Does Systemic Risk in the Financial Sector Predict Future Economic Downturns?

Abstract

We derive a measure of aggregate systemic risk using the 1% VaR measures of a cross-section of financial firms, designated *CATFIN*. In out-of-sample tests, *CATFIN* forecasts economic downturns almost one year in advance. Even the *CATFIN* of small banks has predictive power, thereby suggesting that our findings are not the result of too-big-to-fail subsidies. A similarly defined risk measure for non-financial firms has no marginal predictive ability, consistent with bank specialness. The *CATFIN* measure can be used in conjunction with micro-level systemic risk measures (such as *CoVaR*) to calibrate regulatory limits and risk premiums on individual bank systemic risk taking.

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1. Introduction

The full details of the regulatory reforms to be enacted in the wake of the financial crisis of 2007-2009 are not fully formed, but one thing is clear - the regulatory mandate will include some oversight of systemic risk. Bank regulation has historically been disaggregated, with the focus mainly on the safety and soundness of the individual institution, implicitly assuming that if each individual institution was sound, then the entire system was safe.[1] If there is a bright spot in all of the pain associated with the global financial meltdown, it is a new focus on the systemic consequences of individual bank risk taking activity. Thus, a series of proposals to measure systemic risk have been advanced, such as *CoVaR* (Adrian and Brunnermeier (2009)), co-risk (Chan-Lau (2009)), a contingent claims approach (Gray and Jobst (2009)), Shapely values (Tarashev, Borio, and Tsatsaronis (2009)) and the IMF risk budgeting and standardized approaches (Espinosa-Vega, Kahn, and Sole (2010)).

The common theme in these "micro-level" systemic risk measurement proposals is that they measure the systemic risk exposure of each bank. That is, these measures provide empirical measures of the interrelationships across individual banks so as to forecast the potential for contagious risk transmission throughout the banking system. This is a necessary and worthwhile endeavor, but not the subject of this paper. Thus, we will not comment on the relative merits of each of these micro-level proposals in accomplishing their goal of measuring each bank's risk transmission potential.

Instead, we focus on a new measure to forecast the likelihood that systemic risk taking in the banking system as a *whole* will have detrimental macroeconomic effects. That is, we present an early warning system that will signal whether aggressive *aggregate* systemic risk taking in the financial sector presages future macroeconomic declines. It should be clear that both exercises must be undertaken in tandem if bank regulators are to fulfill their mandate as

[1] Acharya, Pedersen, Philippon, and Richardson (2008) note that this focus ignores negative externalities as "each institution manages its own risk but does not consider its impact on the risk of the system as a whole." (Chapter 13, Executive Summary). They call for a micro-level measure of each bank's systemic risk exposure, but do not address the need for a macro-level measure of systemic risk.

systemic risk regulators. Thus, our measure is complementary to measures such as *CoVaR*, co-risk, risk budgeting, etc. A macroeconomic systemic risk measure would be used to determine whether individual micro-level risk taking poses a risk to the entire economy. Our measure can forecast whether systemic risk taking in the financial sector is likely to generate an epidemic that will infect the entire macroeconomic system. The proposed measure, denoted *CATFIN*, can forecast significant declines in U.S. economic conditions approximately one year into the future. All data used to construct the *CATFIN* measure are available at each point in time (monthly, in our analysis), and we utilize an out-of-sample forecasting methodology. *CATFIN* can, therefore, provide a valuable early warning system that could be used to trigger the more extensive micro-level analysis of risk taking and contagion at individual banks.

The economic intuition for the *CATFIN* measure is that banks are special.[2] This concept has a long history in the traditional banking literature.[3] One might be tempted to conclude that, given all of the recent changes in the structure of the banking industry, particularly the convergence across types of financial intermediaries, banks would no longer be special. Our empirical results, estimated over 40 years (from 1973-2009), suggest that financial institutions are still special. Moreover, bank specialness is not limited to big banks that are Too Big to Fail (TBTF). Indeed, even the smallest banks are special in that their risk taking drives economic activity.

Financial institutions are special because they are fundamental to the operation of the economy. Their critical intermediation function links sources and uses of financial capital (by providing both credit and transaction accounts), and fuels the engines of investment and aggregate economic activity. Indeed, the specialness of banks is indicated by the economic

[2]We utilize the term bank broadly to include all financial intermediaries: commercial banks, savings banks, investment banks, broker/dealers, insurance companies, mutual funds, etc.

[3]Bernanke (1983) identified the special role of bank lending in exacerbating the economic declines of the Great Depression, finding that the detrimental effects of bank failures went beyond the bank's immediate stakeholders (e.g., borrowers, shareholders, depositors). Ashcraft (2003) found further evidence of economic consequences of bank failures resulting from declines in lending activity. In a series of essays (Corrigan 1982, 2000), former President of both the Federal Reserve Banks of Minneapolis and New York E. Gerald Corrigan stressed banks' special role as issuers of demand deposits acceptable as money, back-up sources of liquidity, and a transmission belt for monetary policy. See James and Smith (2000) for a survey of the literature.

devastation that results when financial firms fail to operate. The 2007-2009 financial crisis became a global economic crisis because banks shut down, hoarded liquidity and failed to perform their primary tasks of absorbing risk and cash flow mismatches from their customers - consumers, businesses, governments - thereby depressing economic conditions worldwide.

Since banks are special, we can derive a barometer forecast of economic conditions by examining the aggregate level of bank risk taking. The economic intuition behind the *CATFIN* measure is simple. If the banking system *collectively* takes on excessive risk, economic conditions will be in danger of decline. Since we can forecast this decline approximately a year before it happens, we can presumably mobilize the remedy by using the micro-level measures of systemic risk to identify which individual banks are the primary sources of the systemic risk exposure. Deploying the micro-level systemic risk measures without first obtaining an overall macroeconomic systemic risk signal is detrimental, as regulators run the risk of false positives. That is, even if a large, individual bank is an aggressive risk taker, this may pose no systemic risk hazard if the aggregate level of risk in the banking system is manageable (i.e., there is no risk of an economic crisis). Indeed, the way to mitigate the TBTF moral hazard problem in bank regulation is to allow banks to choose their own levels of risk taking, as long as they bear the consequences of their actions. Thus, if the high risk strategy is unsuccessful, then the bank should be allowed to fail, as long as the *CATFIN* measure has signaled that the failure will not cause systemic detrimental effects on the economy.

In this paper, we develop an early warning system that signals an impending economic crisis if *CATFIN* is above certain historical levels. Utilizing the *CATFIN* early warning signal in conjunction with micro-level systemic risk measures allows the permissible level of risk taking, on an individual bank level, to be calibrated to forecast macroeconomic conditions. Thus, when *CATFIN* signals a relatively robust economic forecast, a more laissez-faire policy toward bank risk taking can be pursued, and the systemic risk premium could be set rather low. However, when *CATFIN* signals trouble ahead, the regulator can take preemptive action and set a more constraining limit and/or a higher systemic risk premium on micro-level bank risk exposures. Thus, *CATFIN* can be used to calibrate a micro-level measure of systemic risk, thereby introducing a forward looking approach to systemic risk management that can be applied counter cyclically to stabilize economic fluctuations and offset some of the inherently procyclical incentives in banking. We present analysis to show the forecasting robustness of this early warning signal.

In this paper, *CATFIN* is the first principal component extracted from the 1% VaR measures for a cross-section of financial firms estimated from both parametric and non-parametric VaR estimation methodologies. We construct a similar measure using non-financial firms and a variety of industry groupings. We find that only the measure estimated using financial firms has predictive power in forecasting macroeconomic conditions. We utilize the Chicago Fed National Activity Index (CFNAI) as an index of U.S. macroeconomic activity, but our results are robust to other indices of aggregate economic activity. Finally, we estimate *CATFIN* for small banks only and compare the predictive power to that of *CATFIN* for large banks only. Both large and small bank *CATFIN* measures forecast macroeconomic activity approximately one year into the future, although the results are stronger for the large banks. However, this indicates that the specialness of banks is not related to those banks that are TBTF, but is inherent in financial intermediation.

The paper is organized as follows. We present the *CATFIN* measure in Section 2. Section 3 tests the predictive power of the *CATFIN* measure for future economic downturns. The early warning system is developed in Section 4. Some robustness checks are provided in Section 5. Section 6 concludes the paper.

2. Estimating Catastrophic Risk in the Financial Sector

We introduce a new measure of systemic risk that quantifies the risk of catastrophic losses in the financial system that has predictive power in forecasting future macroeconomic downturns. The statistical approaches to estimating VaR serve as natural candidates for modeling catastrophic losses. The methodologies used in the VaR literature are broadly divided into three categories: (i) Models that directly estimate tail risk based on the extreme value distributions (e.g., the generalized Pareto distribution (GPD) of Pickands (1975)); (ii) Models that investigate the shape of the entire return distribution, while providing flexibility of modeling tail thickness and skewness (the skewed generalized error distribution (SGED) of Bali and Theodossiou (2008)); and (iii) Estimation of VaR based on the left tail of the actual empirical distribution without any assumptions about the underlying return distribution. The first two approaches are known as the parametric methods, whereas the last one is considered a non-parametric method.

In this paper, we do not take a stance on any particular VaR estimation methodology.[4] We first estimate VaR at the 99% confidence level using three different methodologies - the GPD, the SGED and the non-parametric method. We then extract the first principal component, designated *CATFIN*, from the three measures.

2.1. Generalized Pareto distribution (GPD)

The generalized Pareto distribution of Pickands (1975) is utilized to model return distribution conditioning on extreme losses. Extremes are defined as the 10% left (lower) tail of the distribution of monthly returns for financial firms (SIC code $\geq$ 6000 and SIC code $\leq$ 6999) in excess of the one-month Treasury bill rate.

Let us call $f(r)$ the probability density function (pdf) and $F(r)$ the cumulative distribution function (cdf) of monthly excess stock returns r. First, we choose a low threshold l, so that all $r_i < l < 0$ are defined to be in the negative tail of the distribution, where $r_1, r_2, \cdots, r_n$ are a

[4]The interested reader may wish to consult Christoffersen (1998), Christoffersen and Diebold (2000), Berkowitz (2001), Berkowitz and O'Brian (2002), and Berkowitz, Christoffersen, and Pelletier (2010) for alternative methods to evaluate the empirical performance of VaR models.

sequence of excess stock returns. Then we denote the number of exceedances of l (or excess stock returns lower than l) by

$$N_l = card\{i : i = 1, \cdots, n, r_i < l\}, \tag{1}$$

and the corresponding excesses by $M_1, M_2, \cdots, M_{N_l}$. The excess distribution function of r is given by:

$$F_l(y) = P(r - l \geq y | r < l) = P(M \geq y | r < l), y \leq 0. \tag{2}$$

Using the threshold l, we now define the probabilities associated with r:

$$P(r \leq l) = F(l), \tag{3}$$

$$P(r \leq l + y) = F(l + y), \tag{4}$$

where $y < 0$ is an exceedance of the threshold l. Finally, let $F_l(y)$ be given by

$$F_l(y) = \frac{F(l) - F(l + y)}{F(l)}. \tag{5}$$

We thus obtain the $F_l(y)$, the conditional distribution of how extreme a r_i is, given that it already qualifies as an extreme. Pickands (1975) shows that $F_l(y)$ is very close to the generalized Pareto distribution $G_{min,\xi}$ in equation (6):

$$G_{min,\xi}(M; \mu, \sigma) = \left[1 + \xi\left(\frac{\mu - M}{\sigma}\right)\right]^{-\frac{1}{\xi}}, \tag{6}$$

where μ , σ , and ξ are the location, scale, and shape parameters of the GPD, respectively. The shape parameter ξ , called the tail index, reflects the fatness of the distribution (i.e., the weight of the tails), whereas the parameters of scale σ and of location μ represent the dispersion and average of the extremes, respectively.[5]

[5] The generalized Pareto distribution presented in equation (6) nests the Pareto distribution, the uniform distribution, and the exponential distribution. The shape parameter ξ, determines the tail behavior of the distributions.

The GPD presented in equation (6) has a density function:

$$g_{min}(\Phi; x) = \left(\frac{1}{\sigma}\right)\left[1 + \xi\left(\frac{\mu - M}{\sigma}\right)\right]^{-\left(\frac{1+\xi}{\xi}\right)}. \tag{7}$$

The GPD parameters are estimated by maximizing the log-likelihood function of M_i with respect to μ, σ, and ξ:

$$LogL_{GDP} = -nln(\sigma) - n\left(\frac{1+\xi}{\xi}\right)\sum_{i=1}^{T} ln\left(1 + \xi\left(\frac{\mu - M_i}{\sigma}\right)\right). \tag{8}$$

Bali (2003) shows that the GPD distribution yields a closed form solution for the VaR threshold:[6]

$$\vartheta_{GPD} = \mu + \left(\frac{\sigma}{\xi}\right)\left[\left(\frac{\alpha N}{n}\right)^{-\xi} - 1\right], \tag{9}$$

where n and N are the number of extremes and the number of total data points, respectively. Once the location μ, scale σ, and shape ξ parameters of the GPD distribution are estimated, one can find the VaR threshold ϑ_{GPD} based on the choice of the loss probability level α.[7]

In this paper, we first take the excess monthly returns on all financial firms from January 1973 to December 2009, and then for each month in our sample we define the extreme returns as the 10% left tail of the cross-sectional distribution of excess returns on financial firms. Assume that in month t we have 300 financial firms that yield 30 extreme return observations that are used to estimate the parameters of the generalized Pareto distribution. Once we have the location, scale, and shape parameters of the GPD, we estimate the 1% VaR measure using equation (9) with N = 300, n = 30, and α = 1%. This estimation process is repeated for each month using the extreme observations in the cross-section of excess returns on financial firms, and generates an aggregate 1% VaR measure of the U.S. financial system.

For $\xi > 0$, the distribution has a polynomially decreasing tail (Pareto). For $\xi = 0$, the tail decreases exponentially (exponential). For $\xi < 0$, the distribution is short tailed (uniform).

[6]For alternative extreme value approaches to estimating VaR, see Neftci (2000) and McNeil and Frey (2000).

[7]The original VaR values are negative since they are obtained from the left tail of the return distribution. We multiply all VaR values by -1, such that larger VaR measures are associated with more catastrophic losses.

2.2. Skewed generalized error distribution (SGED)

The skewed generalized error distribution (SGED) allows us to investigate the shape of the entire distribution of excess returns on financial firms in a given month, while providing flexibility of modeling tail-thickness and skewness. The probability density function for the SGED is

$$f(r_i;\mu,\sigma,\kappa,\lambda) = \frac{C}{\sigma}\exp\left(-\frac{1}{[1+sign(r_i-\mu+\delta\sigma)\lambda]^{\kappa}\theta^{\kappa}\sigma^{\kappa}}|r_i-\mu+\delta\sigma|^{\kappa}\right), \qquad (10)$$

where $C=\kappa/(2\theta\Gamma(1/\kappa))$, $\theta=\Gamma(1/\kappa)^{0.5}\Gamma(3/\kappa)^{-0.5}S(\lambda)^{-1}$, $S(\lambda)=\sqrt{1+3\lambda^2-4A^2\lambda^2}$, $A=\Gamma(2/\kappa)\Gamma(1/\kappa)^{-0.5}\Gamma(3/\kappa)^{-0.5}$, μ and σ are the mean and standard deviation of excess stock returns r, λ is a skewness parameter, *sign* is the sign function, and $\Gamma(.)$ is the gamma function. The scaling parameters κ and λ obey the following constraints $\kappa>0$ and $-1<\lambda<1$. The parameter κ controls the height and tails of the density function, and the skewness parameter λ controls the rate of descent of the density around the mode of r, where mode(r) $=\mu-\delta\sigma$. In the case of positive skewness ($\lambda>0$), the density function is skewed to the right. This is because for values of $r<\mu-\delta\sigma$, the return variable r is weighted by a greater value than unity and for values of $r>\mu-\delta\sigma$ by a value less than unity. The opposite is true for negative λ . Note that λ and δ have the same sign, thus, in case of positive skewness ($\lambda>0$), the mode(r) is less than the expected value of r. The parameter δ is Pearson's skewness $(\mu-mode(r))/\sigma=\delta$.[8]

The SGED parameters are estimated by maximizing the log-likelihood function of r_i with respect to the parameters μ, σ, κ, and λ:

$$LogL(r_i;\mu,\sigma,\kappa,\lambda) = Nln(C)-Nln(\sigma)-\frac{1}{\theta^{\kappa}\sigma^{\kappa}}\sum_{i=1}^{N}\left(\frac{|r_i-\mu+\delta\sigma|^{\kappa}}{(1+sign(r_i-\mu+\delta\sigma)\lambda)^{\kappa}}\right), \qquad (11)$$

[8]The SGED reduces to the generalized error distribution of Subbotin (1923) for $\lambda=0$, the Laplace distribution for $\lambda=0$ and $\kappa=1$, the normal distribution for $\lambda=0$ and $\kappa=2$, and the uniform distribution for $\lambda=0$ and $\kappa=\infty$.

where C, θ, and δ are defined below equation (10), *sign* is the sign of the residuals $(r_i - \mu + \delta\sigma)$, and N is the sample size.

To come up with an aggregate 1% VaR measure of the entire financial sector, for each month we use the cross-section of excess returns on financial firms and estimate the parameters of the SGED density. Given the estimates of the four parameters $(\mu, \sigma, \kappa, \lambda)$, we solve for the SGED VaR threshold ϑ_{SGED} numerically by equalizing the area under the SGED density to the coverage probability at the given loss probability level α:

$$\int_{-\infty}^{\vartheta_{SGED}(\alpha)} f_{\mu,\sigma,\kappa,\lambda}(z)dz = \alpha. \tag{12}$$

Numerical solution of equation (12) for each month from January 1973 to December 2009 yields monthly time-series of the 1% VaR measures from the SGED density.

2.3. Non-parametric method

The non-parametric approach to estimating VaR is based on analysis of the left tail of the empirical return distribution conducted without imposing any restrictions on the moments of the underlying density. Specifically, the 1% VaR measure ϑ_{NP} in a given month is measured as the cut-off point for the lower one percentile of the monthly excess returns on financial firms. Assuming that we have 300 financial firms in month t, the non-parametric measure of 1% VaR is the $30th$ lowest observation in the cross-section of excess returns. For each month, we determine the one percentile of the cross-section of excess returns on financial firms, and obtain an aggregate 1% VaR measure of the financial system for the sample period of $1973-2009$.

2.4. Principal component analysis

The above methodologies yield three VaR measures for each month over the sample period between January 1973 and December 2009. Rather than taking a stance on any particular methodology, we use the principal component analysis (PCA) to extract the common component of catastrophic risk embedded in the three proxies in a parsimonious manner, while suppressing potential measurement error associated with the individual VaR measures. We first standardize each of the three measures before performing PCA. The Eigen values of the three components are 2.6715, 0.2161, and 0.1124, respectively. The first principal component explains about 90 percent of the corresponding sample variance. We, therefore, conclude that the first principal component amply capture the common variation among the three VaR measures. This leads us to measure the catastrophic risk in the financial system as of month t, denoted *CoVaR*, as:

$$CATFIN_t = 0.5710 \times \vartheta^{STD}_{GPD} + 0.5719 \times \vartheta^{STD}_{SGED} + 0.5889 \times \vartheta^{STD}_{NP}, \tag{13}$$

where ϑ^{STD}_{GPD}, ϑ^{STD}_{SGED}, and ϑ^{STD}_{NP} correspond to the standardized VaR measures based on the GPD, the SGED, and the non-parametric methods, respectively.

Equation (13) indicates that the *CATFIN* loads almost equally on the three VaR measures. Panel A in Table 1 shows that the Pearson correlation coefficients between *CATFIN* and the three VaR measures are in the range of 0.9333 and 0.9626. Although the three VaR measures are significantly correlated with each other, they are not as highly correlated as with *CATFIN*. This suggests that the first principal component sufficiently summarizes the common variation among the three VaR measures, while reducing the potential measurement error associated with the individual VaR measures.

Panel B in Table 1 provides descriptive statistics for *CATFIN* and the three VaR measures.[9] By construction the mean *CATFIN* is zero. The three VaR measures have similar mean, me-

[9] The monthly estimates of the parameters that govern the GPD and the SGED are available upon request.

dian, and standard deviation estimates. Figure 1 depicts the three monthly 1% VaR measures in Panel A and the *CATFIN* measure in Panel B over the sample period January 1973 - December 2009. A cursory glance at the results reflects increases in *CATFIN* around the periods of the 1991-1992 credit crunch, the 1998 Russian default and LTCM debacle, the 2000-2001 bursting of the tech bubble and the 2007-2009 global financial crisis.

3. Predictive Power of Systemic Risk for Future Macroeconomic Downturns

3.1. Predictive ability of *CATFIN* for future macroeconomic activity

We test the predictive power of *CATFIN* in forecasting economic downturns. The Chicago Fed National Activity Index (CFNAI) is used to measure the U.S. aggregate economy. The CFNAI is a monthly index that determines increases and decreases in economic activity and is designed to assess overall economic activity and related inflationary pressure. It is a weighted average of 85 existing monthly indicators of national economic activity, and is constructed to have an average value of zero and a standard deviation of one. Since economic activity tends toward a trend growth rate over time, a positive index reading corresponds to growth above trend and a negative index reading corresponds to growth below trend.[10]

We estimate the time-series regressions of CFNAI n-months after the estimate of *CATFIN* in month t:

$$CFNAI_{t+n} = \alpha + \gamma CATFIN_t + \varepsilon_{t+n}. \tag{14}$$

Table 2 shows that the γ coefficient on *CATFIN* is statistically significant (at the 5% level or better), thereby forecasting the CFNAI index up to 13 months in advance. From the one-

[10]The 85 economic indicators that are included in the CFNAI are drawn from four broad categories of data: production and income; employment, unemployment, and hours; personal consumption and housing; and sales, orders, and inventories. Each of these data series measures some aspect of overall macroeconomic activity. The derived index provides a single, summary measure of a factor common to these national economic data.

month to twelve-month ahead prediction of the CFNAI index, the coefficient estimates are found to be in the range of -0.1186 and -0.2745 and highly significant with the Newey and West (1987) t-statistics ranging from -2.92 to -5.22. The slope coefficient γ forecasting thirteen-month ahead CFNAI index is somewhat lower in absolute magnitude, -0.0924, but it is still significant at the 5% level.

The results indicate that a one standard deviation (1.6345) increase in *CATFIN* in month t leads to a decrease in CFNAI in months $t+1$ through $t+3$ by more than 0.4. This is economically meaningful given that by construction CFNAI has zero mean and unit standard deviation. The adjusted R^2 values from the predictive regressions are economically significant as well. For example, *CATFIN* in month t explains, respectively, 16.16%, 18.39%, and 19.86% variations in one-, two-, and three-month ahead CFNAI index. We notice that the adjusted R^2 is the largest when we predict the three-month ahead CFNAI possibly because it takes several months for the negative effects of catastrophic losses of financial firms on the aggregate economy to become evident.

To alleviate the concern that the negative predictive relation is driven by the PCA construction of the *CATFIN* measure, we rerun equation (14) by replacing *CATFIN* with the individual VaR measures obtained from the parametric and non-parametric methods. We find similar results based on the individual VaR estimates. That is, the catastrophic risk in the financial sector derived from the GPD and SGED densities, as well as the left tail of the non-parametric empirical return distribution successfully predict the one-month to twelve-month ahead CFNAI index. The slope coefficients on ϑ_{GPD} , ϑ_{SGED} , and ϑ_{NP} are negative, similar in magnitude, and statistically significant at the 5% level or better. The results are qualitatively similar to our findings using *CATFIN*, showing that extreme downside risk in the financial system strongly predicts lower U.S. economic activity about one year into the future.

3.2. Catastrophic risk of non-financial firms and future economic activity

In this subsection, we investigate the question whether catastrophic risk of non-financial firms (denoted *CATnonFIN*) forecasts lower economic activity after controlling for *CATFIN*. Following the methodology outlined in Section 2, for each month in our sample we measure the catastrophic risk of all non-financial firms separately, as well as the catastrophic risk of the five broad non-financial sectors by extracting the first principal component of the three VaR measures.[11] We then estimate the following predictive regressions:

$$CFNAI_{t+1/t+3} = \alpha + \gamma CATFIN_t + \beta CATnonFIN_t + \varepsilon_{t+1/t+3}, \tag{15}$$

where $CATnonFIN_t$ denotes the catastrophic risk measure in month t for all non-financial firms or for each of the five broad sectors. In addition to testing the predictive power of *CATnonFIN* for CFNAI in month $t+1$, we examine the three-month ahead predictability of CFNAI to account for the possibility that it takes several months for *CATnonFIN* to have significant effect on the macroeconomic activity.

Table 3 shows that none of the non-financial sectors significantly forecasts the aggregate economy after controlling for *CATFIN*.[12] For the one-month ahead prediction of the CFNAI index, the coefficient estimates on *CATFIN* are in the range of -0.1929 and -0.2432 and statistically significant at the 1% level, whereas the slope coefficients on *CATnonFIN* are insignificant for all non-financial firms and five industry groupings. The adjusted R^2 values from the one-month ahead predictive regressions are economically large, ranging from 15.98% to 16.78%. Similar results are obtained from forecasting CFNAI three months in advance: *CATFIN* successfully predicts, whereas *CATnonFIN* has no significant association with the three-month ahead CFNAI index.

[11] Definitions of the five broad non-financial sectors are obtained from Kenneth French's online data library.

[12] We obtain qualitatively similar results when we use the twelve industries. The results are available upon request. We should note that some of the industries do not have enough left-tail observations to estimate ϑ_{GPD} measures.

4. Developing a Warning System

In Section 3, we show that the *CATFIN* measure extracted from the VaR measures based on the three different VaR estimation methodologies predicts changes in U.S. macroeconomic activity. Since the sign of the relationship is negative, we find that increased catastrophic risk exposure in the financial system has detrimental consequences on the aggregate economy. The predictive power of *CATFIN* can be fundamentally traced to the notion that banks are special. Indeed, our results show that catastrophic losses of non-financial firms do not possess such predictive power.

In this section, we develop a warning system based on the *CATFIN* measure. Our objective is to find a critical value of the *CATFIN* measure, such that if *CATFIN* in a given month exceeds the critical value, the regulators can take preemptive action and set a more constraining limit and/or a higher systemic risk premium on micro-level bank risk exposures. In contrast, if *CATFIN* is below the critical value, a more laissez-faire policy toward bank risk taking can be pursued.

The strategy that we implement hinges on the CFNAI's -0.7 turning point indicating economic contraction as suggested by the Federal Reserve Bank of Chicago. We calculate the median *CATFIN* for those observations in which the three-month moving average CFNAI (CFNAI-MA3) falls below -0.7. We then construct two new variables: $CATFIN_t^+$ taking the value of *CATFIN* in month t if it is greater than the median CFNAI or 0.7680,[13] and zero otherwise; $CATFIN_t^-$ equals *CATFIN* in month t if it less than or equal to the median CFNAI, and zero otherwise. Once we generate $CATFIN_t^+$ and $CATFIN_t^-$, we estimate the following predictive regression:

$$CFNAI_{t+n} = \alpha + \gamma^+ CATFIN_t^+ + \gamma^- CATFIN_t^- + \varepsilon_{t+n}, \tag{16}$$

[13]In our sample, the median *CATFIN* during months in which CFNAI-MA3 was below -0.7 is 0.7680. 74 of the 444 monthly observations have *CATFIN* greater than 0.7680, with a mean *CATFIN* of 2.8033 and a standard deviation of 1.4400.

where CFNAI_{t+n} is the n-month ahead CFNAI index.

The left panel of Table 4 shows that $CATFIN_t^+$ significantly predicts lower economic activity 1 month to 13 months in advance, whereas $CATFIN_t^-$ does not have significant predictive power (at the 5% level or better) for all time horizons. Moreover, the coefficients on $CATFIN_t^-$ are consistently smaller than the corresponding coefficients on $CATFIN_t^+$. Specifically, the slope coefficients on $CATFIN_t^+$ are in the range of -0.1194 and -0.3818 and statistically significant at the 1% level, whereas the estimated slopes on $CATFIN_t^-$ range from -0.0497 to -0.1075 with no statistical significance. These results indicate that when the catastrophic risk in the financial sector exceeds a certain threshold (determined by CFNAI-MA3 < -0.7), it successfully predicts future economic downturns. However, when the catastrophic risk is below the critical value, systemic risk taking in the financial sector is not likely to generate an epidemic that will infect the entire macroeconomic system.

Although *CATFIN* is a pure out-of-sample measure in that it is based on realized returns for financial firms without invoking any future information, the median early warning threshold of *CATFIN* is calculated using the full-sample information, and may induce potential in-sample bias. To alleviate this concern, we perform an expanding-window out-of-sample procedure. The median *CATFIN* is calculated using all observations available up to month t in which CFNAI-MA3 falls below -0.7. $CATFIN_t^+$ and $CATFIN_t^-$ are defined similarly by comparing *CATFIN* in month t with the time-varying median cut-off threshold for *CATFIN*. A value of CFNAI-MA3 below -0.7 occurs in only 73 months over the sample period from January 1973 to December 2009, and 40 of them occur in the first half of our sample period. Table 4 shows the results of our estimation of equation (16) using an expanding-window cut-off threshold for the early warning system. The slope coefficients on $CATFIN_t^+$ are between -0.1288 and -0.3932 and significant (at the 5% level or better), whereas the estimated slopes on $CATFIN_t^-$ are statistically insignificant for all forecast horizons. Thus, an early warning system can be implemented using this out-of-sample procedure to differentiate $CATFIN_t^+$ from $CATFIN_t^-$ that can be used by regulators to take preemptive action so as to avert a macroeconomic crisis.

5. Robustness Check

5.1. Catastrophic risk measure based on daily stock returns

We have so far estimated the catastrophic risk of financial and nonfinancial institutions using the cross-sectional distribution of monthly excess returns. In this section, we introduce an alternative risk measure based on the time-series distribution of daily excess returns. For each month in our sample, we first determine the lowest daily excess returns on financial institutions over the past 1 to 12 months. The catastrophic risk of financial institutions, denoted VaR_{FIN}^{daily}, is then computed by taking the average of these lowest daily excess returns obtained from alternative measurement windows. The estimation windows are fixed at 1 to 12 months, and each fixed estimation window is updated on a monthly basis.

Assuming that we have 21 daily return observations in a month, the lowest daily return over the past 1, 2, 3, 4, 5, 6, and 12 months, respectively, yield 4.76%, 2.38%, 1.59%, 1.19%, 0.95%, 0.79%, and 0.40% non-parametric VaR measures. For example, if one would like to measure aggregate systemic risk based on the 1% nonparametric VaR of the financial sector, she first finds the lowest daily return observation over the past 100 days for each financial institution and then takes the equal-weighted average of these 1% VaR measures.

Once we generate VaR_{FIN}^{daily} for the entire financial sector, we test its predictive power for forecasting future economic downturns proxied by the CFNAI index:

$$CFNAI_{t+n} = \alpha + \gamma VaR_{FIN,t}^{daily} + \varepsilon_{t+n}, \tag{17}$$

where CFNAI_{t+n} is the n-month ahead CFNAI index.

Table 5 shows that the γ coefficients on VaR_{FIN}^{daily} are negative and highly significant (at the 5% level or better), and forecasting the CFNAI index up to 9 to 11 months in advance depending on the estimation window used in computing the average non-parametric VaR measure. The coefficient estimates are economically comparable to those on the *CATFIN* measure. For example, a one-standard deviation increase in VaR^{daily}_{FIN} calculated using the one-month rolling window (1.9235%) leads to a decrease in the CFNAI in months $t+1$ through $t+3$ by about -0.47.

Following the approach to estimating VaR^{daily}_{FIN}, for each month in our sample we calculate the catastrophic risk of all non-financial firms separately, as well as the catastrophic risk of the five broad non-financial sectors by taking the average of the lowest daily excess returns for non-financial firms in a given measurement window. Then, we investigate whether the aggregate downside risk of non-financial firms obtained from the time-series distribution of daily returns, denoted VaR^{daily}_{nonFIN}, predicts future economic activity after controlling for VaR^{daily}_{FIN}:

$$CFNAI_{t+n} = \alpha + \gamma VaR^{daily}_{FIN,t} + \beta VaR^{daily}_{nonFIN,t} + \varepsilon_{t+n}, \tag{18}$$

where CFNAI$_{t+n}$ is the n-month ahead CFNAI index.

Table 6 shows that none of the non-financial sectors significantly predicts the one-month and three-month ahead CFNAI index after accounting for the impact of VaR^{daily}_{FIN}, whereas downside risk of financial institutions strongly predicts future downturns of the overall economy with and without controlling for VaR^{daily}_{nonFIN}. These results are robust across different estimation windows.

5.2. Does size matter?

In this section, we investigate whether our findings are related to TBTF premiums. That is, we examine whether aggregate levels of catastrophic risk exposure for large banks are driving the predictive power of *CATFIN*, or whether small banks' aggregate risk taking also has forecasting ability.

For each month in our sample, we use the NYSE top size quintile breakpoint to decompose the financial sector into two groups: big financial firms with market cap above the breakpoint, and small firms with market cap below the breakpoint. Figure 2 shows that the big-firm group on average contains less than 6% of the financial firms but accounts for about 70% of the aggregate market capitalization of the financial sector.

To determine whether bank size impacts the model's predictive ability, we first estimate the 1% VaR thresholds based on the SGED and the non-parametric methods for each bank size group.[14] Then, the first principal component of the SGED and the non-parametric VaR measures are extracted, denoted *CATFINBIG* for big firms and *CATFINSML* for small firms. Finally, the n-month ahead CFNAI index is regressed on *CATFINBIG* and *CATFINSML* in month t. Table 7 shows that *CATFINBIG* successfully forecasts lower economic activity up to 18 months in advance. Although the predictive power of *CATFINSML* is not as strong as that of *CATFINBIG*, it strongly predicts macroeconomic activity 8 months into the future, remains somewhat significant for 9 and 11 months, but then dies out after 12 months. Thus, in contrast to the insignificance of the aggregate catastrophic risk measure for non-financial firms (see Table 3), the catastrophic risk of small banks has statistically significant power to forecast future macroeconomic conditions. These results provide evidence that the specialness of banks is not limited to those banks that are TBTF, but is inherent in financial intermediation.

5.3. Predictive power of *CATFIN* for other macroeconomic indicators

In this section, we test whether the predictive power of *CATFIN* is robust to using alternative macroeconomic indicators (as opposed to CFNAI) that proxy for the state of the aggregate economy. The first alternative is a dummy variable taking the value of 1 if the U.S. economy is in recession in a month as marked by the National Bureau of Economic Statistics, and zero otherwise.

The second one is the Aruoba-Diebold-Scotti (ADS) Business Conditions Index maintained by the Federal Reserve of Bank of Philadelphia. The ADS index is based on a smaller

[14]The VaR measure based on the GPD method is not calculated because enough data points do not exist for the big-firm group.

number of economic indicators than the CFNAI, and designed to track real business conditions at the weekly frequency. The average value of the ADS index is zero. Progressively bigger positive values indicate progressively better-than-average conditions, whereas progressively more negative values indicate progressively worse-than-average conditions. Details about the ADS index can be found in Aruoba, Diebold, and Scotti (2009). Since *CATFIN* is a monthly measure, we use the value of the ADS index at the end of each month in our predictive regressions.[15]

The last alternative macroeconomic index used to test the robustness of our model is the Kansas City Financial Stress Index (KCFSI); see Hakkio and Keeton (2009). The KCFSI is a monthly measure of stress in the U.S. financial system based on 11 financial market variables. A positive value indicates that financial stress is above the long-run average, while a negative value signifies that financial stress is below the long-run average.

To perform robustness tests, we run probit regressions when the NBER recession dummy is the dependent variable and we run OLS regressions when the ADS index and the KCFSI are the dependent variables. Table 8 shows that *CATFIN* predicts these popular macroeconomic indicators 11 to 14 months in advance, and that the slope coefficients on *CATFIN* are highly significant (at the 5% level or better) for all horizons considered in the paper. Hence, we conclude that systemic risk taking in the financial sector successfully predicts future economic downturns and this result is robust across different indices proxying for the state of the aggregate economy.

6. Conclusion

We derive a measure of the financial system's systemic risk that can forecast macroeconomic downturns approximately one year before they occur. The aggregate catastrophic risk exposure of financial firms is shown to be a robust measure of systemic risk in the financial system.

[15]We also used the average of the weekly values in a month and obtained qualitatively similar results.

That is, increases in the collective level of bank risk exposure have statistically significant power in forecasting economic declines.

We utilize the 1% Value at Risk (VaR) of financial firms in order to measure aggregate systemic risk exposure. The VaR is estimated using three approaches: (i) a parametric extreme value method using estimates of the generalized Pareto distribution (GPD); (ii) a parametric estimate of the skewed generalized error distribution (SGED); and (iii) a non-parametric approach. Our new systemic risk measure, denoted *CATFIN*, is constructed using a principal component analysis of the three VaR estimates. However, our results are robust to use of each of the individual VaR measures.

The predictive ability of *CATFIN* emanates from the special role of banks in the economy. There is no marginal predictive ability for the aggregate level of catastrophic risk exposure of non-financial industry groups. Moreover, *CATFIN* has predictive power even if estimated using a subsample of small banks, thereby indicating that the results are not driven by too-big-to-fail subsidies, but rather by the specialness of banks in driving economic activity.

We measure macroeconomic conditions using the Chicago Fed National Activity Index (CFNAI), but our results are robust to three other measures of macroeconomic conditions. Using an established recession cut-off value of the CFNAI, we determine an early warning critical value for *CATFIN*, such that if the monthly value of *CATFIN* exceeds this amount (0.7680 in our sample period), there is an increased chance of macroeconomic decline. We also estimate an out-of-sample critical value using an expanding estimation window that can be used as an early warning system. Thus, regulators can utilize readily available information to intervene expeditiously in order to prevent a financial crisis that has macroeconomic implications. Our new *CATFIN* measure is an important complement to proposed micro-level measures of individual bank systemic risk exposure, and can be used to calibrate systemic risk premiums and/or permissible systemic risk exposure set by bank regulators.

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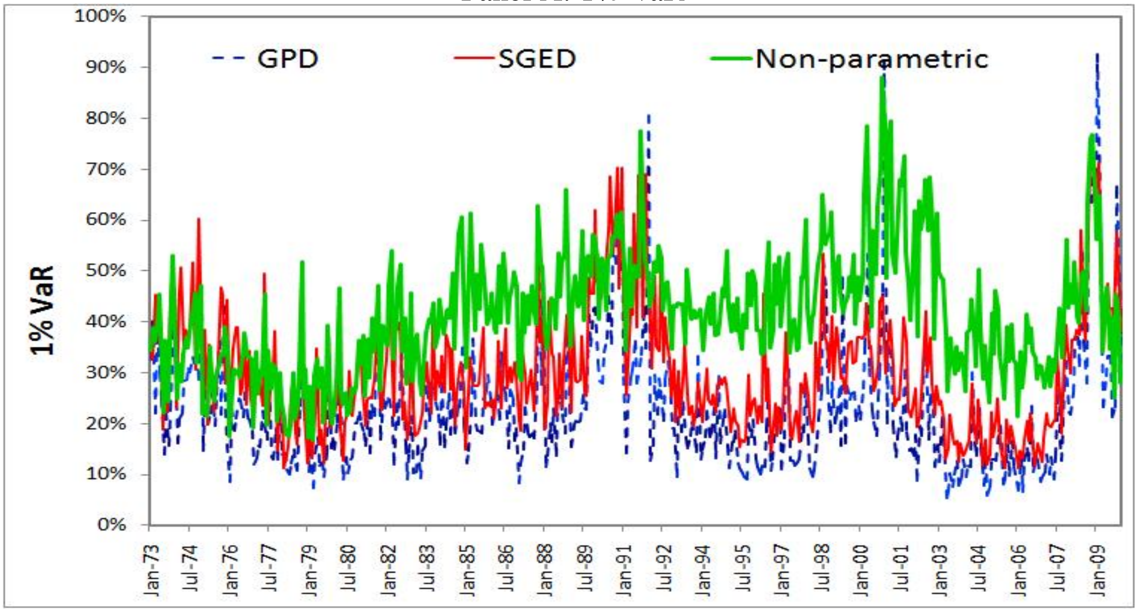
Panel A: 1% VaR



Panel B: *CATFIN*

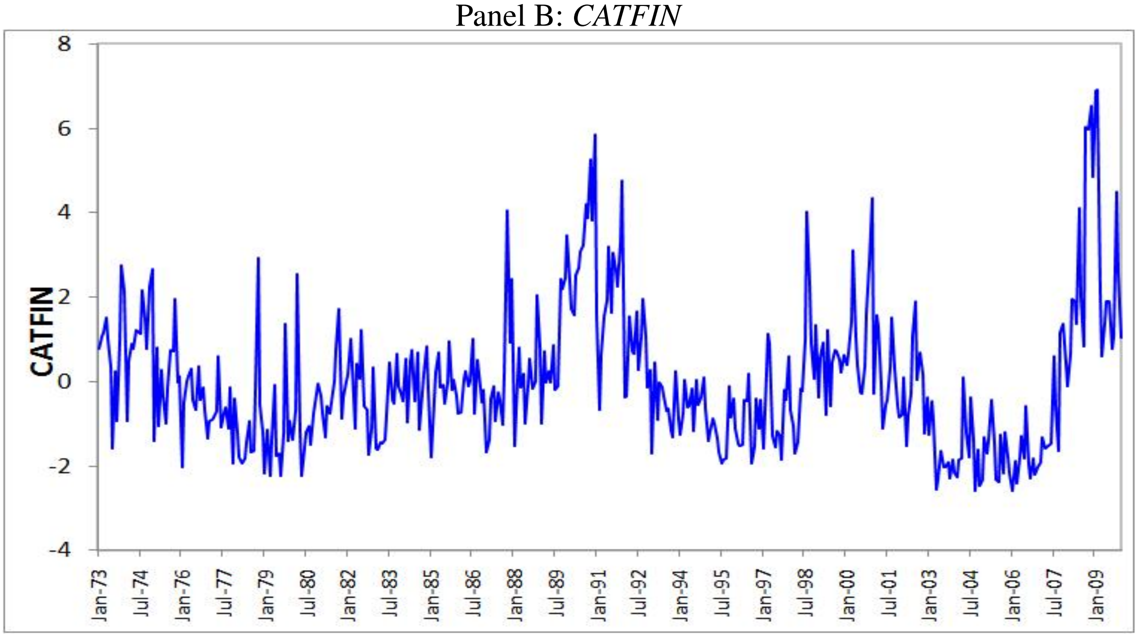


Figure 1. 1% VaR and the *CATFIN*. The top figure depicts the monthly 1% VaR, estimated from the GPD, the SGED, and the non-parametric methods. The bottom figure plots the monthly *CATFIN*, measured as the first principal component of the three 1% VaR measures. The sample period is from January 1973 to December 2009.

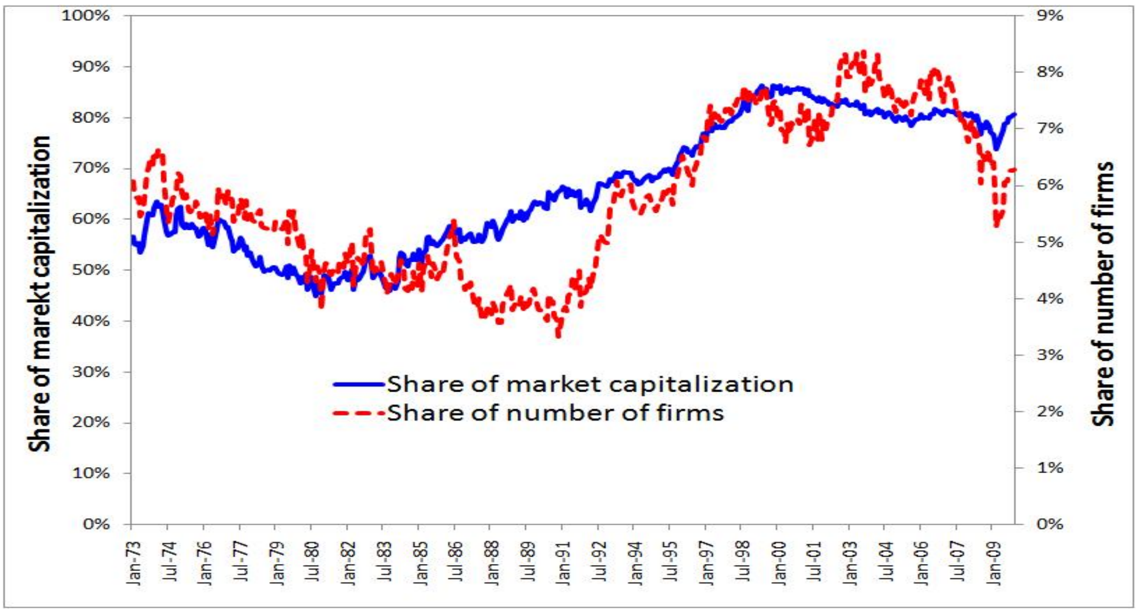


Figure 2. Market share of the big-firm group. This figure depicts the share of market cap and the number of firms in the big-firm group relative to the aggregate market cap and the total number of firms in the financial sector. The big-firm group includes all financial firms with market cap above the NYSE top size quintile breakpoint. The sample period is from January 1973 to December 2009.

Table 1
Summary statistics on the monthly catastrophic risk measures in the financial sector

Entries in Panel A report the Pearson correlation coefficients among the monthly VaR measures and the *CATFIN*. ϑ_{GPD}, ϑ_{SGED}, and ϑ_{NP} denote the 1% VaR estimated from the GPD, the SGED, and the non-parametric method, respectively. *CATFIN* is the first principal component of the three VaR measures. Entries in Panel B report the descriptive statistics for the three VaR measures and the *CATFIN*. The sample period is from January 1973 to December 2009. Significance at the 10%, 5%, and 1% level is respectively denoted *, **, and ***.

Panel A: Pearson correlation coefficients

	ϑ_{GPD}	ϑ_{SGED}	ϑ_{NP}
CATFIN	0.9333***	0.9348***	0.9626***
ϑ_{GPD}		0.7839***	0.8594***
ϑ_{SGED}			0.8631***

Panel B: Descriptive statistics

	Mean	Median	Std. dev.
CATFIN	0.0000	-0.2769	1.6345
ϑ_{GPD}	22.76%	20.27%	12.47%
ϑ_{SGED}	30.17%	27.84%	12.00%
ϑ_{NP}	28.75%	27.42%	10.44%

Table 2

Predictive ability of *CATFIN* and VaR measures for the Chicago Fed National Activity Index (CFNAI)

Entries report the coefficient estimates from the predictive regressions: $CFNAI_{t+n} = \alpha + \gamma X_t + \varepsilon_{t+n}$, where X_t is either the *CATFIN* or one of the three VaR measures ϑ_{GPD}, ϑ_{SGED}, and ϑ_{NP}, and CFNAI_{t+n} denotes the n-month ahead CFNAI. Newey and West (1987) t-statistics are reported in parentheses. The sample period is from January 1973 to December 2009. Significance at the 10%, 5%, and 1% level is respectively denoted *, **, and ***.

CFNAI_{t+n}	Intercept	$CATFIN_t$	Adj. R^2	Intercept	ϑ_{GPD}	Adj. R^2	Intercept	ϑ_{SGED}	Adj. R^2	Intercept	ϑ_{NP}	Adj. R^2
n=1	-0.0591	-0.2464***	16.16%	0.6396	-3.0686***	14.58%	0.8376	-2.9726***	12.62%	1.0433	-3.8344***	15.96%
	(-0.72)	(-4.81)		(4.43)	(-4.63)		(3.98)	(-3.83)		(4.88)	(-4.94)	
n=2	-0.0653	-0.2622***	18.39%	0.6607	-3.1860***	15.84%	0.9129	-3.2425***	15.10%	1.1068	-4.0765***	18.13%
	(-0.81)	(-4.93)		(4.47)	(-4.44)		(4.53)	(-4.34)		(4.91)	(-4.86)	
n=3	-0.0702	-0.2745***	19.86%	0.6776	-3.2834***	16.38%	0.9531	-3.3898***	16.35%	1.1722	-4.3184***	20.23%
	(-0.87)	(-5.22)		(4.67)	(-4.69)		(4.69)	(-4.46)		(5.36)	(-5.33)	
n=4	-0.0710	-0.2454***	15.82%	0.5888	-2.8942***	12.68%	0.8514	-3.0561***	13.23%	1.0465	-3.8856***	16.30%
	(-0.87)	(-4.85)		(4.31)	(-4.39)		(4.53)	(-4.37)		(4.78)	(-4.79)	
n=5	-0.0726	-0.2113***	11.68%	0.4651	-2.3560***	8.34%	0.7320	-2.6672***	10.01%	0.9230	-3.4622***	12.91%
	(-0.86)	(-4.34)		(3.47)	(-3.69)		(4.06)	(-4.11)		(4.40)	(-4.52)	
n=6	-0.0750	-0.2115***	11.68%	0.4790	-2.4262***	8.85%	0.6838	-2.5136***	8.85%	0.9489	-3.5617***	13.62%
	(-0.88)	(-4.34)		(3.66)	(-3.94)		(4.02)	(-4.02)		(4.48)	(-4.52)	
n=7	-0.0768	-0.1883***	9.19%	0.4078	-2.1207***	6.70%	0.6245	-2.3244***	7.51%	0.8195	-3.1178***	10.37%
	(-0.88)	(-4.14)		(3.29)	(-3.77)		(3.76)	(-3.85)		(4.13)	(-4.30)	
n=8	-0.0763	-0.1651***	6.99%	0.3481	-1.8561***	5.08%	0.5152	-1.9600***	5.25%	0.7349	-2.8222***	8.44%
	(-0.85)	(-3.82)		(2.85)	(-3.72)		(3.02)	(-3.37)		(3.66)	(-3.99)	
n=9	-0.0785	-0.1554***	6.18%	0.3105	-1.6998***	4.23%	0.5074	-1.9423***	5.16%	0.6701	-2.6045***	7.17%
	(-0.87)	(-3.58)		(2.48)	(-3.39)		(2.98)	(-3.29)		(3.26)	(-3.68)	
n=10	-0.0822	-0.1383***	4.86%	0.2683	-1.5312***	3.40%	0.4311	-1.7008***	3.92%	0.5860	-2.3246***	5.68%
	(-0.89)	(-3.51)		(2.15)	(-3.43)		(2.70)	(-3.15)		(2.96)	(-3.54)	
n=11	-0.0874	-0.1402***	4.79%	0.2706	-1.5633***	3.37%	0.4039	-1.6247***	3.46%	0.6102	-2.4281***	5.99%
	(-0.94)	(-3.63)		(2.12)	(-3.48)		(2.56)	(-3.03)		(3.16)	(-3.85)	
n=12	-0.0874	-0.1186***	3.20%	0.2096	-1.2970***	2.06%	0.3550	-1.4621***	2.69%	0.4777	-1.9645***	3.74%
	(-0.92)	(-2.92)		(1.60)	(-2.68)		(2.22)	(-2.64)		(2.47)	(-3.01)	
n=13	-0.0859	-0.0924**	1.81%	0.1219	-0.9037*	0.85%	0.2254	-1.0258*	1.18%	0.4192	-1.7598**	2.90%
	(-0.89)	(-2.19)		(0.92)	(-1.85)		(1.36)	(-1.79)		(2.11)	(-2.59)	

Table 3

Predictive ability of *CATFIN* and *CATnonFIN* for the CFNAI

Entries report the coefficient estimates from the predictive regressions: $CFNAI_{t+1/t+3} = \alpha + \gamma CATFIN_t + \beta CATnonFIN_t + \varepsilon_{t+1/t+3}$, where CFNAI_{t+1} and CFNAI_{t+3} are the one- and three-month ahead CFNAI, *CATFIN* and *CATnonFIN* are respectively the catastrophic risk measure for the financial sector and all non-financial firms or the five broad non-financial sectors, calculated as the first principal component of the GPD, SGED and non-parametric 1% VaR measures. The definitions of the five sectors are obtained from Kenneth French's online data library. Newey and West (1987) t-statistics are reported in parentheses. The sample period is from January 1973 to December 2009. Significance at the 10%, 5%, and 1% level is respectively denoted *, **, and ***.

	Dependent variable: CFNAI_{t+1}				Dependent variable: CFNAI_{t+3}			
Industry	Intercept	$CATFIN_t$	$CATnonFIN_t$	Adj. R^2	Intercept	$CATFIN_t$	$CATnonFIN_t$	Adj. R^2
All non-financial firms	-0.0589	-0.2205***	-0.0389	16.22%	-0.0695	-0.2458***	-0.0421	19.97%
	(-0.72)	(-3.46)	(-0.72)		(-0.86)	(-3.77)	(-0.82)	
Consumer goods	-0.0590	-0.2292***	-0.0255	16.07%	-0.0699	-0.2596***	-0.0215	19.75%
& services	(-0.72)	(-3.92)	(-0.46)		(-0.87)	(-4.04)	(-0.40)	
Manufacturing, energy	-0.0586	-0.1929***	-0.0768	16.78%	-0.0690	-0.2320***	-0.0596	20.16%
& utilities	(-0.72)	(-3.43)	(-1.57)		(-0.86)	(-3.66)	(-1.12)	
Hitech, business equipment,	-0.0591	-0.2415***	-0.0082	15.98%	-0.0694	-0.2463***	-0.0455	20.02%
telephone & TV	(-0.72)	(-3.86)	(-0.16)		(-0.86)	(-4.12)	(-1.02)	
Healthcare, medical equipment,	-0.0591	-0.2186***	-0.0562	16.35%	-0.0698	-0.2447***	-0.0595	20.11%
& drugs	(-0.72)	(-3.97)	(-0.87)		(-0.87)	(-4.07)	(-0.97)	
All other non-financial firms	-0.0591	-0.2432***	-0.0053	15.98%	-0.0701	-0.2704***	-0.0064	19.68%
	(-0.72)	(-3.62)	(-0.10)		(-0.87)	(-4.00)	(-0.13)	

Table 4

The warning system

Entries report coefficient estimates from the predictive regressions: $CFNAI_{t+n} = \alpha + \gamma^{+} CATFIN_t^{+} + \gamma^{-} CATFIN_t^{-} + \varepsilon_{t+n}$, where CFNAI_{t+n} is the n-month ahead CFNAI; $CATFIN_t^{+}$ ($CATFIN_t^{-}$) equals *CATFIN* in month t if it is greater than (less than or equal to) a given cut-off point, and zero otherwise. In the left panel, the cut-off point is the median *CATFIN* for those observations in which the three-month moving average of CFNAI (CFNAI-MA3) falls belows -0.7 over the full sample period. In the right panel, the cut-off points are calculated similarly, except that the expanding-window procedure is implemented. The first expanding window covers the first half of the original sample period. Newey and West (1987) t-statistics are reported in parentheses. Columns χ^2 and p-value respectively report the Chi-square statistics with one degree of freedom and the corresponding p-value from Wald tests. The sample period is from January 1973 to December 2009. Significance at the 10%, 5%, and 1% level is respectively denoted *, **, and ***.

	Cut-off points using the full sample							Cut-off points using the expanding window						
CFNAI_{t+n}	Intercept	$CATFIN_t^{+}$	$CATFIN_t^{-}$	Adj. R^2	$\gamma^{+}-\gamma^{-}$	χ^2	P-value	Intercept	$CATFIN_t^{+}$	$CATFIN_t^{-}$	Adj. R^2	$\gamma^{+}-\gamma^{-}$	χ^2	P-value
n=1	0.0996	-0.3480***	-0.0581	18.60%	-0.2900	8.52	0.00	0.0205	-0.3510***	-0.0825	34.21%	-0.2685	4.43	0.04
	(1.04)	(-5.63)	(-0.89)					(0.17)	(-4.37)	(-1.10)				
n=2	0.0869	-0.3599***	-0.0816	20.65%	-0.2783	7.19	0.01	0.0621	-0.3932***	-0.0535	39.02%	-0.3397	6.35	0.01
	(0.89)	(-5.20)	(-1.35)					(0.53)	(-4.54)	(-0.72)				
n=3	0.0944	-0.3818***	-0.0796	22.54%	-0.3023	10.25	0.00	0.0826	-0.3902***	-0.0241	36.73%	-0.3662	9.86	0.00
	(0.99)	(-5.94)	(-1.29)					(0.78)	(-4.68)	(-0.38)				
n=4	0.0670	-0.3354***	-0.0820	17.64%	-0.2533	6.94	0.01	0.0323	-0.3425***	-0.0491	29.54%	-0.2934	6.34	0.01
	(0.67)	(-5.35)	(-1.24)					(0.28)	(-4.41)	(-0.66)				
n=5	0.0151	-0.2683***	-0.1075	12.29%	-0.1608	2.63	0.10	-0.0587	-0.2743***	-0.1156	22.35%	-0.1587	1.95	0.16
	(0.14)	(-4.26)	(-1.52)					(-0.48)	(-3.51)	(-1.49)				
n=6	0.0223	-0.2749***	-0.0964	12.47%	-0.1785	3.87	0.05	-0.0707	-0.2636***	-0.1235	21.18%	-0.1401	1.34	0.25
	(0.22)	(-4.10)	(-1.62)					(-0.56)	(-2.97)	(-1.64)				
n=7	-0.0305	-0.2185***	-0.1335*	9.20%	-0.0850	0.83	0.36	-0.1068	-0.2109***	-0.1332	14.93%	-0.0777	0.45	0.50
	(-0.28)	(-3.69)	(-1.90)					(-0.74)	(-2.82)	(-1.52)				
n=8	-0.0211	-0.2011***	-0.0997	7.10%	-0.1013	1.17	0.28	-0.1317	-0.1814***	-0.1441	12.19%	-0.0374	0.11	0.74
	(-0.19)	(-3.81)	(-1.30)					(-0.84)	(-2.86)	(-1.53)				
n=9	-0.0377	-0.1819***	-0.1072	6.14%	-0.0746	0.51	0.47	-0.1286	-0.1768**	-0.1333	11.11%	-0.0435	0.12	0.73
	(-0.32)	(-3.36)	(-1.27)					(-0.78)	(-2.55)	(-1.33)				
n=10	-0.0575	-0.1543***	-0.1092	4.70%	-0.0451	0.20	0.65	-0.1887	-0.1337**	-0.1688	8.17%	0.0351	0.07	0.79
	(-0.47)	(-3.38)	(-1.29)					(-1.08)	(-2.35)	(-1.53)				
n=11	-0.0803	-0.1450***	-0.1319*	4.58%	-0.0131	0.02	0.89	-0.2010	-0.1400**	-0.1808	8.56%	0.0408	0.09	0.77
	(-0.66)	(-3.10)	(-1.67)					(-1.12)	(-2.23)	(-1.62)				
n=12	-0.0438	-0.1496***	-0.0682	3.18%	-0.0814	0.78	0.38	-0.1751	-0.1192**	-0.1288	4.69%	0.0096	0.00	0.94
	(-0.36)	(-2.97)	(-0.92)					(-0.97)	(-2.06)	(-1.17)				
n=13	-0.0488	-0.1194**	-0.0497	1.72%	-0.0697	0.49	0.48	-0.240	-0.1662	-0.0524	2.84%	-0.1138	0.63	0.43
	(-0.40)	(-2.34)	(-0.61)					(-1.25)	(-1.41)	(-0.97)				

Table 5

Predictive ability of VaR^{daily}_{FIN} for the CFNAI

Entries report the coefficient estimates on VaR^{daily}_{FIN} from the predictive regressions: $CFNAI_{t+n} = \alpha + \gamma VaR^{daily}_{FIN,t} + \varepsilon_{t+n}$, where CFNAI_{t+n} denotes the n-month ahead CFNAI, and $VaR^{daily}_{FIN,t}$ is the catastrophic risk measure in month t, is computed by first extracting the lowest daily excess returns on financial institutions over the past 1 to 12 months, and then taking the average of the lowest daily excess returns for the financial sector obtained from alternative measurement windows. The estimation windows are fixed at one to 12 months, and each fixed estimation window is updated on a monthly basis. Newey and West (1987) t-statistics are reported in parentheses. The sample period is from January 1973 to December 2009. Significance at the 10%, 5%, and 1% level is respectively denoted *, **, and ***.

	1 month		2 months		3 months		4 months		5 months		6 months		12 months	
CFNAI_{t+n}	$VaR^{daily}_{FIN,t}$	Adj. R^2	$VaR^{daily}_{FIN,t}$	Adj. R^2	$VaR^{daily}_{FIN,t}$	Adj. R^2	$VaR^{daily}_{FIN,t}$	Adj. R^2	$VaR^{daily}_{FIN,t}$	Adj. R^2	$VaR^{daily}_{FIN,t}$	Adj. R^2	$VaR^{daily}_{FIN,t}$	Adj. R^2
n=1	-23.8912***	21.11%	-21.7333***	24.77%	-20.3375***	26.21%	-18.8213***	25.58%	-17.5388***	24.58%	-16.5091***	23.61%	-12.2938***	17.07%
	(-5.83)		(-6.41)		(-6.60)		(-6.24)		(-5.87)		(-5.51)		(-4.06)	
n=2	-25.1436***	23.54%	-22.0133***	25.34%	-19.7102***	24.52%	-17.9648***	23.25%	-16.7493***	22.32%	-15.5652***	20.87%	-11.5658***	14.69%
	(-5.91)		(-6.15)		(-5.76)		(-5.41)		(-5.13)		(-4.84)		(-3.73)	
n=3	-24.1862***	21.71%	-20.2062***	21.26%	-17.9464***	20.27%	-16.5197***	19.56%	-15.2292***	18.33%	-14.0976***	16.97%	-10.5222***	11.74%
	(-5.60)		(-5.27)		(-4.97)		(-4.78)		(-4.56)		(-4.30)		(-3.46)	
n=4	-20.7577***	15.90%	-17.5989***	16.06%	-16.0206***	16.06%	-14.5622***	15.08%	-13.3952***	14.03%	-12.6012***	13.39%	-9.4119***	9.00%
	(-4.54)		(-4.39)		(-4.34)		(-4.22)		(-4.03)		(-3.92)		(-3.23)	
n=5	-18.4372***	12.47%	-16.1310***	13.40%	-14.3386***	12.73%	-12.9811***	11.83%	-12.1041***	11.29%	-11.3947***	10.75%	-8.4667***	6.91%
	(-4.05)		(-4.10)		(-4.04)		(-3.89)		(-3.81)		(-3.70)		(-3.07)	
n=6	-17.4676***	11.09%	-14.5152***	10.71%	-12.8339***	10.04%	-11.7539***	9.53%	-10.9258***	8.99%	-10.2976***	8.53%	-7.6351***	5.31%
	(-3.91)		(-3.89)		(-3.75)		(-3.68)		(-3.58)		(-3.49)		(-2.91)	
n=7	-14.6618***	7.66%	-12.3670***	7.61%	-11.1890***	7.46%	-10.2194***	6.99%	-9.5536***	6.64%	-8.8895***	6.08%	-6.6509***	3.77%
	(-3.69)		(-3.56)		(-3.54)		(-3.43)		(-3.35)		(-3.19)		(-2.71)	
n=8	-12.6891***	5.61%	-10.8998***	5.76%	-9.7739***	5.49%	-8.9982***	5.21%	-8.2866***	4.75%	-7.7788***	4.39%	-5.9749**	2.83%
	(-3.19)		(-3.24)		(-3.16)		(-3.09)		(-2.94)		(-2.81)		(-2.51)	
n=9	-11.2608***	4.26%	-9.5946***	4.25%	-8.7085***	4.15%	-7.8636***	3.74%	-7.3129**	3.45%	-6.7189**	3.04%	-5.2683**	2.03%
	(-3.05)		(-2.97)		(-2.93)		(-2.74)		(-2.61)		(-2.44)		(-2.27)	
n=10	-9.8622***	3.05%	-8.4860***	3.13%	-7.4838**	2.85%	-6.8162**	2.59%	-6.1853**	2.25%	-5.8051**	2.06%	-4.5715*	1.38%
	(-2.62)		(-2.64)		(-2.45)		(-2.31)		(-2.13)		(-2.05)		(-1.95)	
n=11	-9.0680**	2.43%	-7.3421**	2.16%	-6.5421**	1.98%	-5.7913*	1.68%	-5.3911*	1.53%	-4.9296*	1.30%	-3.7287	0.98%
	(-2.41)		(-2.18)		(-2.04)		(-1.85)		(-1.77)		(-1.68)		(-1.55)	

Table 6

Predictive ability of VaR^{daily}_{FIN} and VaR^{daily}_{nonFIN} for the CFNAI

Entries report the coefficient estimates on VaR^{daily}_{FIN} and VaR^{daily}_{nonFIN} from the predictive regressions: $CFNAI_{t+n} = \alpha + \gamma VaR^{daily}_{FIN,t} + \beta VaR^{daily}_{nonFIN,t} + \varepsilon_{t+n}$, where CFNAI$_{t+1}$ and CFNAI$_{t+3}$ are the one- and three-month ahead CFNAI, and VaR^{daily}_{FIN} and VaR^{daily}_{nonFIN} respectively denote the catastrophic risk measure in month t for the financial sector and a non-financial grouping, computed by first extracting the lowest daily excess returns for firms in each grouping over the past 1 to 12 months, and then taking the average of the lowest daily excess returns for each grouping obtained from alternative measurement windows. The estimation windows are fixed at 1 to 12 months, and each fixed estimation window is updated on a monthly basis. Newey and West (1987) t-statistics are reported in parentheses. The sample period is from January 1973 to December 2009. Significance at the 10%, 5%, and 1% level is respectively denoted *, **, and ***.

Panel A: Measurement window - 1 month

	Dependent variable: CFNAI$_{t+1}$			Dependent variable: CFNAI$_{t+3}$		
Industry	$VaR^{daily}_{FIN,t}$	$VaR^{daily}_{nonFIN,t}$	Adj. R^2	$VaR^{daily}_{FIN,t}$	$VaR^{daily}_{nonFIN,t}$	Adj. R^2
All non-financial firms	-26.9589***	3.7593	21.14%	-27.7846***	4.3711	21.82%
	(-4.71)	(0.67)		(-3.93)	(0.69)	
Consumer goods	-30.8155***	8.3321	21.76%	-33.0100***	10.5319	22.84%
& services	(-6.05)	(1.41)		(-4.67)	(1.52)	
Manufacturing, energy & utilities	-19.6238***	-5.7106	21.13%	-21.8542***	-3.0976	21.59%
	(-2.55)	(-0.61)		(-2.51)	(-0.34)	
Hitech, business equipment,	-26.2786***	2.8258	21.14%	-26.1480***	2.2954	21.67%
telephone & TV	(-5.26)	(0.66)		(-4.34)	(0.48)	
Healthcare, medical equipment,	-31.3911***	8.7753	22.45%	-31.1857***	8.1234	22.83%
& drugs	(-6.24)	(1.80)		(-4.96)	(1.56)	
All other non-financial firms	-29.4791***	6.8835	21.76%	-30.3307***	7.4968	22.51%
	(-5.04)	(1.25)		(-4.28)	(1.22)	

Table 6 (Continued)

Panel B: Measurement window - 2 months

	Dependent variable: CFNAI_{t+1}			Dependent variable: CFNAI_{t+3}		
Industry	$VaR^{daily}_{FIN,t}$	$VaR^{daily}_{nonFIN,t}$	Adj. R^2	$VaR^{daily}_{FIN,t}$	$VaR^{daily}_{nonFIN,t}$	Adj. R^2
All non-financial firms	-23.6692***	2.4452	24.73%	-23.0275***	3.5331	21.35%
	(-4.98)	(0.49)		(-3.68)	(0.62)	
Consumer goods	-27.2717***	6.8264	25.42%	-27.4124***	8.8108	22.43%
& services	(-6.15)	(1.26)		(-4.25)	(1.40)	
Manufacturing, energy & utilities	-18.6195***	-4.2605	24.75%	-20.0025***	-0.2767	21.08%
	(-2.68)	(-0.47)		(-2.48)	(-0.03)	
Hitech, business equipment,	-22.9014***	1.4308	24.67%	-21.5765***	1.6594	21.18%
telephone & TV	(-5.69)	(0.38)		(-4.04)	(0.39)	
Healthcare, medical equipment,	-27.4568***	6.8271	25.91%	-25.2677***	5.9962	22.09%
& drugs	(-6.10)	(1.51)		(-4.45)	(1.27)	
All other non-financial firms	-25.1784***	4.4265	25.08%	-24.9307***	6.0091	21.97%
	(-5.33)	(0.93)		(-3.98)	(1.09)	

Panel C: Measurement window - 3 months

	Dependent variable: CFNAI_{t+1}			Dependent variable: CFNAI_{t+3}		
Industry	$VaR^{daily}_{FIN,t}$	$VaR^{daily}_{nonFIN,t}$	Adj. R^2	$VaR^{daily}_{FIN,t}$	$VaR^{daily}_{nonFIN,t}$	Adj. R^2
All non-financial firms	-21.4203***	1.3918	26.09%	-20.6111***	3.3971	20.39%
	(-4.85)	(0.30)		(-3.51)	(0.63)	
Consumer goods	-24.7786***	5.5496	26.72%	-24.2487***	7.8154	21.41%
& services	(-5.72)	(1.09)		(-4.00)	(1.33)	
Manufacturing, energy & utilities	-17.0718***	-4.5209	26.26%	-19.8168***	2.5710	20.15%
	(-2.66)	(-0.54)		(-2.60)	(0.30)	
Hitech, business equipment,	-20.7892***	0.5653	26.05%	-19.3245***	1.7060	20.21%
telephone & TV	(-5.62)	(0.16)		(-3.82)	(0.41)	
Healthcare, medical equipment,	-24.6237***	5.1584	26.98%	-22.0829***	4.9464	20.94%
& drugs	(-5.74)	(1.24)		(-4.17)	(1.12)	
All other non-financial firms	-22.6280***	3.0161	26.32%	-22.0878***	5.3986	20.95%
	(-5.18)	(0.69)		(-3.73)	(1.03)	

Table 6 (Continued)

Panel D: Measurement window - 4 months

Industry	Dependent variable: CFNAI_{t+1}			Dependent variable: CFNAI_{t+3}		
	$VaR^{daily}_{FIN,t}$	$VaR^{daily}_{nonFIN,t}$	Adj. R^2	$VaR^{daily}_{FIN,t}$	$VaR^{daily}_{nonFIN,t}$	Adj. R^2
All non-financial firms	-19.7521***	1.2124	25.46%	-18.5977***	2.6824	19.60%
	(-4.53)	(0.27)		(-3.30)	(0.52)	
Consumer goods	-22.9053***	5.1570	26.10%	-21.6761***	6.4574	20.43%
& services	(-5.18)	(1.04)		(-3.70)	(1.15)	
Manufacturing, energy & utilities	-16.4237***	-3.3468	25.55%	-18.3605***	2.5494	19.46%
	(-2.63)	(-0.41)		(-2.48)	(0.31)	
Hitech, business equipment,	-19.1248***	0.3860	25.42%	-17.5646***	1.3135	19.46%
telephone & TV	(-5.19)	(0.12)		(-3.57)	(0.33)	
Healthcare, medical equipment,	-22.3051***	4.2299	26.16%	-19.6151***	3.7332	19.96%
& drugs	(-5.31)	(1.08)		(-3.85)	(0.88)	
All other non-financial firms	-20.8952***	2.7814	25.68%	-20.0533***	4.6869	20.12%
	(-4.81)	(0.65)		(-3.50)	(0.92)	

Panel E: Measurement window - 5 months

Industry	Dependent variable: CFNAI_{t+1}			Dependent variable: CFNAI_{t+3}		
	$VaR^{daily}_{FIN,t}$	$VaR^{daily}_{nonFIN,t}$	Adj. R^2	$VaR^{daily}_{FIN,t}$	$VaR^{daily}_{nonFIN,t}$	Adj. R^2
All non-financial firms	-18.5458***	1.3260	24.47%	-17.0842***	2.4172	18.35%
	(-4.26)	(0.31)		(-3.16)	(0.49)	
Consumer goods	-21.4426***	4.9734	25.12%	-19.7340***	5.6848	19.07%
& services	(-4.80)	(1.03)		(-3.51)	(1.07)	
Manufacturing, energy & utilities	-16.4844***	-1.4819	24.43%	-17.5474***	3.2301	18.29%
	(-2.71)	(-0.19)		(-2.49)	(0.41)	
Hitech, business equipment,	-17.8840***	0.4456	24.42%	-16.2340***	1.2785	18.23%
telephone & TV	(-4.79)	(0.14)		(-3.41)	(0.33)	
Healthcare, medical equipment,	-20.4795***	3.5947	25.02%	-17.7864***	3.1032	18.60%
& drugs	(-4.95)	(0.96)		(-3.61)	(0.77)	
All other non-financial firms	-19.5100***	2.6832	24.68%	-18.3977***	4.2551	18.83%
	(-4.46)	(0.64)		(-3.30)	(0.87)	

Table 6 (Continued)

Panel F: Measurement window - 6 months

Industry	Dependent variable: $CFNAI_{t+1}$ $VaR^{daily}_{FIN,t}$	$VaR^{daily}_{nonFIN,t}$	Adj. R^2	Dependent variable: $CFNAI_{t+3}$ $VaR^{daily}_{FIN,t}$	$VaR^{daily}_{nonFIN,t}$	Adj. R^2
All non-financial firms	-17.2852***	1.0298	23.48%	-15.8204***	2.2600	16.97%
	(-3.92)	(0.24)		(-3.04)	(0.48)	
Consumer goods	-19.8893***	4.3304	24.04%	-18.1362***	5.1236	17.61%
& services	(-4.37)	(0.92)		(-3.37)	(1.01)	
Manufacturing, energy & utilities	-15.7338***	-1.0932	23.46%	-16.9472***	3.9836	17.01%
	(-2.60)	(-0.15)		(-2.50)	(0.52)	
Hitech, business equipment,	-16.6693***	0.2093	23.44%	-15.0427***	1.2146	16.87%
telephone & TV	(-4.35)	(0.06)		(-3.25)	(0.33)	
Healthcare, medical equipment,	-18.7916***	2.8034	23.86%	-16.3739***	2.7736	17.19%
& drugs	(-4.53)	(0.77)		(-3.45)	(0.71)	
All other non-financial firms	-18.3050***	2.4710	23.69%	-17.1029***	4.0709	17.45%
	(-4.11)	(0.60)		(-3.15)	(0.85)	

Panel G: Measurement window - 12 months

Industry	Dependent variable: $CFNAI_{t+1}$ $VaR^{daily}_{FIN,t}$	$VaR^{daily}_{nonFIN,t}$	Adj. R^2	Dependent variable: $CFNAI_{t+3}$ $VaR^{daily}_{FIN,t}$	$VaR^{daily}_{nonFIN,t}$	Adj. R^2
All non-financial firms	-13.0590***	1.0342	16.93%	-11.7295***	1.5992	11.68%
	(-3.14)	(0.28)		(-2.73)	(0.42)	
Consumer goods	-14.2734***	2.5755	17.19%	-12.4664***	2.4902	11.83%
& services	(-3.38)	(0.66)		(-2.91)	(0.64)	
Manufacturing, energy & utilities	-14.3925***	2.9762	17.07%	-14.3167***	5.3605	12.16%
	(-2.76)	(0.50)		(-2.59)	(0.87)	
Hitech, business equipment,	-12.7212***	0.5719	16.90%	-11.5353***	1.3126	11.68%
telephone & TV	(-3.26)	(0.19)		(-2.84)	(0.42)	
Healthcare, medical equipment,	-13.5684***	1.5914	17.09%	-11.6735***	1.4160	11.70%
& drugs	(-3.50)	(0.52)		(-2.98)	(0.45)	
All other non-financial firms	-13.9779***	2.3678	17.20%	-12.8578***	3.0693	12.38%
	(-3.14)	(0.63)		(-3.27)	(0.97)	

Table 7
Catastrophic risk of big and small financial firms

For each month in our sample the NYSE top size quintile breakpoint is used to divide financial firms into two groups: big firms with market cap above the breakpoint and small firms with market cap below the breakpoint. *CATFIN* for big and small firms is denoted *CATFINBIG* and *CATFINSML*, respectively. Entries report the coefficient estimates from regressions of the n-month ahead CFNAI on *CATFINBIG* and *CATFINSML*. Newey and West (1987) t-statistics are reported in parentheses. The sample period is from January 1973 to December 2009. Significance at the 10%, 5%, and 1% level is respectively denoted *, **, and ***.

CFNAI_{t+n}	Intercept	*CATFINBIG*	*CATFINSML*	Adj. R^2
n=1	-0.0591	-0.1325***	-0.2100***	17.09%
	(-1.37)	(-3.55)	(-5.52)	
n=2	-0.0642	-0.1968***	-0.1846***	21.29%
	(-1.53)	(-5.39)	(-4.95)	
n=3	-0.0680	-0.2176***	-0.1921***	24.59%
	(-1.65)	(-6.09)	(-5.23)	
n=4	-0.0684	-0.2114***	-0.1632***	20.61%
	(-1.62)	(-5.75)	(-4.32)	
n=5	-0.0695	-0.2085***	-0.1272***	16.76%
	(-1.60)	(-5.52)	(-3.28)	
n=6	-0.0714	-0.2202***	-0.1239***	17.74%
	(-1.66)	(-5.86)	(-3.20)	
n=7	-0.0737	-0.1893***	-0.1135***	13.55%
	(-1.66)	(-4.91)	(-2.85)	
n=8	-0.0730	-0.1731***	-0.0906**	10.30%
	(-1.61)	(-4.40)	(-2.23)	
n=9	-0.0754	-0.1752***	-0.0779*	9.63%
	(-1.66)	(-4.44)	(-1.91)	
n=10	-0.0784	-0.1633***	-0.0621	7.71%
	(-1.71)	(-4.09)	(-1.50)	
n=11	-0.0850	-0.1432***	-0.0816**	6.99%
	(-1.84)	(-3.55)	(-1.96)	
n=12	-0.0860	-0.1658***	-0.0435	6.07%
	(-1.85)	(-3.99)	(-1.04)	
n=13	-0.0847	-0.1314***	-0.0389	3.79%
	(-1.80)	(-3.12)	(-0.91)	
n=14	-0.0844	-0.1152***	-0.0310	2.64%
	(-1.77)	(-2.71)	(-0.71)	
n=15	-0.0847	-0.1313***	0.0073	2.15%
	(-1.77)	(-3.00)	(0.17)	
n=16	-0.0836	-0.1237***	0.0352	1.20%
	(-1.73)	(-2.62)	(0.80)	
n=17	-0.0842	-0.1070***	0.0381	0.73%
	(-1.74)	(-2.25)	(0.86)	
n=18	-0.0845	-0.1195***	0.0505	0.96%
	(-1.74)	(-2.47)	(1.14)	

Table 8
Alternative macroeconomic indicators

Entries report the coefficient estimates on the *CATFIN* from the predictive regressions: $Y_{t+n} = \alpha + \gamma CATFIN_t + \varepsilon_{t+n}$, where Y is one of the three macroeconomic indicators: the dummy variable (NBER) taking the value of 1 if the U.S. economy is in recession in a month as marked by the National Bureau of Economic Statistics, and zero otherwise, the Aruoba-Diebold-Scotti (ADS) Business Conditions Index, and the Kansas City Financial Stress Index (KCFSI). Probit regression is implemented when NBER is the dependent variable, and OLS regression is estimated when the ADS index and the KCFSI are the dependent variable. Z-statistics from probit regression and Newey and West (1987) t-statistics from the OLS regressions are reported in parentheses. Significance at the 10%, 5%, and 1% level is respectively denoted *, **, and ***.

	$NBER_{t+n}$		ADS_{t+n}		$KCFSI_{t+n}$	
	$CATFIN_t$	Adj. R^2	$CATFIN_t$	Adj. R^2	$CATFIN_t$	Adj. R^2
n=1	0.3536*** (7.58)	15.73%	-0.2004*** (-4.17)	13.51%	0.3596*** (4.26)	48.19%
n=2	0.3608*** (7.65)	16.17%	-0.2232*** (-4.65)	16.80%	0.3367*** (4.30)	42.44%
n=3	0.3874*** (7.88)	17.74%	-0.2239*** (-4.73)	16.62%	0.3210*** (4.23)	37.93%
n=4	0.3493*** (7.49)	15.22%	-0.1930*** (-4.25)	12.28%	0.3029*** (4.08)	33.86%
n=5	0.3159*** (6.99)	12.86%	-0.1653*** (-3.72)	8.94%	0.2716*** (3.94)	27.31%
n=6	0.2936*** (6.65)	11.37%	-0.1476*** (-3.36)	7.07%	0.2464*** (3.71)	22.31%
n=7	0.2821*** (6.44)	10.59%	-0.1301*** (-3.12)	5.42%	0.2201*** (3.47)	17.66%
n=8	0.2692*** (6.20)	9.71%	-0.1105*** (-2.67)	3.84%	0.1956*** (3.40)	13.83%
n=9	0.2516*** (5.86)	8.59%	-0.0985** (-2.41)	3.00%	0.1708*** (3.19)	10.45%
n=10	0.2169*** (5.15)	6.52%	-0.0853** (-2.15)	2.20%	0.1540*** (3.03)	8.38%
n=11	0.1986*** (4.67)	5.31%	-0.0791** (-2.10)	1.77%	0.1448*** (2.91)	6.95%
n=12	0.1612*** (3.74)	3.36%	-0.0641* (-1.67)	1.03%	0.1331*** (2.76)	5.46%
n=13	0.1311*** (3.01)	2.18%	-0.0482 (-1.38)	0.46%	0.1100** (2.39)	3.49%
n=14	0.1014** (2.27)	1.23%	-0.0320 (-0.82)	0.06%	0.0894** (1.96)	2.02%
Sample period	01/1973 - 12/2009		01/1973 - 12/2009		02/1990 - 12/2009	