Rare Disaster Concerns Everywhere*

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Abstract

We propose an empirical framework of disaster concerns to explain cross-sectional return variation both within and across asset classes. Using a large set of out-of-the-money options on international equity indices, foreign currencies, and global government bonds, we measure the global financial market's rare disaster concerns under only no-arbitrage conditions. Assets that have low return covariations with such concerns earn high excess returns in the future. The return predictability driven by rare disaster concerns is distinct from that driven by exposures to realized disaster shocks such as macroeconomic downturns and liquidity crunches, and is not attributed to effects of global value and momentum, downside risk, and leverage and margin constraints.

Keywords: Disaster risk; Rare disaster concerns; Global equity; Currency; Bond; 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

We propose a unified empirical framework of *ex ante* market disaster concerns to explain cross-sectional return variation both within and across asset classes. This framework 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. The *ex ante* concerns of rare disasters on financial markets (hereafter rare disaster concerns) often deviate from the *ex post* disaster shocks based on (limited) historical observations, which is not surprising because rare disasters are, after all, rarely realized.[1] Our framework of rare disaster concerns is capable of jointly reconciling cross-sectional return variation of international equity indices, foreign currencies, and global government bond futures, echoing the importance of the economic mechanism of "concerns about 'tail' risks" emphasized by Ben Bernanke in designing the U.S. monetary policies.[2]

To capture such *ex ante* disaster concerns, we first propose a rare disaster concern index ($\mathbb{RIX}$)

[1] Our focus is on disasters of financial markets (the extreme downside movements of financial asset prices), while Rietz (1988), Veronesi (2004), Barro (2006), Gabaix (2012), Gourio (2012), and Wachter (2013) study disaster risks of consumptions and macroeconomic fundamentals. Therefore, our results do not directly speak to the macroeconomic driver of the finanical market's disasters; instead, we present evidence that the *ex ante* disaster perception on financial markets drives asset prices universally both within and across asset classes. 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), which are based on constant and time-varying disaster risk models, respectively.

[2] The meaning of rare disaster concerns in our framework also coincides with "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."

based on out-of-the-money (OTM) put options on 30 international equity indices, 32 currencies, and 14 government bond futures. Assuming only no-arbitrage conditions, our $\mathbb{RIX}$ measure equals to a disaster insurance price and does not separate risk aversion and the physical distribution of asset returns: An increase in $\mathbb{RIX}$ can be due to increasing disaster risk, increasing crash aversion, and/or increasing funding and capital constraints of institutional investors (Barberis, 2013; Barro, 2006; Bates, 2008; Brunnermeier and Pedersen, 2009; He and Krishnamurthy, 2012, 2013; Liu, Pan, and Wang, 2005). Our focus, however, is to show that the empirical framework of rare disaster concerns can explain cross-sectional return variation across multiple asset classes. To further understand possible theoretical explanations behind our framework, we document that the asset return pattern driven by disaster concerns is distinct from that driven by exposures to realized disaster shocks such as macroeconomic downturns and liquidity crunches. This evidence suggests that economic channels generalizing preferences and/or beliefs in standard disaster risk models of Barro (2006), Gabaix (2012), and Wachter (2013) seem to be important in understanding our empirical framework of rare disaster concerns.[3]

Our construction of the $\mathbb{RIX}$ employs OTM put options that contain rich information about the *ex ante* market's expectations on future rare disasters.[4] However, this exercise is not trivial because (1) OTM puts with multiple moneyness levels are available, and (2) perceptions of risks other than disaster risk (e.g., volatility and frequent jumps of moderate sizes) are also embedded in option prices. A measure of disaster concern/perception 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. To achieve these two goals, 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, and bonds. The construction of these disaster concern indices build on the literature of model-free implied volatility measures (Carr and Madan, 1998; Bakshi and Madan, 2000; Britten-Jones and Neuberger, 2000; Carr and Wu, 2009; Du and Kapadia, 2012). Technically, the $\mathbb{RIX}$ captures all high-order moments (≥ 3) of the jump measure. Economically, the $\mathbb{RIX}$ is the price of a disaster insurance contract against unlikely but (only) extreme downside price movements. Empirical estimates show that $\mathbb{RIX}$s

[3]The time-varying perceived probability of rare disasters is often regarded as the "dark matter" of finance in explaining asset prices (Campbell, 2008; Chen, Dou, and Kogan, 2013; Weitzman, 2007).

[4]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)

are rather informative about the market's perception of future disaster events of 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 $\mathbb{RIX}$-beta 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 $\mathbb{RIX}$-beta assets on average earn higher excess returns than high $\mathbb{RIX}$-beta assets in each asset class we study. For example, when portfolios are monthly formed, the low-minus-high $\mathbb{RIX}$-beta portfolios on average significantly earn 0.75%, 0.37%, and 0.22% per month in equity indices, currencies, and bonds, respectively. Moreover, this $\mathbb{RIX}$-beta effect is not short-lived. At the semi-annual frequency of portfolio formation, return spreads of these low-minus-high $\mathbb{RIX}$-beta portfolios are even larger, 0.97%, 0.54%, and 0.28%, 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).[5] We show the $\mathbb{GRIX}$ is important in explaining cross-sectional return variation across markets and asset classes. In particular, we rank all 76 global investment assets into five $\mathbb{GRIX}$-beta quintiles. On the monthly and quarterly frequencies of portfolio formation, the low-minus-high $\mathbb{GRIX}$-beta portfolios on average significantly earn 0.62% and 0.65% per month, with t-statistics of 2.8 and 3.3, 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 0.63% to 0.80% per month with t-statistics larger than three most of time. More importantly, both low and high $\mathbb{GRIX}$-beta portfolios contain

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

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 in our study (equity, currency, and bond over the sample period from 1996 through 2012). 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.

Return patterns associated with rare disaster concerns are also robust. Our portfolio analysis indicates that rare disaster concerns as assets' characteristics cannot explain cross-sectional average returns, and indeed it is the $\mathbb{RIX}$ (and $\mathbb{GRIX}$) betas 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.

Are standard disaster risk channels sufficient to understand our empirical framework with $\mathbb{RIX}$? Do we need non-standard channels such as non-expected utility components of either preferences or beliefs about disaster risk?[6] We answer these questions by investigating whether return patterns driven by rare disaster concerns are distinct from those driven by exposures to realized disaster shocks. We collect a large set of variables of macroeconomic risk for both U.S. and global economies (U.S., U.K., Japan, and Europe), and also construct various measures of funding liquidity and market liquidity risk. We perform both correlation analyses and time-series regressions of low-minus-high $\mathbb{RIX}$-beta (and $\mathbb{GRIX}$-beta) portfolio returns on macroeconomic and liquidity risk factors. Our results strongly indicate that the global asset return predictability driven by market concerns about future rare disasters is distinct from the related disaster risk exposure with respect to macroeconomic downturns and liquidity crunches (Barro, 2006; Brunnermeier, Nagel, and Pedersen, 2008). The robustness of $\mathbb{RIX}$-driven global asset return predictability to funding liquidity shocks also rules out the case that rare disaster concerns are simply phantom of liquidity/capital constraints of financial intermediaries (Brunnermeier and Pedersen, 2009; Garleanu, Pedersen, and Poteshman, 2009; Garleanu and Pedersen, 2011). We stress that such empirical evidence does not imply that standard disaster risk channels in Barro (2006), Gabaix (2012), Martin (2013c), and

[6]Studies of tail risk with non-expected utility mechanisms include Barberis (2013) and Barberis and Huang (2008) using probability weighting functions, Bates (2008) and Liu, Pan, and Wang (2005) using crash or uncertainty aversion, and Chen, Joslin, and Tran (2012) and Weitzman (2007) using subjective beliefs about disaster risk, among many others.

Wachter (2013) are unimportant; instead, our results suggest the extension of standard disaster risk channels, either on preferences or beliefs about disaster risk, may be useful to reconcile with our empirical framework of rare disaster concerns on jointly pricing global assets.

Our study contributes to the growing literature that explores the joint cross section of multiple markets and asset classes. Asness, Moskowitz, and Pedersen (2013), and Koijen, Moskowitz, Pedersen, and Vrugt (2012) document cross-sectional return patterns of value, momentum, and carry across asset classes. Moskowitz, Ooi, and Pedersen (2012) document time-series futures momentum across equity index, currency, commodity, and bond markets. In global equity markets, Fama and French (2012) study the relation between size, value, and momentum strategies, and Hou, Karolyi, and Kho (2011) compare the performance of global, local, and "international" versions of various multifactor models. Complementing these studies that document various characteristic-based return patterns, we propose a unified framework with an important economic mechanism, i.e., rare disaster concerns, which explains cross-sectional return variation of different assets across asset classes. As discussed above, the $\mathbb{RIX}$-beta asset return patterns cannot be attributed to characteristic effects of global value and momentum.

In other studies on global asset pricing, Frazzini and Pedersen (2012) show that leverage and margin constraints, summarized empirically by their betting-against-beta (BAB) factors, can describe returns of multiple asset classes. Lettau, Maggiori, and Weber (2013) show that the downside risk CAPM (DR-CAPM), originally proposed by Ang, Chen, and Xing (2006) for the U.S. equity market, can explain expected returns of currency, equity, commodity, and bond markets. Our paper differs from these two studies by considering the economic force of *ex ante* concerns of financial market disasters, motivated by the strong co-movement of global assets from different markets and asset classes during times of high concerns on financial market meltdown. Our documented $\mathbb{RIX}$-beta asset return patterns are also robust to effects of margin and leverage constraints, and the DR-CAPM betas.

Our study also contributes to the disaster risk literature by documenting the explanatory power of rare disaster concerns on asset returns across multiple 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).[7] Our joint approach of studying multiple asset classes suggests disaster concerns as a potential framework to unify "*how* discount rates vary over time and across assets" (Cochrane, 2011). The focus on *ex ante* disaster concerns also distinguishes our study from other studies proposing tail risk measures based on historical return observations (Bali, Cakici, and Whitelaw, 2011; Kelly, 2012).[8]

The rest of the paper is organized as follows. Section 2 constructs $\mathbb{RIX}$s for different markets and asset classes to measure rare disaster concerns. Section 3 systematically examines rare disaster concerns and asset returns. Section 4 studies how rare disaster concerns are related to measures of realized disaster shocks associated with macroeconomic downturn and liquidity crunch. We discuss alternative explanations and perform robustness checks in Section 5, and conclude in Section 6. The appendix provides additional empirical results and detailed information on options data.

2 Measure Rare Disaster Concerns

Throughout the paper we measure rare disaster concerns from the perspective of a U.S. investor who invests in various asset classes such as equity, currency, and bond globally. Extending the work of Gao, Gao, and Song (2013) that develops the rare disaster concern index ($\mathbb{RIX}$) only for the U.S. equity market, we construct a set of rare disaster concern indices for international equity index, foreign currency, and global government bond. We first briefly review the methodology of $\mathbb{RIX}$ construction, and then discuss option data. Finally, we present $\mathbb{RIX}$ estimates of different asset classes.

[7] 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 (2012), Drechsler and Yaron (2011), but with a focus on option pricing.

[8] Our paper is also related to two recent studies, Martin (2013b) and Ross (2013), which characterize the empirical patterns of expected returns extracted exclusively from option prices and find that expected market return spikes dramatically during financial crises, in sharp contrast to the prevailing view based on historical returns. Our study is parallel to Martin (2013b) and Ross (2013) in the sense that they focus on the *ex ante* expected returns, while we focus on the *ex ante* perception of tail risks that drives expected returns. In fact, our results suggest that the extremely high perception of tail risk (rather than tail risk itself) explains the frequently high expected returns they document. Besides market expected return, Ross (2013) also proposes an estimator for the *ex-ante* physical distribution of market return. In his empirical exercises, however, he only provides snapshot estimates on such distribution using S&P 500 index options on several dates. In contrast, we examine both time series and cross-sectional asset pricing implications of rare disaster concerns.

2.1 Methodology

The $\mathbb{RIX}$ is constructed as the price difference between two option-based replication portfolios of variance swap contracts: one accounts for mild market volatility shocks, and the other incorporates extreme volatility shocks induced by jumps associated with rare disaster risks. Consider an underlying asset whose time-t price is S_t. An investor holding this security is concerned about its price fluctuations over a time period $[t, T]$. One way to protect herself against price changes is to buy a contract that delivers payments equal to the extent of price variations over $[t, T]$, minus a prearranged price. Such a contract is called a variance swap contract as the price variations are essentially about the stochastic variance of the price process.[9] The standard variance swap contract in practice pays

$$\left(\ln \frac{S_{t+\Delta}}{S_t}\right)^2 + \left(\ln \frac{S_{t+2\Delta}}{S_{t+\Delta}}\right)^2 + \cdots + \left(\ln \frac{S_T}{S_{T-\Delta}}\right)^2$$

minus the prearranged price $\mathbb{VP}$. That is, the variance swap contract uses the sum of squared log returns to measure price variations, which is a standard practice in the finance literature (Singleton, 2006).[10]

In principle, replication portfolios consisting of OTM options written on S_t can be used to replicate the time-varying payoff associated with the variance swap contract and hence to determine the price $\mathbb{VP}$. We now introduce two replication portfolios and their implied prices for the variance swap contract. The first, underlying the construction of VIX by the CBOE, focuses on the limit of the discrete sum of squared log returns and determines $\mathbb{VP}$ as

$$\mathbb{IV} \equiv \frac{2e^{r\tau}}{\tau} \left\{ \int_{K>S_t} \frac{1}{K^2} C(S_t; K, T) dK + \int_{K<S_t} \frac{1}{K^2} P(S_t; K, T) dK \right\}, \tag{1}$$

where r is the constant risk-free rate, $\tau \equiv T - t$ is the time-to-maturity, and $C(S_t; K, T)$ and $P(S_t; K, T)$ are prices of call and put options with strike K and maturity date T, respectively. As observed from equation (1), this replication portfolio contains positions in OTM calls and puts with a weight inversely proportional to their squared strikes. $\mathbb{IV}$ has been employed in the literature to construct measures of variance risk premiums (Bollerslev, Tauchen, and Zhou, 2009; Carr and Wu,

[9] The variance here refers to stochastic changes of the asset price, and hence is different from (more general than) the seond-order moment of the asset return distribution (see Equation (5)).

[10] Martin (2013b) uses a simple variance swap contract with payments in the form of simple returns rather than log returns.

2009; Drechsler and Yaron, 2011).

The second replication portfolio relies on risk-neutral variance $Var_t^{\mathbb{Q}}(\ln S_T/S_t)$, which avoids the discrete sum approximation, determines $\mathbb{VP}$ as

$$\mathbb{V} \equiv \frac{2e^{r\tau}}{\tau}\left\{\int_{K>S_t}\frac{1-\ln(K/S_t)}{K^2}C(S_t;K,T)dK + \int_{K<S_t}\frac{1-\ln(K/S_t)}{K^2}P(S_t;K,T)dK\right\}. \quad (2)$$

This replication portfolio differs from the first in equation (1) by assigning larger (smaller) weights to more deeply OTM put (call) options. As strike price K declines (increases), i.e., put (call) options become more out of the money, $1-\ln(K/S_t)$ becomes larger (smaller). 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.

Our rare disaster concern index ($\mathbb{RIX}$) is essentially equal to the difference between $\mathbb{V}$ and $\mathbb{IV}$ that is caused by the extreme deviation of S_T from S_t. However, both upside and downside price jumps contribute to this difference. Motivated by prior studies that investors are more concerned about downside price swings (Liu, Pan, and Wang, 2005; Ang, Chen and Xing, 2006; Barro, 2006; Gabaix, 2012; Wachter, 2013), we focus on downside rare events associated with unlikely but extreme negative price jumps. In particular, we consider the downside versions of both $\mathbb{IV}$ and $\mathbb{V}$:

$$\begin{aligned}\mathbb{IV}^- &\equiv \frac{2e^{r\tau}}{\tau}\int_{K<S_t}\frac{1}{K^2}P(S_t;K,T)dK,\\ \mathbb{V}^- &\equiv \frac{2e^{r\tau}}{\tau}\int_{K<S_t}\frac{1-\ln(K/S_t)}{K^2}P(S_t;K,T)dK,\end{aligned} \quad (3)$$

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

$$\mathbb{RIX} \equiv \mathbb{V}^- - \mathbb{IV}^- = \frac{2e^{r\tau}}{\tau}\int_{K<S_t}\frac{\ln(S_t/K)}{K^2}P(S_t;K,T)dK. \quad (4)$$

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 $\lambda\frac{1}{\sqrt{2\pi}\sigma_J}\exp\left(-(x-\mu_J)^2/2\right)$.

We can show that

$$\mathbb{RIX} \equiv 2\mathbb{E}_t^{\mathbb{Q}} \int_t^T \int_{R_0} \left(1 + x + x^2/2 - e^x\right) \omega^- [dx, dt], \tag{5}$$

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 $e^x - (1 + x + x^2/2) = x^3/3 + x^4/4 + \cdots$.

2.2 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).[11] The sample period is from January 1996 through October 2012, with 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.

Foreign Currencies. We obtain daily prices of over-the-counter (OTC) currency options from

[11] Except for 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 region.

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.[12] The market of these currency options is the deepest, largest, and most liquid market for options of any kind.[13] 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.[14]

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 rates obtained from Datastream as the interest rates of US Dollar (USD) $R_t^{f,US}$. 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

[12] 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.

[13] 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.

[14] 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.

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.[15] 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.[16] 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.

2.3 Empirical estimation

Following the literature, we clean option data of the three 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

[15] 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 (CTD) restriction, which has a certain range of maturity close to but not necessarily equal to the original maturity underlying these futures contracts.

[16] 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.

shorter than 30 days. We keep only OTM puts for equity indices and bonds, and only OTM calls for currencies, and exclude days with fewer than two option quotes of different moneyness levels for each chosen maturity.[17] As observed from (4), 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.

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 (4) 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 foreign currencies, and 14 global government bonds (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.

After constructing each asset's $\mathbb{RIX}$ at month t and averaging the cross-section of $\mathbb{RIX}$s using all

[17] Recall the definition of $\mathbb{RIX}$ in (5) is for an asset's value and currency options are written on USD-based exchange rates. Throughout the paper, we always define an asset's $\mathbb{RIX}$ from a U.S. investor's perspective, that is, the $\mathbb{RIX}$ increase means increased concerns on the crash of asset's future value. For instance, an extreme upside movement of Euro/USD exchange rate means a disaster for a U.S. investor holding Euro.

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 three asset-class-specific rare disaster concern indices: $\mathbb{EQRIX}$ for equity index, $\mathbb{FXRIX}$ for currency, and $\mathbb{BDRIX}$ for bond. 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. 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 three asset-class-specific $\mathbb{RIX}$s. We further discuss co-movement in rare disaster concerns in Section 3.[18]

3 Rare Disaster Concerns and Asset Returns

In this section, we study how rare disaster concerns drive global asset returns by examining the cross-sectional relation between loadings on rare disaster concern indices (i.e., "$\mathbb{RIX}$ beta") and future asset returns. After discussing the return data for international equity indices, currencies, and bond futures, we present empirical evidence within each asset class. We then document the strong co-movement of $\mathbb{RIX}$s across asset classes. Finally, we construct a global rare disaster concern index ($\mathbb{GRIX}$) and study returns across markets and asset classes.

3.1 Return data

Our return data on equity indices, currencies, and bonds match the sample of options introduced in Section 2.2. 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.

[18] 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.

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

$$r_{t+1}^k = S_t(1 + r_{t+1}^{f,k})/S_{t+1} - 1 \tag{6}$$

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 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).[19] 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: $f_t^k - s_t^k \approx R_t^{f,k} - R_t^{f,US}$.[20] Because we will perform portfolio analyses on combined

[19] 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.

[20] Based on the large failure of CIP, we delete the following observations from our sample: Malaysia (August 1998

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, 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] 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 in (6).[22]

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 standard deviation of 7.6%, currency earns 0.45% per month with a standard deviation of 3.6%, and bond futures earns 0.20% per month with a standard deviation of 1.3%. Regarding skewness and kurtosis, equity index return is left skewed whereas currency and bond futures returns are right skewed; and interestingly bond futures have heavier return tails than equity index and currency. Turning into individual assets within each asset class, the Russia investable market index, the

- 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.

[21] 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).

[22] 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.

currency of Indonesian Rupiah, and the Spain 10-year bond futures yield the highest mean excess returns of 2.56%, 3.26%, and 0.35% per month, within the asset classes of equity index, currency, and bond, 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 $\mathbb{RIX}$ beta 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 $\mathbb{RIX}$ beta. 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 $\mathbb{RIX}$ beta 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 $\mathbb{FXRIX}$; and in the bond class we regress bond futures returns on the Barclays Capital global government bond index return and $\mathbb{BDRIX}$. Our option sample in measuring rare disaster concerns and return sample in estimating $\mathbb{RIX}$ betas 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 $\mathbb{RIX}$ beta 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 $\mathbb{RIX}$ beta and examine future asset returns. When analyzing returns within an asset class, we rank assets into four groups based on their $\mathbb{RIX}$ betas, 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 three global asset classes into five quintiles based on their loadings on the global rare disaster concern index that we will discuss shortly. We construct the low-minus-high $\mathbb{RIX}$-beta portfolio that is long low $\mathbb{RIX}$-beta assets and short high $\mathbb{RIX}$-beta assets, both within and across asset classes. To study the horizons of $\mathbb{RIX}$ beta in explaining asset returns, we consider portfolio formation at monthly, quarterly, semi-annual, and annual frequency.

We employ the following set of factors as benchmark models in estimating alphas. For international equity we use the Fama-French three factors augmented with the Carhart's momentum factor in the international context (Fama and French, 2012). For currency we use the Lustig-Roussanov-Verdelhan two common risk factors in currency markets (Lustig, Roussanov, and Verdelhan, 2011). We also use the Asness-Moskowitz-Pedersen value and momentum everywhere factors for global equity indices, currencies, government bonds, and all global asset classes (Asness, Moskowitz, and Pedersen, 2013). Last, we use the Frazzini-Pedersen betting-against-beta factors for equity indices, currencies, country bond indices, and global all asset classes (Frazzini and Pedersen, 2012).

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

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

Three main results arise. First, we find consistent patterns that low $\mathbb{RIX}$-beta assets earn higher returns than high $\mathbb{RIX}$-beta assets in each asset class. The return differences between low and high $\mathbb{RIX}$-beta assets are not only statistically significant but also economically large. For example, when we monthly form portfolios (Panel A), the low-minus-high (LMH) $\mathbb{RIX}$-beta portfolios on average significantly earn 0.75%, 0.37%, and 0.22% per month within asset classes of equity, currency, and bond, respectively.

Second, asset return predictability associated with $\mathbb{RIX}$ beta is not short-lived. For example, at the semi-annual frequency of portfolio formation (Panel C), these portfolios earn even higher average returns (0.97%, 0.54%, and 0.28% per month), all close to three standard errors from zero. In addition, at various frequencies of portfolio formation, the spreads of LMH $\mathbb{RIX}$-beta portfolios mainly come from high excess returns earned by low $\mathbb{RIX}$-beta assets (the long side).

Third, these return patterns from assets' return covariation with rare disaster concerns are largely unexplained by well-known benchmark factors of different asset classes. Specifically, alphas of LMH $\mathbb{EQRIX}$-beta portfolios are significant at all frequencies of portfolio formation (0.65% to

0.97% per month); those of LMH $\mathbb{FXRIX}$-beta portfolios are significant at quarterly and semi-annual frequencies (0.46% to 0.51%); and those of LMH $\mathbb{BDRIX}$-beta portfolios are marginally significant at semi-annual frequency (0.17% with a t-statistic of 1.9). Furthermore, the LMH $\mathbb{RIX}$-beta portfolio from the simple combination strategy yields 0.41% to 0.51% (0.37% to 0.55%) monthly mean returns (alphas) depending on portfolio formation frequency, all statistically significant (most of time t-statistics are larger than three). This result illustrates an important diversification effect of $\mathbb{RIX}$-beta portfolios across asset classes.

Figure 3 shows year-by-year annual returns and Sharpe ratios of the LMH $\mathbb{RIX}$-beta portfolios within each asset class and through the asset-class combination. The outperformance of low $\mathbb{RIX}$-beta assets is not restricted to a particular year. Importantly, the return spreads of LMH $\mathbb{RIX}$-beta portfolios are positive during 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 associated with *ex post* disaster risk exposure. In the latter case, if one interprets low $\mathbb{RIX}$-beta assets as risky because of their high sensitivity to tail risk (or downside risk), then the return spreads of LMH $\mathbb{RIX}$-beta 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, and 0.28 within equity, currency, and bond, respectively. We also compute the pairwise correlations of $\mathbb{RIX}$s across assets from different classes. The mean (median) correlations are the following: 0.54 (0.65) between equity and non-equity classes, 0.54 (0.64) between currency and non-currency classes, and 0.30 (0.37) between bond and non-bond 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, and $\mathbb{BDRIX}$ for bond). The eigenvector weights of $\mathbb{GRIX}$ on $\mathbb{EQRIX}$, $\mathbb{FXRIX}$, and $\mathbb{BDRIX}$ are

0.54, 0.62, and 0.58, respectively. The first principal component, which essentially averages rare disaster concerns across asset classes, accounts for 70% of the covariations of these three asset-class-specific rare disaster concern indices. 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 $\mathbb{EQRIX}$, $\mathbb{FXRIX}$, and $\mathbb{BDRIX}$ range between 64% to 89%, with statistical significance at 1% level.

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

To set up the stage, we first investigate whether $\mathbb{GRIX}$ betas can explain returns within each asset class. In other words, we estimate each asset's loading on the $\mathbb{GRIX}$ factor using its past 18-24 monthly returns, and then form four $\mathbb{GRIX}$-beta portfolios in an asset class. Table 4 reports returns of these portfolios. When portfolios are monthly formed, we find significant return spreads between low and high $\mathbb{GRIX}$-beta 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 $\mathbb{GRIX}$-beta 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 $\mathbb{GRIX}$-beta 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.

Our main focus is on the relation between $\mathbb{GRIX}$ betas and returns across asset classes, i.e., portfolios that potentially consist of different asset classes given the global nature of $\mathbb{GRIX}$. We rank all 76 global investment assets into five $\mathbb{GRIX}$-beta quintiles and examine their future returns. Table 5 presents portfolio returns and exposures of these portfolios to the Asness-Moskowitz-Pedersen value-momentum-everywhere (VME) factors and the Frazzini-Pedersen betting-against-beta (BAB) factors. On average, there are 11 assets in each $\mathbb{GRIX}$-beta portfolio. We consider portfolio formation on different frequency and report results separately in each panel.

Table 5 shows that global rare disaster concerns (channeled through $\mathbb{GRIX}$ beta) are key drivers of global asset return variations across markets and asset classes. In particular, when portfolios are monthly formed, the return spread between low and high $\mathbb{GRIX}$-beta portfolios is 0.62% per month with a significant t-statistic of 2.8. This return spread becomes even larger when portfolios are quarterly formed, at 0.65% with a t-statistic of 3.3, and it gradually decreases as portfolios are formed at further lower frequencies (0.42% with a t-statistic of 1.90 at semi-annual frequency, and 0.40% with a t-statistic of 1.50 at annual frequency). In addition, these return spreads are mainly driven by assets with low $\mathbb{GRIX}$ betas – all low $\mathbb{GRIX}$-beta quintiles earn significant excess returns around 0.70% per month at different portfolio formation frequencies. In contrast, all high $\mathbb{GRIX}$-beta quintiles do not earn monthly excess returns that are statistically different from zero.

Table 5 also shows that asset returns associated with the common variations of rare disaster concerns across global markets are not attributed to effects of global value and momentum, and leverage and margin constraints. Monthly alphas of LMH $\mathbb{GRIX}$-beta portfolios are all economically large, especially at monthly and quarterly frequencies of portfolio formation, ranging from 0.63% to 0.80% (with t-statistics mostly bigger than three). Furthermore, loadings on the market factor, the VME factors, and the BAB factor have little explanatory power for the return spread between low and high $\mathbb{GRIX}$-beta quintiles.

Does the low (or high) $\mathbb{GRIX}$-beta portfolio only contain assets from a single asset class? Moreover, does the asset composition across equity indices, currencies, and bond futures vary over time in the low (or high) $\mathbb{GRIX}$-beta portfolio? Given that our $\mathbb{GRIX}$ captures time-varying disaster concerns about the global financial market across asset classes, we expect both low and high $\mathbb{GRIX}$-beta portfolios contain assets from multiple asset classes, and the asset composition varies over time in response to the time-varying $\mathbb{GRIX}$. Figure 4 presents asset class distributions over time of both low (top panel) and high (bottom panel) $\mathbb{GRIX}$-beta portfolios.[23] Take the allocation distribution of the equity index as an example. We first count the number of equity indices within the low (or high) $\mathbb{GRIX}$-beta 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 $\mathbb{GRIX}$-beta portfolios.

Two main results arise from Figure 4. First, no single asset class fills up the low or high $\mathbb{GRIX}$-beta portfolio at any time. That is, both low and high $\mathbb{GRIX}$-beta portfolios contain assets

[23] In Appendix 4, within each asset class we report the frequency of each of its assets appearing in low and high asset-class-specific $\mathbb{RIX}$-beta portfolios.

from multiple asset classes in our sample. Second, the composition of low and high $\mathbb{GRIX}$-beta 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 the $\mathbb{GRIX}$ are indeed pervasive across all asset classes (equity, currency, and bond) in response to time-varying global rare disaster concerns.

4 Rare Disaster Concerns and Realized Disaster Shocks

In this section, we study how *ex ante* rare disaster concerns are related to, and importantly, different from, *ex post* disaster shocks in driving asset returns. Motivated by the existing literature of disaster risk and financial crisis (Barro, 2006; Brunnermeier, Nagel, and Pedersen, 2008; Farhi and Gabaix, 2011; Gabaix, 2012; Gourio, 2011; Wachter, 2013), we consider realized disaster shocks associated with macroeconomic downturns and liquidity crunch.

4.1 Macroeconomic and liquidity data

Macroeconomic Risk. We obtain various measures of macroeconomic risk, including GDP growth, inflation, recession indicator, aggregate market return, corporate default risk, and term spread of bond yields, for both the U.S. and 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).[24] 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.

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

For the market return, we use the MSCI U.S. and World Indices in excess of the U.S. T-bill rate. 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 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)).

Liquidity Risk. Following Asness, Moskowitz, and Pedersen (2013), we consider both funding liquidity shocks and market liquidity shocks. The funding liquidity variables are the 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.[25]

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, innovations of the liquidity factor in Pastor and Stambaugh (2003) (obtained from Robert Stambaugh's webpage), and the "noise" measure in Hu, Pan, and Wang (2012) (obtained from Jun

[25] 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.

Pan's webpage) associated with the abundance of arbitrage capital. In addition, we extract first principal components based on various correlation matrices of the U.S. funding liquidity shocks, the U.S. market liquidity shocks, the U.S. all liquidity shocks, global funding liquidity shocks, and global all liquidity shocks.

4.2 Relation to macroeconomic risk

Panel A of Table 6 reports correlations between rare disaster concern indices and various measures of macroeconomic risk for both U.S. and global variables. We find that $\mathbb{RIX}$s are high when an economy enters into recessions or deflations, real per-capita GDP decreases, default risk increases, and the term structure slope rises, across both U.S. and global economies. In particular, the global rare disaster concern index is negatively correlated with real per-capita GDP growth (-0.2 for the U.S. economy and -0.3 for the global economy) and inflation (-0.3 for the U.S. economy and -0.1 for the global economy), and positively correlated with default risk and term risk (correlations about 0.1 to 0.2). Within asset classes, equity $\mathbb{RIX}$ is most negatively related to real GDP growth and positively related to default risk, currency $\mathbb{RIX}$ is most negatively related to both real GDP growth and inflation, and bond $\mathbb{RIX}$ is most negatively related to U.S. inflation and positively related to global term risk.

Panel B of Table 6 reports regression results of low-minus-high (LMH) asset-class-specific $\mathbb{RIX}$-beta (and across-asset-class $\mathbb{GRIX}$-beta) portfolio returns on both U.S. and global macroeconomic risk factors. We observe that macroeconomic risk factors are generally not significant in explaining the return spreads between low and high $\mathbb{RIX}$-beta portfolios, with the regression adjusted R^2 mostly small and oftentimes negative. Several factors do show certain statistical significance in driving return spreads of $\mathbb{RIX}$-beta portfolios, including the U.S. default risk and both the U.S. and global market returns. However, their economic significance is contradictory with interpreting the macroeconomic risk as driving our $\mathbb{RIX}$-beta portfolio returns. Specifically, when the market return is low or the default risk is high, low $\mathbb{GRIX}$-beta assets earn even higher returns than high $\mathbb{GRIX}$-beta assets. 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 such as market crash and default risk spike.

4.3 Relation to liquidity risk

Panel A of Table 7 reports correlations between rare disaster concern indices and various measures of liquidity risk. We observe that the correlations are mostly lower than 20%, with the U.S. market liquidity risk as the only exception that has correlations around 30% with $\mathbb{EQRIX}$. In general, when the U.S. market becomes less liquid, the rare disaster concerns on global equity market increase. And somewhat surprisingly, both currency and bond $\mathbb{RIX}$s are most negatively (but still with magnitude less than 15%) related to funding liquidity risk. That is, when the U.S. funding liquidity dries up, the rare disaster concerns on foreign currency and global bond markets decrease, probably due to the portfolio reallocation effect from equity class to currency and bond classes.

Panel B of Table 7 reports regression results for LMH asset-class-specific $\mathbb{RIX}$-beta (and across-asset-class $\mathbb{GRIX}$-beta) portfolio returns on liquidity risk factors of both U.S. and global economies. Reported regression adjusted R^2 is based on the specification that uses "All Liquidity Risk" factor as the regressor (i.e., the first principal component of the correlation matrix of all available market liquidity and funding liquidity measures for both U.S. and global economies). Similar to macroeconomic risk factors, liquidity factors can hardly explain the time-series variability of the LMH $\mathbb{GRIX}$-beta portfolio return, with the regression adjusted R^2 mostly around zero. Furthermore, although both U.S. and global liquidity risk factors show consistent statistical significance in driving return spreads of $\mathbb{RIX}$-beta portfolios, the positive economic significance implies that low $\mathbb{GRIX}$-beta assets earn even higher returns than high $\mathbb{GRIX}$-beta assets when the market liquidity and/or the funding liquidity tighten, contradictory to the interpretation regarding liquidity risk exposure as drivers of our $\mathbb{RIX}$-beta portfolio returns. These results reiterate our main point in this section that the global asset return variation affected by *ex ante* disaster concerns is distinct from *ex post* disaster shocks such as liquidity crunch.

4.4 Cross-sectional asset pricing test

Table 8 reports Fama-MacBeth (1973) regression coefficient estimates and t-statistics from cross-sectional regressions of USD-based excess returns of the 76 global assets on their betas 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 $\mathbb{GRIX}$ beta 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 $\mathbb{RIX}$-beta portfolios within each asset class and use these rankings for "Asset-Class $\mathbb{RIX}$ beta"; we form 10 $\mathbb{GRIX}$-beta deciles across all assets and use these rankings for "Global $\mathbb{RIX}$ beta". 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 $\mathbb{RIX}$-beta and $\mathbb{GRIX}$-beta 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.

5 Alternative Explanations and Robustness

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

5.1 Downside risk CAPM betas

Can the downside risk CAPM (DR-CAPM) in Lettau, Maggiori, and Weber (2013) price the cross section of $\mathbb{RIX}$-beta 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 $\mathbb{RIX}$-beta 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 $\mathbb{RIX}$-beta 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 $\mathbb{RIX}$-beta assets.

Among the set of $\mathbb{RIX}$-beta 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 $\mathbb{RIX}$-beta portfolios during market downstates are captured by the corresponding market excess returns.[26] 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 $\mathbb{RIX}$-beta assets. The DR-CAPM betas of low-minus-high $\mathbb{RIX}$-beta 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 $\mathbb{GRIX}$-beta portfolios formed across 76 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 $\mathbb{GRIX}$-beta portfolios. The downside beta of low $\mathbb{GRIX}$-beta portfolio (0.87 with a t-statistic of 4.6), if anything, is lower than that of high $\mathbb{GRIX}$-beta 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 $\mathbb{GRIX}$-beta portfolio 0.62% (see Panel A of Table 5).[27] Although our analysis suggests that the downside risk

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

[27] 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

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.

5.2 Rare disaster concerns as characteristics

So far we have focused on assets' covariation with rare disaster concerns (i.e., $\mathbb{RIX}$ beta). In the asset pricing literature, there is an overarching debate between firm characteristics and covariances (Daniel and Titman, 1997). We therefore also investigate whether rare disaster concerns as assets' characteristics rather than betas (covariances) explain cross-sectional asset returns. Within each asset class, we rank assets into four portfolios using their $\mathbb{RIX}$s as asset-specific characteristics. Among all 76 assets across markets and asset classes, we rank assets into five quintiles using a normalized version of $\mathbb{RIX}$s (each asset's monthly $\mathbb{RIX}$ is divided by the standard deviation of its daily $\mathbb{RIX}$) because the scale of $\mathbb{RIX}$ varies across asset classes (see Figure 1 in detail). To examine characteristic and beta effects together, we further rank all 76 assets into 2×3 portfolios by independently sorting on assets' $\mathbb{RIX}$s and their covariations with the $\mathbb{GRIX}$ factor ($\mathbb{GRIX}$ betas).

Table 9 presents mean excess returns of these portfolios. In equity and currency classes, there are no significant return differences between high and low $\mathbb{RIX}$ assets on various frequencies of portfolio formation; in the bond class, high-$\mathbb{RIX}$ bonds significantly earn 0.25%-0.27% higher returns than low-$\mathbb{RIX}$ bonds per month. Across all 76 assets, we find that $\mathbb{RIX}$ as assets' characteristics cannot explain cross-sectional return variation.[28] In contrast, $\mathbb{GRIX}$ betas are significantly associated with asset returns, although the return spreads of low-minus-high $\mathbb{GRIX}$-beta portfolios are larger among assets with higher level of rare disaster concerns. Our analysis overall indicates that the systematic co-movement between assets' returns and the global market's rare disaster concerns, rather than asset-specific characteristics of concerns, drives global asset return variation in the cross section of

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

[28] Conclusions are similar when we form five quintiles using assets' original version of $\mathbb{RIX}$. For example, when portfolios are monthly formed the return spread between high and low $\mathbb{RIX}$ assets is 0.07% with an insignificant t-statistic of 0.26.

markets and asset classes.

5.3 Robustness checks on asset return data

We evaluate the strength of our main results of asset-class $\mathbb{RIX}$-beta 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]

Table 11 reports mean excess returns of $\mathbb{RIX}$-beta 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.

6 Conclusions

We propose a unified empirical asset pricing framework, based on *ex ante* concerns of rare disasters on financial markets, that can explain the joint cross-sectional return variations of multiple asset classes. Using a large set of out-of-the-money options on 30 international equity indices, 32 curren-

[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.

cies, and 14 global government bonds, we construct the $\mathbb{RIX}$ measure to capture *ex ante* disaster concerns of global financial markets, which essentially equals to a disaster insurance price. We show that the $\mathbb{RIX}$ framework explains return variations across international equity indices, currencies, and global government bonds well, distinct from global value and momentum, downside risk, and leverage and margin constraints.

To further shed light on possible theoretical explanations behind our framework of rare disaster concerns, we provide evidence that the asset return pattern driven by disaster concerns is distinct from that driven by exposures to realized disaster shocks such as macroeconomic downturns and liquidity crunches. Such evidence suggests that economic channels generalizing either preferences or beliefs of standard disaster risk models seem to be important in understanding our empirical results. Overall, the framework based on rare disaster concerns can potentially unify "*how* discount rates vary over time and across assets" (Cochrane, 2011), though more work is needed to pin down the exact theoretical channel behind our empirical framework.

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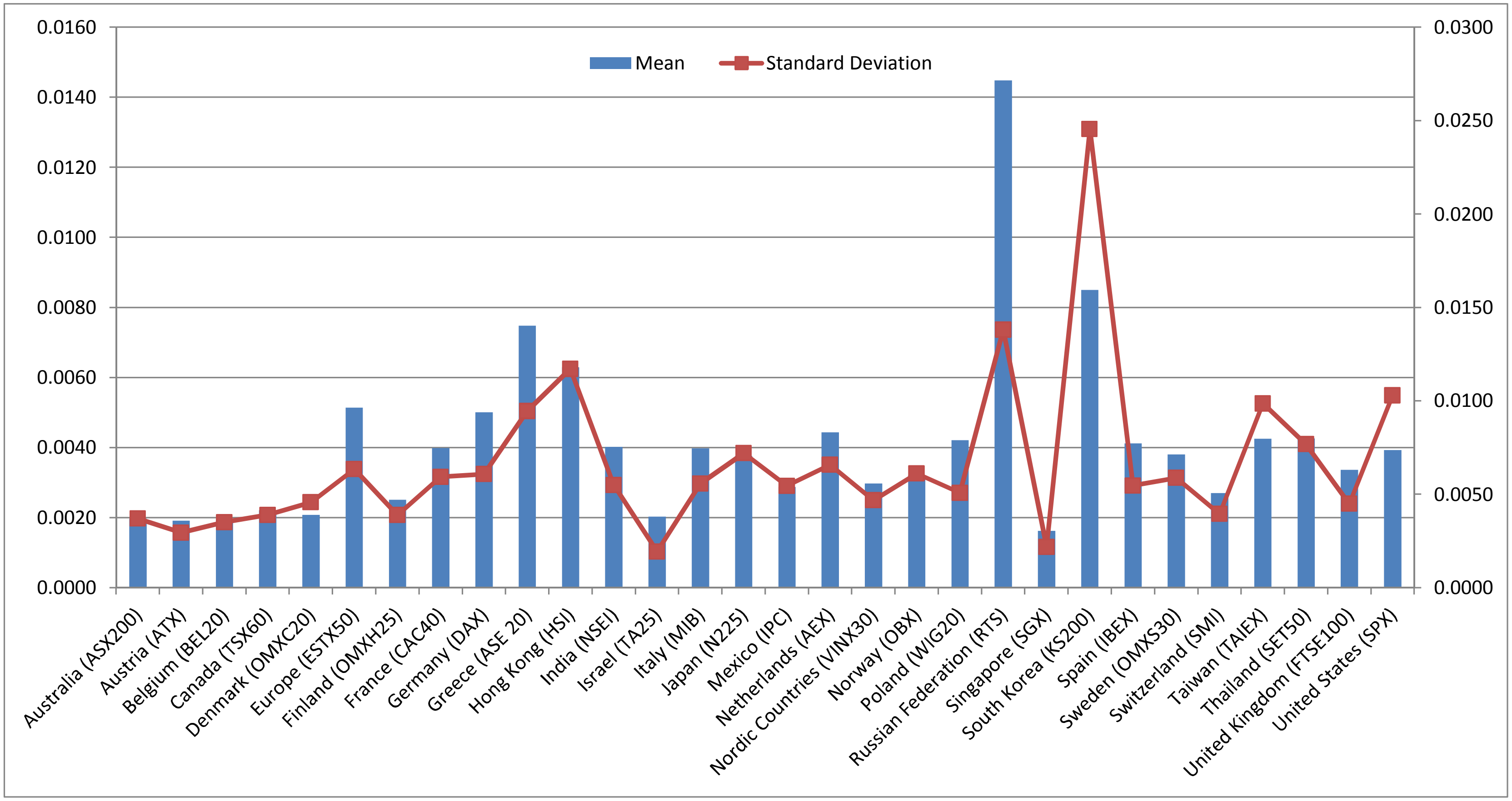
Figure 1: Rare disaster concern index (RIX) for international equity index, foreign currency, and global government bond

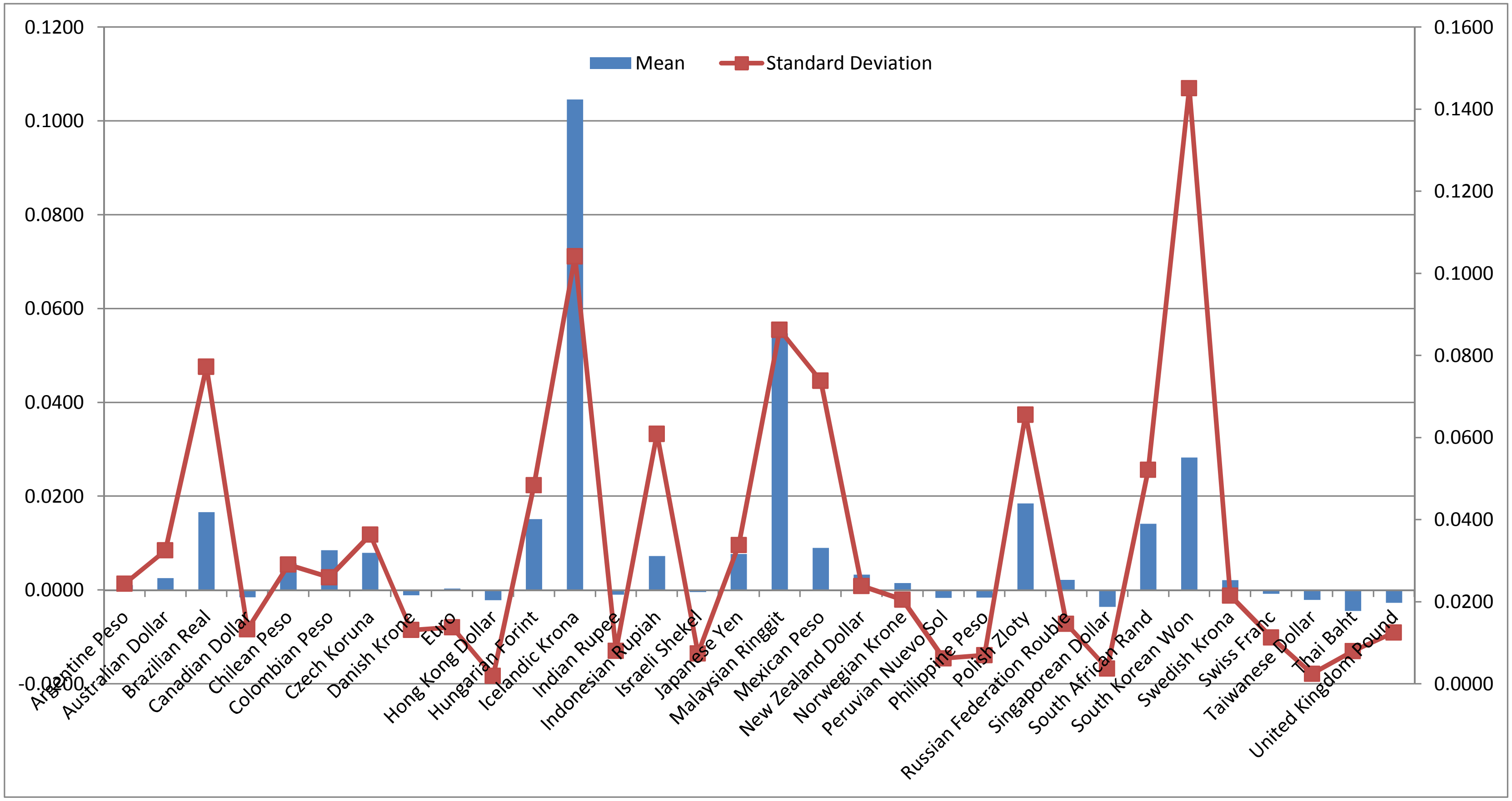
This figure shows time-series mean (left axis) and standard deviation (right axis) of monthly RIX for each of 30 international equity indices (Panel A), 32 foreign currencies (Panel B), and 14 global government bond (Panel C). We also list option sample period below each panel.

Panel A: International equity index



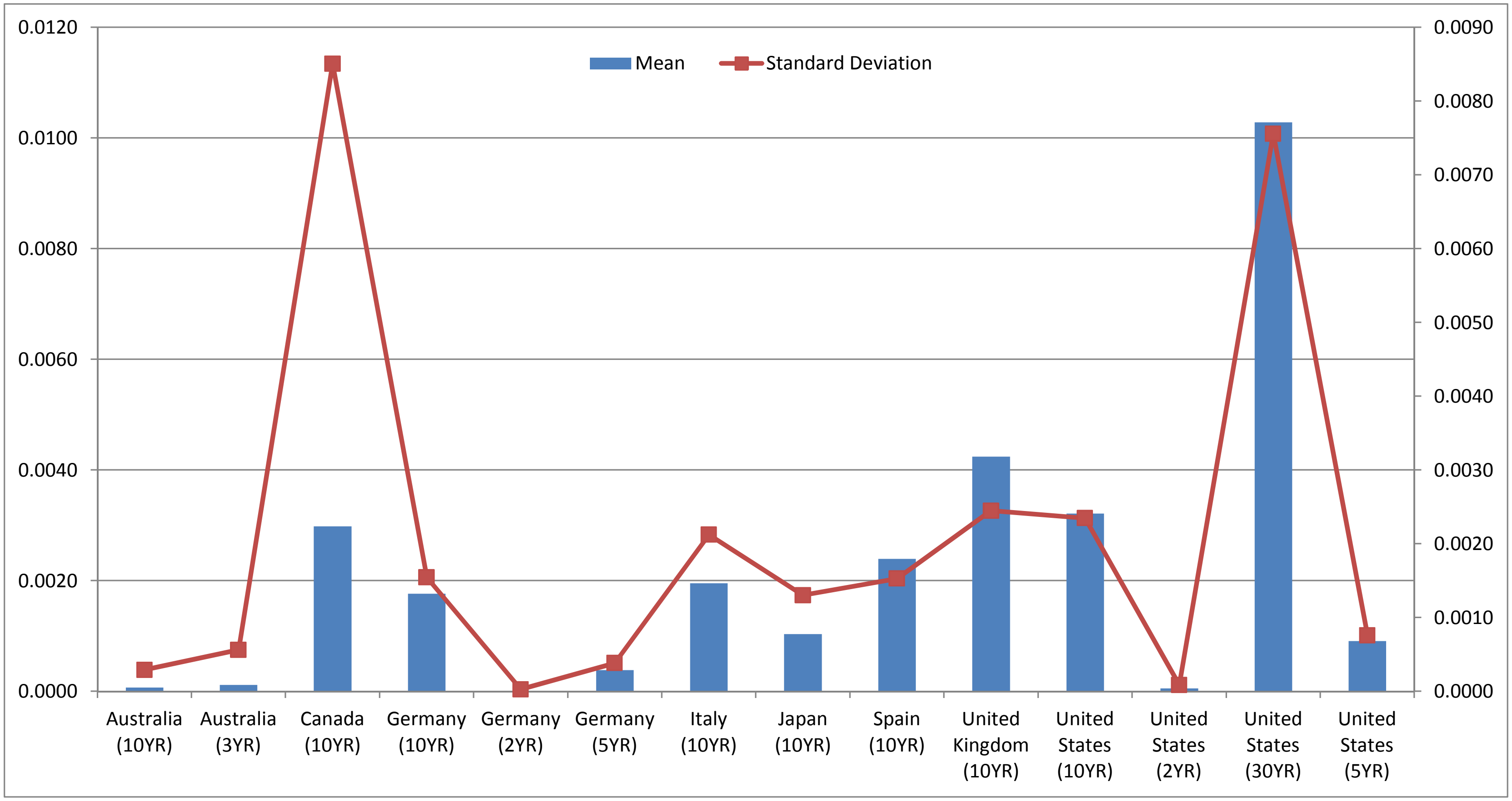
Equity index option sample period: ASX200 (2001:02 - 2012:10), ATX (1996:01 - 2012:10), BEL20 (1996:01 - 2012:10), TSX60 (1999:09- 2012:10), OMXC20 (2005:10 - 2012:01), ESTX50 (2001:07 - 2012:10), OMXH25 (2005:02 - 2012:10), CAC40 (2005:05 - 2012:10), DAX (2001:07 - 2012:10), ASE20 (2000:10 - 2012:10), 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.

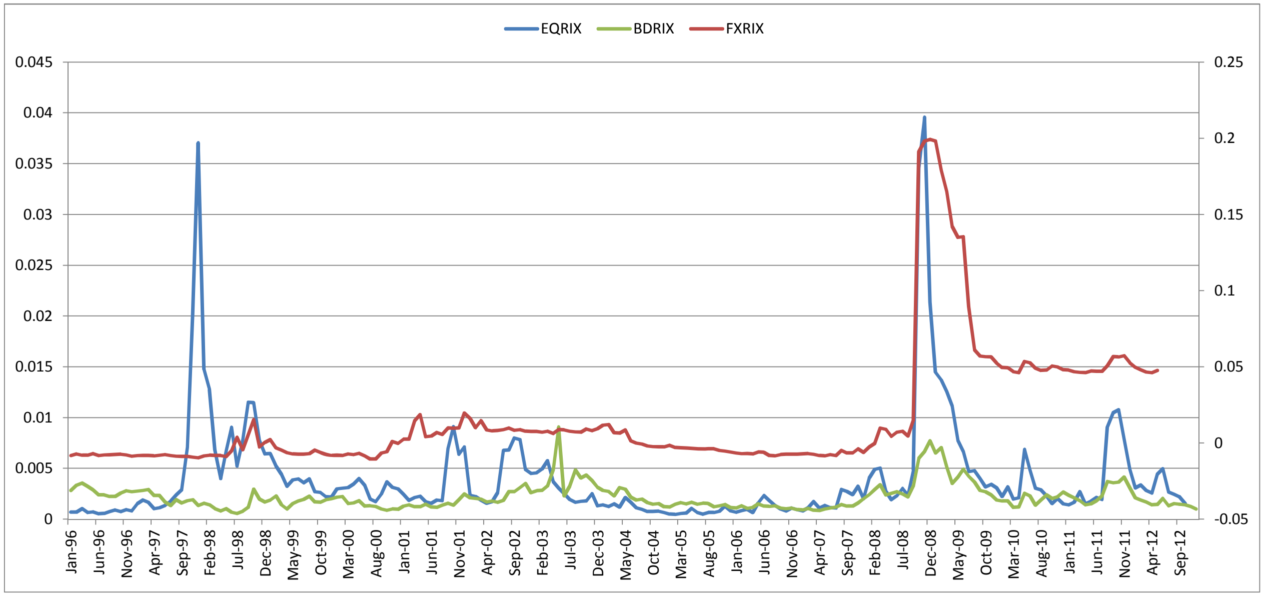
Panel C: Glboal government bond



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).

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

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 for three asset classes: international equity index (EQRIX), foreign currency (FXRIX), and global government bond (BDRIX). The values of EQRIX and BDRIX are on left axis, and the values of FXRIX are on right axis. We also multiply the original values of FXRIX and BDRIX by 100 to facilitate the presentation. The bottom figure marks important events associated with EQRIX spikes.



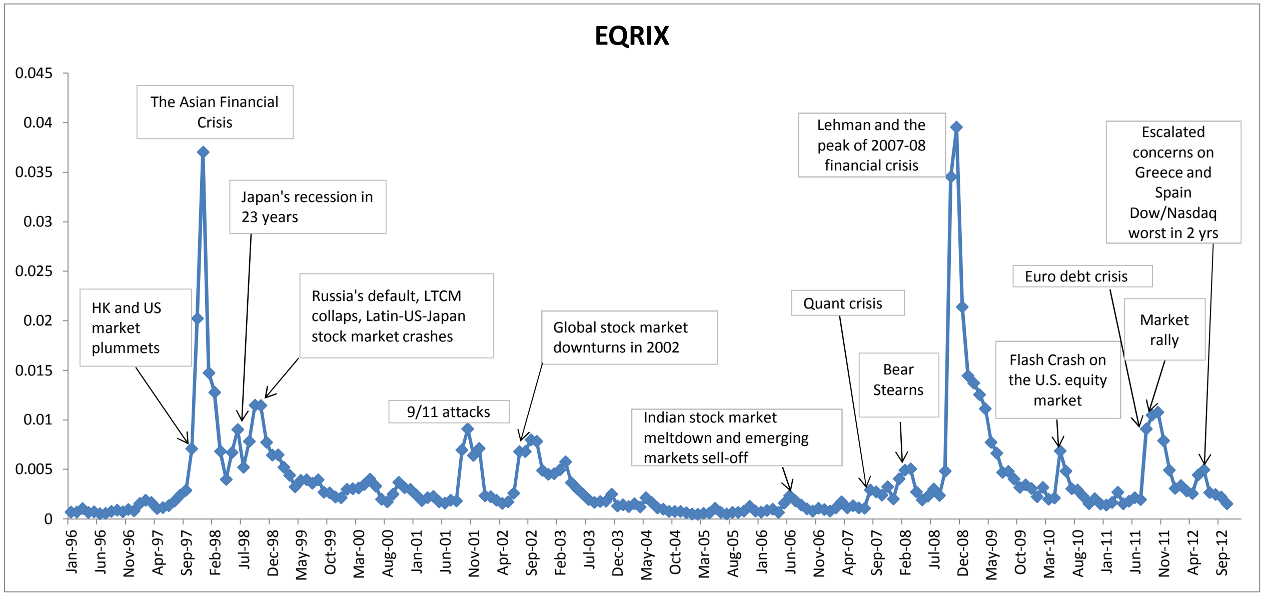
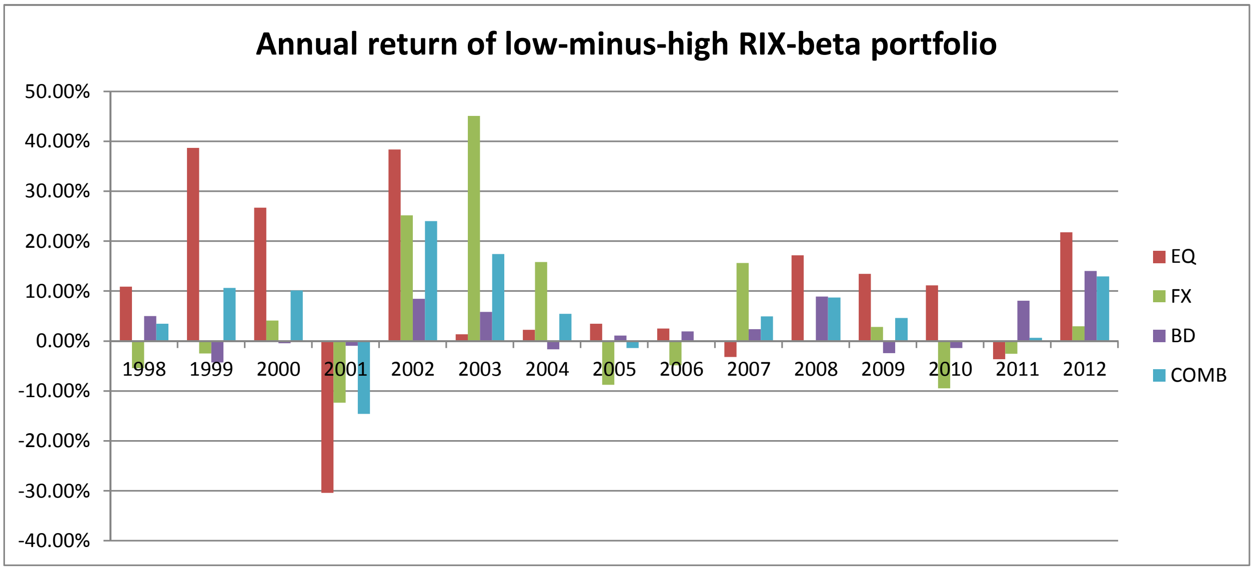


Figure 3: Annual low-minus-high RIX-beta portfolio returns and Sharpe ratios

This figure shows the annual return and Sharpe ratio each year from the strategy of going long assets with the lowest RIX beta and short assets with the highest RIX beta. We peform the strategy within each of the following asset classes: international equity index (EQ), foreign currency (FX), global government bond futures (BD). We also consider the strategy that takes the equal weighted combination across these three asset classes (COMB). Within an asset class, we use its rare disaster concern index (RIX) to estimate beta through 18-24 month rolling-window regression, and then monthly formulate four RIX-beta portfolios. See details in Table 2.



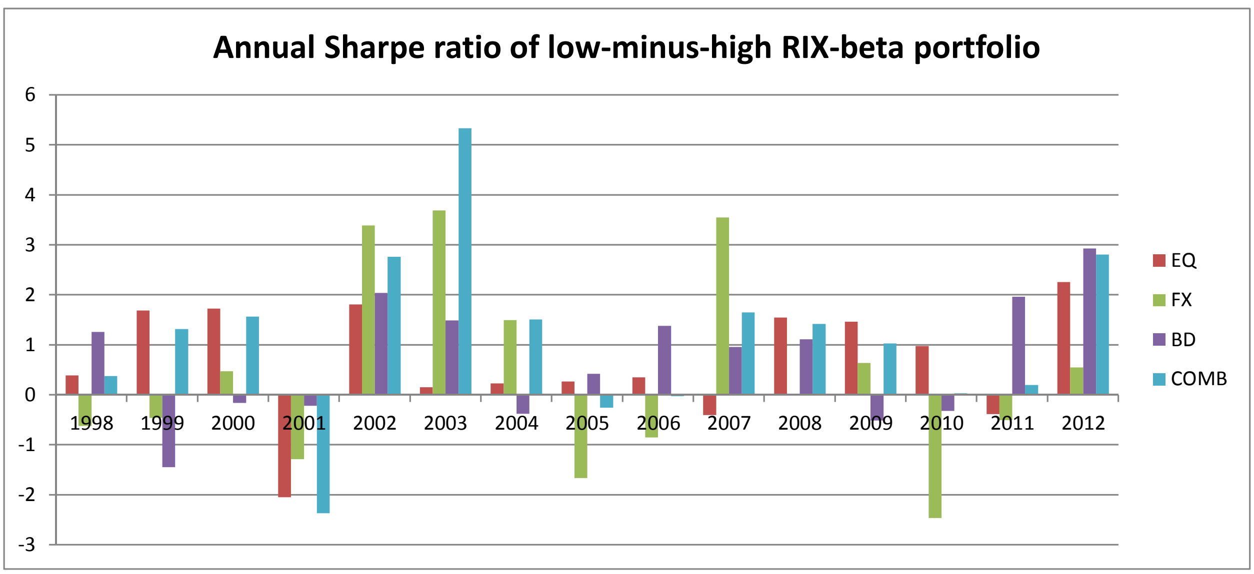
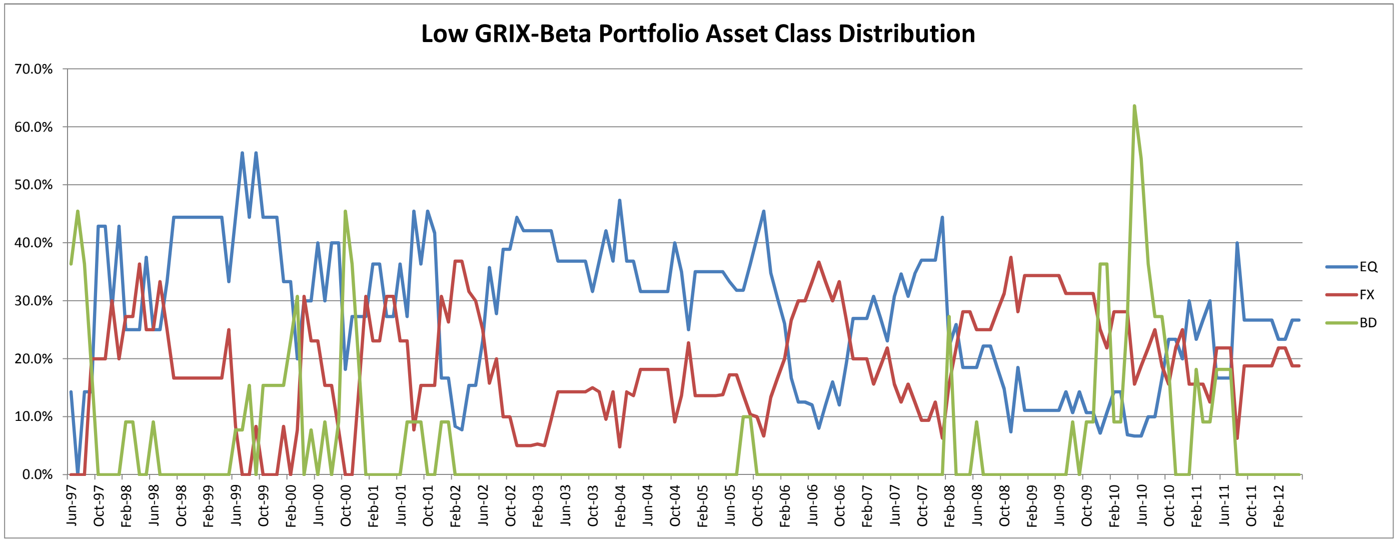


Figure 4: Asset class distribution

This figure shows the time series of asset class distributions across equity index (EQ), currency (FX), and bond futures (BD) within the low GRIX-beta portfolio (top panel) and the high GRIX-beta portfolio (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, and BDRIX). At the end of each month from June 1997 to May 2012, we rank global assets (30 equity indices, 32 foreign currencies, and 14 bond futures in total) into quintiles according to their GRIX betas. 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%.



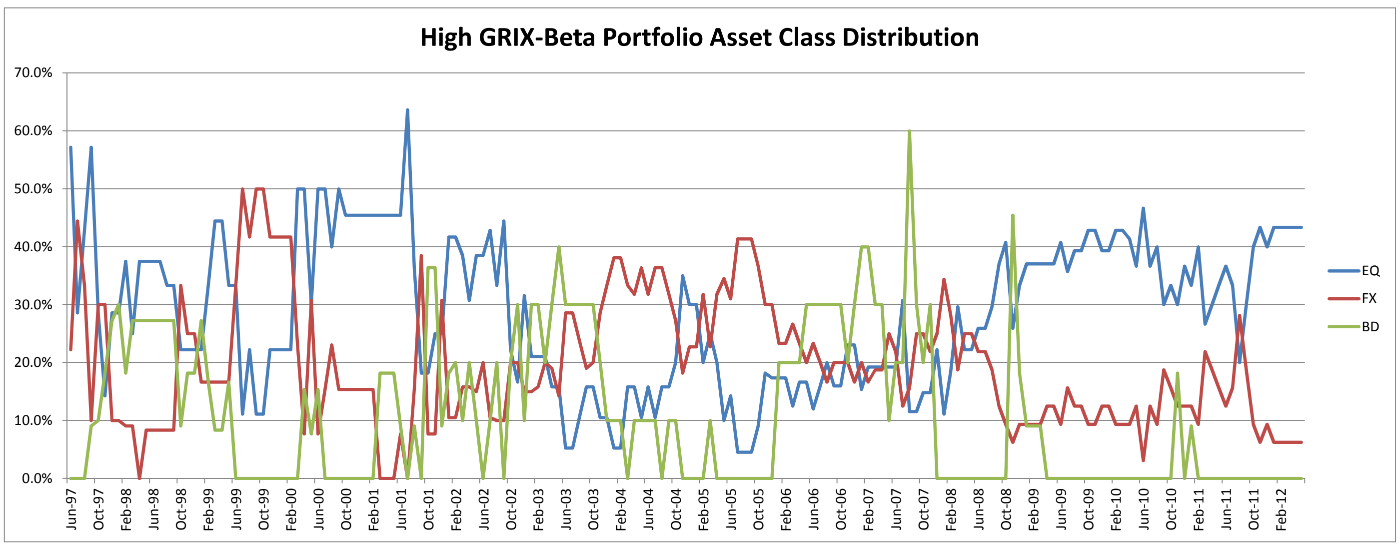


Figure 5: Downside risk and return relations of GRIX-beta portfolios

This figure presents mean excess returns of five GRIX-beta quintiles against their downside risk CAPM (DR-CAPM) betas. We monthly form GRIX-beta portfolios across 76 global assets of equity indices, currencies, and government bonds (see Table 5 in detail). Quintile 1 (5) contains assets with low (high) GRIX betas. 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 July 1997 through May 2012. The DR-CAPM beta of low-minus-high GRIX-beta portfolio is -0.11 (with a *t*-statistic of -0.57).

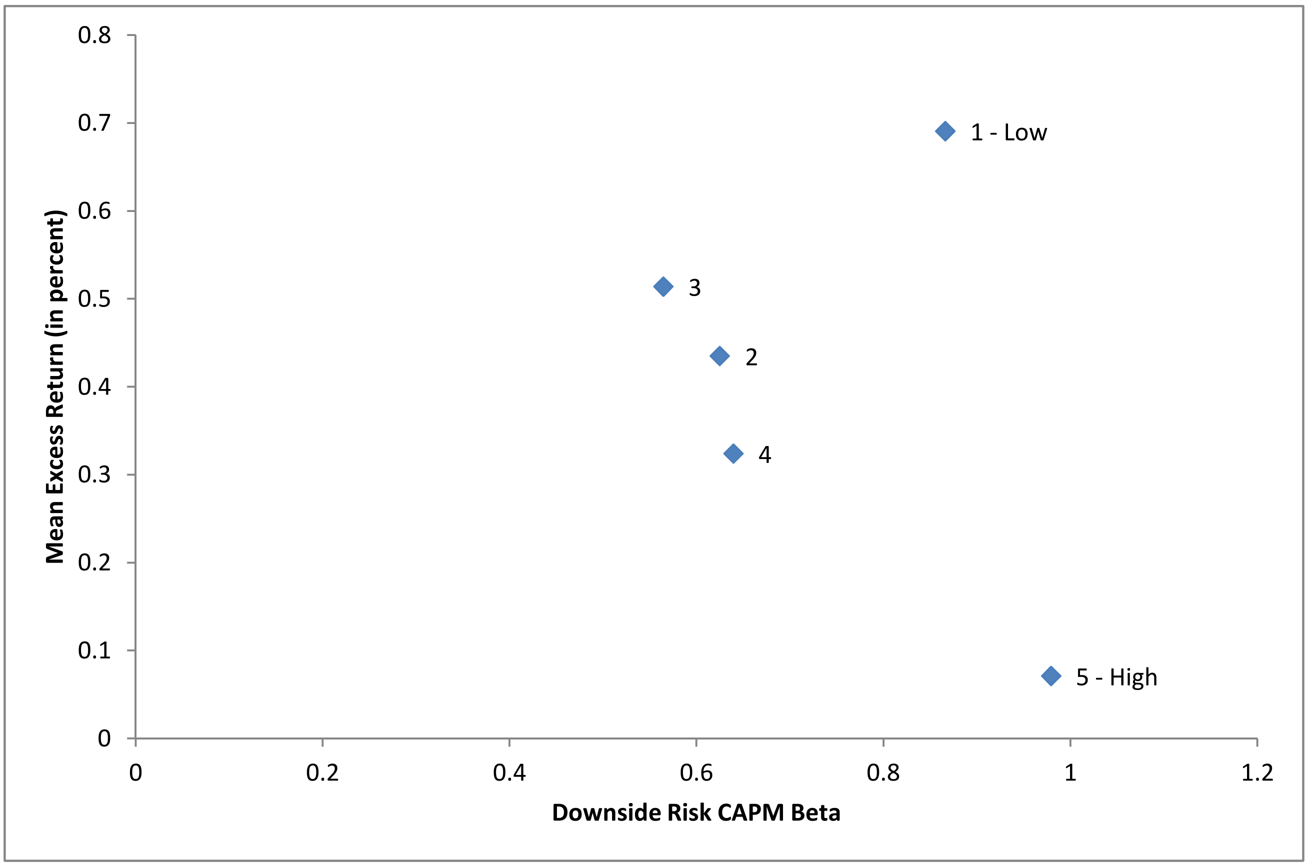


Table 1: Summary statistics of global asset returns by markets and asset classes

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 (the 1st column shows the full name of currency), and Panel C presents returns of global government bond futures (the 1st column shows country name and bond maturity). 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%

Table 2: Asset-class-specific RIX-beta portfolio returns

We report 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 *t* -statistics (in parentheses) of each RIX-beta portfolio in each market and asset class we study: international equity index, currency, and global government bond futures. Within each asset class, we estimate each 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. We also report results of each combination RIX-beta portfolio that generates equal weighted return across three asset classes. We consider portfolio formation at monthly (Panel A), quarterly (Panel B), semi-annual (Panel C), and annual frequency (Panel D), and report results separately in each panel. The last two rows of each panel report the results of high-minus-low RIX-beta portfolio that is long high RIX-beta assets and short low RIX-beta assets. To measure alphas, we use the following benchmark factors for different asset classes: Fama-French (FF) three factors augemented with Carhart's momentum factor, Asness-Moskowitz-Pedersen (AMP) three factors, Frazzini-Pedersen (FP) betting-against-beta factor, and Lustig-Roussanov-Verdelhan (LRV) two factors. Particularly, we use AMP value and momentum factors for country indices, currencies, fixed income, and global all asset classes; we use LRV currency factors based on all countries; and we use FP betting-against-beta factor for equity indices, currencies, country bond indices, and all assets. Returns are reported in percent. On average, there are 5 equity indices, 6 currencies, and 3 bond futures in each RIX-beta portfolio.

Panel A: monthly portfolio formation

	Global Equity Index (EQ)				Foreign Currency (FX)				Global Bond Futures (BD)			EQ-FX-BD Combination		
	Excess Ret	FF alpha	AMP alpha	FP alpha	Excess Ret	LRV alpha	AMP alpha	FP alpha	Excess Ret	AMP alpha	FP alpha	Excess Ret	AMP alpha	FP alpha
Low - 1	0.936	0.398	0.471	0.665	0.827	0.526	0.775	0.348	0.373	0.037	0.359	0.712	0.435	0.330
	(1.87)	(1.74)	(1.48)	(2.45)	(3.39)	(3.07)	(4.19)	(2.58)	(3.44)	(0.53)	(4.83)	(3.25)	(2.98)	(2.40)
2	0.561	0.113	0.247	0.386	0.147	-0.084	-0.032	-0.187	0.193	0.023	0.183	0.245	0.023	0.036
	(1.17)	(0.58)	(0.98)	(1.79)	(0.86)	(-0.92)	(-0.31)	(-2.25)	(2.75)	(0.49)	(3.91)	(1.21)	(0.18)	(0.29)
3	0.324	-0.127	-0.223	0.041	0.327	0.138	0.201	-0.032	0.156	0.022	0.159	0.257	-0.048	-0.029
	(0.68)	(-0.72)	(-0.87)	(0.22)	(1.95)	(1.70)	(2.54)	(-0.44)	(2.53)	(0.47)	(3.70)	(1.33)	(-0.54)	(-0.31)
High - 4	0.184	-0.248	-0.310	0.002	0.454	0.248	0.294	0.043	0.150	-0.020	0.159	0.251	-0.055	-0.096
	(0.38)	(-1.16)	(-1.17)	(0.01)	(2.35)	(2.40)	(2.88)	(0.49)	(1.89)	(-0.34)	(2.79)	(1.25)	(-0.52)	(-0.91)
High - Low	-0.752	-0.645	-0.781	-0.663	-0.373	-0.278	-0.480	-0.306	-0.222	-0.057	-0.200	-0.462	-0.491	-0.426
	(-2.48)	(-2.10)	(-2.23)	(-2.08)	(-2.00)	(-1.38)	(-2.22)	(-1.60)	(-2.53)	(-0.63)	(-2.29)	(-3.46)	(-3.22)	(-2.94)

Panel B: quarterly portfolio formation

	Global Equity Index (EQ)				Foreign Currency (FX)				Global Bond Futures (BD)			EQ-FX-BD Combination		
	Excess Ret	FF alpha	AMP alpha	FP alpha	Excess Ret	LRV alpha	AMP alpha	FP alpha	Excess Ret	AMP alpha	FP alpha	Excess Ret	AMP alpha	FP alpha
Low - 1	1.015	0.515	0.557	0.771	0.873	0.592	0.818	0.655	0.280	-0.019	0.260	0.650	0.404	0.306
	(1.97)	(2.08)	(1.62)	(2.58)	(3.58)	(3.65)	(4.61)	(4.10)	(2.82)	(-0.30)	(3.99)	(2.99)	(2.68)	(2.09)
2	0.599	0.122	0.292	0.426	0.246	0.008	0.051	0.061	0.205	0.031	0.197	0.314	0.047	0.065
	(1.22)	(0.62)	(1.17)	(2.00)	(1.43)	(0.08)	(0.49)	(0.64)	(2.84)	(0.64)	(4.12)	(1.53)	(0.38)	(0.54)
3	0.316	-0.141	-0.250	-0.002	0.318	0.140	0.219	0.144	0.165	0.020	0.167	0.255	-0.033	-0.030
	(0.67)	(-0.83)	(-0.97)	(-0.01)	(1.94)	(1.99)	(3.47)	(2.37)	(2.66)	(0.41)	(3.68)	(1.34)	(-0.40)	(-0.33)
High - 4	0.156	-0.270	-0.306	-0.015	0.352	0.127	0.185	0.147	0.194	0.011	0.205	0.237	-0.062	-0.090
	(0.32)	(-1.22)	(-1.15)	(-0.06)	(1.85)	(1.25)	(1.85)	(1.58)	(2.36)	(0.19)	(3.54)	(1.18)	(-0.58)	(-0.85)
High - Low	-0.859	-0.785	-0.863	-0.786	-0.521	-0.464	-0.632	-0.508	-0.086	0.030	-0.055	-0.413	-0.466	-0.396
	(-2.56)	(-2.36)	(-2.23)	(-2.23)	(-2.97)	(-2.47)	(-3.17)	(-2.79)	(-1.08)	(0.36)	(-0.70)	(-3.00)	(-2.98)	(-2.65)

Panel C: semi-annual portfolio formation

	Global Equity Index (EQ)				Foreign Currency (FX)				Global Bond Futures (BD)			EQ-FX-BD Combination		
	Excess Ret	FF alpha	AMP alpha	FP alpha	Excess Ret	LRV alpha	AMP alpha	FP alpha	Excess Ret	AMP alpha	FP alpha	Excess Ret	AMP alpha	FP alpha
Low - 1	1.072	0.565	0.553	0.799	0.928	0.642	0.871	0.456	0.412	0.101	0.401	0.721	0.473	0.396
	(2.10)	(2.23)	(1.61)	(2.62)	(3.89)	(3.97)	(4.92)	(3.59)	(3.74)	(1.31)	(5.37)	(3.32)	(3.11)	(2.71)
2	0.415	-0.086	0.092	0.256	0.073	-0.148	-0.077	-0.291	0.176	0.018	0.164	0.194	-0.090	-0.088
	(0.86)	(-0.44)	(0.35)	(1.21)	(0.42)	(-1.70)	(-0.77)	(-3.68)	(2.81)	(0.45)	(4.10)	(0.96)	(-0.73)	(-0.73)
3	0.499	0.101	0.028	0.184	0.367	0.165	0.224	0.026	0.153	0.014	0.156	0.318	0.034	0.050
	(1.04)	(0.60)	(0.11)	(1.02)	(2.21)	(1.98)	(2.92)	(0.36)	(2.63)	(0.31)	(3.72)	(1.62)	(0.39)	(0.53)
High - 4	0.104	-0.354	-0.416	-0.090	0.392	0.169	0.224	-0.018	0.133	-0.064	0.141	0.210	-0.081	-0.118
	(0.22)	(-1.64)	(-1.61)	(-0.39)	(2.02)	(1.63)	(2.23)	(-0.20)	(1.52)	(-1.06)	(2.34)	(1.05)	(-0.78)	(-1.16)
High - Low	-0.968	-0.919	-0.969	-0.889	-0.535	-0.473	-0.647	-0.474	-0.279	-0.165	-0.260	-0.510	-0.553	-0.514
	(-2.91)	(-2.81)	(-2.54)	(-2.54)	(-3.03)	(-2.47)	(-3.16)	(-2.63)	(-3.30)	(-1.89)	(-3.06)	(-3.74)	(-3.52)	(-3.47)

Panel D: annual portfolio formation

	Global Equity Index (EQ)				Foreign Currency (FX)				Global Bond Futures (BD)			EQ-FX-BD Combination		
	Excess Ret	FF alpha	AMP alpha	FP alpha	Excess Ret	LRV alpha	AMP alpha	FP alpha	Excess Ret	AMP alpha	FP alpha	Excess Ret	AMP alpha	FP alpha
Low - 1	1.010	0.419	0.439	0.691	0.836	0.506	0.783	0.364	0.368	0.071	0.372	0.702	0.386	0.349
	(1.93)	(1.81)	(1.31)	(2.36)	(3.44)	(2.96)	(4.18)	(2.67)	(3.08)	(0.80)	(4.56)	(3.14)	(2.75)	(2.43)
2	0.478	-0.055	-0.012	0.293	0.132	-0.087	-0.020	-0.252	0.158	0.021	0.158	0.204	-0.119	-0.134
	(1.02)	(-0.28)	(-0.05)	(1.36)	(0.74)	(-0.99)	(-0.20)	(-3.25)	(2.50)	(0.48)	(3.84)	(1.02)	(-0.97)	(-1.17)
3	0.360	-0.033	0.018	0.160	0.367	0.147	0.212	0.024	0.128	-0.004	0.134	0.276	-0.013	0.054
	(0.77)	(-0.21)	(0.08)	(0.94)	(2.10)	(1.64)	(2.37)	(0.30)	(2.12)	(-0.09)	(3.13)	(1.44)	(-0.16)	(0.60)
High - 4	0.080	-0.306	-0.343	-0.139	0.420	0.257	0.254	0.031	0.174	-0.019	0.199	0.226	0.016	-0.057
	(0.17)	(-1.54)	(-1.39)	(-0.65)	(2.26)	(2.46)	(2.63)	(0.35)	(2.00)	(-0.29)	(3.29)	(1.18)	(0.15)	(-0.58)
High - Low	-0.930	-0.725	-0.782	-0.829	-0.416	-0.248	-0.529	-0.333	-0.194	-0.090	-0.174	-0.475	-0.370	-0.406
	(-3.13)	(-2.53)	(-2.28)	(-2.69)	(-2.23)	(-1.26)	(-2.48)	(-1.77)	(-2.04)	(-0.85)	(-1.84)	(-3.83)	(-2.61)	(-3.03)

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 three asset classes (international equity index, currency, and global government bond), 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, FXRIX for currency, and BDRIX for bond. 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, and BDRIX. 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, and between equity's RIXs and bond's RIXs, and report summary statistics in the second row. We do the same for the currency and bond 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 global equity index	0.78	0.83	0.70	0.93	435
Between equity index and non-equity asset classes	0.54	0.65	0.34	0.79	1331
Within the class of foreign currency	0.61	0.69	0.47	0.83	496
Between foreign currency and non-currency classes	0.54	0.64	0.34	0.79	1360
Within the class of global bond futures	0.28	0.22	-0.01	0.58	88
Between bond futures and non-bond asset classes	0.30	0.37	0.03	0.58	771

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

	EQRIX	FXRIX	BDRIX	GRIX
EQRIX	1	0.55	0.43	0.78
FXRIX	0.39	1	0.65	0.89
BDRIX	0.27	0.44	1	0.83
GRIX	0.64	0.70	0.78	1

Table 4: Returns of GRIX-beta portfolios within asset classes

The global rare disaster concern index (GRIX) is based on the first principal component of the correlation matrix of three asset-class-specific rare disaster concern indices (EQRIX for equity, FXRIX for currency, and BDRIX for bond). We estimate each asset's GRIX beta using its past 18-24 monthly returns and then form four GRIX-beta portfolios within each asset class. We also report results of each combination GRIX-beta portfolio that generates equal weighted return across three asset classes. We consider portfolio formation at monthly (Panel A), quarterly (Panel B), semi-annually (Panel C), and annually frequency (Panel D), and report results separately in each panel. Benchmark factors are Fama-French (FF) three factors augemented with Carhart's momentum factor, Asness-Moskowitz-Pedersen (AMP) three factors, Frazzini-Pedersen (FP) betting-against-beta factor, and Lustig-Roussanov-Verdelhan (LRV) two factors.

Panel A: monthly portfolio formation

	Global Equity Index (EQ)				Foreign Currency (FX)				Global Bond Futures (BD)			EQ-FX-BD Combination		
	Excess Ret	FF alpha	AMP alpha	FP alpha	Excess Ret	LRV alpha	AMP alpha	FP alpha	Excess Ret	AMP alpha	FP alpha	Excess Ret	AMP alpha	FP alpha
Low - 1	1.032	0.501	0.671	0.772	0.792	0.553	0.753	0.388	0.583	0.331	0.574	0.661	0.415	0.385
	(1.91)	(1.83)	(2.08)	(2.54)	(3.64)	(4.04)	(5.22)	(3.46)	(5.36)	(3.97)	(6.90)	(2.98)	(3.03)	(2.91)
2	0.291	-0.132	0.007	0.139	0.591	0.338	0.539	0.219	0.431	0.264	0.419	0.296	0.039	0.036
	(0.65)	(-0.61)	(0.03)	(0.61)	(3.27)	(3.41)	(5.36)	(2.60)	(5.97)	(5.95)	(8.78)	(1.57)	(0.35)	(0.33)
3	0.454	0.007	0.141	0.171	0.608	0.445	0.468	0.247	0.381	0.278	0.392	0.339	0.013	0.019
	(1.01)	(0.04)	(0.54)	(0.87)	(3.35)	(4.45)	(4.60)	(2.68)	(5.90)	(5.92)	(9.75)	(1.77)	(0.13)	(0.18)
High - 4	0.241	-0.160	-0.165	0.026	0.625	0.360	0.502	0.211	0.320	0.187	0.337	0.254	-0.029	-0.083
	(0.48)	(-0.79)	(-0.63)	(0.11)	(3.31)	(3.32)	(4.36)	(2.38)	(3.17)	(2.40)	(4.94)	(1.22)	(-0.28)	(-0.80)
High - Low	-0.791	-0.662	-0.836	-0.747	-0.167	-0.193	-0.251	-0.176	-0.264	-0.144	-0.236	-0.407	-0.444	-0.468
	(-2.44)	(-1.99)	(-2.29)	(-2.25)	(-1.02)	(-1.12)	(-1.40)	(-1.06)	(-2.17)	(-1.12)	(-1.99)	(-3.33)	(-3.21)	(-3.54)

Panel B: quarterly portfolio formation

	Global Equity Index (EQ)				Foreign Currency (FX)				Global Bond Futures (BD)			EQ-FX-BD Combination		
	Excess Ret	FF alpha	AMP alpha	FP alpha	Excess Ret	LRV alpha	AMP alpha	FP alpha	Excess Ret	AMP alpha	FP alpha	Excess Ret	AMP alpha	FP alpha
Low - 1	0.901	0.445	0.524	0.677	0.712	0.470	0.651	0.300	0.484	0.273	0.473	0.557	0.299	0.283
	(1.69)	(1.58)	(1.51)	(2.18)	(3.24)	(3.39)	(4.57)	(2.69)	(4.86)	(3.71)	(6.46)	(2.51)	(2.10)	(2.03)
2	0.491	0.008	0.204	0.331	0.663	0.411	0.624	0.294	0.453	0.290	0.443	0.394	0.138	0.120
	(1.07)	(0.04)	(0.75)	(1.42)	(3.58)	(4.27)	(6.01)	(3.40)	(6.16)	(6.47)	(9.20)	(2.02)	(1.19)	(1.05)
3	0.154	-0.241	-0.194	-0.114	0.635	0.477	0.497	0.296	0.388	0.261	0.399	0.250	-0.060	-0.044
	(0.35)	(-1.37)	(-0.79)	(-0.63)	(3.78)	(5.18)	(5.19)	(3.54)	(5.52)	(5.26)	(8.50)	(1.36)	(-0.62)	(-0.46)
High - 4	0.352	-0.067	-0.007	0.116	0.602	0.334	0.494	0.177	0.347	0.208	0.364	0.292	0.014	-0.045
	(0.69)	(-0.32)	(-0.03)	(0.50)	(3.15)	(3.01)	(4.18)	(1.96)	(3.58)	(2.85)	(5.50)	(1.38)	(0.13)	(-0.43)
High - Low	-0.549	-0.512	-0.530	-0.561	-0.110	-0.136	-0.157	-0.123	-0.138	-0.066	-0.109	-0.265	-0.285	-0.328
	(-1.63)	(-1.50)	(-1.38)	(-1.62)	(-0.68)	(-0.81)	(-0.89)	(-0.76)	(-1.22)	(-0.57)	(-0.99)	(-2.03)	(-1.94)	(-2.31)

Panel C: semi-annual portfolio formation

	Global Equity Index (EQ)				Foreign Currency (FX)				Global Bond Futures (BD)			EQ-FX-BD Combination		
	Excess Ret	FF alpha	AMP alpha	FP alpha	Excess Ret	LRV alpha	AMP alpha	FP alpha	Excess Ret	AMP alpha	FP alpha	Excess Ret	AMP alpha	FP alpha
Low - 1	0.808	0.367	0.398	0.576	0.730	0.473	0.673	0.326	0.516	0.348	0.504	0.543	0.301	0.282
	(1.55)	(1.37)	(1.19)	(1.91)	(3.47)	(3.64)	(5.14)	(3.30)	(5.26)	(4.63)	(6.70)	(2.51)	(2.14)	(2.10)
2	0.524	0.015	0.268	0.351	0.579	0.319	0.486	0.208	0.414	0.225	0.406	0.364	0.079	0.047
	(1.12)	(0.06)	(0.92)	(1.41)	(3.11)	(3.34)	(4.55)	(2.46)	(4.92)	(4.22)	(7.25)	(1.83)	(0.66)	(0.39)
3	0.271	-0.125	-0.071	0.031	0.694	0.530	0.591	0.359	0.400	0.290	0.409	0.313	-0.018	0.049
	(0.58)	(-0.68)	(-0.27)	(0.17)	(4.24)	(5.85)	(6.27)	(4.59)	(6.34)	(6.05)	(9.54)	(1.63)	(-0.18)	(0.50)
High - 4	0.234	-0.159	-0.123	-0.008	0.638	0.405	0.538	0.201	0.351	0.195	0.368	0.266	0.011	-0.073
	(0.48)	(-0.76)	(-0.48)	(-0.04)	(3.23)	(3.72)	(4.73)	(2.23)	(3.56)	(2.63)	(5.46)	(1.29)	(0.11)	(-0.70)
High - Low	-0.574	-0.525	-0.520	-0.584	-0.092	-0.068	-0.135	-0.125	-0.165	-0.154	-0.136	-0.277	-0.290	-0.354
	(-1.78)	(-1.61)	(-1.42)	(-1.76)	(-0.59)	(-0.42)	(-0.80)	(-0.80)	(-1.43)	(-1.33)	(-1.19)	(-2.14)	(-1.95)	(-2.53)

Panel D: annual portfolio formation

	Global Equity Index (EQ)				Foreign Currency (FX)				Global Bond Futures (BD)			EQ-FX-BD Combination		
	Excess Ret	FF alpha	AMP alpha	FP alpha	Excess Ret	LRV alpha	AMP alpha	FP alpha	Excess Ret	AMP alpha	FP alpha	Excess Ret	AMP alpha	FP alpha
Low - 1	0.881	0.389	0.472	0.653	0.703	0.401	0.626	0.274	0.443	0.288	0.430	0.534	0.260	0.255
	(1.69)	(1.47)	(1.44)	(2.16)	(3.09)	(2.75)	(4.23)	(2.37)	(4.17)	(2.93)	(4.91)	(2.39)	(1.85)	(1.81)
2	0.353	-0.135	0.038	0.203	0.522	0.316	0.397	0.164	0.332	0.194	0.319	0.260	-0.092	-0.083
	(0.73)	(-0.59)	(0.13)	(0.85)	(2.98)	(3.76)	(4.22)	(2.03)	(4.88)	(4.27)	(7.12)	(1.29)	(-0.80)	(-0.73)
3	0.491	0.032	0.178	0.259	0.719	0.532	0.636	0.374	0.451	0.314	0.463	0.412	0.095	0.161
	(1.12)	(0.21)	(0.80)	(1.56)	(4.24)	(5.71)	(6.48)	(4.52)	(6.24)	(5.74)	(9.08)	(2.24)	(1.06)	(1.71)
High - 4	0.195	-0.123	-0.103	-0.066	0.698	0.480	0.616	0.281	0.443	0.255	0.464	0.304	0.130	0.009
	(0.40)	(-0.55)	(-0.37)	(-0.28)	(3.65)	(4.47)	(5.40)	(3.14)	(4.28)	(3.68)	(7.11)	(1.49)	(1.14)	(0.08)
High - Low	-0.686	-0.512	-0.575	-0.720	-0.005	0.079	-0.010	0.007	-0.000	-0.034	0.033	-0.230	-0.130	-0.246
	(-2.09)	(-1.54)	(-1.53)	(-2.14)	(-0.03)	(0.44)	(-0.05)	(0.04)	(-0.00)	(-0.25)	(0.27)	(-1.71)	(-0.83)	(-1.68)

Table 5: Returns and factor loadings of GRIX-beta portfolios across markets and asset classes

Our sample consists of 76 global investment assets across three asset classes that include 30 equity indices, 32 currencies, and 14 government bonds. The global rare disaster concern index (GRIX) is based on the first principal component of the correlation matrix of three asset-class-specific rare disaster concern indices (EQRIX for equity, FXRIX for currency, and BDRIX for bond). We estimate each asset's GRIX beta using its past 18-24 monthly returns and then form five GRIX-beta quintiles across these 76 global assets. We consider portfolio formation at monthly (Panel A), quarterly (Panel B), semi-annual (Panel C), and annual frequency (Panel D). In each panel we report mothly mean excess returns (in percent), alphas, and factor loadings. The last two rows of each panel report the results of high-minus-low RIX-beta portfolio that is long high GRIX-beta assets and short low GRIX-beta assets. We use three factor models as benchmarks to estimate alphas: (1) global CAPM based on MSCI world equity index returns; (2) Asness-Moskowitz-Pedersen (AMP) value and momentum everywhere factors in global all asset classes; and (3) Frazzini-Pedersen (FP) betting-against-beta (BAB) factor in all asset classes. On average, there are 11 assets in each GRIX-beta quintile.

Panel A: monthly portfolio formation

		CAPM		AMP value-momentum factors			FP BAB factor	
	Excess Return	Alpha	Market Beta	Alpha	Value Beta	Momentum Beta	Alpha	BAB Beta
Low - 1	0.691	0.537	0.733	0.473	-0.318	-0.146	0.400	0.397
	(2.13)	(2.89)	(19.19)	(2.24)	(-1.88)	(-1.04)	(2.08)	(2.79)
2	0.435	0.355	0.384	0.194	0.006	-0.017	0.140	0.518
	(2.39)	(3.04)	(16.02)	(1.66)	(0.07)	(-0.21)	(1.25)	(6.23)
3	0.514	0.450	0.305	0.238	0.118	0.111	0.243	0.482
	(3.17)	(3.80)	(12.49)	(2.03)	(1.26)	(1.42)	(2.08)	(5.58)
4	0.324	0.236	0.421	-0.016	0.208	0.125	-0.020	0.565
	(1.54)	(1.63)	(14.10)	(-0.12)	(1.92)	(1.38)	(-0.13)	(5.26)
High - 5	0.071	-0.092	0.780	-0.327	-0.198	-0.279	-0.353	0.657
	(0.22)	(-0.54)	(22.32)	(-1.90)	(-1.44)	(-2.43)	(-2.11)	(5.30)
High - Low	-0.619	-0.629	0.047	-0.800	0.119	-0.132	-0.753	0.260
	(-2.75)	(-2.79)	(1.01)	(-3.13)	(0.58)	(-0.78)	(-3.12)	(1.45)

Panel B: quarterly portfolio formation

		CAPM		AMP value-momentum factors			FP BAB factor	
	Excess Return	Alpha	Market Beta	Alpha	Value Beta	Momentum Beta	Alpha	BAB Beta
Low - 1	0.715	0.570	0.696	0.446	-0.309	-0.091	0.437	0.384
	(2.32)	(3.24)	(19.24)	(2.15)	(-1.86)	(-0.66)	(2.40)	(2.85)
2	0.496	0.423	0.352	0.327	0.029	-0.040	0.195	0.566
	(2.76)	(3.34)	(13.51)	(2.69)	(0.30)	(-0.50)	(1.62)	(6.33)
3	0.357	0.287	0.336	0.019	0.136	0.174	0.062	0.498
	(2.10)	(2.43)	(13.83)	(0.16)	(1.47)	(2.25)	(0.53)	(5.78)
4	0.420	0.333	0.417	0.106	0.124	0.056	0.087	0.558
	(1.97)	(2.21)	(13.49)	(0.78)	(1.14)	(0.62)	(0.58)	(4.99)
High - 5	0.067	-0.100	0.798	-0.313	-0.149	-0.284	-0.353	0.635
	(0.20)	(-0.61)	(23.63)	(-1.83)	(-1.09)	(-2.49)	(-2.18)	(5.29)
High - Low	-0.649	-0.670	0.103	-0.759	0.160	-0.193	-0.790	0.251
	(-3.11)	(-3.25)	(2.42)	(-3.28)	(0.87)	(-1.25)	(-3.59)	(1.54)

Panel C: semi-annual portfolio formation

		CAPM		AMP value-momentum factors			FP BAB factor	
	Excess Return	Alpha	Market Beta	Alpha	Value Beta	Momentum Beta	Alpha	BAB Beta
Low - 1	0.742	0.598	0.640	0.428	-0.249	0.031	0.449	0.420
	(2.46)	(3.19)	(16.61)	(2.05)	(-1.50)	(0.22)	(2.32)	(2.96)
2	0.464	0.381	0.372	0.331	-0.027	-0.153	0.204	0.400
	(2.41)	(2.83)	(13.47)	(2.31)	(-0.24)	(-1.59)	(1.47)	(3.93)
3	0.174	0.072	0.455	-0.188	-0.045	0.065	-0.222	0.606
	(0.79)	(0.51)	(15.77)	(-1.32)	(-0.39)	(0.67)	(-1.61)	(5.98)
4	0.375	0.279	0.431	-0.002	0.178	0.062	0.016	0.564
	(1.79)	(2.04)	(15.34)	(-0.02)	(1.86)	(0.77)	(0.12)	(5.69)
High - 5	0.322	0.162	0.712	-0.077	0.028	-0.042	-0.133	0.707
	(1.01)	(0.91)	(19.49)	(-0.46)	(0.21)	(-0.38)	(-0.76)	(5.51)
High - Low	-0.420	-0.436	0.073	-0.505	0.277	-0.074	-0.583	0.288
	(-1.91)	(-1.99)	(1.62)	(-2.05)	(1.42)	(-0.45)	(-2.48)	(1.67)

Panel D: annual portfolio formation

		CAPM		AMP value-momentum factors			FP BAB factor	
	Excess Return	Alpha	Market Beta	Alpha	Value Beta	Momentum Beta	Alpha	BAB Beta
Low - 1	0.702	0.547	0.690	0.165	-0.184	0.140	0.210	0.804
	(2.09)	(2.52)	(15.49)	(0.73)	(-1.03)	(0.93)	(0.97)	(5.08)
2	0.411	0.318	0.418	0.238	-0.059	-0.212	0.172	0.326
	(2.05)	(2.50)	(15.99)	(1.66)	(-0.52)	(-2.21)	(1.30)	(3.35)
3	0.314	0.238	0.338	0.003	0.048	0.156	-0.074	0.663
	(1.65)	(1.65)	(11.43)	(0.02)	(0.44)	(1.69)	(-0.53)	(6.51)
4	0.293	0.196	0.432	-0.008	0.132	0.021	0.005	0.413
	(1.42)	(1.50)	(16.09)	(-0.07)	(1.53)	(0.28)	(0.04)	(4.18)
High - 5	0.305	0.140	0.735	0.034	-0.042	-0.173	-0.055	0.494
	(0.95)	(0.83)	(21.16)	(0.20)	(-0.32)	(-1.56)	(-0.32)	(3.89)
High - Low	-0.397	-0.407	0.045	-0.131	0.143	-0.313	-0.265	-0.310
	(-1.54)	(-1.58)	(0.85)	(-0.49)	(0.67)	(-1.75)	(-0.96)	(-1.53)

Table 6: Relation to macroeconomic risk

This table reports relations between rare disaster concerns and macroeonomic risk. The U.S. macroeconomic variables are quarterly real GDP growth per capita, inflation based on the change of CPI, recession dummy based on NBER 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 U.S. government bonds). We obtain similar variables for the global version. Panel A presents sample correlations between various RIXs and the macroeconomic variables. Three asset-class-specific RIXs are for equity (EQRIX), currency (FXRIX), and bond (BDRIX), and the global RIX (GRIX) is based on the first principal component of the correlation matrix of these RIXs. Panel B reports coefficient estimates and t-statistics (in parentheses) from regressing low-minus-high (LMH) RIX-beta portfolio returns on the market return and other macroeconomic variables. The market return is equal to the MSCI world equity index return in excess of the one-month U.S. T-bill rate. The details of various RIX-beta portfolio construction are given in Tables 2 and 5.

Panel A: Correlation with macro variables

	Real GDP Growth	Inflation	Recession	Default Risk	Term Risk
			U.S. variables		
EQRIX	-0.29	-0.04	0.34	0.39	0.05
FXRIX	-0.16	-0.41	0.46	0.07	0.07
BDRIX	-0.07	-0.30	0.36	0.09	0.09
GRIX	-0.21	-0.31	0.46	0.21	0.09
			Global variables		
EQRIX	-0.34	0.10	0.39	0.38	0.18
FXRIX	-0.24	-0.25	0.42	0.07	0.20
BDRIX	-0.20	-0.05	0.36	-0.01	0.20
GRIX	-0.32	-0.09	0.48	0.14	0.24

Panel B: Macroeconomic risk exposures

	EQRIX-Beta LMH Return	FXRIX-Beta LMH Return	BDRIX-Beta LMH Return	Combined RIX-Beta LMH Return	GRIX-Beta LMH Return
U.S. values for regressors					
MSCI market return	0.025	0.004	-0.041	-0.001	-0.083
	(0.34)	(0.11)	(-2.06)	(-0.04)	(-1.84)
Real GDP growth	0.004	-0.003	0.000	0.000	0.002
	(0.87)	(-1.34)	(0.32)	(0.14)	(0.81)
Inflation	-0.001	-0.009	0.000	-0.003	0.005
	(-0.16)	(-2.03)	(0.05)	(-1.02)	(0.97)
Recession	0.003	-0.008	-0.000	-0.002	-0.002
	(0.29)	(-1.25)	(-0.06)	(-0.38)	(-0.24)
Default risk	0.009	-0.016	0.010	0.002	0.035
	(0.37)	(-1.10)	(1.41)	(0.16)	(2.13)
Term risk	-0.013	0.010	-0.002	-0.002	0.004
	(-0.97)	(1.36)	(-0.54)	(-0.30)	(0.47)

Adj. R-square	-0.02	0.02	0.01	-0.02	0.03
Global values for regressors					
MSCI market return	-0.018	0.019	-0.031	-0.007	-0.108
	(-0.25)	(0.42)	(-1.46)	(-0.23)	(-2.24)
Real GDP growth	0.002	-0.001	-0.001	0.000	0.001
	(0.48)	(-0.28)	(-0.75)	(0.06)	(0.49)
Inflation	-0.000	0.000	-0.001	-0.000	0.011
	(-0.05)	(0.05)	(-0.31)	(-0.01)	(1.65)
Recession	-0.003	-0.005	0.002	-0.002	-0.001
	(-0.23)	(-0.63)	(0.55)	(-0.31)	(-0.15)
Default risk	-0.004	-0.006	0.001	-0.003	-0.000
	(-0.49)	(-1.14)	(0.61)	(-0.75)	(-0.07)
Term risk	-0.002	0.013	-0.001	0.003	0.004
	(-0.15)	(2.04)	(-0.33)	(0.71)	(0.61)
Adj. R-square	-0.03	0.00	0.00	-0.03	0.03

Table 7: Relation to liquidity risk

This table reports relations between rare disaster concerns and liquidity risk. The U.S. funding liquidity variables are the Treasury-Eurodollar (TED) spread, the spread between interest rate swap and T-bill, the spread between LIBOR and repo. We also construct the aggregated U.S. funding liquidity risk based on the first principal component of the correlation matrix of these funding liquidity shocks. The U.S. market liquidity variables are the Pastor-Stambaugh innovation measure, the Hu-Pan-Wang noise measure, and the spread between on-the-run and off-the-run 10-year government Treasury notes. We also construct the aggregated U.S. market liquidity risk based on the first principal component of the correlation matrix of these market liquidity shocks. All of these liquidity variables represent illiquidity (e.g., an increase of noise means the market becomes less liquid). Finally, the aggregated all liquidity risk is based on the principal component analysis using all available market liquidity and funding liquidity measures. For global liquidity variables we do the same except that the global market liquidity variables are not available. Panel A presents sample correlations between various RIXs and the liquidity variables. Three asset-class-specific RIXs are for equity (EQRIX), currency (FXRIX), and bond (BDRIX), and the global RIX (GRIX) is based on the first principal component of the correlation matrix of these RIXs. Panel B reports coefficient estimates and t-statistics (in parentheses) from regressing low-minus-high (LMH) RIX-beta portfolio returns on the liquidity risk variables. The details of various RIX-beta portfolio construction are given in Tables 2 and 5. When regressors are U.S. values of liquidity risk, model specifications are the following: (1) TED spread, Swap - T-bill, Libor - Repo; (2) Funding liquidity risk; (3) Pastor-Stambaugh, Noise, On-Off Run; (4) Market liquidity risk; and (5) All liquidity risk. When regressors are global values of liquidity risk, model specifications are the following: (1) TED spread, Swap - T-bill, Libor - Repo; (2) Funding liquidity risk; and (3) All liquidity risk. Adjusted R-squares are based on the speficiation using the regressor of all liquidity risk.

Panel A: Correlation with liquidity variables

	TED Spread	Swap - T-bill	Libor - Repo	Pastor-Stambaugh	Noise	On-Off Run	Market Liquidity Risk	Funding Liquidity Risk	All Liquidity Risk
					U.S. variables				
EQRIX	-0.03	-0.18	-0.03	0.10	0.33	0.32	0.37	-0.05	0.16
FXRIX	-0.12	-0.20	-0.11	0.06	-0.01	0.09	0.05	-0.14	-0.06
BDRIX	-0.09	-0.13	-0.08	0.10	0.06	0.09	0.09	-0.10	-0.02
GRIX	-0.10	-0.21	-0.09	0.10	0.14	0.20	0.20	-0.12	0.02
					Global variables				
EQRIX	0.10	0.13	0.11	-	-	-	-	0.16	0.22
FXRIX	-0.12	0.19	-0.09	-	-	-	-	-0.07	-0.05
BDRIX	-0.08	0.11	-0.06	-	-	-	-	-0.05	-0.03
GRIX	-0.04	0.18	-0.03	-	-	-	-	0.01	0.05

Panel B: Liquidity risk exposures

	EQRIX-Beta LMH Return	FXRIX-Beta LMH Return	BDRIX-Beta LMH Return	Combined RIX-Beta LMH Return	GRIX-Beta LMH Return
U.S. values for regressors					
TED Spread	-0.034	-0.010	0.009	-0.012	-0.002
	(-1.03)	(-0.52)	(1.00)	(-0.86)	(-0.10)
Swap - T-bill	-0.055	-0.049	-0.036	-0.046	0.033
	(-1.00)	(-1.55)	(-2.38)	(-2.06)	(0.95)
Libor - Repo	0.043	0.005	-0.020	0.009	0.029
	(1.14)	(0.23)	(-1.98)	(0.59)	(1.23)
Funding Liquidity Risk	0.000	-0.001	-0.002	-0.001	0.004
	(0.00)	(-0.97)	(-2.59)	(-1.03)	(2.62)
Pastor-Stambaugh	0.072	0.012	-0.017	0.023	0.017
	(1.58)	(0.48)	(-1.37)	(1.23)	(0.57)
Noise	0.001	-0.001	0.004	0.001	0.003
	(0.11)	(-0.19)	(3.22)	(0.70)	(1.08)
On-Off Run	-0.002	-0.000	-0.000	-0.001	0.001
	(-1.52)	(-0.43)	(-0.36)	(-1.53)	(0.73)
Market Liquidity Risk	-0.004	-0.001	0.002	-0.001	0.003
	(-1.46)	(-0.66)	(3.10)	(-0.83)	(2.14)
All Liquidity Risk	-0.001	-0.001	-0.000	-0.001	0.004
	(-0.70)	(-0.97)	(-0.31)	(-1.11)	(2.89)
Adj. R-square	0.00	0.00	-0.01	0.00	0.04
Global values for regressors					
TED Spread	0.006	-0.002	-0.000	0.001	0.002
	(1.20)	(-0.72)	(-0.21)	(0.54)	(0.63)
Swap - T-bill	-0.001	0.003	0.001	0.001	-0.002
	(-0.37)	(1.87)	(1.73)	(1.08)	(-1.30)
Libor - Repo	-0.005	0.003	0.000	-0.001	0.002
	(-0.79)	(0.59)	(0.07)	(-0.35)	(0.46)
Funding Liquidity Risk	0.000	-0.000	-0.000	-0.000	0.004
	(0.24)	(-0.39)	(-0.02)	(-0.06)	(3.02)
All Liquidity Risk	-0.001	-0.001	0.000	-0.000	0.004
	(-0.33)	(-0.59)	(0.64)	(-0.46)	(3.04)
Adj. R-square	-0.01	0.00	0.00	0.00	0.04

Table 8: Fama-MacBeth cross-sectional regressions of global asset returns

We report Fama-MacBeth (1973) coefficient estimates (in percent) and *t*-statistics (in parentheses) of regressing global assets' realized USD-based excess returns in month *t+1* on asset-class-specific RIX beta, global RIX beta, and other betas in month *t*. Our sample consists of 76 global investment assets across three asset classes that include 30 equity indices, 32 currencies, and 14 bond futures. The global rare disaster concern index (GRIX) is based on the first principal component of EQRIX, FXRIX, and BDRIX. Each asset's RIX beta is estimated using only its asset-class RIX and each asset's GRIX beta is estimated using GRIX. We also estimate each asset's betas with respect to the following macroeconomic and liqudity 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, and (7) the global version of these liquidity and macroeconomic variables. 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. For example, to estimate an asset's GRIX beta we regress the asset's excess returns on the market factor and the GRIX factor based on the past 18-24 monthly observations. To reduce beta estimation error, we use each asset's beta rankings as regressors in performing cross-sectional regressions at each point of time. Specifically, we form 4 RIX-beta portfolios within each asset class and use these rankings for "Asset-Class RIX beta"; we form 10 GRIX-beta deciles across all assets and use these rankings for "Global RIX beta". For other macro and liquidity betas, we do the same by forming 10 beta deciles and use their rankings.

	(1)	(2)	(3)	(4)	(5)	(6)
Asset-Class RIX beta	-0.126		-0.099	-0.122		
	(-3.08)		(-2.40)	(-3.10)		
Global RIX beta		-0.067			-0.039	-0.054
		(-2.70)			(-1.41)	(-2.03)
Market beta			0.019	0.016	0.031	0.030
			(0.31)	(0.24)	(0.49)	(0.43)
U.S. Liquidity risk beta			-0.034		-0.043	
			(-1.13)		(-1.50)	
U.S. Real GDP growth beta			0.004		0.015	
			(0.14)		(0.59)	
U.S. Inflation beta			-0.062		-0.051	
			(-2.61)		(-2.12)	
U.S. Default risk beta			0.029		0.004	
			(0.85)		(0.12)	
U.S. Term risk beta			-0.028		-0.029	
			(-0.95)		(-0.98)	
Global Liquidity risk beta				-0.063		-0.067
				(-2.51)		(-2.60)
Global Real GDP growth beta				0.016		0.011
				(0.80)		(0.47)
Global Inflation beta				-0.048		-0.053
				(-1.89)		(-2.16)
Global Default risk beta				0.063		0.063
				(2.47)		(2.27)
Global Term risk beta				0.000		0.007
				(0.01)		(0.29)
Average No. of assets	52	53	52	54	53	56
Average R-square	0.01	0.04	0.36	0.37	0.37	0.38
No. of months in time series	173	179	173	159	179	159

Table 9: Downside risk CAPM betas of asset-class-specific RIX-beta portfolios

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 10: Rare disaster concerns: assets' characteristics vs. betas

Panel A presents the mean excess returns of RIX-characteristic portfolios both within and across asset classes. Within an asset class, we form four portfolios based on the available assets' RIXs; across asset classes, we form five portfolios based on all 76 assets' normalized RIXs (i.e., each asset's monthly RIX scaled by the standard deviation of its daily RIX). Panel B presents the mean excess returns of two-dimension (2x3) portfolios that are independently formed on all 76 assets' normalized RIXs and GRIX betas (see Table 5 for details of estimating GRIX beta). We report return results using four different frequencies of portfolio formation. In Panel A, there are 5 equity indices, 6 currencies, 3 bonds, and 11 assets in each RIX-characteristic portfolio; in Panel B, there are 8-11 assets in each portfolio.

Panel A: Returns of one-dimension portfolios sorted by RIXs

	Monthly Portfolio Formation				Quarterly Portfolio Formation			
	Equity Class	Currency Class	Bond Class	All (76 assets)	Equity Class	Currency Class	Bond Class	All (76 assets)
RIX - Low	0.585	0.718	0.051	0.324	0.637	0.733	0.052	0.311
	(1.57)	(4.53)	(2.12)	(2.55)	(1.66)	(4.49)	(2.31)	(2.63)
RIX - High	0.585	0.499	0.302	0.545	0.618	0.537	0.314	0.460
	(1.09)	(2.46)	(2.41)	(2.54)	(1.16)	(2.66)	(2.46)	(2.04)
High - Low	-0.000	-0.218	0.251	0.221	-0.018	-0.195	0.262	0.149
	(-0.00)	(-1.31)	(2.25)	(1.27)	(-0.05)	(-1.15)	(2.30)	(0.81)
	Semi-Annual Portfolio Formation				Annual Portfolio Formation			
	Equity Class	Currency Class	Bond Class	All (76 assets)	Equity Class	Currency Class	Bond Class	All (76 assets)
RIX - Low	0.869	0.715	0.050	0.244	0.886	0.696	0.040	0.273
	(2.28)	(4.44)	(2.19)	(2.04)	(2.29)	(4.30)	(1.72)	(2.20)
RIX - High	0.483	0.573	0.314	0.417	0.643	0.737	0.306	0.364
	(0.94)	(2.79)	(2.37)	(1.80)	(1.28)	(3.73)	(2.29)	(1.85)
High - Low	-0.386	-0.141	0.265	0.173	-0.243	0.041	0.266	0.091
	(-1.21)	(-0.86)	(2.23)	(0.95)	(-0.79)	(0.24)	(2.24)	(0.59)

Panel B: Returns of two-dimension portfolios sorted by RIXs and GRIX betas (76 assets)

	Monthly Portfolio Formation				Quarterly Portfolio Formation			
	GRIX Beta Low	GRIX Beta Middle	GRIX Beta High	GRIX Beta High - Low	GRIX Beta Low	GRIX Beta Middle	GRIX Beta High	GRIX Beta High - Low
RIX - Low	0.609	0.349	0.268	-0.331	0.591	0.387	0.249	-0.342
	(2.57)	(2.33)	(1.09)	(-1.76)	(2.00)	(2.51)	(0.79)	(-1.62)
RIX - High	0.682	0.575	0.000	-0.682	0.632	0.420	-0.043	-0.675
	(1.86)	(2.92)	(0.00)	(-2.82)	(1.69)	(1.83)	(-0.11)	(-2.45)
High - Low	0.091	0.226	-0.268	-0.323	0.041	0.033	-0.292	-0.333
	(0.33)	(1.54)	(-1.10)	(-1.17)	(0.14)	(0.20)	(-1.16)	(-1.02)
	Semi-Annual Portfolio Formation				Annual Portfolio Formation			
	GRIX Beta Low	GRIX Beta Middle	GRIX Beta High	GRIX Beta High - Low	GRIX Beta Low	GRIX Beta Middle	GRIX Beta High	GRIX Beta High - Low
RIX - Low	0.483	0.267	0.430	-0.052	0.251	0.347	0.496	0.246
	(1.75)	(1.53)	(1.41)	(-0.31)	(0.70)	(1.73)	(1.58)	(1.22)
RIX - High	0.533	0.441	0.085	-0.448	0.549	0.419	0.258	-0.291
	(1.56)	(1.59)	(0.20)	(-1.35)	(1.14)	(1.57)	(0.55)	(-1.68)
High - Low	0.050	0.174	-0.345	-0.396	0.298	0.072	-0.238	-0.536
	(0.18)	(0.83)	(-1.05)	(-1.10)	(0.81)	(0.38)	(-0.64)	(-2.08)

Table 11: Robustness checks on global asset returns

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)

Internet Appendix for "Rare Disaster Concerns Everywhere"

Appendix 1: Option data sources

This table provides detailed sources from Thomson Reuters Tick History (TRTH) on equity index options (Panel A) and bond futures options (Panel B). We also list abbreviations for each index and bond that we use in figures and tables throughout the paper. As mentioned in the text, we also collect data of over-the-counter currency options from J.P. Morgan.

Panel A: international equity index options

Equity Market	Index Name (abbreviation)	Exchange
Australia	S&P/ASX 200 Index (ASX200)	Australian Securities Exchange
Austria	Austrian Traded Index (ATX)	Austrian Future and Option Exchange
Belgium	BEL20 Index (BEL20)	LIFFE
Canada	S&P/TSX 60 Index (TSX60)	Montreal Exchange
Denmark	OMX Copenhagen 20 (OMXC20)	NASDAQ OMX Copenhagen
Europe	Euro Stoxx 50 (ESTX50)	Eurex
Finland	OMX Helsinki 25 (OMXH25)	Eurex
France	*CAC quarante* (CAC40)	LIFFE
Germany	*Deutscher Aktien IndeX* (DAX)	Eurex
Greece	FTSE/ASE 20 Index (ASE20)	Athens Derivatives Exchange
Hong Kong	Hang Seng Index (HSI)	Hong Kong Futures Exchange
India	S&P CNX Nifty Index (NSEI)	National Stock Exchange of India
Israel	Tel Aviv 25 Index (TA25)	Tel Aviv Stock Exchange
Italy	FTSE Milano Italia Borsa (MIB)	Borsa Italiana
Japan	Nikkei 225 (N225)	Osaka
Mexico	Mexican Bolsa IPC Index (IPC)	Bolsa Mexicana De Valores
Netherlands	Amsterdam Exchange index (AEX)	LIFFE
Nordic Countries	The VINX30™ index (VINX30)	NASDAQ OMX
Norway	The OBX Index (OBX)	NASDAQ OMX Oslo
Poland	Warsaw Stock Exchange Top 20 Index (WIG20)	Warsaw Stock Exchange
Russian Federation	The RTS Index (RTS)	Moscow Interbank Currency Exchange
Singapore	SGX MSCI Singapore Index (SGX)	Singapore Exchange - Derivatives Trading
South Korea	KOSPI 200 Index (KS200)	Korea Stock Exchange
Spain	IBEX 35 Index (IBEX)	MEFF Renta Variable
Sweden	OMX Stockholm 30 Index (OMXS30)	NASDAQ OMX Stockholm
Switzerland	Swiss Market Index (SMI)	Eurex
Taiwan	Taiwan Capitalization Weighted Stock Index (TAIEX)	Taiwan Futures Exchange
Thailand	Thailand SET 50 Index (SET50)	Thailand Futures Exchange
United Kingdom	FTSE 100 Index (FTSE100)	LIFFE
United States	S&P 500 Index (SPX)	CBOE

Panel B: global government bond futures options

Bond Market	Bond Maturity (abbreviation)	Exchange
Australia	10 Years (AUS_10YR)	Australian Securities Exchange
Australia	3 Years (AUS_3YR)	Australian Securities Exchange
Canada	10 Years (CAN_10YR)	Montreal Exchange
Germany Bund	8.5 - 10.5 Years (DEU_10YR)	Eurex
Germany Schatz	1.75 - 2.25 Years (DEU_2YR)	Eurex
Germany Bobl	4.5 - 5.5 Years (DEU_5YR)	Eurex
Italy	10 Years (ITA_10YR)	LIFFE
Japan	10 Years (JPN_10YR)	Tokyo Stock Exchange
Spain	10 Years (ESP_10YR)	MEFF RF
United Kingdom Gilt	10 Years (GBR_10YR)	Athens Derivatives Exchange
United States	10 Years (USA_10YR)	CME
United States	2 Years (USA_2YR)	CME
United States	30 Years (USA_30YR)	CME
United States	5 Years (USA_5YR)	CME

Panel C: Descriptive statistics of currency options

This table provides summary statistics of the implied volatilities (IV) of one-month options on exchange rates of individual currencies against the US dollar, with developed economies in Panel A and emerging economies in Panel B. We have optionsof five different strikes, with standardized Black-Scholes deltas: at the money (ATM), 10-delta call, 10-delta put, 25-delta call and 25 delta put. We convert the deltas into strikes using the extended Black-Scholes formula in Garman and Kohlhagen (1983). We report the time-series average of the annualized implied volatilities and corresponding moneyness (in the column "Money") defined as the strike over one-month forward exchange rate. The sample period is from January 1996 through June 2012, with variations depending on specific currencies.

	10-delta put		25-delta put		ATM		25-delta call		10-delta call	
	IV	Money	IV	Money	IV	Money	IV	Money	IV	Money
A: Developed Markets										
Australia	0.14	0.95	0.13	0.98	0.12	1.00	0.12	1.02	0.12	1.05
Canada	0.09	0.97	0.09	0.98	0.08	1.00	0.08	1.02	0.09	1.03
Denmark	0.12	0.96	0.11	0.98	0.11	1.00	0.11	1.02	0.11	1.04
Euro	0.12	0.96	0.11	0.98	0.11	1.00	0.11	1.02	0.11	1.04
Japan	0.11	0.96	0.11	0.98	0.11	1.00	0.12	1.02	0.13	1.05
New Zealand	0.15	0.95	0.14	0.97	0.13	1.00	0.13	1.03	0.13	1.05
Norway	0.13	0.96	0.12	0.98	0.12	1.00	0.12	1.02	0.12	1.05
Sweden	0.13	0.95	0.12	0.98	0.12	1.00	0.12	1.02	0.12	1.05
Switzerland	0.11	0.96	0.11	0.98	0.11	1.00	0.11	1.02	0.12	1.05
United Kingdom	0.10	0.96	0.10	0.98	0.09	1.00	0.09	1.02	0.10	1.04
B: Emerging Markets										
Argentina	0.13	0.96	0.10	0.98	0.07	0.99	0.06	1.01	0.06	1.02
Brazil	0.21	0.93	0.18	0.97	0.15	0.99	0.14	1.03	0.14	1.05
Chile	0.17	0.94	0.14	0.97	0.12	1.00	0.12	1.02	0.12	1.05
Columbia	0.18	0.94	0.16	0.97	0.14	1.00	0.13	1.03	0.13	1.05
Czech	0.14	0.95	0.13	0.98	0.13	1.00	0.13	1.03	0.13	1.05
Hong-Kong	0.02	0.99	0.01	1.00	0.01	1.00	0.01	1.00	0.01	1.01
Hungary	0.19	0.94	0.16	0.97	0.15	1.00	0.14	1.03	0.15	1.06
Iceland	0.36	0.88	0.36	0.94	0.38	0.99	0.41	1.09	0.46	1.20
India	0.11	0.96	0.09	0.98	0.08	1.00	0.08	1.02	0.08	1.03
Indonesia	0.16	0.94	0.14	0.97	0.12	0.97	0.12	1.02	0.12	1.05
Israel	0.10	0.96	0.09	0.98	0.08	1.00	0.08	1.02	0.09	1.03
Malaysia	0.15	0.95	0.14	0.97	0.14	0.98	0.14	1.03	0.15	1.06
Mexico	0.15	0.95	0.13	0.98	0.11	1.00	0.10	1.02	0.10	1.04
Peru	0.08	0.97	0.07	0.99	0.05	1.00	0.05	1.01	0.05	1.02
Philippines	0.11	0.96	0.09	0.98	0.08	1.00	0.08	1.02	0.08	1.03
Poland	0.18	0.94	0.16	0.97	0.15	1.00	0.14	1.03	0.14	1.06
Russia	0.14	0.95	0.12	0.98	0.10	1.00	0.10	1.02	0.10	1.04
Singapore	0.07	0.97	0.07	0.99	0.06	1.00	0.06	1.01	0.07	1.03
South Africa	0.21	0.93	0.18	0.97	0.16	0.99	0.15	1.03	0.15	1.06
South Korea	0.14	0.95	0.12	0.98	0.11	1.00	0.11	1.02	0.11	1.04
Taiwan	0.07	0.98	0.06	0.99	0.06	1.00	0.06	1.01	0.07	1.03
Thailand	0.08	0.97	0.07	0.99	0.07	0.99	0.07	1.01	0.07	1.03

Appendix 2: Summary statistics of monthly rare disaster concern index (RIX) for each of 76 global assets

Panel A: International equity index

Equity Market	Index Abb.	Option Sample	Mean	Std	Min	P25	Median	P75	Max	N
Australia	ASX200	2001:02 - 2012:10	0.0020	0.0037	0.0000	0.0003	0.0008	0.0021	0.0280	141
Austria	ATX	1996:01 - 2012:10	0.0019	0.0030	0.0002	0.0005	0.0011	0.0020	0.0276	201
Belgium	BEL20	1996:01 - 2012:10	0.0020	0.0035	0.0001	0.0005	0.0010	0.0020	0.0356	202
Canada	TSX60	1999:09- 2012:10	0.0022	0.0039	0.0002	0.0006	0.0011	0.0021	0.0306	154
Denmark	OMXC20	2005:10 - 2012:01	0.0021	0.0046	0.0002	0.0004	0.0006	0.0013	0.0278	76
Europe	ESTX50	2001:07 - 2012:10	0.0051	0.0063	0.0006	0.0015	0.0031	0.0050	0.0429	136
Finland	OMXH25	2005:02 - 2012:10	0.0025	0.0039	0.0001	0.0007	0.0013	0.0026	0.0230	83
France	CAC40	2005:05 - 2012:10	0.0040	0.0059	0.0002	0.0011	0.0023	0.0039	0.0372	90
Germany	DAX	2001:07 - 2012:10	0.0050	0.0061	0.0005	0.0015	0.0026	0.0052	0.0375	136
Greece	ASE20	2000:10 - 2012:10	0.0075	0.0095	0.0005	0.0014	0.0036	0.0096	0.0544	145
Hong Kong	HSI	1996:01 - 2012:10	0.0063	0.0117	0.0003	0.0012	0.0023	0.0067	0.1045	202
India	NSEI	2001:07 - 2012:10	0.0040	0.0055	0.0001	0.0014	0.0022	0.0041	0.0447	136
Israel	TA25	1996:01 - 2012:10	0.0020	0.0019	0.0003	0.0008	0.0015	0.0025	0.0124	202
Italy	MIB	2004:05 - 2012:10	0.0040	0.0056	0.0002	0.0005	0.0020	0.0046	0.0301	102
Japan	N225	1996:01 - 2012:10	0.0038	0.0072	0.0003	0.0012	0.0020	0.0039	0.0647	202
Mexico	IPC	2004:06 - 2012:10	0.0029	0.0055	0.0002	0.0005	0.0014	0.0025	0.0398	101
Netherlands	AEX	1997:01 - 2012:10	0.0044	0.0066	0.0004	0.0013	0.0024	0.0040	0.0526	190
Nordic Countries	VINX30	2006:09 - 2012:10	0.0030	0.0047	0.0003	0.0009	0.0014	0.0025	0.0249	55
Norway	OBX	1999:02 - 2012:10	0.0032	0.0061	0.0003	0.0009	0.0015	0.0032	0.0477	165
Poland	WIG20	2003:09 - 2012:10	0.0042	0.0051	0.0003	0.0015	0.0024	0.0050	0.0291	110
Russian Federation	RTS	2009:03 - 2012:10	0.0145	0.0138	0.0026	0.0045	0.0081	0.0196	0.0665	44
Singapore	SGX	2009:04 - 2012:10	0.0016	0.0022	0.0003	0.0004	0.0007	0.0019	0.0114	42
South Korea	KS200	1997:07 - 2012:10	0.0085	0.0246	0.0005	0.0013	0.0029	0.0067	0.2939	184
Spain	IBEX	2001:11 - 2012:10	0.0041	0.0055	0.0002	0.0008	0.0024	0.0053	0.0382	132
Sweden	OMXS30	2004:11 - 2012:10	0.0038	0.0059	0.0003	0.0010	0.0019	0.0036	0.0354	96
Switzerland	SMI	2001:07 - 2012:10	0.0027	0.0040	0.0002	0.0007	0.0013	0.0028	0.0272	136
Taiwan	TAIEX	2001:06 - 2012:10	0.0043	0.0099	0.0003	0.0009	0.0017	0.0037	0.0800	135
Thailand	SET50	2008:06 - 2012:10	0.0043	0.0077	0.0003	0.0011	0.0021	0.0042	0.0499	53
United Kingdom	FTSE100	1996:01 - 2012:10	0.0034	0.0045	0.0002	0.0009	0.0019	0.0038	0.0353	202
United States	SPX	1996:01 - 2012:10	0.0039	0.0103	0.0003	0.0011	0.0020	0.0035	0.1307	202
EQRIX			0.0040	0.0053	0.0005	0.0014	0.0024	0.0045	0.0396	202

Panel B: Foreign currency

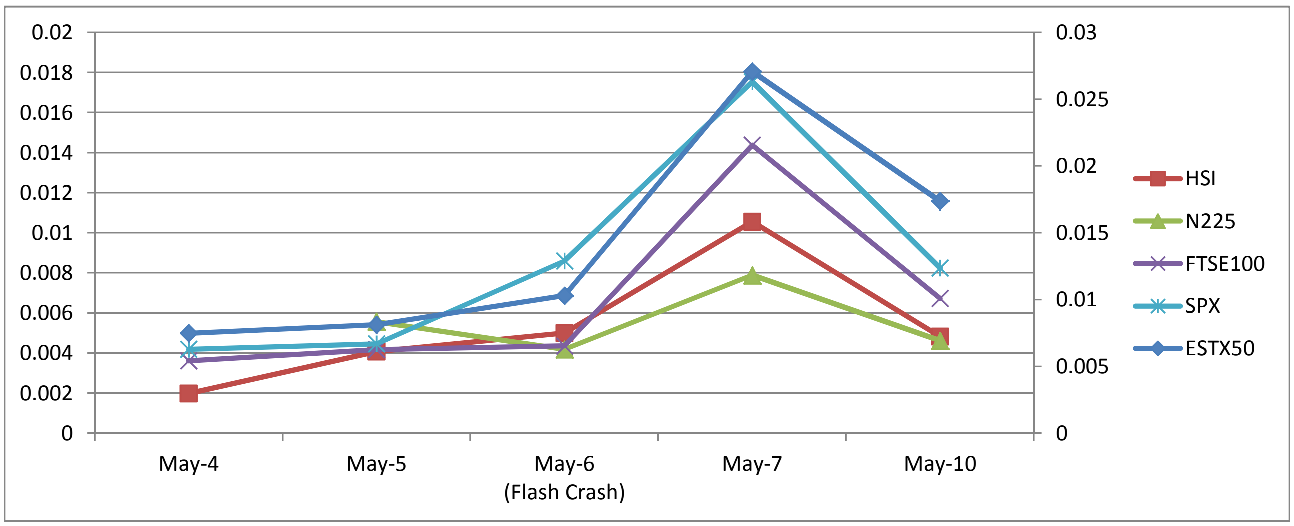
Foreign Currency	FX Abb.	Option Sample	Mean	Std	Min	P25	Median	P75	Max	N
Argentine Peso	ARS	2004:03 - 2012:05	0.0011	0.0244	-0.0103	-0.0047	-0.0029	-0.0008	0.1944	99
Australian Dollar	AUD	1996:01 - 2012:05	0.0026	0.0325	-0.0122	-0.0085	-0.0024	0.0010	0.3008	197
Brazilian Real	BRL	2004:03 - 2012:05	0.0166	0.0772	-0.0118	-0.0050	-0.0001	0.0094	0.6373	99
Canadian Dollar	CAD	1996:02 - 2012:05	-0.0016	0.0133	-0.0104	-0.0073	-0.0042	-0.0007	0.0993	196
Chilean Peso	CLP	2004:03 - 2012:05	0.0057	0.0291	-0.0097	-0.0068	0.0014	0.0053	0.2327	99
Colombian Peso	COP	2004:03 - 2012:05	0.0085	0.0260	-0.0102	-0.0049	0.0015	0.0099	0.1604	99
Czech Koruna	CZK	2000:11 - 2012:05	0.0080	0.0363	-0.0087	-0.0055	-0.0003	0.0050	0.2736	139
Danish Krone	DKK	1996:07 - 2012:05	-0.0011	0.0131	-0.0117	-0.0077	-0.0033	0.0011	0.0846	191
Euro	EUR	1999:01 - 2012:05	0.0003	0.0138	-0.0114	-0.0067	-0.0020	0.0014	0.0843	161
Hong Kong Dollar	HKD	1996:01 - 2012:05	-0.0022	0.0020	-0.0076	-0.0037	-0.0017	-0.0003	0.0000	197
Hungarian Forint	HUF	2000:11 - 2012:05	0.0152	0.0484	-0.0137	-0.0067	0.0001	0.0117	0.2579	139
Icelandic Krona	ISK	2006:01 - 2012:05	1.0461	1.0413	-0.0108	0.0136	1.4422	1.4494	3.6142	77
Indian Rupee	INR	2004:03 - 2012:05	-0.0010	0.0081	-0.0104	-0.0053	-0.0016	-0.0001	0.0392	99
Indonesian Rupiah	IDR	2001:03 - 2012:05	0.0073	0.0609	-0.0535	-0.0188	-0.0027	0.0030	0.4238	133
Israeli Shekel	ILS	2004:03 - 2012:05	-0.0004	0.0074	-0.0094	-0.0055	-0.0003	0.0005	0.0360	99
Japanese Yen	JPY	1996:02 - 2012:05	0.0077	0.0338	-0.0110	-0.0058	-0.0004	0.0065	0.2755	196
Malaysian Ringgit	MYR	2000:11 - 2012:05	0.0547	0.0863	-0.0098	-0.0040	0.0000	0.1769	0.1895	139
Mexican Peso	MXN	2000:11 - 2012:05	0.0090	0.0739	-0.0139	-0.0065	-0.0028	0.0003	0.8198	139
New Zealand Dollar	NZD	1996:12 - 2012:05	0.0033	0.0239	-0.0116	-0.0083	-0.0010	0.0031	0.1765	186
Norwegian Krone	NOK	1996:02 - 2012:05	0.0015	0.0205	-0.0120	-0.0085	-0.0028	0.0023	0.1354	196
Peruvian Nuevo Sol	PEN	2004:03 - 2012:05	-0.0016	0.0062	-0.0221	-0.0039	-0.0014	-0.0001	0.0427	99
Philippine Peso	PHP	2003:02 - 2012:05	-0.0016	0.0070	-0.0099	-0.0053	-0.0020	-0.0001	0.0343	107
Polish Zloty	PLN	2000:11 - 2012:05	0.0185	0.0656	-0.0166	-0.0061	-0.0015	0.0141	0.4443	139
Russian Federation Rouble	RUB	2006:01 - 2012:05	0.0022	0.0146	-0.0073	-0.0057	0.0000	0.0027	0.0802	77
Singaporean Dollar	SGD	1997:03 - 2012:05	-0.0036	0.0037	-0.0127	-0.0060	-0.0029	-0.0008	0.0072	183
South African Rand	ZAR	1996:01 - 2012:05	0.0141	0.0522	-0.0180	-0.0090	0.0031	0.0144	0.4379	197
South Korean Won	KRW	2002:02 - 2012:05	0.0283	0.1452	-0.0075	-0.0043	-0.0016	0.0011	1.2734	124
Swedish Krona	SEK	1996:01 - 2012:05	0.0021	0.0215	-0.0114	-0.0083	-0.0028	0.0024	0.1435	197
Swiss Franc	CHF	1996:01 - 2012:05	-0.0008	0.0113	-0.0114	-0.0076	-0.0031	0.0022	0.0740	197
Taiwanese Dollar	TWD	2004:08 - 2012:05	-0.0021	0.0025	-0.0068	-0.0045	-0.0021	0.0002	0.0029	94
Thai Baht	THB	2000:11 - 2012:05	-0.0045	0.0080	-0.0420	-0.0056	-0.0015	-0.0002	0.0166	139
United Kingdom Pound	GBP	1996:01 - 2012:05	-0.0027	0.0125	-0.0126	-0.0086	-0.0051	-0.0009	0.0936	197
FXRIX			0.0162	0.0407	-0.0105	-0.0072	0.0005	0.0148	0.1992	197

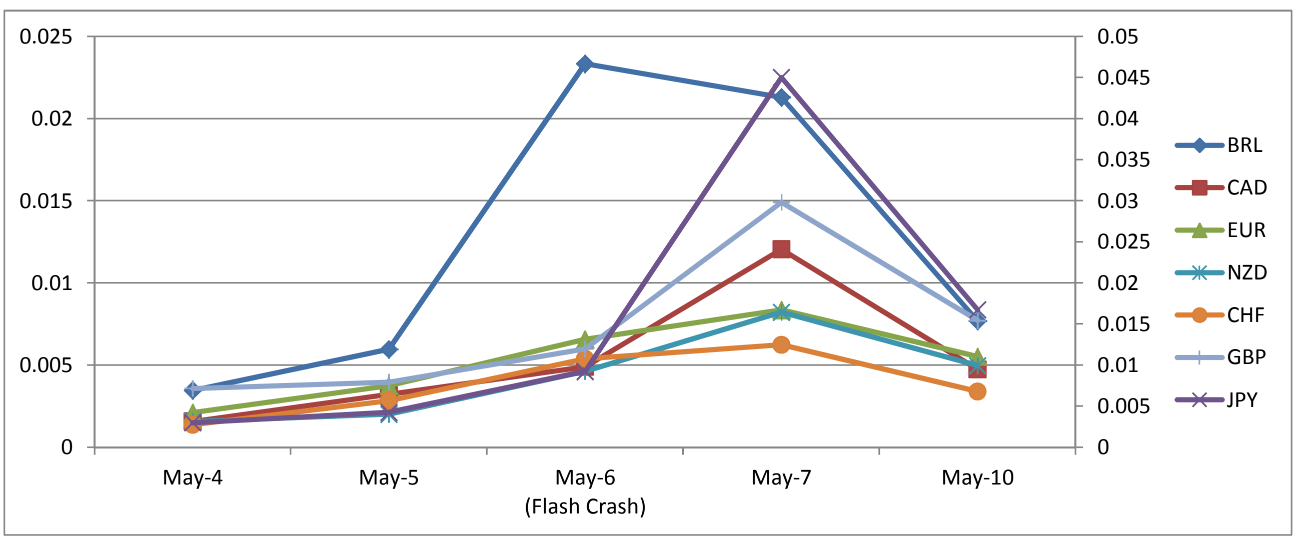
Panel C: Global government bond futures

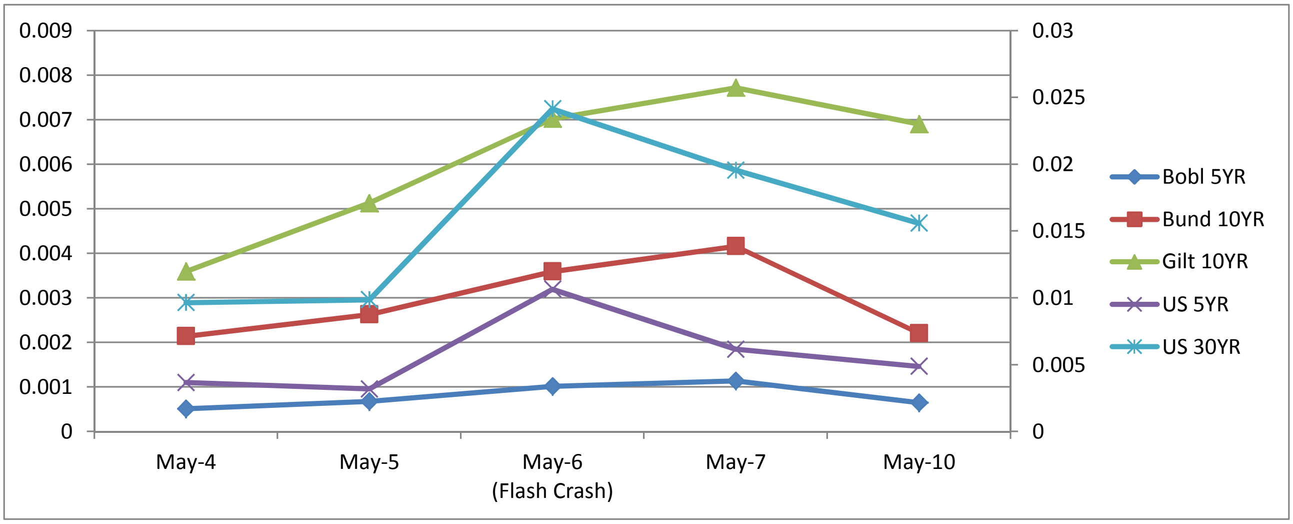
Country	Bond Abb.	Option Sample	Mean	Std	Min	P25	Median	P75	Max	N
Australia	AUS_10YR	1996:01 - 2012:12	0.0001	0.0003	-0.0014	-0.0001	0.0000	0.0001	0.0010	204
Australia	AUS_3YR	1996:01 - 2012:12	0.0001	0.0006	-0.0005	-0.0001	0.0000	0.0000	0.0043	204
Canada	CAN_10YR	1996:01 - 2003:05	0.0030	0.0085	0.0004	0.0008	0.0009	0.0030	0.0751	83
Germany (Bund)	DEU_10YR	1996:01 - 2012:12	0.0018	0.0015	0.0003	0.0008	0.0014	0.0020	0.0108	204
Germany (Schatz)	DEU_2YR	1998:02 - 2012:12	0.0000	0.0000	-0.0001	0.0000	0.0000	0.0000	0.0001	179
Germany (Bobl)	DEU_5YR	1996:01 - 2012:12	0.0004	0.0004	0.0000	0.0002	0.0003	0.0005	0.0024	204
Italy	ITA_10YR	1996:01 - 2000:06	0.0020	0.0021	0.0001	0.0002	0.0010	0.0035	0.0071	54
Japan	JPN_10YR	1996:01 - 2012:12	0.0010	0.0013	0.0001	0.0004	0.0007	0.0012	0.0130	201
Spain	ESP_10YR	1996:01 - 2000:08	0.0024	0.0015	0.0002	0.0011	0.0023	0.0033	0.0076	56
United Kingdom (Gilt)	GBR_10YR	1996:01 - 2012:12	0.0042	0.0024	0.0008	0.0021	0.0036	0.0058	0.0125	204
United States	USA_10YR	1996:01 - 2012:12	0.0032	0.0023	0.0004	0.0016	0.0025	0.0040	0.0138	204
United States	USA_2YR	2006:11 - 2012:12	0.0001	0.0001	-0.0001	0.0000	0.0000	0.0001	0.0004	74
United States	USA_30YR	1996:01 - 2012:12	0.0103	0.0076	0.0014	0.0057	0.0083	0.0127	0.0488	204
United States	USA_5YR	1996:01 - 2012:12	0.0009	0.0008	0.0001	0.0004	0.0007	0.0013	0.0046	204
BDRIX			0.0022	0.0013	0.0006	0.0014	0.0019	0.0027	0.0091	204

Appendix 3: Rare disaster concerns: the 2010 Flash Crash

This figure presents the estimates of global market's rare disaster concerns during the five-day period surrounding the event of 2010 Flash Crash. The Flash Crash occured on the U.S. equity market on Thursday May 6, 2010. We plot rare disaster concern indices (RIXs) of selected markets and assets in three panels. The top panel cotains RIXs for five equity indices: the Hang Seng Index (HSI) in Hong Kong, the Nikkei 225 Index in Japan (N225), the FTSE 100 Index in the U.K. (FTSE100), the S&P 500 Index (SPX) in the U.S., and the Euro STOXX 50 Index in the Eurozone (ESTX50). The middle panel contains RIXs for seven currencies: Brazilian Real (BRL), Canadian Dollar (CAD), Euro (EUR), New Zealand Dollar (NZD), Swiss Franc (CHF), United Kingdom Pound (GBP), and Japanese Yen (JPY). The bottom panel contains RIX for five government bonds: Germany Bobl, Germany Bund, United Kingdom Gilt, and U.S. 5-year and 30-year bonds. We also report daily asset-class-specific RIX mean and standard deviation (EQRIX for equity, FXRIX for currency, and BDRIX for bond) below the bottom panel (see Figure 2 in detail).





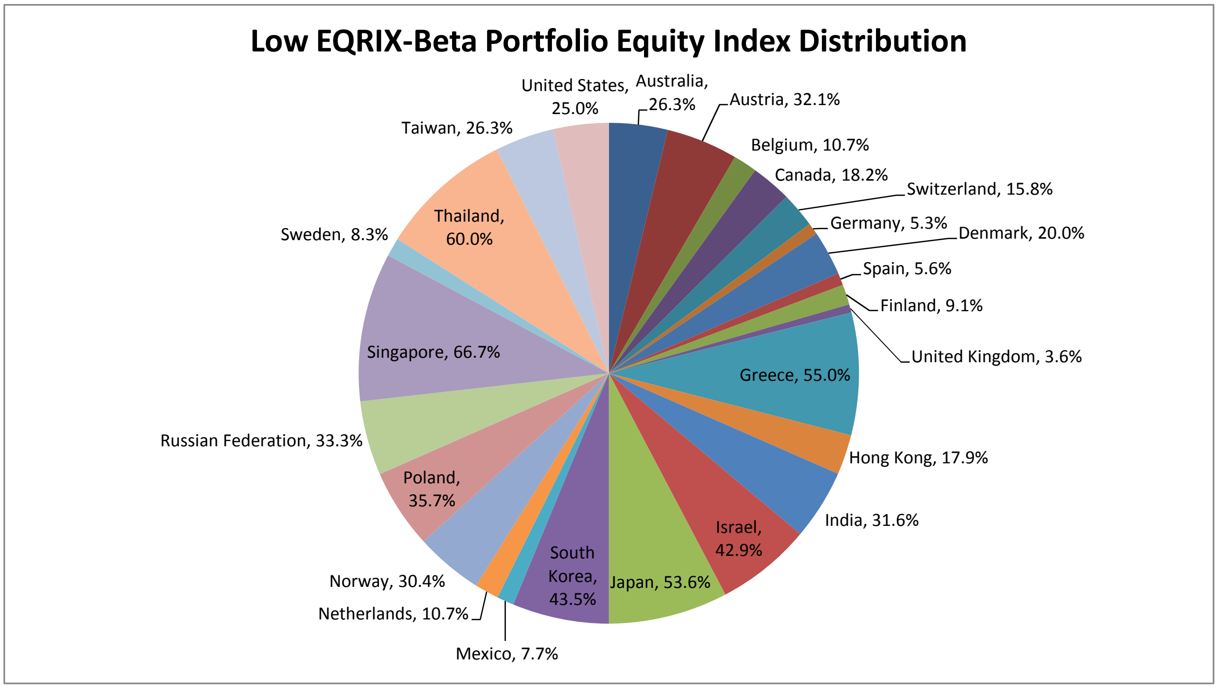


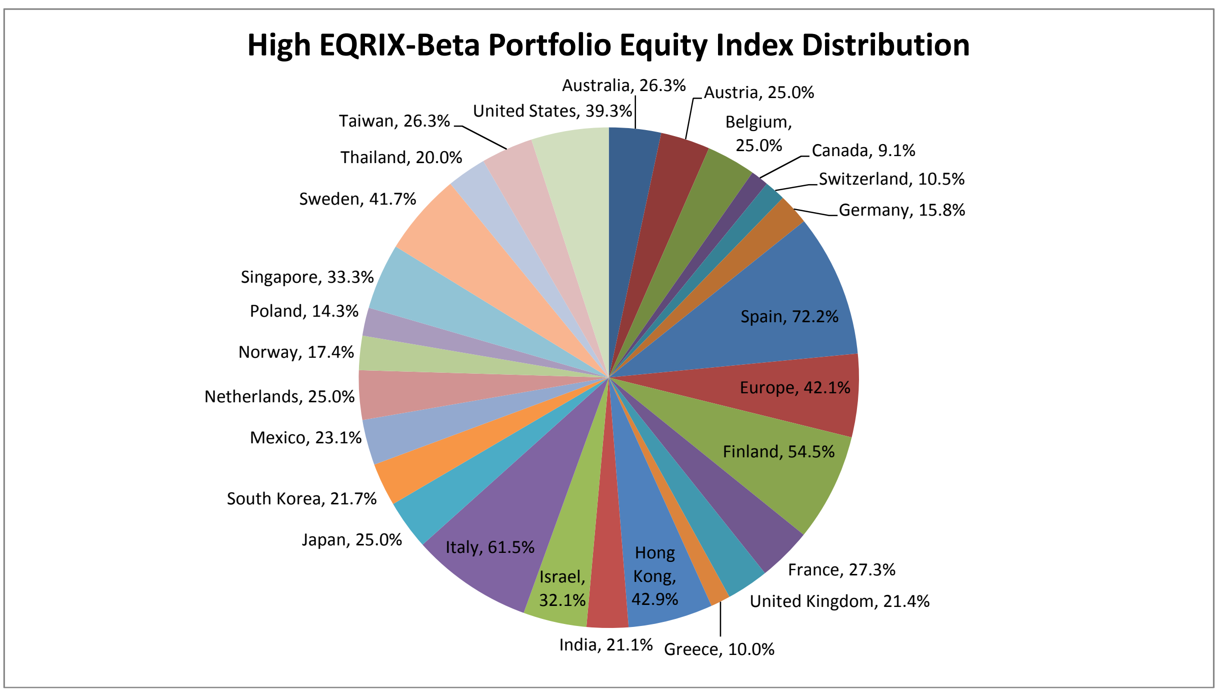
	EQRIX		FXRIX		BDRIX	
	Mean	Std.	Mean	Std.	Mean	Std.
May-4	0.0036	0.003	0.0472	0.254	0.0018	0.003
May-5	0.0046	0.004	0.0486	0.254	0.0020	0.003
May-6	0.0051	0.005	0.0516	0.254	0.0042	0.007
May-7	0.0100	0.008	0.0542	0.254	0.0036	0.006
May-10	0.0072	0.006	0.0514	0.254	0.0028	0.005

Appendix 4: Global asset distribution

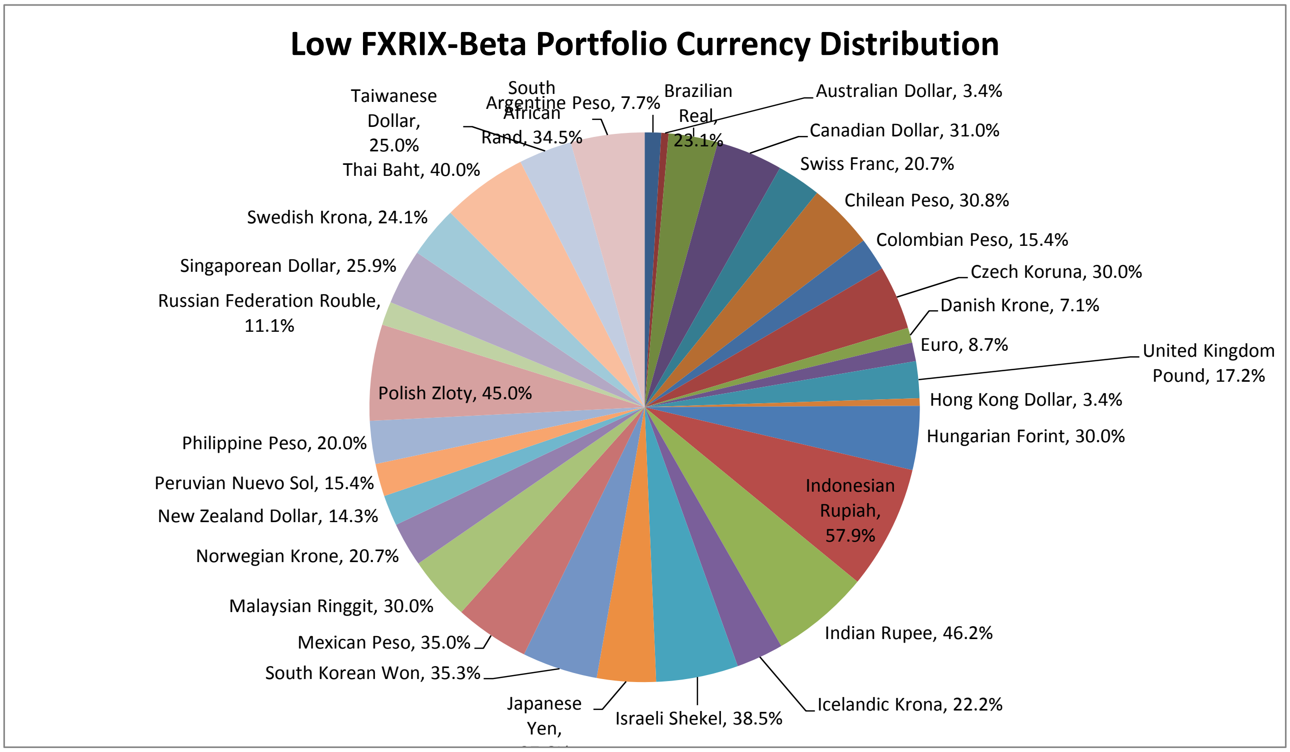
Within each of asset classes of international equity index (Panel A), currency (Panel B), and global government bond (Panel C), we form four RIX-beta portfolios using each asset's beta with respect to its corresponding asset-class-specific RIX (see Table 2 in detail). Within a RIX-beta portfolio, for each asset we first count the total number of months in which this asset is ranked into the portfolio, and then divide it by the total number of months in which this asset has available returns in estimating its RIX beta. In each panel, the top figure shows asset distribution within the low RIX-beta portfolio, and the bottom section shows asset distribution within the high RIX-beta portfolio. Note that it is possible for an asset to never enter into low or high RIX-beta portfolio.

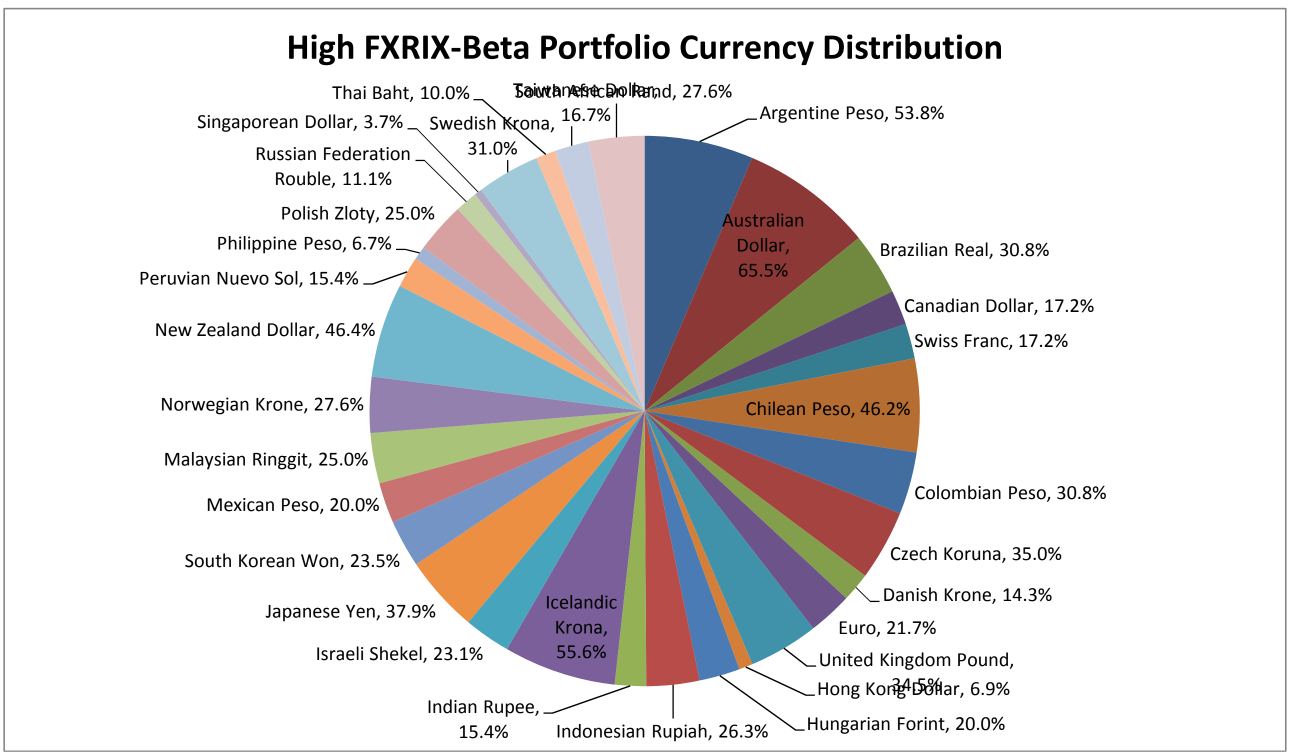
Panel A: International equity index



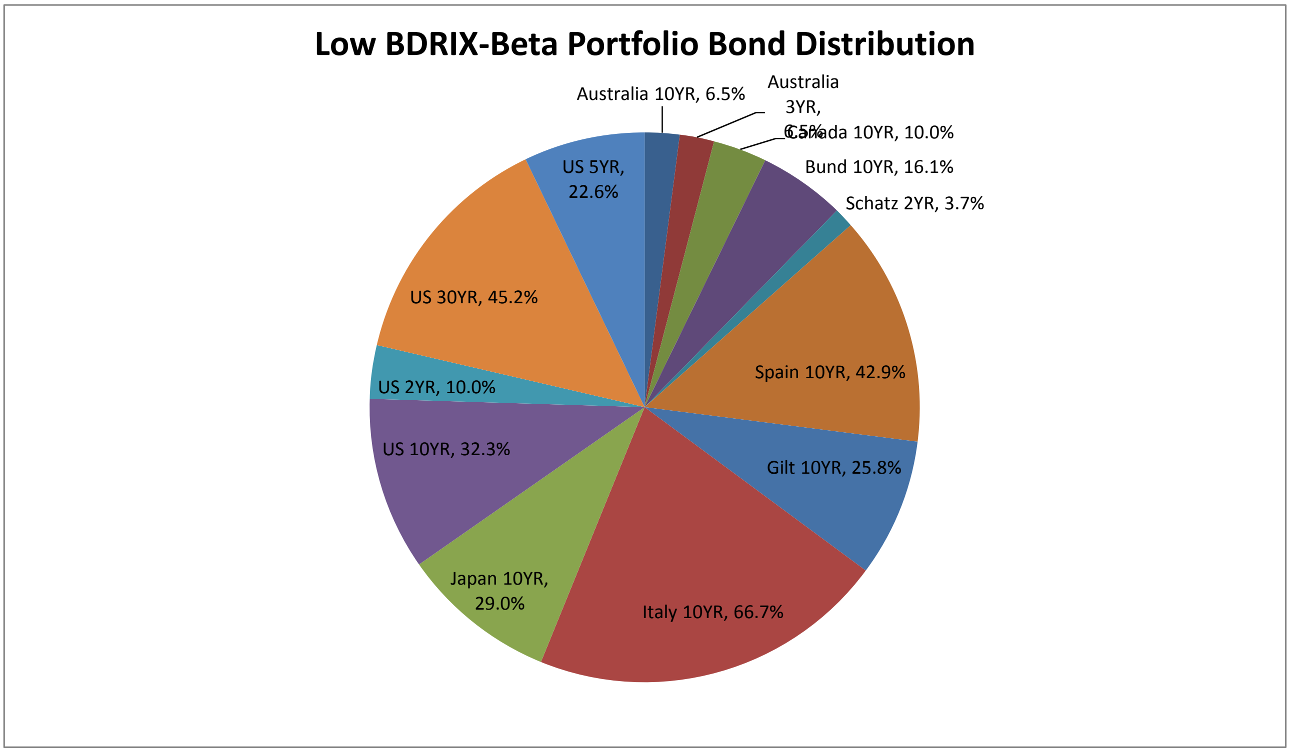


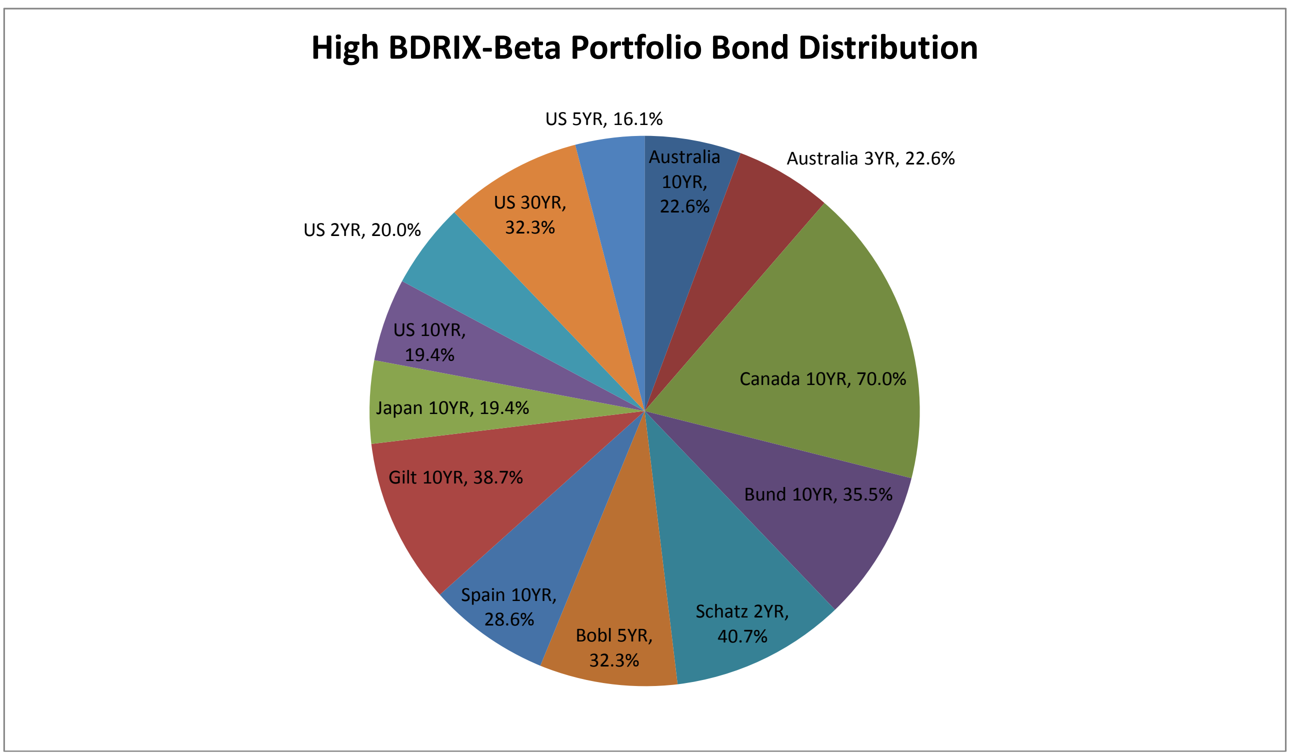
Panel B: Foreign currency





Panel C: Global government bond





Appendix 5: U.S. exchange trade funds (ETFs)

This table presents ETFs that have available monthly returns in CRSP. We use these 28 ETFs to track our sample of international equity indices in the main analysis. There are two ETFs ("iShares MSCI Denmark Cppd Investable Mkt" and "iShares MSCI Finland Capped Inv Mkt") that have no available CRSP returns, and hence we exclude them in tracking market index returns of Denmark and Finland.

ETF Full Name	Ticker	Inception Date	CUSIP
SPDR S&P 500	SPY	22-Jan-1993	78462F103
iShares MSCI Australia Index	EWA	12-Mar-1996	464286103
iShares MSCI Austria Capped Invstbl Mkt	EWO	12-Mar-1996	464286202
iShares MSCI Belgium Capped Invstbl Mkt	EWK	12-Mar-1996	464286301
iShares MSCI Canada Index	EWC	12-Mar-1996	464286509
iShares MSCI France Index	EWQ	12-Mar-1996	464286707
iShares MSCI Germany Index	EWG	12-Mar-1996	464286806
iShares MSCI Hong Kong Index	EWH	12-Mar-1996	464286871
iShares MSCI Italy Capped Index	EWI	12-Mar-1996	464286855
iShares MSCI Japan Index	EWJ	12-Mar-1996	464286848
iShares MSCI Mexico Capped Invstbl Mkt	EWW	12-Mar-1996	464286822
iShares MSCI Netherlands Invstbl Mkt Idx	EWN	12-Mar-1996	464286814
iShares MSCI Singapore Index	EWS	12-Mar-1996	464286673
iShares MSCI Spain Capped Index	EWP	12-Mar-1996	464286764
iShares MSCI Sweden Index	EWD	12-Mar-1996	464286756
iShares MSCI Switzerland Capped Index	EWL	12-Mar-1996	464286749
iShares MSCI United Kingdom Index	EWU	12-Mar-1996	464286699
iShares MSCI South Korea Capped Index	EWY	9-May-2000	464286772
iShares MSCI Taiwan Index	EWT	20-Jun-2000	464286731
Vanguard FTSE Europe ETF	VGK	4-Mar-2005	922042874
iShares MSCI Israel Cap Invest Mkt Index	EIS	26-Mar-2008	464286632
iShares MSCI Thailand Capped Invstbl Mkt	THD	26-Mar-2008	464286624
Global X FTSE Nordic Region ETF	GXF	17-Aug-2009	37950E101
iShares S&P India Nifty 50 Index	INDY	18-Nov-2009	464289529
iShares MSCI Poland Capped Invstbl Mkt	EPOL	25-May-2010	46429B606
Global X FTSE Norway 30 ETF	NORW	9-Nov-2010	37950E747
iShares MSCI Russia Capped Index	ERUS	9-Nov-2010	46429B705
Global X FTSE Greece 20 ETF	GREK	7-Dec-2011	37950E366