Dependence between Extreme Events in the Real and Financial Sectors

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January 24, 2013

Abstract

Extreme events affect both the real economy and financial markets, and it is valuable to understand their interrelationship. We analyze the likelihood of crises in the macroeconomy and in financial markets. We compare rare disaster data from Barro and Jin (2011), crisis data from Reinhart and Rogoff (2009b), real time macroeconomic data from Aruoba et al. (2009), and a unique industry dataset of Turbulence Indices. We examine dependence across the various measures of crises, as well as predictability, using annual and daily data. For annual data, the dependence between crises in the real and financial sectors increases over time for emerging markets, but decreases for OECD countries. We also document persistence at the one year and two year horizons for disasters in the real economy. For daily data, there is, surprisingly, little relation between turbulence in US equity and the real economy. However, there is strong evidence of two-way predictability up to two weeks out for the US economy and global turbulence. A dynamic copula model indicates that the real economy and various turbulence indices alternate between regimes of positive and negative dependence.

Keywords: Crisis; Dependence Regimes; Extreme Event; Predictability; Rare Disaster; Turbulence

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1 Introduction

How do financial and economic extreme events relate to each other? In this paper we address the important question of comovement in various extreme event measures, for both real and financial markets. We build on three strands of academic literature. First, we build on the rare disaster approach of Barro (2006); Barro and Jin (2011); and Barro and Ursua (2011). These authors analyze global rare disasters, where GDP and consumption fall by a large amount. They find interesting power law behavior, and that accounting for rare disasters helps explain the equity premium puzzle and other macro stylized facts. Second, we build on Reinhart and Rogoff (2009a), who examine several centuries of economic and financial crises. These latter authors construct an index of crises, and document interesting relations between domestic debt, public debt, and other crises.[1] At the same time, there is a growing interest in linkages between the real economy and financial markets during crisis periods.[2] Therefore in this paper, we combine the rare disaster and financial crisis approaches, in order to glean an understanding of their linkages. Third, we build on the high-frequency macro approach of Aruoba et al. (2009). These authors filter economic stock and flow data at different frequencies, in order to extract dynamic daily measures of macroeconomic activity. In addition to analyzing data based on the above academic sources, we utilize turbulence indices from State Street. These latter indices are of daily frequency and, as in Kritzman and Li (2010), analyze extreme events based on the multivariate distance of various asset returns from historical benchmark levels.

Our paper complements the analysis of the above research and attempts to answer three outstanding questions: First, is there any pattern over time in the behavior of extreme events? Second, how are extreme events in the macroeconomy and financial markets related? Third, what is the predictive power of the different extreme event measures for each other?

1.1 Contributions

Existing research underscores the importance of accounting for extreme events in the the real and financial sectors of an economy. We contribute to this research in four dimensions. First we estimate dependence of extreme events across the real and financial sectors, at both low and high frequencies. Second, we assess systematic differences in dependence across economic regions. Third, we characterize the predictive power of different disaster measures for each other. Finally, we uncover potentially rich dynamics in dependence between the real and financial sectors. Our findings of predictive ability for some disaster measures, and dynamic real-financial dependence, may be valuable for policy analysis.

[1] In related work, Reinhart and Rogoff (2011a) construct a database of domestic debt for more than 80 countries. They document that domestic debt typically accounts for a large fraction of public debt. A separate paper by Reinhart and Rogoff (2011b) establishes that private debt increases before banking crises, which have predictive power for sovereign debt crises.

[2] See Krishnamurthy (2010); Hall (2011); Ramey (2011).

1.2 Literature Review

Extreme events have been explored in a variety of socioeconomic settings. We may categorize this literature into two broad categories: general, methodological research on univariate and joint extremes, and specific work on rare disasters and crises. Regarding general background on tail events, Mandelbrot (1963) and Fama (1965) show that US stocks are not gaussian and have univariate heavy tails. Fama (1965) documents that stock crashes occur more frequently than booms. Jansen and de Vries (1991) investigate extreme stock prices using a univariate, nonparametric approach. They analyze daily data from ten $S\&P500$ stocks, and document that the magnitude of 1987's crash was somewhat exceptional, occurring once in 6 to 15 years. Susmel (2001) investigates the univariate tail distributions for international stock returns. He documents that Latin American markets have significantly heavier left tails than other industrialized markets. Susmel combines extreme value theory with the safety-first criterion of Roy (1952), and demonstrates improved asset allocation relative to the mean-variance approach. Longin and Solnik (2001) use a parametric multivariate approach to derive a general distribution of extreme correlation. The authors examine G5 equity index data to test for multivariate normality in both positive and negative tails. They document that tail correlations approach zero (consistent with normality) in the positive tail but not the negative tail. Further, Longin and Solnik (2001) show that correlations increase during market downturns. Hartmann et al. (2003) use an extreme value approach to analyze the behavior of currencies during crisis periods. Their results show that Latin American currencies have less extreme dependence than in east Asia, and that the developing markets often have a smaller likelihood of joint extremes than do the industrialized nations. Liu et al. (2003) analyze rare events and asset allocation in a jump diffusion setting. They demonstrate that consideration of rare events discourages individual investors from holding leveraged positions. Longin (2005) develops hypothesis tests that differentiate between candidates for the distribution of stock returns, including the gaussian and stable Paretian. He then tests the distribution of daily returns from the $S\&$P500, and documents that only the student-t distribution and ARCH processes can plausibly characterize the data. Liu et al. (2005) develop an equilibrium model of asset prices with rare events. The authors find that the equity premium comprises three parts, depending on risk aversion to jumps, aversion to diffusion movements, and aversion to uncertainty about rare events. The authors document that aversion to rare events can help ameliorate option mispricing. Chollete et al. (2009) use general dependence measures to model portfolios of international stock returns from the G5 and Latin America. They find that an empirical model that allows for asymmetric dependence outperforms standard models, and improves Value-at-Risk computations.

Regarding rare disasters and crises, Hartmann et al. (2004) report that stock markets crash together in one out of five to eight crashes, and that G5 markets are statistically dependent during crises. Poon et al. (2004) model multivariate tails of stock index returns from G5 markets. They document that in only 13 of 84 cases is there evidence of asymptotic dependence, suggesting that the probability of systemic risk may be overestimated in financial research. Barro (2006) builds a representative agent economy that incorporates the risk of a rare disaster, modelled as a large drop in the economy's wealth endowment. When this model is calibrated to the global economy, it can explain the equity premium and low risk free rate puzzles, and can help account for stock market volatility. Gabaix et al. (2006) develop a theory of stock volatility, where the driving force is trading by large investors, during illiquid markets. Weitzman (2007) constructs a Bayesian model of asset returns. He discovers that when agents consider the possibility of extremes, there is a reversal of all major asset pricing puzzles. Gabaix (2008), Gabaix (2010), and Wachter (2011) generalize the Barro (2006) framework to account for dynamic probability of extreme events. These latter models are capable of explaining several macroeconomic and finance puzzles as well as the behavior of stock volatility. Reinhart and Rogoff (2009b) analyze more than 800 years of crises and conclude that the biggest factors in crises are excessive debt and sudden shifts of confidence. During booms, governments, banks or corporations increase borrowing, and underestimate aggregate risk. The authors emphasize a ”This time is different” mentality, where market participants downplay the likelihood of extreme events during the boom period preceding crises. Adrian and Brunnermeier (2010) analyze a systemic risk measure, CoVaR, which summarizes the dependence of Value at Risk for different institutions, and represents the conditional likelihood of an institution's experiencing a tail event, given that other institutions are in distress. They estimate CoVaR for commercial banks, investment banks and hedge funds in the US. They document statistically significant spillover risk across institutions. Bollerslev and Todorov (2011) use high frequency options data to construct an index of implicit disaster fears among investors. This method is motivated by a jump-diffusion model that separates out disasters from smaller jumps in asset prices. The authors find that their method helps explain patterns in the equity premium and stock market variance.

The remainder of the paper is organized as follows. Section 2 outlines our empirical approach and data construction. Section 3 describes our empirical results, and Section 4 concludes.

2 Empirical Method and Data Construction

2.1 Empirical Method

Our approach comprises two steps. First, we compute various disaster and crisis measures for the real economy and the financial economy. Second, we analyze the following three empirical issues: patterns over time; dependence between crises in the real and financial economy, assessed by correlations, copulas and cointegration tests; and predictive power of the various crisis measures, assessed by vector autoregressions. While these techniques are standard in applied econometrics (see Hamilton (1994) and Greene (2008)), they have not been applied often to analysis of financial and economic extreme events.

2.2 Construction of the Data

We analyze four datasets: the economic disaster data of Barro (2009); the crisis data of Reinhart and Rogoff (2009b); the high frequency macro data of Aruoba et al. (2009); and a daily turbulence index generously provided by State Street, based on Kritzman and Li (2010).

Annual Data. The annual data comprise two types of indices, based on the work of Barro (2009) and Reinhart and Rogoff (2009b). The full sample is from 1900 to 2009. For some of the empirical analysis we split the sample into two periods, 1900-1969 and 1970-2009, in order to assess potential effects of worldwide market liberalizations, which led to increased market integration. Each index is based on at least two types of disasters. For any given year, Barro and Reinhart disaster indicators for a country are 1 if a disaster of that type was present in that country during that year, and zero otherwise. Thus, our indices are constructed as follows: Barro index is constructed based on GDP and Consumption disasters. Under this index, the maximum disaster number a country can be assigned in any given year is 2. Reinhart Financial Economy (FE) index is constructed based on the stock market and sovereign debt (both domestic and external) disasters. Under this index, the maximum disaster number a country can be assigned in any given year is 3. Reinhart Real Economy (RE) index is constructed based on the currency, inflation and banking disasters. Under this index, the maximum disaster number a country can be assigned in any given year is 3. Reinhart Total Index (TI) is constructed based on the stock market, sovereign debt, currency, inflation and banking disasters. Under this index, the maximum disaster number a country can be assigned in any given year is 6. To create any of the above indices for any given year, we average the disaster number for all countries included in the index, and then divide the average by the number of types of disasters the index contains. We performed the last calculation to make indices comparable in scale. Thus, we use Barro and Reinhart RE as proxies for disasters in the real economy, and Reinhart FE as a proxy for disasters in the financial economy. Reinhart TI encompasses both types of crisis.

Daily Data. The daily analysis is based on two datasets. The first is a macroeconomic index (ADS) Aruoba et al. (2009). This index is available on a daily frequency from the Federal Reserve Bank of Philadelphia, from March 1, 1960 to the present. It tracks real business conditions in the USA, based on a dynamic factor analysis that combines several economic indicators–weekly initial jobless claims; monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales; and quarterly real GDP. The mean ADS value is zero. Larger positive values indicate progressively better than-average conditions, and vice versa. The second set of indices are called Turbulence indices, and are based on the multivariate distance away from a benchmark level in the particular asset class, as described in Kritzman and Li (2010). The indices commence coverage at various dates, described below, and end on January 17, 2012. Turbulence is computed for several asset classes, including: currencies (from November 24, 1977); European stocks (from November 26, 1975); international assets (from November 27, 1995); international stock indices (from November 25, 1975); sovereign debt instruments (from November 25, 1991);

US credit instruments (July 12, 2000); US stocks (from November 26, 1975); US corporate bonds (from November 14, 2002); and US government bonds (from August 4, 2000).

For relevant economic comparisons, the analysis is performed on three different samples: OECD, Emerging and All. 'OECD' denotes OECD countries, and includes Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, UK, and the USA. 'EM' denotes emerging markets, and includes Argentina, Brazil, Chile, Colombia, India, Korea, Malaysia, Mexico, Peru, Singapore, Turkey, Uruguay, and Venezuela. 'All' includes both OECD and emerging countries.

3 Empirical Results

Our empirical analysis focuses on annual data and daily data. We discuss each set of results below.

3.1 Annual Extreme Events

Summary Statistics. We first examine graphs and summary statistics. Figure 1 shows the average turbulence index and the Reinhart-Rogoff stock market crash index. Evidently the turbulence index spikes at the same time or just before the spikes in the crash index. Since the turbulence index's deviations may also be relevant, we display its volatility during each year, in Figure 2. A similar pattern obtains, namely a coincidence or near coincidence of spikes. We also examine correlations of the various crisis measures, in Table 2. Let us first examine Panels A and B. The most striking finding is that correlations decreased over time for OECD countries, but increased for emerging markets, in both panels. For example, in Panel A, the Pearson correlation of 0.5229 for the 1900-1969 period decreased more than 50% (to 0.1653) in the 1970-2009 period. By contrast, the corresponding number for emerging markets more than doubled, from 0.2191 to 0.5554. A similar pattern obtains in Panels C and D. Thus, the dependence between crises in the real and financial sectors, has a different pattern, depending on whether we look at OECD or emerging markets. In particular, for OECD countries, crises in the financial sector and real sector were more correlated in the earlier period of 1900 to 1969, while the opposite pattern holds for emerging markets. This pattern may reflect heterogeneous correlations in technology shocks for OECD vs emerging markets (Curdia and Reis (2011)).

Cointegration. Two important issues in the disaster literature concern cointegration and predictability. Two nonstationary series $[X_t, Y_t]$ are cointegrated if a linear combination of them is stationary. Economically speaking, cointegrated series tend to move together over long periods of time. It can be tested by examining the least squares residuals $\hat{e}_t = Y_t - \beta_1 - \beta_2 X_t$. These are based on the Engle and Granger (1987) test.[3] The null hypothesis of nonstationary residuals $\hat{e}$ is evaluated in the test that $\alpha = 0$ and $\beta = 1$ in the expression

$$\Delta \hat{e}_t = \alpha + \beta \hat{e}_{t-1} + \mu_t$$

Assessing potential for cointegration is important for extreme events, since in the long run one might expect the frequency of disasters in the financial economy to reflect structural weaknesses in the real economy.

The results of our cointegration tests, reported in Table 3, show that the only case in which the null hypothesis of cointegration cannot be rejected is for the link between real crises and financial crises in emerging markets (see Panel A). For all other crises, there is strong evidence against long run linkages.

Predictability. Predictability between extreme events is important in today's economy, from a policy perspective, because if one disaster index can predict others, it gives policymakers a single variable on which to focus attention. That is, if one primary class of disaster can be used to forecast another, the primary one can in principle provide valuable information for economic policy. Predictability between two series X_t and Y_t may be evaluated using the vector autoregression (VAR) framework of Sims (1980), in an equation system of the form

$$\Delta Y_t = \alpha_1 + \sum_{k=1}^{p} \beta_{1k} \Delta Y_{t-k} + \sum_{k=1}^{p} \lambda_{1k} \Delta X_{t-k} + \epsilon_{1t}$$

$$\Delta X_t = \alpha_2 + \sum_{k=1}^{p} \beta_{2k} \Delta Y_{t-k} + \sum_{k=1}^{p} \lambda_{2k} \Delta X_{t-k} + \epsilon_{2t},$$

where Y and X comprise the various disaster and crisis measures.

Our findings from the VAR analysis are summarized in Table 4. Based on the results of Models 1 and 2, we argue that financial crises can be predicted by disasters in the real economy up to three years in advance. The prediction power of financial disasters, however, is limited to GDP and consumption crises, and is significant only for the full sample. For models 2 through 4, a particularly striking finding is the strong predictability of the Barro disaster index for the coming year in All as well as the OECD samples.

3.2 High Frequency Extreme Events

Often the most compelling extreme events occur within a single day. For example, the 1987 stock market crash was punctuated by a loss in the Dow Jones index in excess of 20%, on October 19. These large losses signal market inefficiency, since they often occur in absence of significant news, while the efficient markets hypothesis suggests that prices respond only to news. Moreover, these daily large movements are important

[3] For further details, see Hamilton (1994) and Hill et al. (2011).

for macroprudential and economic policy, since central banks have to guard against the potent threat of financial and economic contagion.

Therefore, in addition to understanding dependence at the annual frequency, it is important to understand the daily relation between financial disaster measures and the real economy. In order to analyze this frequency of financial data, we use various daily turbulence indices from State Street. These indices are based on the multivariate distance of observed asset levels from a central moment, as described in Kritzman and Li (2010). For the real economy, we utilize the daily index of business conditions from Aruoba et al. (2009).[4]

Summary Statistics. Table 5 presents both Pearson and rank correlations between the ADS business conditions index and various turbulence indices. The largest correlations are for the ADS index and US credit and Treasury turbulence indices. This is intuitive because the ADS index is constructed using factor analysis related to US credit and government borrowing conditions.

Predictability. The results from estimating VAR models using the ADS index and turbulence indices are summarized in Tables 6 to Table 9.[5] In general there is evidence of persistence from previous lags of the same variable. For the purposes of our paper we focus on the *interaction* from one variable to the other. First, results from the VAR model using ADS and the US equity turbulence index are reported in Table 6. Surprisingly, this table shows no evidence of interaction at any lags. Second, the VAR mofel for ADS and European Equity is summarized in Table 7. This table shows effects from European Equity to the ADS index at 5, 6 and 10 days. Third, the VAR model for ADS and Global Equity is summarized in Table 8, which two-way interaction. Global Equity turbulence has a significant effect on current ADS for 2, 6, 7 and 10 days ahead, while ADS affects current Global equity turbulence at 8 and 9 days. Finally, the VAR model for ADS and Global Asset is summarized in Table 9. This table again shows two-way interaction between the real economy and financial turbulence. In particular, Global asset turbulence predicts current ADS 2, 5 and 10 days ahead, while ADS predicts current Global asset turbulence from days 4, 5, 9 and 10.

To summarize the VAR results, the most striking finding is evidence of interaction between the US-based ADS index and both Global equity and Global asset turbulence, up to 10 business days or two weeks. Moreover, it appears that the turbulence index for European equities leads the US-based ADS index.

3.3 Copula Models

An important statistical aspect of the relation between real and financial sectors involves dependence of higher moments. Thus far, our estimation strategy has focused on second moments. It is desirable to utilize

[4]We are grateful to State Street for providing us with their turbulence indices. We are also grateful to Professor Frank Diebold for making his business index available on his website.

[5]All indices are stationary, so unlike the annual data from the previous section, no cointegration tests are necessary. For the VARS, we use ten lags as a tradeoff between minimizing AIC and model parsimony.

dependence functions that can capture the entire structure of dependence, not just second moments. Copulas are a useful class of measures that can characterize dependence structure of data series.[6] A copula $C(\cdot)$ is a joint distribution with uniform marginals. The bivariate representation is therefore

$$C(u,v) = \Pr[U \leq u, V \leq v],$$

where U and V are uniformly distributed.[7] Intuitively, copulas "couple" or join marginals into a joint distribution, and summarize the dependence structure between variables (Sklar (1959)). In particular, for any joint distribution $F_{X,Y}(x,y)$ with marginals $F_X(x)$ and $F_Y(y)$, we can write the distribution as

$$F_{X,Y}(x,y) = C(F_X(x), F_Y(y)). \tag{1}$$

For empirical implementation, we differentiate equation (1) and use a corresponding density version

$$f(x,y) = c(F_X(x), F_Y(y)) \cdot f_X(x) \cdot f_Y(y), \tag{2}$$

where $f(x,y)$ and $c(F_X, F_Y)$ are the joint and copula densities, respectively. In the sequel, we estimate dependence parameters in (2), for different copula specifications.

Static Copulas. There are a number of parametric copula specifications. We estimate three families, the normal, the student-t, and the Clayton copulas. These copulas are well known and displayed in Table 1. They possess different tail dependence properties: the normal has no tail dependence, the t has symmetric dependence, and the Clayton has asymmetric dependence. We also utilize the Symmetrized Joe Clayton copula, as presented in the Appendix. This copula is very flexible since it allows for both asymmetric upper and lower tail dependence, with symmetric dependence as a special case. The above copulas represent the most important shapes for economics, and are frequently used in recent research.[8] Copula estimation requires that the series be independently and identically distributed, so we first filter the data with ARMA-GARCH models. In particular, we utilize a combination of an AR(30) and asymmetric GARCH model.[9] We then compute the empirical distributions of the filtered variables, which are used to estimate the copula parameters by maximum likelihood.[10]

Results for Static Dependence. The estimates for static copulas are in Table 10. Our main finding is that dependence is typically lower than in previous estimates. For example, in Table 5, the correlation between ADS and US Treasury was estimated to be -0.28, while in the current table, dependence ρ (in Panels A and

[6]For background on copulas, see Embrechts et al. (2005).
[7]See and Cherubini et al. (2004); and Embrechts (2009).
[8]See Patton (2006); Rosenberg and Schuermann (2006); and Chollete et al. (2009).
[9]Further details of the filtering procedure are available from the authors, upon request.
[10] For statistical properties of the estimates, see Joe (1997), and Chen and Fan (2006).

B) is less than one-third that value, at -0.0082. In addition, the tail dependence in Panel C is close to zero for all series. Thus, when we estimate static copula models, there seems to be little dependence between the variables. In order to examine the robustness of this finding, we consider a simple dynamic dependence model below.

Regime-Switching Copulas. We examine the possibility of time varying dependence in the data, which may be masked from a simple static copula. There are several methods to assess dynamic dependence, including conditional copulas (Patton (2006)), dynamic conditional correlation (Cappiello et al. (2006)), and regime-switching copulas (Chollete et al. (2009)). Our individual marginal series display complex structures which could easily defy parametric estimation, so we decided not to use the dynamic conditional correlation model, as it involves a joint parametric estimation of marginals and correlations. We applied the conditional copula of Patton (2006) to our data, using asymmetric copulas, which did not fit very well and had very low densities near the tails. This implies that a regime-switching copula with no tail dependence might be appropriate for our data. We therefore elected to use a mixture of normal copulas.

Results for Dynamic Dependence. The regime-switching copula results are in Table 11. In contrast to the previous static dependence results, many variables in this table display rich dependence dynamics, with two quite different regimes of high dependence (ρ_1) and low dependence (ρ_2). For example, the currency turbulence index exhibits a statistically significant high dependence regime with a value of 0.01654, as well as a negative dependence regime of -0.03078. The unconditional probability for the positive dependence regime is given by $\phi_1 = 0.6487$: thus, in high frequency data, the US real economy is positively related with currency turbulence nearly 2/3 of the time. A similar split between positive and negative dependence occurs for all variables in Table 11, with most of them statistically significant for the positive dependence regime. This finding underscores that a finding of zero correlation in a static model can mask important dynamic dependence patterns.

3.4 Summary and Implications

Research on extreme events has burgeoned in the last few years, in wake of the financial crisis. One important aspect of extreme events is temporal heterogeneity: they may occur within a single day, or manifest themselves over long, protracted periods. Taking such heterogeneity seriously involves examining extreme events at different frequencies. We therefore analyze both annual and daily data. For annual data we find little evidence of cointegration. At both low and high frequencies, we uncover significant dependence and predictive ability for important classes of financial extreme events and the real economy.

When we examine copula based measures for the high frequency data, we obtain a further insight into the dependence structure of the real and financial sectors. Static copulas suggest little evidence of tail dependence, while regime-switching copulas uncover rich dynamics between the real and financial sectors.

In many instances the US real economy and turbulence indices alternate between two distinct regimes of positive and negative dependence.

There are a number of implications of these findings. The lack of cointegration in annual data suggests that in the long run the frequency of disasters in the financial sector does not necessarily reflect structural weaknesses in the real economy. The predictability of the Barro disaster index (annual data), and feedback between the ADS real economy index and global financial turbulence measures (daily data) suggest that policymakers may use some disaster measures as warning signs for other extreme events. The (daily data) evidence on time varying dependence between the real economy and financial sector may also be useful for policy analysis.

4 Conclusions

In this paper we analyze several indices of disasters in the real economy and financial markets. These indices cover disasters in the real and financial sectors, and include annual and daily frequency. For the annual frequency, we utilize data similar to Barro (2009) and Reinhart and Rogoff (2009b). We find that the dependence between crises in the real and financial sectors, increases over time for emerging markets, but decreases over time for OECD countries. We find little evidence of cointegration of disasters except in emerging markets. In addition, we document strong persistence at the one year and two year horizons for real-economy disasters.

For the higher frequency data, we utilize the turbulence indices of State Street, which measure large movements in various US and global asset classes, and the daily business conditions index (ADS) of Aruoba et al. (2009). Surprisingly, we discover little relation between turbulence in US equity and the real economy. We uncover interesting interaction up to two weeks out for the US economy and global turbulence. Last of all, dynamic copulas uncover rich dynamics between the real and financial sectors: The US real economy and many turbulence indices appear to alternate between two distinct regimes of positive and negative dependence. In sum, our paper documents significant dependence and predictive ability for important classes of financial extreme events and the real economy, at both annual and daily frequency.

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A Functional Forms of Copulas

Table 1: Distribution of various copulas

Copula	Distribution	Parameter Range	Complete Dependence	Independence
Normal	$C_N(u,v;\rho) = \Phi_\rho(\Phi^{-1}(u), \Phi^{-1}(v))$	$\rho \in (-1,1)$	$\rho = 1$, or-1	$\rho = 0$
Student-t	$C_t(u,v;\rho,d) = t_{d,\rho}(t_d^{-1}(u), t_d^{-1}(v))$	$\rho \in (-1,1)$	$\rho = 1$, or-1	$\rho = 0$
Clayton	$C_c(u,v) = (u^{-\theta} + v^{-\theta} - 1)^{-1/\theta}$	$\theta \geq 0$	$\theta = \infty$	$\theta = 0$

$\Phi_\rho(x,y)$ and $t_{\nu,\rho}(x,y)$ denote the standard bivariate normal and Student-*t* cumulative distributions, respectively: $\Phi_\rho(x,y) = \int_{-\infty}^{x}\int_{-\infty}^{y} \frac{1}{2\pi|\Sigma|} \exp\{-\frac{1}{2}(x\ \ y)\Sigma^{-1}(x\ \ y)'\}dxdy$, and $t_{\nu,\rho}(x,y) = \int_{-\infty}^{x}\int_{-\infty}^{y} \frac{\Gamma(\frac{\nu+2}{2})}{\Gamma(\nu/2)(\nu\pi)|\Sigma|^{1/2}}\{1 + (s\ \ t)\Sigma^{-1}(s\ \ t)'/\nu\}^{\frac{-(\nu+2)}{2}} dsdt$. The correlation matrix is given by $\Sigma = \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$.

Symmetrised Joe-Clayton (SJC) Copula. The SJC copula of Patton (2006) is constructed as

$$C_{SJC}(u,v|\lambda_r,\lambda_l) = 0.5 \times (C_{JC}(u,v|\lambda_r,\lambda_l) + C_{JC}(1-u, 1-v|\lambda_l,\lambda_r) + u + v - 1), \quad (3)$$

where $C_{JC}(u,v|\lambda_r,\lambda_l)$ denotes the Joe-Clayton copula. The Joe-Clayton copula is in turn defined as

$$C_{JC}(u,v|\lambda_r,\lambda_l) = 1 - (1 - \left\{\left[1-(1-u)^k\right]^{-r} + \left[1-(1-v)^k\right]^{-r} - 1\right\}^{-1/r})^{1/k},$$

where $k = 1/log_2(2-\lambda_r)$, $r = -1/log_2(\lambda_l)$, and λ_l and $\lambda_r \in (0,1)$. The SJC copula is symmetric when λ_l=λ_r.

Figure 1: Comparison of Average TI and Stock Market Crash Index

The figure shows the interrelation of two extreme event indices: the Reinhart-Rogoff index and the Turbulence Index (TI). SS MeanTI and R MarketCrash denote the average annual State Street Index, and a Stock Crash index based on the Reinhart-Rogoff data, respectively. European countries in the Reinhart index are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK.

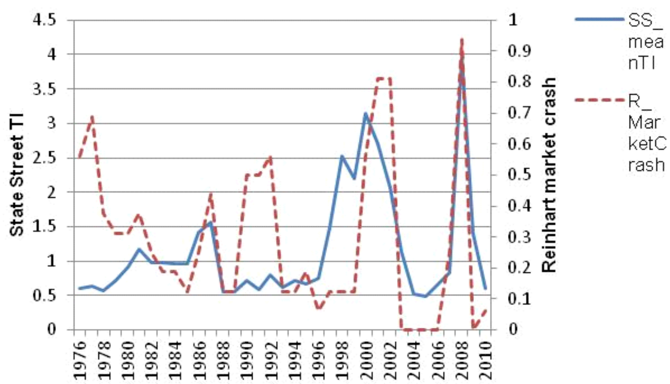

Figure 2: Comparison of Volatility of TI and Stock Market Crash Index

The figure shows the interrelation of two extreme event indices: the Reinhart-Rogoff index and the Turbulence Index (TI). SS stdTI and R MarketCrash denote the annual volatility of the State Street Index, and a Stock Crash index based on the Reinhart-Rogoff data, respectively. European countries in the Reinhart index are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK.

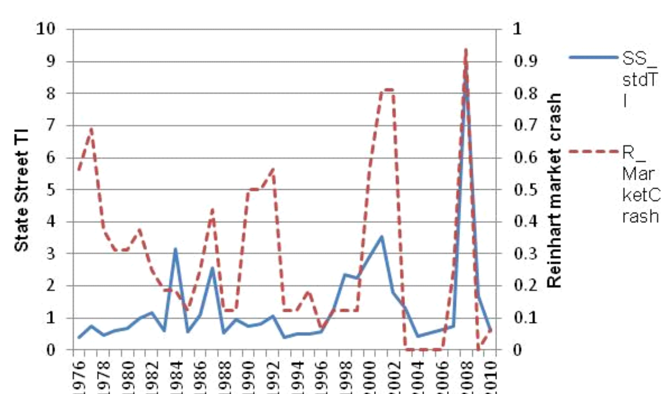

Table 2: Correlations of Barro and Reinhart-Rogoff Disaster Measures

The table presents Pearson correlation estimates for various disaster measures based on Barro (2009) and Reinhart and Rogoff (2009b). Each index is based on at least two types of disasters. For any given year, Barro and Reinhart disaster indicators for a country are 1 if a disaster of that type was present in that country during that year, and zero otherwise. Barro index is based on GDP and Consumption disasters. Under this index, the maximum disaster number a country can be assigned in any given year is 2. Reinhart Financial Economy (FE) index is based on the stock market and sovereign debt (both domestic and external) disasters. Under this index, the maximum disaster number a country can be assigned in any given year is 3. Reinhart Real Economy (RE) index is based on the currency, inflation and banking disasters. Under this index, the maximum disaster number a country can be assigned in any given year is 3. Reinhart Total Index (TI) is based on the stock market, sovereign debt, currency, inflation and banking disasters. Under this index, the maximum disaster number a country can be assigned in any given year is 6. To create annual indices, we average the number of disasters for all countries included in the index, then divide by the number of types of disasters the index contains. 'OECD' denotes OECD countries, and includes Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, UK, and the USA. 'EM' denotes emerging markets, and includes Argentina, Brazil, Chile, Colombia, India, Korea, Malaysia, Mexico, Peru, Singapore, Turkey, Uruguay, and Venezuela. 'All' includes both OECD and emerging countries. The full sample is from 1900 to 2009. P-values are in parentheses.

Panel A: Reinhart FE vs. Reinhart RE

	All Countries		*OECD Countries*		*Emerging Markets*	
	Correlation		Correlation		Correlation	
1900 - 2009	0.4046	(< 0.0001)	0.3708	(< 0.0001)	0.4892	(< 0.0001)
1900 - 1969	0.4935	(< 0.0001)	0.5229	(< 0.0001)	0.2191	(0.0684)
1970 - 2009	0.3455	(0.0290)	0.1653	(0.3080)	0.5554	(0.0002)

Panel B: Barro vs. Reinhart FE

	All Countries		*OECD Countries*		*Emerging Markets*	
	Correlation		Correlation		Correlation	
1900 - 2009	0.0669	(0.4876)	0.3715	(< .0001)	0.1102	(0.2518)
1900 - 1969	0.3334	(0.0048)	0.4989	(< 0.0001)	-0.0377	(0.7565)
1970 - 2009	0.6323	(< .0001)	0.4080	(0.0090)	0.6844	(< .0001)

Panel C: Barro vs. Reinhart RE

	All countries		*OECD*		*EM*	
	Correlation		Correlation		Correlation	
1900 - 2009	0.3270	(0.0005)	0.3702	(< .0001)	0.2844	(0.0026)
1900 - 1969	0.4526	(< .0001)	0.4973	(< .0001)	0.2270	(0.0588)
1970 - 2009	0.6323	(< .0001)	0.4080	(0.0090)	0.6844	(< .0001)

Panel D: Barro vs. Reinhart All

	All countries		*OECD*		*EM*	
	Correlation		Correlation		Correlation	
1900 - 2009	0.2217	(0.0199)	0.4577	(< .0001)	0.1931	(0.0433)
1900 - 1969	0.4457	(0.0001)	0.5567	(< .0001)	0.1129	(0.3520)
1970 - 2009	0.6317	(< .0001)	0.4012	(0.0103)	0.7256	(< .0001)

Table 3: Cointegration Tests for Crisis Measures

The table presents results from the cointegration test of Engle and Granger (1987). We test whether the various crisis measures are cointegrated. Reinhart Financial Economy (FE) index is based on the stock market and sovereign debt (both domestic and external) disasters. Reinhart Real Economy (RE) index is based on the currency, inflation and banking disasters. Reinhart Total Index (TI) is based on the stock market, sovereign debt, currency, inflation and banking disasters. 'OECD' denotes OECD countries, and includes Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, UK, and the USA. 'EM' denotes emerging markets, and includes Argentina, Brazil, Chile, Colombia, India, Korea, Malaysia, Mexico, Peru, Singapore, Turkey, Uruguay, and Venezuela. 'All' includes both OECD and emerging countries. F denotes the F-statistic from testing the null hypothesis $\alpha = 0, \beta = 1$. The full sample is from 1900 to 2009. P-values are in parentheses.

	F	p-value
Panel A: Reinhart FE vs. Reinhart RE		
$FEI_{ALL} = \alpha + \beta * REI_{ALL}$	11.79	(< 0.0001)
$FEI_{OECD} = \alpha + \beta * REI_{OECD}$	34.88	(< 0.0001)
$FEI_{EM} = \alpha + \beta * REI_{EM}$	1.74	(0.1802)
Panel B: Barro vs. Reinhart FE		
$FEI_{ALL} = \alpha + \beta * Barro_{ALL}$	186.08	(< 0.0001)
$FEI_{OECD} = \alpha + \beta * Barro_{OECD}$	305.67	(< 0.0001)
$FEI_{EM} = \alpha + \beta * Barro_{EM}$	38.94	(< 0.0001)
Panel C: Barro vs. Reinhart RE		
$REI_{ALL} = \alpha + \beta * Barro_{ALL}$	247.14	(< 0.0001)
$REI_{OECD} = \alpha + \beta * Barro_{OECD}$	271.34	(< 0.0001)
$REI_{EM} = \alpha + \beta * Barro_{EM}$	153.97	(< 0.0001)
Panel D: Barro vs. Reinhart all		
$FEI_{ALL} = \alpha + \beta * Barro_{ALL}$	304.41	(< 0.0001)
$FEI_{OECD} = \alpha + \beta * Barro_{OECD}$	441.00	(< 0.0001)
$FEI_{EM} = \alpha + \beta * Barro_{EM}$	88.60	(< 0.0001)

Table 4: VAR Analysis of Predictability for Crisis Measures

The table presents the results of a vector autoregression (VAR) analysis of the various crisis measures. The optimal lag length is determined by the Akaike Information Criterion (AIC). The equation system is of the form

$$\Delta Y_t = \alpha_1 + \sum_{k=1}^{p} \beta_{1k} \Delta Y_{t-k} + \sum_{k=1}^{p} \lambda_{1k} \Delta X_{t-k} + \epsilon_{1t}$$

$$\Delta X_t = \alpha_2 + \sum_{k=1}^{p} \beta_{2k} \Delta Y_{t-k} + \sum_{k=1}^{p} \lambda_{2k} \Delta X_{t-k} + \epsilon_{2t},$$

where Y and X comprise the various disaster and crisis measures. Estimation is performed by least squares. 'OECD' denotes OECD countries, and includes Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, UK, and the USA. 'EM' denotes emerging markets, and includes Argentina, Brazil, Chile, Colombia, India, Korea, Malaysia, Mexico, Peru, Singapore, Turkey, Uruguay, and Venezuela. 'All' includes both OECD and emerging countries. * and ** denote significance at the 95 percentile and 99-percentile, respectively. The full sample is from 1900 to 2009. P-values are in parentheses.

Model 1: Reinhart RE vs. Reinhart FE

		ΔREI_{t-1}	ΔREI_{t-2}	ΔREI_{t-3}	ΔFEI_{t-1}	ΔFEI_{t-2}	ΔFEI_{t-3}
All	ΔREI_t	-0.1926	-0.3318**	-0.0840	-0.0624	-0.1342	0.1352
	ΔFEI_t	0.2940**	0.1659	0.1682	-0.4262**	-0.2683*	0.0651
OECD	ΔREI_t	-0.1149	-0.3473**	-0.0558	-0.0652	-0.1558	0.1224
	ΔFEI_t	0.2592*	0.1771	0.2336*	-0.4709**	-0.3094**	0.0214
EM	ΔREI_t	-0.3799**	-0.3622**	-0.1174	0.1185	0.0156	0.1120
	ΔFEI_t	0.2189	0.1229	-0.0358	-0.3621**	-0.1910	-0.1471

Model 2: Barro vs. Reinhart FE

		ΔBI_{t-1}	ΔBI_{t-2}	ΔBI_{t-3}	ΔFEI_{t-1}	ΔFEI_{t-2}	ΔFEI_{t-3}
All	ΔBI_t	0.3671**	0.0649	0.0616	-0.1796	-0.4241**	-0.2372
	ΔFEI_t	0.0835	0.1472	0.0263	-0.3421**	-0.2518*	0.0528
OECD	ΔBI_t	0.3131**	0.0188	0.1042	-0.2378	-0.2699	-0.1648
	ΔFEI_t	0.0226	0.1084	0.1131	-0.3788**	-0.2585*	0.0047
EM	ΔBI_t	0.3115**	-0.1012	0.0171	0.0632	-0.2300	-0.1342
	ΔFEI_t	0.1876*	0.0529	0.0355	-0.3892**	-0.2366*	-0.1530

Model 3: Barro vs. Reinhart RE

		ΔBI_{t-1}	ΔBI_{t-2}	ΔBI_{t-3}	ΔREI_{t-1}	ΔREI_{t-2}	ΔREI_{t-3}
All	ΔBI_t	0.3950**	-0.0209	0.0086	-0.0062	-0.0441	-0.0449
	ΔREI_t	0.0757	0.0870	0.0713	-0.2865*	-0.4152**	-0.1548
OECD	ΔBI_t	0.2974**	-0.0170	0.0562	0.0637	0.0099	0.0446
	ΔREI_t	0.0806	0.0218	0.0132	-0.1864	-0.3843**	-0.0945
EM	ΔBI_t	0.3255**	-0.0998	-0.0007	-0.1405	-0.2195	-0.0767
	ΔREI_t	0.0476	0.1208	0.1284	-0.4365**	-0.3848**	-0.1655

Model 4: Barro vs. Reinhart All

		ΔBI_{t-1}	ΔBI_{t-2}	ΔBI_{t-3}	ΔTI_{t-1}	ΔTI_{t-2}	ΔTI_{t-3}
All	ΔBI_t	0.3853**	0.0393	0.0280	-0.0825	-0.3400*	-0.1610
	ΔTI_t	0.0639	0.1309	0.0210	-0.2633*	-0.3650**	0.0499
OECD	ΔBI_t	0.3158**	0.0026	0.0671	-0.1017	-0.1253	-0.0435
	ΔTI_t	0.0315	0.0759	0.0305	-0.2288*	-0.2973*	0.0754
EM	ΔBI_t	0.3066**	-0.0648	0.0119	0.0128	-0.4248*	-0.1455
	ΔTI_t	0.1088	0.0817	0.0753	-0.3085**	-0.3055*	-0.1301

Table 5: Correlations of High Frequency Disaster Measures

The table presents Pearson and Spearman correlation estimates for various financial turbulence measures with the real economy index (ADS Index) of Aruoba et al. (2009). The Turbulence indices, denoted TI, are in the first column, and are provided by State Street. The turbulence indices are based on the multivariate distance away from a benchmark level in the particular asset class, as described in Kritzman and Li (2010). Currency TI is the turbulence index calculated for a basket of currencies; Europe Equity TI is the index calculated for a basket of European stocks; Global Asset TI is the index calculated for a basket of international assets; Global Equity TI is the index calculated for a basket of international stock indices; Sovereign Debt TI is the index calculated for a basket of sovereign debt instruments; US credit TI is the index calculated for US credit instruments; US Equity TI is the index calculated for a basket of US stocks; US Fixed Income TI is the index calculated for a basket of US corporate bonds; and US Treasury TI is the index calculated for a basket of US government bonds. The data sample is of daily frequency. P-values are in parentheses.

		ADS Index	
		Estimate	
Currency TI	Pearson	-0.1038	(< 0.0001)
	Spearman	-0.1358	(< 0.0001)
EuropeEquityTI	Pearson	-0.1450	(< 0.0001)
	Spearman	-0.1069	(< 0.0001)
Global Asset TI	Pearson	-0.2431	(< 0.0001)
	Spearman	-0.1274	(< 0.0001)
Global Equity TI	Pearson	-0.1373	(< 0.0001)
	Spearman	-0.1422	(< 0.0001)
Sovereign Debt TI	Pearson	-0.0730	(< 0.0001)
	Spearman	0.0285	(0.0389)
US Credit TI	Pearson	-0.2989	(< 0.0001)
	Spearman	-0.2784	(< 0.0001)
US Equity TI	Pearson	-0.1267	(< 0.0001)
	Spearman	-0.0808	(< 0.0001)
US Fixed Income TI	Pearson	-0.2463	(< 0.0001)
	Spearman	-0.2561	(< 0.0001)
US Treasury TI	Pearson	-0.2828	(< 0.0001)
	Spearman	-0.2812	(< 0.0001)

Table 6: VAR Analysis of Predictability for Daily Crisis Measures: ADS Index and US Equity

The table presents the results of a vector autoregression (VAR) analysis of the daily business index (ADS) of Aruoba et al. (2009) and the State Street Turbulence Index for US equities. The optimal lag length is determined by the Akaike Information Criterion (AIC). The equation system is of the form

$$\Delta Y_t = \alpha_1 + \sum_{k=1}^{p} \beta_{1k} \Delta Y_{t-k} + \sum_{k=1}^{p} \lambda_{1k} \Delta X_{t-k} + \epsilon_{1t}$$

$$\Delta X_t = \alpha_2 + \sum_{k=1}^{p} \beta_{2k} \Delta Y_{t-k} + \sum_{k=1}^{p} \lambda_{2k} \Delta X_{t-k} + \epsilon_{2t},$$

where Y and X denote the ADS index and US equity turbulence index. Estimation is performed by least squares. The data frequency is daily. P-values are in parentheses.

	ADS (t)		*US Equity(t)*	
	Estimate		Estimate	
ADS (t-1)	1.3674	(0.0001)	-0.7467	(0.5782)
ADS (t-2)	-0.1328	(0.0001)	0.6895	(0.7620)
ADS (t-3)	-0.0967	(0.0001)	0.2657	(0.9072)
ADS (t-4)	-0.0657	(0.0002)	-0.6572	(0.7728)
ADS (t-5)	0.7713	(0.0001)	1.3481	(0.4023)
ADS (t-6)	-1.1966	(0.0001)	-0.4220	(0.7931)
ADS (t-7)	0.1366	(0.0001)	-0.5979	(0.7927)
ADS (t-8)	0.0946	(0.0001)	0.0956	(0.9665)
ADS (t-9)	0.0607	(0.0005)	-0.4972	(0.8270)
ADS (t-10)	0.0605	(0.0001)	0.4777	(0.7218)
US Equity(t-1)	0.0000	(0.8879)	0.4169	(0.0001)
US Equity(t-2)	-0.0001	(0.3786)	0.0287	(0.0100)
US Equity(t-3)	0.0001	(0.1308)	0.0461	(0.0001)
US Equity(t-4)	-0.0001	(0.4230)	0.0521	(0.0001)
US Equity(t-5)	-0.0000	(0.6622)	0.0500	(0.0001)
US Equity(t-6)	0.0000	(0.6086)	0.0475	(0.0001)
US Equity(t-7)	-0.0001	(0.4937)	0.0426	(0.0001)
US Equity(t-8)	0.0000	(0.8525)	0.0379	(0.0007)
US Equity(t-9)	0	(0.9537)	0.0422	(0.0002)
US Equity(t-10)	-0.0001	(0.0696)	0.0463	(0.0001)

Table 7: VAR Analysis of Predictability for Daily Crisis Measures: ADS Index and European Equity

The table presents the results of a vector autoregression (VAR) analysis of the daily business index (ADS) of Aruoba et al. (2009) and the State Street Turbulence Index for European equities. The optimal lag length is determined by the Akaike Information Criterion (AIC). The equation system is of the form

$$\Delta Y_t = \alpha_1 + \sum_{k=1}^{p} \beta_{1k} \Delta Y_{t-k} + \sum_{k=1}^{p} \lambda_{1k} \Delta X_{t-k} + \epsilon_{1t}$$

$$\Delta X_t = \alpha_2 + \sum_{k=1}^{p} \beta_{2k} \Delta Y_{t-k} + \sum_{k=1}^{p} \lambda_{2k} \Delta X_{t-k} + \epsilon_{2t},$$

where Y and X denote the ADS index and the European Equity Turbulence index, respectively. Estimation is performed by least squares. The data frequency is daily. P-values are in parentheses.

	ADS (t)		*European Equity(t)*	
	Estimate		Estimate	
ADS (t-1)	1.3682	(0.0001)	-2.8634	(0.1296)
ADS (t-2)	-0.1329	(0.0001)	-0.5894	(0.8540)
ADS (t-3)	-0.0976	(0.0001)	4.0816	(0.2032)
ADS (t-4)	-0.0655	(0.0002)	1.6759	(0.6007)
ADS (t-5)	0.7710	(0.0001)	0.1569	(0.9447)
ADS (t-6)	-1.1974	(0.0001)	-1.7415	(0.4413)
ADS (t-7)	0.1371	(0.0001)	2.8365	(0.3753)
ADS (t-8)	0.0962	(0.0001)	-4.4194	(0.1679)
ADS (t-9)	0.0603	(0.0006)	-1.9270	(0.5471)
ADS (t-10)	0.0599	(0.0001)	2.6955	(0.1533)
European Equity(t-1)	0.0001	(0.1440)	0.4541	(0.0001)
European Equity(t-2)	0.0000	(0.7305)	0.0770	(0.0001)
European Equity(t-3)	-0.0001	(0.0659)	-0.0479	(0.0001)
European Equity(t-4)	-0.0000	(0.9122)	0.0386	(0.0007)
European Equity(t-5)	**-0.0001**	(0.0242)	0.0516	(0.0001)
European Equity(t-6)	**0.0002**	(0.0118)	0.0615	(0.0001)
European Equity(t-7)	0	(0.9706)	-0.0005	(0.9625)
European Equity(t-8)	-0.0000	(0.5408)	0.0542	(0.0001)
European Equity(t-9)	0.0001	(0.1279)	-0.0007	(0.9481)
European Equity(t-10)	**-0.0002**	(0.0030)	0.0819	(0.0001)

Table 8: VAR Analysis of Predictability for Daily Crisis Measures: ADS Index and Global Equity

The table presents the results of a vector autoregression (VAR) analysis of the daily business index (ADS) of Aruoba et al. (2009) and the State Street Turbulence Index for Global Equities. The optimal lag length is determined by the Akaike Information Criterion (AIC). The equation system is of the form

$$\Delta Y_t = \alpha_1 + \sum_{k=1}^{p} \beta_{1k} \Delta Y_{t-k} + \sum_{k=1}^{p} \lambda_{1k} \Delta X_{t-k} + \epsilon_{1t}$$

$$\Delta X_t = \alpha_2 + \sum_{k=1}^{p} \beta_{2k} \Delta Y_{t-k} + \sum_{k=1}^{p} \lambda_{2k} \Delta X_{t-k} + \epsilon_{2t},$$

where Y and X denote the ADS index and the Global Equity turbulence index, respectively. Estimation is performed by least squares. The data frequency is daily. P-values are in parentheses.

	ADS (t)		*Global Equity(t)*	
	Estimate		Estimate	
ADS (t-1)	1.3692	(0.0001)	-2.6994	(0.0893)
ADS (t-2)	-0.1358	(0.0001)	2.6124	(0.3323)
ADS (t-3)	-0.0969	(0.0001)	-1.3798	(0.6093)
ADS (t-4)	-0.0633	(0.0003)	2.6897	(0.3182)
ADS (t-5)	0.7704	(0.0001)	1.2388	(0.5150)
ADS (t-6)	-1.1990	(0.0001)	-0.9437	(0.6199)
ADS (t-7)	0.1405	(0.0001)	-1.7729	(0.5103)
ADS (t-8)	0.0939	(0.0008)	2.3596	(0.3818)
ADS (t-9)	0.0588	(0.0001)	**-5.2802**	(0.0500)
ADS (t-10)	0.0614	(0.0001)	**3.1157**	(0.0497)
Global Equity(t-1)	0.0001	(0.0566)	0.2993	(0.0001)
Global Equity(t-2)	**-0.0002**	(0.0330)	0.0860	(0.0001)
Global Equity(t-3)	0.0001	(0.1529)	0.0428	(0.0001)
Global Equity(t-4)	-0.0001	(0.2953)	0.1138	(0.0001)
Global Equity(t-5)	-0.0001	(0.0977)	0.0393	(0.0003)
Global Equity(t-6)	**0.0002**	(0.0017)	0.0138	(0.2024)
Global Equity(t-7)	**-0.0002**	(0.0304)	0.0327	(0.0024)
Global Equity(t-8)	0	(0.9433)	0.0424	(0.0001)
Global Equity(t-9)	0.0000	(0.6078)	0.0330	(0.0021)
Global Equity(t-10)	**-0.0002**	(0.0097)	0.0940	(0.0001)

Table 9: VAR Analysis of Predictability for Daily Crisis Measures: ADS Index and Global Assets

The table presents the results of a vector autoregression (VAR) analysis of the daily business index (ADS) of Aruoba et al. (2009) and the State Street Turbulence Index for Global Assets. The optimal lag length is determined by the Akaike Information Criterion (AIC). The equation system is of the form

$$\Delta Y_t = \alpha_1 + \sum_{k=1}^{p} \beta_{1k} \Delta Y_{t-k} + \sum_{k=1}^{p} \lambda_{1k} \Delta X_{t-k} + \epsilon_{1t}$$

$$\Delta X_t = \alpha_2 + \sum_{k=1}^{p} \beta_{2k} \Delta Y_{t-k} + \sum_{k=1}^{p} \lambda_{2k} \Delta X_{t-k} + \epsilon_{2t},$$

where Y and X denote the ADS index and the Global Asset turbulence index, respectively. Estimation is performed by least squares. The data frequency is daily. P-values are in parentheses.

	ADS (t)		*Global Asset (t)*	
	Estimate		Estimate	
ADS (t-1)	1.3637	(0.0001)	-3.3980	(0.2889)
ADS (t-2)	-0.1226	(0.0001)	-2.7971	(0.6060)
ADS (t-3)	-0.0973	(0.0002)	0.9541	(0.8605)
ADS (t-4)	-0.0710	(0.0066)	**16.1360**	(0.0029)
ADS (t-5)	0.7557	(0.0001)	**-8.2245**	(0.0348)
ADS (t-6)	-1.1775	(0.0001)	-1.8006	(0.6438)
ADS (t-7)	0.1288	(0.0001)	4.7498	(0.3805)
ADS (t-8)	0.0938	(0.0003)	-0.1312	(0.9807)
ADS (t-9)	0.0653	(0.0125)	**-17.3266**	(0.0014)
ADS (t-10)	0.0605	(0.0001)	**11.6695**	(0.0003)
Global Asset (t-1)	0.0000	(0.7493)	0.1121	(0.0001)
Global Asset (t-2)	**-0.0002**	(0.0071)	0.16276	(0.0001)
Global Asset (t-3)	-0.0001	(0.1706)	0.10399	(0.0001)
Global Asset (t-4)	0.0001	(0.3920)	0.0095	(0.5482)
Global Asset (t-5)	**0.0002**	(0.0136)	0.1645	(0.0001)
Global Asset (t-6)	0.0001	(0.5101)	0.0205	(0.1928)
Global Asset (t-7)	-0.0000	(0.5636)	0.0284	(0.0719)
Global Asset (t-8)	-0.0001	(0.5243)	-0.0094	(0.5489)
Global Asset (t-9)	0.0000	(0.5895)	0.0561	(0.0003)
Global Asset (t-10)	**-0.0002**	(0.0026)	0.0815	(0.0001)

Table 10: Static Copula Models for High Frequency Disaster Measures

The table presents dependence estimates for various financial turbulence measures with the real economy index (ADS Index) of Aruoba et al. (2009). The Turbulence indices, denoted TI, are in the first column, and are provided by State Street. These data are first filtered using a combination of an autoregressive AR(30) model and an asymmetric GARCH(1,1) model. Then the copula parameters are estimated by maximum likelihood. Specific copula functional forms are in the Appendix and Table 1. The turbulence indices are based on the multivariate distance away from a benchmark level in the particular asset class, as described in Kritzman and Li (2010). Currency TI is the turbulence index calculated for a basket of currencies; Europe Equity TI is the index calculated for a basket of European stocks; Global Asset TI is the index calculated for a basket of international assets; Global Equity TI is the index calculated for a basket of international stock indices; Sovereign Debt TI is the index calculated for a basket of sovereign debt instruments; US credit TI is the index calculated for US credit instruments; US Equity TI is the index calculated for a basket of US stocks; US Fixed Income TI is the index calculated for a basket of US corporate bonds; and US Treasury TI is the index calculated for a basket of US government bonds. The data sample is of daily frequency with various starting dates described in section 2.2 and ending on December 31, 2011. ν denotes the degrees of freedom for the t-copula. ρ denotes the correlation coefficient. τ_L and τ_H denote left and right tail dependence. Standard errors are in parentheses to the right of estimates.

Panel A: Normal Copula

	ρ		AIC	BIC
Currency TI	0.0018	(0.0106)	1.97	9.06
Europe Equity TI	-0.0094	(0.0103)	1.17	8.32
Global Asset TI	0.0044	(0.0155)	1.92	8.26
Global Equity TI	-0.0061	(0.0103)	1.65	8.80
Sovereign Debt TI	0.0323	(0.0138)	-3.46	3.11
US Credit TI	0.0248	(0.0184)	0.18	6.18
US Equity TI	-0.0038	(0.0103)	1.87	9.02
US Fixed Income TI	0.0072	(0.0206)	1.88	7.66
US Treasury TI	-0.0080	(0.0184)	1.81	7.81

Panel B: t Copula

	ρ		ν		AIC	BIC
Currency TI	0.0018	(0.0107)	21.5964	(5.5184)	-15.23	-8.13
Europe Equity TI	-0.0091	(0.0105)	54.4166	(2.7813)	-1.77	5.38
Global Asset TI	0.0047	(0.0142)	23.9136	(9.6088)	-4.45	1.89
Global Equity TI	-0.0057	(0.0106)	36.3485	(17.2405)	-5.56	1.59
Sovereign Debt TI	0.0326	(0.0157)	35.3439	(12.3584)	-7.11	-0.54
US Credit TI	0.0244	(0.0192)	41.5133	(29.6184)	-1.58	4.42
US Equity TI	-0.0028	(0.0110)	39.5296	(15.3291)	-4.05	3.10
US Fixed Income TI	0.0065	(0.0196)	99.0167	(0.0174)	2.14	7.92
US Treasury TI	-0.0082	(0.0170)	54.8427	(53.7527)	0.89	6.89

Panel C: SJC Copula

	τ_L		τ_H		AIC	BIC
Currency TI	0.0000	(0.0031)	0.0000	(0.0020)	10.10	17.19
Europe Equity TI	0.0000	(0.0026)	0.0000	(0.0012)	24.08	31.23
Global Asset TI	0.0000	(0.0012)	0.0000	(0.0013)	5.33	11.68
Global Equity TI	0.0000	(0.0339)	0.0000	(0.0015)	19.56	26.71
Sovereign Debt TI	0.0000	(0.0000)	0.0009	(0.0002)	-9.50	-2.93
US Credit TI	0.0000	(0.0000)	0.0027	(0.0000)	-5.81	0.19
US Equity TI	0.0000	(0.0012)	0.0000	(0.0114)	19.04	26.19
US Fixed Income TI	0.0000	(0.0000)	0.0003	(0.0000)	1.02	6.80
US Treasury TI	0.0000	(0.0000)	0.0003	(0.0001)	5.15	11.15

Table 11: Regime-Switching Copula Model for High Frequency Disaster Measures

The table presents dynamic copula estimates for various financial turbulence measures with the real economy index (ADS Index) of Aruoba et al. (2009). The Turbulence indices, denoted TI, are in the first column, and are provided by State Street. These data are filtered using a combination of an autoregressive AR(30) model and a symmetric GARCH(1,1) model. The turbulence indices are based on the multivariate distance away from a benchmark level in the particular asset class, as described in Kritzman and Li (2010). Currency TI is the turbulence index calculated for a basket of currencies; Europe Equity TI is the index calculated for a basket of European stocks; Global Asset TI is the index calculated for a basket of international assets; Global Equity TI is the index calculated for a basket of international stock indices; Sovereign Debt TI is the index calculated for a basket of sovereign debt instruments; US credit TI is the index calculated for US credit instruments; US Equity TI is the index calculated for a basket of US stocks; US Fixed Income TI is the index calculated for a basket of US corporate bonds; and US Treasury TI is the index calculated for a basket of US government bonds. The data sample is of daily frequency with various starting dates described in section 2.2 and ending on December 31, 2011. Significance is represented by asterisks in the following way: ***, ** and * denote a p-value smaller than 0.01, 0.05, and 0.1, respectively. The regime-switching model consists of two states. The unobservable state variables are represented by correlation coefficients of Gaussian copulas. p_{11} and p_{22} are transition probabilities from state 1 to state 1 and state 2 to state 2, respectively. ϕ_1 and ϕ_2 are unconditional state probabilities for states 1 and 2.

	ρ_1	ρ_2	p_{11}	p_{22}	ϕ_1	ϕ_2
Currency TI	0.1654***	-0.3078***	0.9066	0.8276	0.6487	0.3513
Europe Equity TI	0.1211	-0.1872	0.8543	0.7990	0.5799	0.4201
Global Asset TI	0.0742**	-0.4846***	0.9783	0.8461	0.8765	0.1235
Global Equity TI	0.3327**	-0.0972*	0.7420	0.9291	0.2157	0.7843
Sovereign Debt TI	0.6708***	-0.0132	0.3535	0.9522	0.0689	0.9311
US Credit TI	0.1247***	-0.0823	0.0801	0.0000	0.5209	0.4791
US Equity TI	0.4462***	-0.0850***	0.7081	0.9452	0.1581	0.8419
US Fixed Income TI	0.4337**	-0.0104	0.9532	0.9980	0.0417	0.9583
US Treasury TI	0.4620*	-0.0488	0.7959	0.9832	0.0762	0.9238