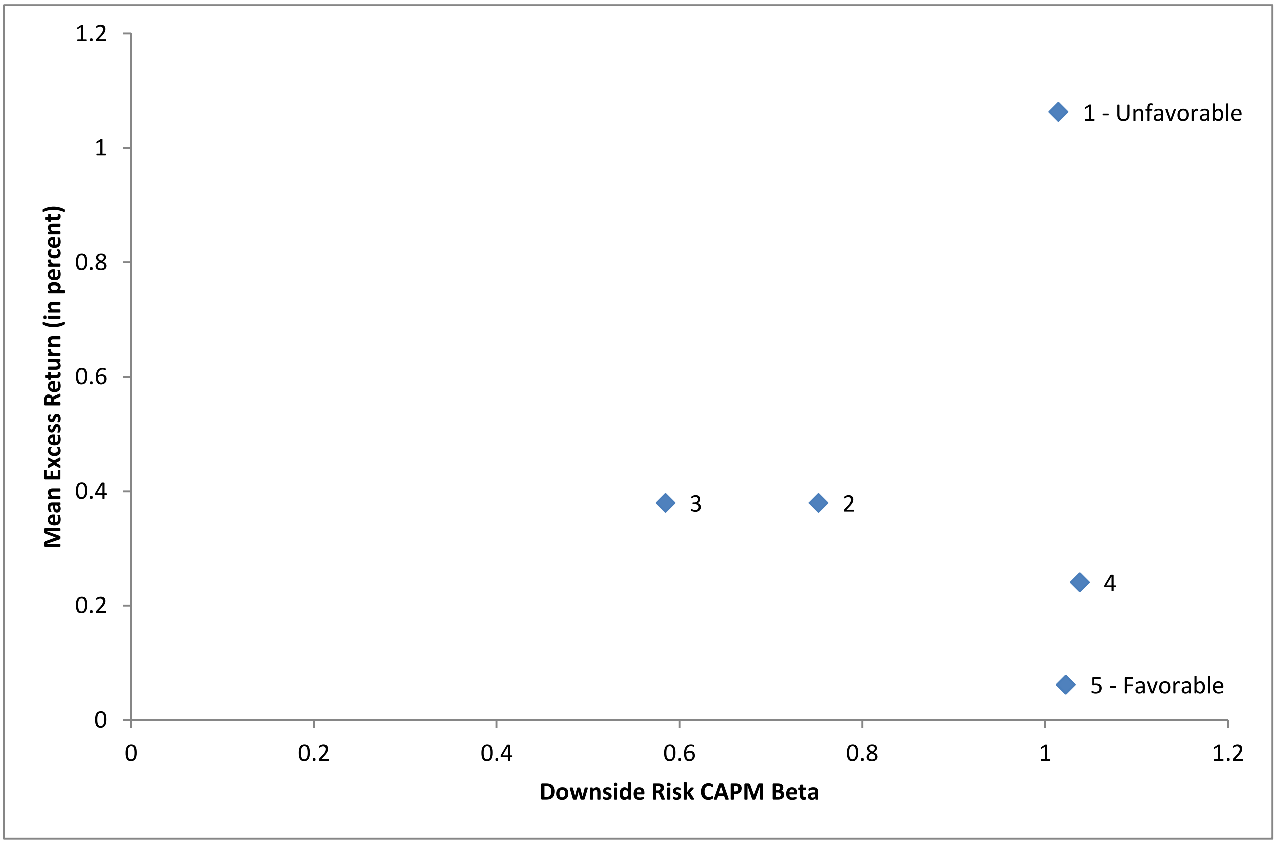


Table A-2: Disaster concern innovation and returns of portfolios within and across asset classes

Within an asset class, we estimate an asset's beta with respect to the innovation of its asset-class-specific RIX, and then form four ΔRIX-β portfolios. Across all global assets from four asset classes, we estimate an asset's beta with respect to the innovation of the GRIX, and then form four ΔGRIX-β portfolios. Both within and across asset classes, we also form hedge portfolios by going long in low beta assets and short in high beta assets. The rolling-window regression setup is similar to that in Table 2. We monthly form portfolios and calculate equal-weighted portfolio returns. This table presents mothly mean excess returns (in percent) and alphas benchmarked on the five-factor global asset pricing model. Newey-West *t* -statistics are reported in parentheses.

β estimated using ΔRIX (or ΔGRIX)	Equity Indices		Currencies		Sovereign Bonds		Commodities		All Assets	
	Excess Return	Alpha	Excess Return	Alpha	Excess Return	Alpha	Excess Return	Alpha	Excess Return	Alpha
Low - β	0.759	0.404	0.549	0.248	0.254	0.263	0.508	0.251	0.633	0.090
	(1.19)	(1.15)	(1.91)	(1.47)	(2.11)	(3.44)	(1.13)	(0.77)	(1.65)	(0.27)
2	0.402	0.100	0.385	0.111	0.174	0.179	0.564	0.339	0.385	-0.081
	(0.78)	(0.42)	(1.86)	(1.25)	(2.54)	(4.56)	(1.65)	(1.34)	(1.71)	(-0.46)
3	0.316	0.006	0.355	0.115	0.198	0.202	0.381	0.148	0.188	-0.090
	(0.66)	(0.04)	(1.87)	(1.30)	(3.25)	(4.76)	(0.98)	(0.57)	(0.78)	(-0.52)
High - β	0.679	0.356	0.448	0.174	0.172	0.176	0.353	0.129	0.449	-0.157
	(1.31)	(1.71)	(2.09)	(1.60)	(2.34)	(3.36)	(0.91)	(0.50)	(1.44)	(-0.82)
High - Low	0.080	0.048	0.101	0.074	0.082	0.087	0.155	0.122	0.184	0.247
	(0.25)	(0.16)	(0.53)	(0.38)	(0.83)	(0.96)	(0.39)	(0.31)	(0.72)	(0.71)

Table A-2: Downside risk CAPM betas of asset-class-specific RIX-beta portfolios (to be updated)

Within an asset class, we form four RIX-beta portfolios using the asset-class-specific rare disaster concern index (see Table 2 for details). We also form combination portfolios that generate equal weighted returns across three asset classes (equity, currency, and bond). The frequency of portfolio formation is monthly (Panel A) and semi-annual (Panel B). To estimate each portfolio's downside risk CAPM (DR-CAPM) beta, we regress its monthly excess returns on the market excess returns using only downsates that are all months in which the market return is at least one standard deviation below its sample mean. We use the following market returns in estimating DR-CAPM betas: (1) the MSCI world equity index excess returns during January 1998 through October 2012 for EQRIX-beta portfolios; (2) the dollar value factor returns during January 1998 through May 2012 for FXRIX-beta portfolios; (3) the Barclays Capital global government bond index returns during January 1998 through December 2012 for BDRIX-beta portfolios; and (4) the MSCI world equity index excess returns during January 1998 through May 2012 for combination portfolios.

Panel A: monthly portfolio formation

	EQRIX-Beta Portfolios			FXRIX-Beta Portfolios			BDRIX-Beta Portfolios			EQ-FX-BD RIX-Beta Comb		
	β	t(β)	Adj. R^2	β	t(β)	Adj. R^2	β	t(β)	Adj. R^2	β	t(β)	Adj. R^2
Low - 1	1.257	4.59	46.6%	1.195	6.49	67.3%	0.535	1.03	0.2%	0.699	4.46	45.1%
2	1.353	6.61	65.0%	0.570	4.10	44.1%	0.693	2.00	9.7%	0.574	5.30	54.1%
3	1.415	7.13	68.5%	1.021	10.05	83.3%	1.038	3.07	23.1%	0.623	5.45	55.5%
High - 4	1.086	4.56	46.2%	1.035	7.12	71.3%	1.104	1.97	9.3%	0.578	4.20	42.0%
Low - High	0.171	0.56	-3.1%	0.160	0.59	-3.4%	-0.569	-0.75	-1.6%	0.121	0.81	-1.5%

Panel B: semi-annual portfolio formation

	EQRIX-Beta Portfolios			FXRIX-Beta Portfolios			BDRIX-Beta Portfolios			EQ-FX-BD RIX-Beta Comb		
	β	t(β)	Adj. R^2	β	t(β)	Adj. R^2	β	t(β)	Adj. R^2	β	t(β)	Adj. R^2
Low - 1	1.431	5.27	54.9%	1.174	6.96	70.3%	1.356	2.41	14.2%	1.431	5.27	54.9%
2	1.348	6.20	63.0%	0.660	3.71	39.0%	0.457	1.54	4.6%	1.348	6.20	63.0%
3	1.498	11.25	85.1%	1.014	6.26	65.6%	0.847	3.09	22.7%	1.498	11.25	85.1%
High - 4	1.284	4.76	49.7%	0.943	6.21	65.2%	0.623	1.15	1.1%	1.284	4.76	49.7%
Low - High	0.148	0.46	-3.7%	0.231	1.02	0.2%	0.732	0.96	-0.3%	0.148	0.46	-3.7%

Table A-3: Robustness checks (more to be added)

This table presents mean excess returns of RIX-beta portfolios based on different specifications of global asset returns. We form four RIX-beta portfolios within each asset class and report results based on different frequencies of portfolio formation. For equity class (Panel A), we use U.S. ETFs to track our original sample of international equity indices, and also use monthly returns in CRSP in estimating ETFs' EQRIX betas and calculating equal weighted portfolio returns. For currency class (Panel B), we use log returns in estimating currencies' FXRIX betas and calculating portfolio returns. For bond class (Panel C), we use interpolated futures returns of 30-day constant maturity in estimating bonds' BDRIX betas and calculating portfolio returns.

Panel A: U.S. ETFs tracking international equity indices

EQRIX Beta	Monthly Portfolio Formation	Quarterly Portfolio Formation	Semi-Annual Portfolio Formation	Annual Portfolio Formation
Low - 1	0.668	0.906	0.904	0.999
	(1.38)	(1.91)	(2.00)	(2.13)
2	0.379	0.241	0.395	0.260
	(0.84)	(0.53)	(0.84)	(0.53)
3	0.271	0.260	0.167	0.254
	(0.59)	(0.55)	(0.36)	(0.57)
High - 4	0.198	0.089	0.234	0.149
	(0.41)	(0.18)	(0.48)	(0.33)
High - Low	-0.471	-0.817	-0.670	-0.850
	(-1.69)	(-2.76)	(-2.27)	(-3.06)

Panel B: Currency log returns

FXRIX Beta	Monthly Portfolio Formation	Quarterly Portfolio Formation	Semi-Annual Portfolio Formation	Annual Portfolio Formation
Low - 1	0.734	0.795	0.802	0.723
	(3.06)	(3.26)	(3.41)	(2.97)
2	0.074	0.163	0.061	0.093
	(0.42)	(0.96)	(0.35)	(0.51)
3	0.319	0.276	0.301	0.318
	(1.94)	(1.71)	(1.84)	(1.88)
High - 4	0.374	0.296	0.342	0.366
	(1.93)	(1.56)	(1.76)	(1.97)
High - Low	-0.360	-0.499	-0.460	-0.357
	(-2.00)	(-2.86)	(-2.72)	(-1.92)

Panel C: Bond futures interpolated returns of 30-day constant maturity

BDRIX Beta	Monthly Portfolio Formation	Quarterly Portfolio Formation	Semi-Annual Portfolio Formation	Annual Portfolio Formation
Low - 1	0.320	0.252	0.353	0.325
	(2.82)	(2.37)	(3.17)	(2.65)
2	0.149	0.153	0.125	0.095
	(2.10)	(2.17)	(1.91)	(1.34)
3	0.116	0.097	0.085	0.070
	(1.83)	(1.52)	(1.33)	(1.06)
High - 4	0.102	0.155	0.124	0.158
	(1.38)	(2.07)	(1.58)	(2.16)
High - Low	-0.219	-0.097	-0.229	-0.167
	(-2.38)	(-1.17)	(-2.62)	(-1.72)