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

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We derive a measure of aggregate systemic risk, designated *CATFIN*, that complements bank-specific systemic risk measures by forecasting macroeconomic downturns six months into the future using out-of-sample tests conducted with U.S., European, and Asian bank data. Consistent with bank "specialness," the *CATFIN* of both large and small banks forecasts macroeconomic declines, whereas a similarly defined measure for both nonfinancial firms and simulated "fake banks" has no marginal predictive ability. High levels of systemic risk in the banking sector impact the macroeconomy through aggregate lending activity. A conditional asset pricing model shows that *CATFIN* is priced for financial and nonfinancial firms. (*JEL* G01, G21, G12, C13, C22)

Bank regulators throughout the world are wrestling with proposals to measure and monitor systemic risk. Focus has been on correlations among pairs of financial firms to determine the most interconnected banks, because these "systemically important" banks can set off a chain reaction of financial contagion when they become distressed.[1] These "microlevel" systemic risk measures determine the contribution of each bank to overall systemic

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[1] Microlevel systemic risk proposals include marginal expected shortfall (*MES*; see Acharya et al. 2010), *CoVaR* (Adrian and Brunnermeier 2009), conditional tail risk (*CTR*; see Kelly 2011), corisk (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).

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risk, which is important because systemic risk exposure may lead to real macroeconomic declines (see DeBandt and Hartmann 2002; Kambhu, Schuermann, and Stiroh 2007). However, our analysis shows that proposed microlevel systemic risk measures have no macroeconomic forecasting power. Thus, in this article, we develop a new macroindex of systemic risk that predicts future real economic downturns. The index measures the aggregate level of risk taking in the financial sector (rather than an individual bank's systemic risk exposure) and is calculated using the cross-sectional distribution of equity returns of financial firms. We utilize the measure, denoted *CATFIN*, to forecast the likelihood that systemic risk taking in the banking system as a whole will have detrimental real macroeconomic effects.

Our new macromeasure of systemic risk, *CATFIN*, complements microlevel systemic risk measures focusing on direct interbank connections, because systemic risk can emerge through general economic factors that cause financial markets to freeze up and/or banks to substantially reduce the supply of credit. Kashyap, Berner, and Goodhart (2011) and Korinek (2011) describe financial amplification effects resulting from fire sales of financial assets by individual banks that trigger the catastrophic declines in asset prices and reduced liquidity that accompany a systemic crisis. These effects transcend pairwise interconnections between banks (particularly if many bank portfolios are overly invested in assets exposed to rollover risk; see Acharya, Gale, and Yorulmazer 2011). Indeed, Bekaert et al. (2011) show that international contagion during the 2007–2009 crisis did not spread through direct trade and financial linkages but rather through a "wake-up call" that "provides new information that may prompt investors to reassess the vulnerability of other market segments or countries, which spreads the crisis across markets and borders."

More generally, financial institutions are "special" because when they are in distress, banks tend to cut back on all of their activities, including lending to their customers (see Ivashina and Scharfstein 2010 for evidence of this in 2008), who in turn reduce their investment activity and hiring, which impacts employment and expenditure on a macroeconomic level. If there are only a limited number of troubled banks at any one point in time, competitor banks may overcome the information destruction inherent in these disruptions in bank-customer relationships and meet the demands of customers formerly served by a distressed bank. However, as more banks enter into crisis, these spillover effects become substantial and competitor banks are unable to prevent macroeconomic contagion (e.g., Jermann and Quadrini 2009 links reductions in credit availability to macroeconomic downturns). This chain reaction of systemic effects extends beyond the web of individual interbank relationships.

Systemic risk could conceivably bubble up from widespread catastrophic risk among smaller, less directly interrelated banks with common risk factors. Indeed, Kashyap and Stein (2000) find that aggregate declines in loan supply are driven by smaller banks (in the bottom ninety-fifth percentile of the size distribution) that are liquidity constrained. Thus, focus on the largest financial firms omits an important potential source of systemic risk. Banks, large and small, tend to take on excessive risk because they do not consider the external costs of their risk taking on nonfinancial firms and on society at large. That is, financial contagion is spread through risk and illiquidity in the financial sector (Longstaff 2010), as liquidity-constrained banks transmit financial shocks to the real economy (Duchin, Ozbas, and Sensoy 2010), thereby creating systemic risk (e.g., through bank transmission of fluctuations in investor sentiment as in Shleifer and Vishny 2010). Indeed, it is because of the risk of macroeconomic contagion that regulators and governments are so concerned about systemic risk. Thus, regulators require a systemic risk measure, such as *CATFIN*, that determines the macroeconomic implications of aggregate risk taking in the financial system.

CATFIN is estimated using both value-at-risk (*VaR*) and expected shortfall (ES) methodologies, each of which are estimated using three approaches: one nonparametric and two different parametric specifications. 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. We find that all versions of *CATFIN* are predictive of future real economic downturns as measured by gross domestic product (GDP), industrial production, the unemployment rate, and an index of eighty-five existing monthly economic indicators (the Chicago Fed National Activity Index, CFNAI), as well as other measures of real macroeconomic activity (e.g., NBER recession periods and the Aruoba-Diebold-Scott [ADS] business conditions index maintained by the Philadelphia Fed). Consistent with an extensive body of literature linking the real and financial sectors of the economy, we find that *CATFIN* forecasts aggregate bank lending activity.[2]

We utilize the *CATFIN* measure to derive an early warning system that will signal whether aggressive aggregate systemic risk taking in the financial sector presages future macroeconomic declines. The usefulness of *CATFIN* as an early warning system to forecast decreases in real economic activity is robust to the inclusion of microlevel systemic risk measures as well as a large set of macroeconomic and financial variables. *CATFIN* can forecast significant declines in U.S. economic conditions approximately six months into the future. We also show similar predictive power internationally. We investigate the predictive ability of regional *CATFIN* for the GDP growth rates in Asian countries and the European Union. The results indicate that the regional *CATFIN* can significantly predict lower GDP growth rates in the European Union and Asian countries up to eight and six months into

[2] Contractions in bank lending impact real investment activity, particularly for bank-dependent firms (see Abel and Blanchard 1986; Kashyap, Stein, and Wilcox 2000; Gorton and He 2005; Ashcraft 2005; Tong and Wei 2008; Byoun and Xu 2011). Peek and Rosengren (2000) use the Japanese banking crisis and Lemmon and Roberts (2010) use the Drexel collapse as exogenous factors that disentangle the supply and demand effects and find that declines in the supply of credit detrimentally impact real macroeconomic activity. Campello, Graham, and Harvey (2010) survey 1,050 CFOs and find reductions in capital spending and employment as a result of cutbacks in credit availability during the financial crisis of 2008.

the future, respectively. Therefore, national bank regulators throughout the world can use the *CATFIN* early warning signal to calibrate a microlevel systemic risk premium (or tax) to macroeconomic conditions. When *CATFIN* signals a relatively robust economic forecast, a more laissez-faire policy toward individual bank risk taking should be pursued and the systemic risk premium should be set rather low. However, when *CATFIN* signals trouble ahead, the regulator should take preemptive action and set a more constraining limit and/or a higher systemic risk premium on microlevel bank risk exposures, indicating the higher systemic cost of marginal increases in bank risk taking. Thus, *CATFIN* can be used to calibrate a microlevel tax on systemic risk. This would introduce a forward-looking approach to systemic risk management that can be applied countercyclically to stabilize economic fluctuations and offset some of the inherently procyclical incentives in banking, thereby mitigating the moral hazard effects associated with bank bailouts.

The article is organized as follows. We present the *CATFIN* measure in Section 1. Section 2 tests the predictive power of *CATFIN* for future economic downturns in the United States, Europe, and Asia and provides a battery of robustness checks. In Section 3, we develop an early warning system and present further empirical results. Section 4 provides economic motivation for using *CATFIN* as a measure of systemic risk and shows that *CATFIN* is priced in the time series and cross-section of individual stocks. Section 5 concludes the article.

1. Estimating Catastrophic Risk in the Financial Sector

We estimate *VaR* at the 99% confidence level using two parametric distributions (the GPD and SGED) and the nonparametric method. *CATFIN* is defined as the average of these three different *VaR* measures.

1.1 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.

Pickands (1975) introduces the generalized Pareto distribution $G_{min,\xi}$ in Equation (1):

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

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. As described in Section 1 of the online appendix, the GPD parameters are estimated using maximum likelihood. Bali (2003, 2007) shows that the GPD distribution yields a closed-form solution for *VaR*:

$$\vartheta_{GPD}=\mu+\left(\frac{\sigma}{\xi}\right)\left[\left(\frac{\alpha N}{n}\right)^{-\xi}-1\right], \tag{2}$$

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.[3]

In this article, 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. Once we estimate the three parameters of the GPD using the extreme observations, for each month we compute an aggregate 1% *VaR* measure of the U.S. financial system using Equation (2).

1.2 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

$$f(r_i;\mu,\sigma,\kappa,\lambda)=\frac{C}{\sigma}\exp\left(-\frac{1}{[1+sign(r_i-\mu+\delta\sigma)\lambda]^{\kappa}\theta^{\kappa}\sigma^{\kappa}}|r_i-\mu+\delta\sigma|^{\kappa}\right), \tag{3}$$

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 parameter κ controls the height and tails of the density function, and the parameter λ controls skewness. In the case of positive skewness ($\lambda>0$), the density function is skewed to the right. The opposite is true for negative λ. As shown in Section 2 of the online appendix, the SGED parameters are estimated by maximum likelihood (see Bali and Theodossiou 2008).

To derive the 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 (μ, σ, κ, λ), we solve for the SGED *VaR* threshold ϑ_{SGED} numerically by

[3] The original *VaR* values are negative because 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.

equalizing the area under the SGED density to the coverage probability at the given loss probability level α:

$$\int_{-\infty}^{\vartheta_{SGED}(\alpha)} f_{\mu,\sigma,\kappa,\lambda}(z)dz=\alpha. \tag{4}$$

The numerical solution of Equation (4) for each month from January 1973 to December 2009 yields monthly time series of the 1% *VaR* measures from the SGED density.

1.3 Nonparametric method

The nonparametric 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% nonparametric *VaR* measure ϑ_{NP} in a given month is measured as the cutoff point for the lower one percentile of the monthly excess returns on financial firms. Assuming that we have 900 financial firms in month t, the nonparametric measure of 1% *VaR* is the ninth 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 period 1973–2009.

1.4 The *CATFIN* measure

The above methodologies yield three *VaR* measures for each month over the sample period between January 1973 and December 2009 (results summarized in Table A1 of the online appendix). Return data include all NYSE-, AMEX-, and NASDAQ-traded financial common stocks (SIC code $\geq$6000 and SIC code $\leq$6999 and SHRCD =10 or 11). We require that a firm's market capitalization at the beginning of each month and monthly stock return be available. We adjust stock returns for delisting in order to avoid survivorship bias (Shumway 1997). There are on average 1,025 cross-sectional return observations in our sample ranging from 604 to 1,432.

Rather than taking a stand on any particular methodology, we define *CATFIN* as the arithmetic average of the GPD, SGED, and nonparametric *VaR* measures.[4] 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.

[4] In the online appendix (Section 3, Table A2), we define *CATFIN* as the first principal component of the SGED, GPD, and nonparametric *VaR* measures and find that this measure predicts future economic downturns seven months in advance. However, the principal component methodology introduces look-ahead bias to the predictability results. Since Section 3 of the online appendix shows that *CATFIN* loads almost equally on the three *VaR* measures in the principal component analysis, we obtain support for the use of the arithmetic average in our derivation.

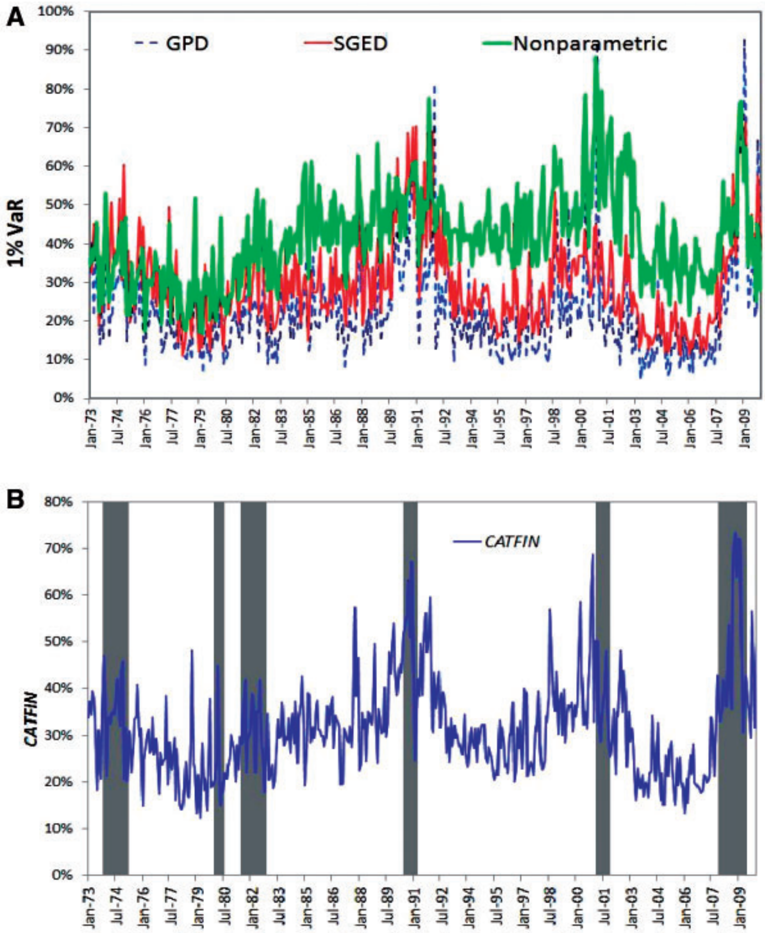

Figure 1
One percent *VaR* and the *CATFIN*
Panel A depicts the monthly 1% *VaR*, estimated from the GPD, the SGED, and the nonparametric methods. Panel B plots recessions (shaded areas) and the monthly *CATFIN*, measured as the arithmetic average of the three 1% *VaR* measures. The sample period is from January 1973 to December 2009.

2. Predictive Power of Systemic Risk for Future Economic Downturns

2.1 Predictive ability of *CATFIN* for future macroeconomic activity

We test the predictive power of *CATFIN* in forecasting future 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 eighty-five monthly indicators of national economic activity and is constructed to have an average value of zero and a standard deviation of one. Because 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.

We estimate the following n-month-ahead multivariate predictive regressions of CFNAI on *CATFIN* after controlling for a large set of macroeconomic and financial variables as well as one-month to twelve-month lags of the CFNAI index:

$$CFNAI_{t+n} = \alpha + \gamma CATFIN_t + \beta X_t + \sum_{i=1}^{12} \lambda_i CFNAI_{t-i+1} + \varepsilon_{t+n}, \qquad (5)$$

where X_t denotes a vector including the following control variables in month t: the default spread, defined as the difference between the BAA-rated and AAA-rated corporate bonds (*DEF*); the term spread, defined as the difference between the ten-year T-bond and one-month T-bill yields (*TERM*); the relative short-term interest rate, defined as the difference between one-month T-bill rate and its twelve-month backward-moving average (*RREL*); *FIN_RET* is the value-weighted average excess returns of all financial firms, which can be viewed as the average excess return on the financial market index; *FIN_VOL* is the realized monthly volatility of excess returns of all financial firms, defined as the square root of the sum of squared daily returns in a month; *FIN_SKEW* is the realized monthly skewness of excess returns of all financial firms; *FIN_BETA* is the average market beta of all financial firms estimated from monthly returns over the past five years; *MKT_RET* is the monthly excess return on the CRSP value-weighted index; *MKT_VOL* is the realized monthly volatility of excess returns of the aggregate stock market portfolio, defined as the square root of the sum of squared daily returns in a month; *CORR* is the average correlation between excess returns on individual financial firms and excess returns on the financial market index, and the correlation measurement window is twenty-four months, updated on a monthly basis; *SIZE* is the natural logarithm of the average market capitalization of firms in the financial sector; and *LEV* is the aggregate leverage in the financial sector defined as the ratio of total liabilities to total assets of the entire financial sector. In addition to these control variables, we include twelve lags of the dependent variable (CFNAI) in the predictive regressions.

Panel A of Figure 2 presents the slope coefficients on *CATFIN* along with the 95% confidence bounds, calculated based on the Newey and West (1987) standard errors.[5] The full set of estimates is reported in Table A3 of the online appendix. The results indicate that after controlling for a wide variety of factors,

[5] Following Newey and West (1987), we set the number of lags q to five using their formula: $q = floor\left(4 \times \left(\frac{T-n}{100}\right)^{\left(\frac{2}{9}\right)}\right)$, where $floor$ denotes the floor function and T equals 444, corresponding to the 444 months between January 1973 to December 2009, and n is the number of month lags (denoted n in Equation (5)), ranging from one to twelve.

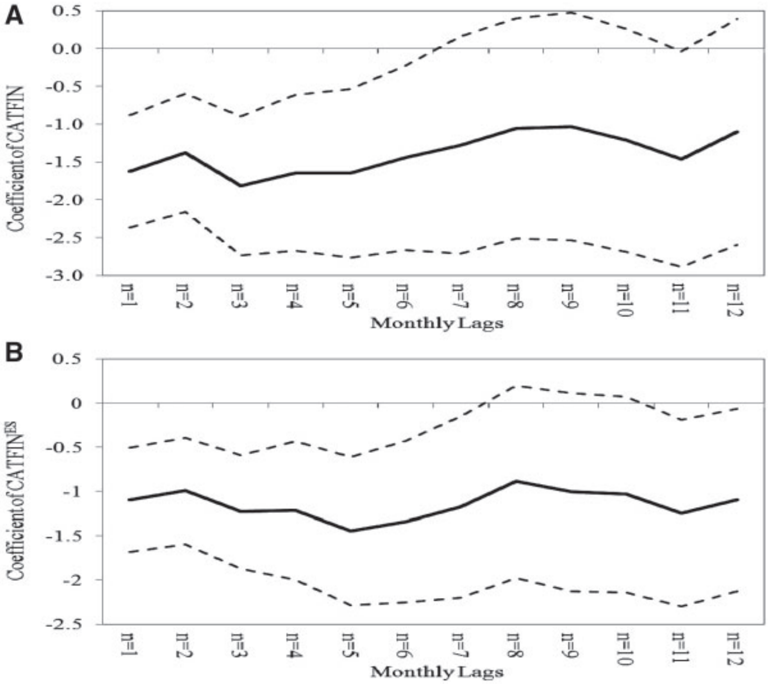

Figure 2
Predictive ability of *CATFIN* for the Chicago Fed National Activity Index (CFNAI)
This figure depicts the coefficients of *CATFIN* (Panel A) and $CATFIN^{ES}$ (Panel B) from the predictive regressions: $CFNAI_{t+n} = \alpha + \gamma CATFIN_t / CATFIN_t^{ES} + \beta X_t + \sum_{i=1}^{12} \lambda_i CFNAI_{t-i+1} + \varepsilon_{t+n}$, where $CATFIN_t$ and $CATFIN_t^{ES}$ are, respectively, computed as the average of the 1% *VaR* measures and the average of the 1% expected shortfall (ES) measures, estimated from the GPD, the SGED, and the nonparametric methods; X_t denotes a vector of control variables: the default spread (*DEF*), the term spread (*TERM*), the relative short-term interest rate (*RREL*), the average monthly excess return return of financial institutions (*FIN_RET*), the monthly volatility of financial firms (*FIN_VOL*), the skewness of financial firms' returns (*FIN_SKEW*), the average market beta of financial firms (*FIN_BETA*), the average monthly excess return on the aggregate stock market portfolio (*MKT_RET*), the monthly volatility of the equity market index (*MKT_VOL*), the average correlations of returns for individual financial firms and returns for the financial sector (*CORR*), the natural logarithm of the average market capitalization of firms in the financial sector (*SIZE*), and the aggregate leverage in the financial sector (*LEV*); and CFNAI_{t+n} denotes the n-month ahead CFNAI. The dashed lines indicate the 95% confidence bounds, calculated based on the Newey-West standard errors. The sample period is from January 1973 to December 2009. The full set of estimates is reported in Table A3 of the online appendix for *CATFIN* and Table A6 for $CATFIN^{ES}$.

the coefficient of *CATFIN* is negative and highly significant, thereby predicting the CFNAI index up to six months in advance. From the one- to six-month-ahead prediction of the CFNAI index, the coefficient estimates are found to be in the range of −1.28 and −1.82 and strongly significant with the Newey and West (1987) t-statistics ranging from −2.31 to −4.29. The adjusted R^2 values from the predictive regressions are economically significant in the range of 32% to 60% for one- to six-month-ahead predictability.

Among the control variables, default spread, term spread, detrended short-term interest rate, volatility of the financial sector, and volatility of the aggregate stock market are significant predictors of future economic downturns. However, the predictive power of these macroeconomic and volatility variables is sensitive to the forecast horizon. We should also note that the weak predictive power of the control variables may be due to a multicollinearity problem because some of these variables are highly correlated with each other. To alleviate this concern, at an earlier stage of the study, we examined the predictive power of *CATFIN* without the control variables and found that *CATFIN* predicted the CFNAI index up to thirteen months in advance. Hence, the statistically significant coefficient estimates on *CATFIN* in Equation (5) are not due to the correlation between *CATFIN* and the control variables.

To provide a further robustness check, we rerun Equation (5) by replacing *CATFIN* with the individual *VaR* measures obtained from the parametric and nonparametric methods. Table A4 of the online appendix shows 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 nonparametric empirical return distribution, successfully predicts the four- to six-month-ahead CFNAI index. The slope coefficients of the three *VaR* measures 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 four to seven months into the future.

We have so far estimated the catastrophic risk of financial institutions using the cross-sectional distribution of monthly excess returns. We now 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 one to six months. The catastrophic risk of financial institutions is then computed by taking the average of these lowest daily excess returns obtained from alternative measurement windows. The estimation windows are fixed at one to six months, and each fixed estimation window is updated on a monthly basis. Section 4 (Table A5) of the online appendix shows that this alternative measure of *CATFIN* based on the time-series return distribution of financial firms predicts the CFNAI index up to five months in advance.

2.2 *CATFIN* measure based on expected shortfall

VaR as a risk measure is criticized for not being subadditive. Moreover, *VaR* does not take into account the severity of an incurred damage event. To alleviate these deficiencies, Artzner et al. (1999) introduce the "expected shortfall" (ES) risk measure, which is defined as the conditional expectation of a loss given that the loss is beyond the *VaR* level. That is, the ES measure is defined as

$$ES_\alpha = E(R|R \leq \vartheta_\alpha), \tag{6}$$

where R represents the extreme return or loss, ϑ_α is the *VaR* or threshold associated with the coverage probability α, and ES_α is the expected shortfall at the $100 \times (1-\alpha)$ percent confidence level. As such, the expected shortfall considers loss beyond the *VaR* level, ϑ_α. Equation (6) can be viewed as a mathematical transcription of the concept "average loss in the worst $100 \times \alpha$ percent cases." We now define an alternative *CATFIN* measure in terms of the expected shortfall of financial institutions.

First, we take the excess monthly returns of all financial firms from January 1973 to December 2009, and then for each month in our sample we estimate the 1% expected shortfall of the financial sector based on the GPD, SGED, and nonparametric methods. The 1% expected shortfall based on the GPD is calculated as (see Embrechts, Kluppelberg, and Mikosch 1997)

$$ES_{GPD} = \frac{\vartheta_{GPD}}{1-\xi} + \frac{\sigma - \mu\xi}{1-\xi}, \tag{7}$$

where ϑ_{GPD} is the 1% *VaR* threshold of the GPD, which is estimated using Equation (2), and μ, σ, and ξ are, respectively, the location, scale, and shape parameters of the GPD that are estimated using the 10% left tail of the cross-sectional distribution of excess returns on financial firms.

To derive an alternative 1% expected shortfall 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 (μ, σ, κ, λ), we solve for the 1% expected shortfall of the SGED numerically using the conditional probability density function:

$$ES_{SEGD} = \int_{-\infty}^{\vartheta_{SGED}} (R|R \le \vartheta_{SGED}) f_{\mu,\sigma,\kappa,\lambda}(R|R \le \vartheta_{SGED}) dR, \tag{8}$$

where ϑ_{SGED} is the 1% *VaR* threshold of the SGED (Equation (3)) and $f_{\mu,\sigma,\kappa,\lambda}(R|R \le \vartheta_{SGED})$ is the conditional SGED density defined in terms of the mean (μ), volatility (σ), skewness (λ), and tail-thickness (κ) parameters.

Finally, the 1% expected shortfall of the financial sector is estimated using the nonparametric methodology, which is simply the average of the extreme returns on financial firms that are beyond the 1% nonparametric *VaR*:

$$ES_{NP} = \frac{1}{n} \sum_{i=1}^{n} (R_i | R_i \le \vartheta_{NP}), \tag{9}$$

where ϑ_{NP} is the 1% nonparametric *VaR* measure in a given month measured as the cutoff point for the lower one percentile of the monthly excess returns on financial firms, and n is the number of extreme returns beyond ϑ_{NP}.

The above methodologies yield three expected shortfall measures for each month over the sample period between January 1973 and December 2009, which are averaged in order to obtain $CATFIN^{ES}$. We test the predictive power of $CATFIN^{ES}$ in forecasting economic downturns as measured by the CFNAI index. We estimate the multivariate predictive regressions of CFNAI on $CATFIN^{ES}$ using the econometric specification in Equation (5).

Panel B of Figure 2 presents the slope coefficients on $CATFIN^{ES}$ along with the 95% confidence bounds. The full set of estimates is reported in Table A6 of the online appendix. The results indicate that the slope coefficient of $CATFIN^{ES}$ is negative and statistically significant (at the 5% level or better), thereby forecasting the CFNAI index up to seven months in advance. From the one- to seven-month-ahead prediction of the CFNAI index, the coefficient estimates are found to be in the range of -0.99 and -1.45 and highly significant with the Newey-West t-statistics ranging from -2.25 to -3.76. Because the *VaR* and *ES* measures of *CATFIN* produce very similar predictability results, we focus on the *VaR* measure of *CATFIN* in the remainder of the article.

2.3 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 the growth rate of the U.S. GDP. We perform a linear interpolation of quarterly nominal GDP data assuming a constant month-to-month GDP growth rate within each quarter, thereby generating a monthly rate of GDP growth. We reestimate Equation (5) using the monthly GDP growth rate instead of the CFNAI index, controlling for the same macroeconomic and financial variables (vector X_t) as well as the one-month to twelve-month lagged GDP growth rate. The first column of Table 1 shows that after controlling for a wide variety of factors, the coefficient of *CATFIN* is negative and highly significant, predicting the GDP growth up to eight months in advance. Hence, the predictive power of *CATFIN* is stronger for forecasting future GDP growth compared to its ability to forecast future values of the CFNAI index.[6]

The second alternative robustness check is to reestimate Equation (5) using another dependent variable in place of the CFNAI index: A dummy variable takes the value of one if the U.S. economy is in recession in a month as marked by the National Bureau of Economic Research (NBER) and is zero otherwise. The lower panel of Figure 1 superimposes NBER recession dates on the *CATFIN* estimates over the 1973–2009 sample period. It is noteworthy that *CATFIN* increases around three months prior to each of the six recessions that occurred during the 1973–2009 estimation period. Therefore, *CATFIN* offers an early warning to alert regulators to the risk of economic recessions. However, there are five instances in which a spike in *CATFIN* is not followed by a recession, thereby providing a false positive signal of future real economic

[6] Because the monthly GDP growth rates are obtained from the interpolation of quarterly data, in the first column of Table 1 we use the Hodrick (1992) standard errors to correct for heteroscedasticity and the moving average error terms that arise from overlap in the dependent variable, which Ang and Bekaert (2007) show have negligible size distortions. We also tested whether *CATFIN* forecasts quarterly GDP and found that *CATFIN* predicts quarterly GDP (at the 5% level or better) two quarters (six months) into the future. Thus, the results are consistent with our results using monthly GDP measures interpolated from quarterly GDP.

Table 1
Alternative macroeconomic conditions

Y_{t+n}	GDP		ADS		NBER		KCSFI		INDP		PAYROLL	
n = 1	−0.003*** (−3.00)	94.58%	−1.138*** (−3.83)	71.14%	0.177* (1.78)	82.70%	1.176*** (5.45)	94.28%	−0.013*** (−3.84)	24.63%	−0.003*** (−3.82)	62.91%
n = 2	−0.007*** (−2.67)	77.57%	−1.561*** (−3.61)	54.22%	0.401** (2.33)	68.81%	0.975*** (2.95)	86.05%	−0.011*** (−3.26)	24.83%	−0.004*** (−4.05)	62.60%
n = 3	−0.013*** (−2.78)	47.63%	−1.577*** (−3.23)	45.19%	0.639*** (2.71)	59.23%	0.967*** (2.63)	83.08%	−0.015*** (−3.54)	23.27%	−0.003*** (−3.54)	56.58%
n = 4	−0.014** (−2.45)	32.78%	−1.534*** (−2.85)	35.27%	0.631* (1.92)	48.65%	1.531*** (2.66)	77.27%	−0.009** (−2.30)	14.05%	−0.004*** (−4.05)	51.07%
n = 5	−0.015** (−2.30)	27.34%	−1.208** (−2.00)	29.43%	0.504 (1.38)	38.34%	1.757** (2.06)	72.32%	−0.010** (−2.10)	11.33%	−0.003*** (−3.37)	46.52%
n = 6	−0.013** (−2.08)	25.44%	−1.034 (−1.60)	24.98%	0.491 (1.30)	28.97%	2.192* (1.90)	71.72%	−0.006 (−1.21)	10.12%	−0.004*** (−3.51)	44.03%
n = 7	−0.013** (−1.99)	23.04%	−0.837 (−1.23)	21.44%	0.585 (1.45)	21.92%	2.404** (2.26)	70.41%	−0.002 (−0.33)	6.46%	−0.004*** (−3.36)	42.25%
n = 8	−0.012* (−1.84)	18.38%	−0.697 (−0.99)	18.78%	0.643 (1.49)	17.33%	2.361*** (2.72)	69.65%	0.000 (−0.09)	7.73%	−0.004*** (−2.66)	38.26%
n = 9	−0.010 (−1.54)	13.39%	−0.784 (−1.13)	16.34%	0.525 (1.18)	12.61%	2.180*** (3.31)	71.14%	−0.003 (−0.63)	5.38%	−0.004*** (−2.91)	33.78%
n = 10	−0.008 (−1.15)	9.41%	−0.827 (−1.20)	15.53%	0.502 (1.09)	9.21%	2.398*** (3.72)	71.43%	−0.003 (−0.54)	6.14%	−0.004** (−2.36)	30.66%
n = 11	−0.006 (−0.92)	8.62%	−0.758 (−1.12)	14.75%	0.505 (1.13)	7.77%	2.630*** (3.94)	70.85%	−0.007 (−1.34)	5.97%	−0.004** (−2.46)	29.73%
n = 12	−0.006 (−0.87)	9.45%	−0.595 (−0.89)	15.94%	0.400 (0.96)	6.39%	2.744*** (3.78)	70.75%	−0.002 (−0.38)	4.26%	−0.004** (−2.49)	28.53%

Entries report the coefficient estimates on the *CATFIN* from the predictive regressions: $Y_{t+n}=\alpha+\gamma CATFIN_t+\beta X_t+\sum_{i=1}^{12}\lambda_i Y_{t-i+1}+\varepsilon_{t+n}$, where Y_{t+n} denotes one of the six measures of macroeconomic conditions: the GDP growth rate (GDP), the Aruoba-Diebold-Scotti Business Conditions Index (ADS), the NBER recession dummy variable (NBER), the Kansas City Financial Stress Index (KCFSI), the industrial production growth rate (INDP), and the nonfarm payroll growth rate (PAYROLL). The probit regression is implemented when NBER is the dependent variable, and the OLS regression is estimated when the other macroindicators are the dependent variable. t-statistics, based on Hodrick's (1992) robust standard errors, are reported in parentheses when the GDP is the dependent variable; for the other macroindicators, z-statistics from the probit regression and Newey and West's (1987) t-statistics from the OLS regressions are reported in parentheses. Significance at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively. For expositional purposes, the slope coefficients on the control variables, including twelve lags of the dependent variable, are suppressed. They are available upon request.

distress. In many of these cases, predicted macroeconomic declines may have been averted by prompt policy intervention. For example, a large increase in *CATFIN* during October 1987 corresponds with the stock market crash of October 19, 1987. A recession may have been averted by publicly visible liquidity support provided by the Federal Reserve to financial institutions early in the morning on October 20, 1987. Similarly, the *CATFIN* spike during August–September 1998 corresponds with the Russian devaluation and sovereign debt default followed by the Long-Term Capital Management (LTCM) debacle. A recession may have been averted by the actions of the New York Fed in organizing a $3.5 billion bailout of LTCM on September 23, 1998. Further, a *CATFIN* spike during November 1988 may have been offset by the release of the thrift bailout plan in February 1989. Finally, although the April 2000 increase in *CATFIN* corresponds with the 35% loss in value in the NASDAQ from March to April 2000, at the time, the U.S. economy was healthy with low inflation, low unemployment, and high corporate profitability. Even given these false positives, *CATFIN* predicts future real economic downturns, thereby providing useful information to regulators.

A third alternative dependent variable used to check the predictive ability of the *CATFIN* measure is the Aruoba-Diebold-Scotti (ADS) Business Conditions Index maintained by the Federal Reserve Bank of Philadelphia. The ADS index is based on a smaller number of economic indicators than the CFNAI and designed to track real business conditions at daily and weekly frequencies. The average value of the ADS index is zero, with increases (decreases) in the ADS index indicating improved (deteriorating) macroeconomic conditions. Table 1 shows that *CATFIN* forecasts ADS up to five months into the future.

A fourth 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 eleven financial market variables. A positive value indicates that financial stress is above the long-run average, whereas a negative value signifies that financial stress is below the long-run average. Table 1 shows that *CATFIN* forecasts KCFSI up to twelve months into the future.

The fifth macroeconomic variable used to proxy for economic downturns is the monthly growth rate of the U.S. industrial production (INDP) available at the Federal Reserve Board. Table 1 shows that *CATFIN* forecasts INDP up to five months into the future. Finally, the sixth macroeconomic indicator is the unemployment rate proxied by nonfarm payroll available at the Bureau of Labor Statistics (denoted PAYROLL). Table 1 shows that *CATFIN* forecasts PAYROLL up to twelve months into the future. Hence, we conclude that systemic risk taking in the financial sector as measured by *CATFIN* successfully predicts future economic downturns, and this result is robust across different macroeconomic indicators proxying for the state of the aggregate economy.

2.4 Controlling for alternative measures of systemic risk

In this section, we test the robustness of the *CATFIN* measure after controlling for microlevel measures of systemic risk in the financial sector. First, following Kelly's (2011) methodology for conditional tail risk, we apply the Hill (1975) tail risk estimator to the cross-section of extreme returns for financial firms each month:

$$\frac{1}{\zeta_t^{upd}} = \frac{1}{K_t} \sum_{i=1}^{K_t} ln\left(\frac{R_{i,t}}{u_t}\right), \tag{10}$$

where ζ_t^{upd} is the observable update of tail risk, and K_t is the number of monthly excess returns exceeding a time-varying cutoff threshold for 1% excess return quantile u_t in month t. The conditional tail risk for month $t+1$ denoted by CTR_{t+1} is the exponentially weighted moving average of the period-by-period update ζ_t^{upd} with the weighting parameter fixed ex ante at 0.94 in order to avoid look-ahead bias.

The second microlevel measure of systemic risk follows Acharya et al. (2010) so that for each month we calculate a financial firm's marginal expected shortfall (*MES*) as its average excess returns for the days on which returns on the CRSP value-weighted index are in the worst 5% quantile in a twelve-month rolling window (updated monthly).

Finally, the third alternative systemic risk measure is a Merton options-theoretic measure of the distance-to-default (DD) for the largest twenty-five financial institutions as derived in Carlson, King, and Lewis (2008). The monthly *MES* and DD values for the financial sector are calculated by averaging the *MES* and DD estimates across all financial firms. The correlation between *CATFIN* and *CTR* equals 0.4047; between *CATFIN* and *MES* equals 0.4145; and between *CATFIN* and DD equals 0.4145, thereby indicating that *CATFIN* as a macroindex of systemic risk is correlated with microlevel measures of systemic risk.

We check whether *CATFIN* has additional explanatory power for future downturns after controlling for these three microlevel measures of systemic risk. Specifically, we regress CFNAI against *CATFIN*, *CTR*, *MES*, and *DD* after controlling for a large set of macroeconomic and financial variables included in Equation (5). As reported in Table A7 of the online appendix, whereas *CATFIN* retains its predictive ability and significantly predicts economic downturns up to six months in advance, none of the microlevel systemic risk measures (*CTR*, *MES*, and *DD*) have robust predictive power. The finding that *CTR*, *MES*, and *DD* do not significantly predict future economic downturns can be attributed to their high correlation with *CATFIN*. To alleviate the multicollinearity problem, therefore, we regress CFNAI on *CATFIN* and *CTR*, *MES*, and *DD* one at a time (instead of simultaneously). Table 2 shows that the strong predictive power of the *CATFIN* measure remains intact, whereas the alternative microlevel measures of systemic risk (*MSE*, *CTR*, and *DD*) display no predictive ability.

Table 2
Predictive ability of *CATFIN* and microlevel systemic risk measures and credit default swap measure

CFNAI_{t+n}	CATFIN	CTR	Adj. R^2 (%)	CATFIN	MES	Adj. R^2 (%)	CATFIN	DD	Adj. R^2 (%)	CATFIN	EWCDS	Adj. R^2 (%)
n = 1	−1.686***	0.080	60.57	−1.679***	0.056	60.62	−1.818***	0.040	52.33	−2.635***	−0.335**	78.69
	(−4.20)	(0.57)		(−4.30)	(0.92)		(−3.86)	(0.79)		(−2.85)	(−2.02)	
n = 2	−1.318***	−0.085	56.90	−1.388***	0.011	56.88	−1.514***	0.009	47.43	−0.452	−0.065	83.15
	(−3.22)	(−0.61)		(−3.40)	(0.15)		(−3.15)	(0.20)		(−0.40)	(−0.21)	
n = 3	−1.712***	−0.154	51.59	−1.792***	−0.037	51.52	−1.670***	0.002	42.05	−7.263***	−0.471**	74.79
	(−3.61)	(−0.98)		(−3.73)	(−0.44)		(−2.99)	(0.04)		(−5.72)	(−2.13)	
n = 4	−1.484***	−0.238	41.12	−1.571***	−0.110	41.16	−1.384**	−0.014	32.04	−6.255***	0.248	61.59
	(−2.80)	(−1.24)		(−3.03)	(−1.03)		(−2.51)	(−0.26)		(−5.57)	(0.70)	
n = 5	−1.493***	−0.237	35.21	−1.585***	−0.110	35.22	−1.535***	−0.033	29.00	−4.574	0.510	54.44
	(−2.67)	(−1.03)		(−2.89)	(−0.79)		(−2.68)	(−0.49)		(−1.56)	(1.31)	
n = 6	−1.206*	−0.381	32.95	−1.394**	−0.118	32.65	−1.689***	0.055	26.87	−4.883**	−0.084	62.29
	(−1.96)	(−1.49)		(−2.29)	(−0.84)		(−2.80)	(0.75)		(−2.52)	(−0.21)	

This table reports the results of predictive regressions of the CFNAI on the *CATFIN*, microlevel systemic risk measures, credit default swap measure, and the control variables. The microlevel measures of systemic risk are the conditional tail risk (*CTR*), marginal expected shortfall (*MES*), and distance to default (DD). *EWCDS* denotes the equal-weighted average of the CDS data across the financial firms. *EWCDS* is standardized to have zero mean and unit standard deviation. Newey and West's (1987) t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively. For expositional purposes, the slope coefficients on the control variables, including twelve lags of the dependent variable, are suppressed. They are available upon request.

As a final robustness test, we investigate the predictive power of *CATFIN* after controlling for an equal-weighted CDS index (EWCDS), comprised of monthly CDS data for seven major financial firms. We download monthly CDS data from Bloomberg. For the sample period January 2004–December 2009, we obtain monthly CDS data for Bank of America (BOA), Citigroup (CICN), Goldman Sachs (GS), J. P. Morgan (JPM), Morgan Stanley (MS), Wells Fargo (WFC), and American Express (AXP). Then, we standardized all CDS data to have zero mean and unit standard deviation. Finally, we formed a standardized CDS index (EWCDS) based on the equal-weighted average of standardized CDS values for the seven major financial firms. The last column of Table 2 shows that after controlling for the firm distress information incorporated in CDS spreads, the slope coefficient on *CATFIN* is still negative and statistically significant (at the 5% level or better) for up to six months, indicating that *CATFIN* can predict economic downturns six months into the future.

2.5 International evidence

In this section, we investigate the predictive ability of regional *CATFIN* for the GDP growth rates of the Asian countries and the European Union. The international regional monthly *CATFIN* is defined in the same manner as the U.S. *CATFIN*, that is, the average of the 1% *VaR* measures, computed from the cross-sectional distribution of monthly returns for financial firms listed on the stock exchanges in a region. The stock price data are extracted from the Datastream database. Stocks with monthly returns more than 300% or falling outside the 0.1 and 99.9 percentiles of the monthly cross-sectional return distribution are eliminated. The real GDP data for the Asian countries and the European Union (EU) are obtained from Datastream. The real GDP data for the Asian region and the EU are constructed by aggregating real GDP of member countries with country GDP weights valued at the IMF purchasing power parity exchange rates.

Panel A of Table 3 provides the number of financial firms that meet the data requirements and the sample period for each country within a region. There are 1,183 firms originated from twenty-seven Asian countries. The number of financial firms in each country varies drastically. For example, although there are 194 Japanese firms, there is one firm from Papua New Guinea and Lebanon that meets the data requirements. On the other hand, there are 607 firms in the European sample that represent twenty-five countries with the number of firms ranging from 136 in the United Kingdom to two in Hungary.

Panel B of Table 3 reports the results of the predictive regressions of regional monthly GDP growth rates, linearly interpolated from quarterly GDP growth rates, on the corresponding regional *CATFIN* after controlling for twelve lags of the dependent variable. The results show that the regional *CATFIN* can significantly (at the 5% or better level) predict lower GDP growth rates of the European Union and the Asian regions eight and five months ahead,

Table 3
Predictive ability of regional *CATFIN* for regional real GDP growth rates

Panel A: Country list

EU Countries	N	Start Date	Asian Countries	N	Start Date
Austria	19	Jan. 1987	Australia	113	Jan. 1992
Belgium	11	Jan. 1987	Bahrain	18	Feb. 1996
Bulgaria	23	Apr. 2005	China	35	Jan. 1994
Cyprus	16	Apr. 2005	Hong Kong	85	Jan. 1992
Czech Republic	3	Apr. 1996	India	83	Nov. 1994
Denmark	47	Jan. 1987	Indonesia	60	Jan. 1992
Finland	6	Jan. 1989	Israel	41	Nov. 1992
France	54	Jan. 1987	Japan	194	Jan. 1992
Germany	94	Jan. 1987	Jordan	60	Feb. 1994
Greece	18	Jan. 1987	Kazakhstan	3	May. 2005
Hungary	2	Apr. 1996	Kuwait	72	Feb. 1996
Ireland	7	Jan. 1987	Lebanon	1	Feb. 2002
Italy	39	Jan. 1987	Malaysia	32	Jan. 1992
Lithuania	4	Apr. 1997	New Zealand	17	Jan. 1997
Luxembourg	10	Jan. 1987	Oman	27	Feb. 1996
Malta	4	Apr. 2005	Pakistan	24	Feb. 1996
Netherlands	6	Jan. 1987	Papua New Guinea	1	Jan. 1992
Poland	27	Jul. 1994	Philippines	45	Jan. 1992
Portugal	7	Oct. 1987	Qatar	14	Nov. 1997
Romania	12	Jan. 1999	Russian Federation	14	Oct. 1997
Slovakia	6	Oct. 1995	Saudi Arabia	19	Oct. 1995
Slovenia	7	Jan. 2004	Singapore	23	Jan. 1992
Spain	21	Jan. 1987	South Korea	83	Jan. 1992
Sweden	28	Jan. 1987	Sri Lanka	14	Mar. 1994
United Kingdom	136	Jan. 1987	Taiwan	34	Jan. 1993
			Thailand	23	Jan. 1992
			Vietnam	48	Aug. 2006
Total	607		Total	1,183	

(continued)

respectively. The statistical significance of *CATFIN* forecasting six-month-ahead GDP growth of the Asian countries is somewhat lower, but it is still significant with a Hodrick (1992) t-statistic of -1.94 (p-value = 5.2%).

3. Further Empirical Results

3.1 Catastrophic risk of nonfinancial firms and future economic activity

In this section, we investigate the question of whether the catastrophic risk of nonfinancial firms (*CATnonFIN*) forecasts lower economic activity after controlling for *CATFIN*. Following the methodology outlined in Section 1, for each month in our sample, we measure the catastrophic risk of all nonfinancial firms separately, as well as the catastrophic risk of the five broad nonfinancial sectors based on the arithmetic average of the three *VaR* measures.[7] We then

[7] Definitions of the five broad nonfinancial sectors are obtained from Kenneth French's online data library.

Table 3
Continued

Panel B: Predictive regressions

GDP_{t+n}	EU Countries *CATFIN*	EU Countries Adj. R^2 (%)	Asian Countries *CATFIN*	Asian Countries Adj. R^2 (%)
n = 1	−0.003*** (−3.03)	96.68	−0.002** (−2.11)	94.36
n = 2	−0.007*** (−3.66)	85.96	−0.006** (−2.08)	76.11
n = 3	−0.011*** (−4.12)	66.10	−0.010** (−2.06)	42.50
n = 4	−0.013*** (−3.87)	51.12	−0.012** (−1.99)	23.52
n = 5	−0.015*** (−3.54)	39.60	−0.013** (−2.01)	13.88
n = 6	−0.014*** (−3.22)	29.58	−0.012* (−1.94)	8.36
n = 7	−0.013*** (−2.67)	21.97	−0.009 (−1.60)	4.06
n = 8	−0.012** (−2.22)	17.10	−0.006 (−1.07)	1.45
n = 9	−0.012* (−1.87)	13.88	−0.004 (−0.71)	0.30
n = 10	−0.012* (−1.69)	10.34	−0.004 (−0.57)	0.16
n = 11	−0.011 (−1.52)	6.36	−0.003 (−0.47)	0.32
n = 12	−0.012 (−1.54)	3.26	−0.001 (−0.12)	0.04

Panel A provides the number of financial firms that meets the data requirements and the sample period for each country within a region. Panel B reports the results of predictive regressions of the real GDP growth rates of the Asian countries and the European Union (EU) against the corresponding regional *CATFIN* after controlling for twelve lags of the dependent variable. The t-statistics in parentheses are based on Hodrick (1992) robust standard errors. Significance at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively. For expositional purposes, the slope coefficients on the twelve lags of the dependent variable are suppressed. They are available upon request.

estimate the following predictive regressions:

$$CFNAI_{t+n} = \alpha + \gamma_1 CATFIN_t + \gamma_2 CATnonFIN_t + \beta X_t + \sum_{i=1}^{12} \lambda_i CFNAI_{t-i+1} + \varepsilon_{t+n}, \tag{11}$$

where $CATnonFIN_t$ denotes the catastrophic risk measure in month t for all nonfinancial 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 4 shows that none of the nonfinancial sectors negatively and significantly forecasts the aggregate economy after controlling for *CATFIN*. For the one-month-ahead prediction of the CFNAI index, the coefficient estimates on *CATFIN* are in the range of −1.24 and −1.85 and statistically significant at the 1% level, whereas the slope coefficients of *CATnonFIN* are insignificant for

Table 4
Predictive ability of *CATFIN* and *CATnonFIN* for the CFNAI

Industry	Dependent Variable: CFNAI_{t+1}			Dependent Variable: CFNAI_{t+3}		
	$CATFIN_t$	$CATnonFIN_t$	Adj. R^2 (%)	$CATFIN_t$	$CATnonFIN_t$	Adj. R^2 (%)
All nonfinancial firms	−1.480***	−0.235	60.56	−2.404***	0.924	51.77
	(−3.40)	(−0.44)		(−3.89)	(1.61)	
Consumer goods and services	−1.239***	−0.612	60.67	−2.280***	0.721	51.68
	(−2.88)	(−1.22)		(−3.68)	(1.30)	
Manufacturing, energy, and utilities	−1.852***	0.413	60.59	−2.465***	1.175*	51.93
	(−4.18)	(0.84)		(−4.40)	(1.83)	
Hitech, business equipment, telephone, and TV	−1.481***	−0.246	60.57	−1.803***	−0.022	51.49
	(−3.63)	(−0.55)		(−3.13)	(−0.04)	
Health care, medical equipment, and drugs	−1.624***	−0.006	60.54	−1.805***	−0.022	51.50
	(−4.27)	(−0.08)		(−3.92)	(−0.40)	
All other nonfinancial firms	−1.806***	0.272	60.58	−2.473***	0.984**	52.04
	(−4.21)	(0.75)		(−4.71)	(2.45)	

Entries report the coefficient estimates from the predictive regressions: $CFNAI_{t+1/t+3} = \alpha + \gamma_1 CATFIN_t + \gamma_2 CATnonFIN_t + \beta X_t + \sum_{i=1}^{12} \lambda_i CFNAI_{t-i+1} + \varepsilon_{t+1/t+3}$, 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 nonfinancial firms or the five broad nonfinancial sectors, calculated as the arithmetic average of the GPD, SGED, and nonparametric 1% *VaR* measures. The definitions of the five sectors are obtained from Kenneth French's online data library. Newey and West's (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 denoted by *, **, and ***, respectively. For expositional purposes, the slope coefficients on the control variables, including twelve lags of the CFNAI, are suppressed. They are available upon request.

all nonfinancial firms and five industry groupings. The adjusted R^2 values from the one-month-ahead predictive regressions are economically large, remaining at above 60%. Similar results are obtained from both forecasting CFNAI three months in advance and without *CATFIN* in Equation (11): After controlling for a large set of macroeconomic and financial variables, *CATFIN* successfully predicts, whereas *CATnonFIN* has no negative and significant association with a three-month-ahead CFNAI index.

3.2 "Fake banks"

In this section, we create "fake banks" from a diversified sample of nonfinancial firms to determine whether our results are driven by bank specialness or simply by the diversification in financial institutions that signals a widespread slowdown in economic conditions. To generate the fake bank sample, we adopt the propensity score matching method. We first divide common stocks that meet the data requirements into the financial sector (SIC code $\geq$6000 and SIC code $\leq$6999) and the nonfinancial sector (all other SIC codes). The propensity score is determined by the firm's size *LNME*, denoting the natural logarithm of its market capitalization, and its level of diversification, as proxied by its systematic risk beta (β_i) estimated following Fama and French (1992). For each month, we run the logistic regressions:

$$D_i = \phi_0 + \phi_1 LNME_i + \phi_2 \beta_i + \varepsilon_i, \tag{12}$$

where D_i is the dummy variable taking the value of one if firm i operates in the financial sector in the month and zero otherwise.

Given the coefficient estimates ϕ_0, ϕ_1, and ϕ_2, we compute the propensity scores of individual firms. We then match each financial firm to the nonfinancial firm that has the nearest propensity score. The matched nonfinancial firms constitute the fake bank sample. We estimate the GDP, SGED, and nonparametric 1% *VaR* and their average (denoted $CATFIN^{fake}$) using the procedures outlined earlier. The descriptive statistics on the *VaR* and $CATFIN^{fake}$ measures for the fake bank sample are reported in Table A8 of the online appendix.

We investigate the predictive power of *CATFIN* after controlling for $CATFIN^{fake}$ measure. Specifically, we run the following predictive regressions of the CFNAI index on *CATFIN*, $CATFIN^{fake}$, and a large set of control variables:

$$CFNAI_{t+n} = \alpha + \gamma_1 CATFIN_t + \gamma_2 CATFIN_t^{fake} + \beta X_t + \sum_{i=1}^{12} \lambda_i CFNAI_{t-i+1} + \varepsilon_{t+n}. \tag{13}$$

Table 5 reports the parameter estimates from the above regression and the Newey-West adjusted t-statistics in parentheses. Table 5 shows that after controlling for $CATFIN^{fake}$, the slope coefficient on *CATFIN* remains negative and statistically significant for up to seven months, indicating that *CATFIN* can predict economic downturns seven months into the future. However, the $CATFIN^{fake}$ measure for the fake bank sample does not negatively predict future economic downturns. These results provide evidence for the special role of financial intermediaries in the macroeconomy.

3.3 Does size matter?

In this section, we investigate whether our findings are related to too-big-to-fail (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 A2 in the online appendix 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 nonparametric distributions for each bank size group. Then, the average *VaR* measures from the SGED and the nonparametric methods are 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 after controlling for a large set of macroeconomic and financial variables. Table A9 of the online appendix shows that *CATFINBIG* successfully forecasts lower

Table 5
Predictive ability of *CATFIN* and *CATFIN*^{fake} for the CFNAI

CFNAI_{t+n}	$CATFIN_t$	$CATFIN_t^{fake}$	Adj. R^2 (%)
n = 1	−1.746***	0.170	60.55
	(−3.46)	(0.32)	
n = 2	−1.659***	0.401	56.92
	(−2.98)	(0.77)	
n = 3	−1.964***	0.210	51.51
	(−2.80)	(0.35)	
n = 4	−2.441***	1.130*	41.30
	(−3.20)	(1.73)	
n = 5	−1.945**	0.418	35.04
	(−2.29)	(0.59)	
n = 6	−1.764**	0.453	32.46
	(−2.12)	(0.70)	
n = 7	−2.137**	1.204	26.80
	(−2.02)	(1.56)	
n = 8	−1.527	0.658	24.61
	(−1.39)	(0.73)	
n = 9	−1.541	0.716	21.29
	(−1.34)	(0.85)	
n = 10	−1.616	0.568	19.67
	(−1.56)	(0.75)	
n = 11	−1.655	0.273	18.32
	(−1.62)	(0.34)	
n = 12	−1.913**	1.149*	17.74
	(−2.02)	(1.74)	

Entries report the coefficient estimates from the predictive regressions: $CFNAI_{t+n} = \alpha + \gamma_1 CATFIN_t + \gamma_2 CATFIN_t^{fake} + \beta X_t + \sum_{i=1}^{12} \lambda_i CFNAI_{t-i+1} + \varepsilon_{t+n}$. Newey and West's (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 denoted by *, **, and ***, respectively. For expositional purposes, the slope coefficients on the control variables, including twelve lags of the CFNAI, are suppressed. They are available upon request.

economic activity up to six months in advance. Although the predictive power of *CATFINSML* is not as strong as that of *CATFINBIG*, it strongly predicts macroeconomic activity four months into the future. Thus, in contrast to the insignificance of the aggregate catastrophic risk measure for nonfinancial firms (see Table 4), the catastrophic risk of small banks has significant power to forecast future macroeconomic conditions. We also test the equality of the slope coefficients on *CATFINBIG* and *CATFINSML*. The last two columns in Table A9 report the Wald statistics and the corresponding p-values. The Wald statistics (distributed as the chi-squared with one degree of freedom) fail to reject the null hypothesis, implying similar impacts of *CATFINBIG* and *CATFINSML* for future economic downturns. These results provide evidence that the specialness of banks is not limited to those banks that are TBTF but is inherent in financial intermediation.

3.4 Developing a warning system

The value of *CATFIN* as an early warning signal is not that it is without error, no model can make that claim, but rather that it gives policymakers valuable information about future macroeconomic declines that can be used in formulating intervention policies. *CATFIN* appears to err on the side of caution, a valuable attribute to regulators. More importantly, however, when *CATFIN* signals that the aggregate level of risk taking in the banking sector is high, the systemic cost of any marginal increase in bank risk taking is higher than when *CATFIN* is low. Thus, whether or not a recession ultimately is realized, our results show that the risk of macroeconomic downturns increases when *CATFIN* is above the early warning level.

The Federal Reserve Bank of Chicago denotes the three-month moving average CFNAI (CFNAI-MA3) value of −0.7 as a turning point indicating economic contraction. We calculate the median *CATFIN* for those observations in which 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 *CATFIN* and is zero otherwise; $CATFIN_t^-$ equals *CATFIN* in month t if it is less than or equal to the median CFNAI and is zero otherwise. Once we generate $CATFIN_t^+$ and $CATFIN_t^-$, we estimate the following multivariate predictive regression:

$$CFNAI_{t+n} = \alpha + \gamma^+ CATFIN_t^+ + \gamma^- CATFIN_t^- + \beta X_t + \sum_{i=1}^{12} \lambda_i CFNAI_{t-i+1} + \varepsilon_{t+n}. \tag{14}$$

Table 6 shows that $CATFIN_t^+$ significantly predicts lower economic activity one month to twelve months in advance, whereas $CATFIN_t^-$ does not have a robust, significant predictive power for all time horizons. The slope coefficients of $CATFIN_t^+$ are in the range of −1.66 and −2.44 and statistically significant at the 5% level. 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. We also test the equality of the slope coefficients on $CATFIN_t^+$ and $CATFIN_t^-$. The last two columns in Table 6 present the Wald statistics and the corresponding p-values for forecast horizons of one to twelve months. The Wald statistics (distributed as the chi-squared with one degree of freedom) reject the null hypothesis for ten out of twelve forecast horizons, implying significantly different impacts of $CATFIN_t^+$ and $CATFIN_t^-$ for future economic downturns.

We should note that *CATFIN* is a pure out-of-sample measure in that it is based on realized returns for financial firms without invoking any future information, but the median early warning threshold of *CATFIN* may be calculated using the full-sample information and may induce potential in-sample bias. To alleviate this concern, the results presented in Table 6 are based on 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

Table 6
The warning system

$CFNAI_{t+n}$	$CATFIN^{+}$	$CATFIN^{-}$	Adj. R^2 (%)	$\gamma^{+}-\gamma^{-}$	Wald	p-Value
n = 1	−1.273***	−1.580**	67.21	0.307	0.73	0.39
	(−3.23)	(−2.35)				
n = 2	−0.907**	−0.167	71.30	−0.740	6.94	0.01
	(−2.52)	(−0.30)				
n = 3	−1.218**	−0.604	61.76	−0.614	4.94	0.03
	(−2.41)	(−0.97)				
n = 4	−1.567***	−0.738	55.83	−0.829	7.22	0.01
	(−2.76)	(−1.07)				
n = 5	−1.615**	−1.070*	48.65	−0.545	3.40	0.07
	(−2.41)	(−1.68)				
n = 6	−2.048***	−1.114	47.83	−0.934	5.61	0.02
	(−2.93)	(−1.28)				
n = 7	−1.707**	−0.995	41.44	−0.712	3.62	0.06
	(−2.04)	(−1.22)				
n = 8	−2.326***	−1.455**	42.74	−0.871	6.78	0.01
	(−3.11)	(−1.99)				
n = 9	−2.889***	−1.471*	48.47	−1.418	6.67	0.01
	(−3.63)	(−1.66)				
n = 10	−2.730***	−1.937**	43.83	−0.793	3.32	0.07
	(−3.33)	(−1.97)				
n = 11	−3.087***	−3.048***	47.49	−0.039	0.01	0.92
	(−4.07)	(−3.30)				
n = 12	−2.244***	−1.394	46.92	−0.850	4.18	0.04
	(−3.00)	(−1.50)				

Entries report coefficient estimates from the predictive regressions: $CFNAI_{t+n}=\alpha+\gamma^{+}CATFIN_t^{+}+\gamma^{-}CATFIN_t^{-}+\beta X_t+\sum_{i=1}^{12}\lambda_i CFNAI_{t-i+1}+\varepsilon_{t+n}$, 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) the median *CATFIN* for those observations in which the three-month moving average of CFNAI (CFNAI-MA3) falls below −0.7 over a period that expands on a monthly basis. The first expanding window covers the first half of the original sample period. The last two columns report the Wald statistics and the corresponding p-values from testing the equality of slope coefficients on $CATFIN^{+}$ and $CATFIN^{-}$. The Wald statistic is distributed as the chi-squared with one degree of freedom. Newey and West's (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 denoted by *, **, and ***, respectively. For expositional purposes, the slope coefficients on the control variables, including twelve lags of the CFNAI, are suppressed. They are available upon request.

CATFIN in month t with the time-varying median cutoff threshold for *CATFIN*. Table 6 shows the results of our estimation of Equation (14) using an expanding-window cutoff threshold for the early warning system. Thus, an early warning system can be implemented using this out-of-sample procedure to differentiate $CATFIN_t^{+}$ from $CATFIN_t^{-}$, which can be used by regulators to take preemptive action so as to avert a macroeconomic crisis.

4. Motivation for Using *CATFIN* as a Systemic Risk Measure

Motivation for the development of a measure of aggregate risk taking by financial institutions can be obtained using a simple supply and demand analysis. That is, the mechanism linking aggregate risk taking in the banking sector to real macroeconomic activity has both a demand and a supply side. Aggregate risk taking by financial institutions injects uncertainty into the financial system and the economy. As aggregate banking sector risk exposure increases, the variability of potential outcomes increases. Thus, there is less certainty about the availability of funding sources and their costs (interest rates). As this uncertainty increases, the potential payoff to real investment projects becomes more variable, leading investors to delay investment until uncertainty is resolved (see, e.g., Bernanke 1983; Dixit and Pindyck 1994). This creates a decline in the demand for investable funds, with the resulting decline in lending and investment activity leading to declines in aggregate demand.

Similarly, on the supply side, the increased volatility in potential outcomes results in a decline in bank lending for illiquid investment projects. That is, the supply of investable funds declines as banks preserve liquidity as a response to their increased risk exposure.[8] Using this simple supply/demand mechanism, increases in aggregate risk taking by financial institutions result in reduced investment activity (and the consumption of durable goods), which contributes to future declines in macroeconomic activity. In time, declines in aggregate risk taking reduce the level of uncertainty in the economy and eventually, with a lag, encourages increased economic activity.

4.1 *CATFIN* as a forecast of aggregate lending activity

An important mechanism that links systemic risk to macroeconomic activity is aggregate bank lending (Kashyap, Stein, and Wilcox 2000). To further validate *CATFIN* as a measure of systemic risk, we test whether *CATFIN* predicts bank lending activity. We obtain five aggregate lending measures from Call Report data: total loans and leases (*LOANS*), commercial and industrial loans (*BUS*), real estate loans (*REAL*), consumer loans (*CSM*), and total loans and investments (*LOANINV*). We construct the monthly growth rate for each lending variable and regress it on *CATFIN* after controlling for the large set of macroeconomic and financial variables as well as twelve lags of the corresponding dependent variable. The results are presented in Table 7. We find that *CATFIN* forecasts total bank lending up to twelve months in advance. *CATFIN*'s predictive ability is most pronounced for commercial and industrial lending (*BUS*). Thus, businesses are most sensitive to the supply and demand shocks engendered by excessive systemic risk exposure in the banking sector.

4.2 Financial sector conditions and the *CATFIN* measure

The predictive ability of *CATFIN* also emanates from its link to the financial health of financial institutions. That is, illiquid and undercapitalized banks with large losses and low rates of profitability will be unable to perform their fundamental risk management and capital allocations in the economy.[9] Panel A of Table 8 provides correlation coefficients between the *CATFIN* measure and

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[8] Because investment project returns are uncertain, and information is asymmetric, bank risk taking increases the cost of capital and reduces lending activity (see Froot and Stein 1998).

[9] For example, Brunnermeier, Dong, and Palia (2011) find a positive correlation between bank systemic risk and noninterest income (measuring non-traditional banking activity).

Table 7
Predictive ability of *CATFIN* for aggregate lending

Y_{t+n}	*LOANS*	Adj. R^2 (%)	*BUS*	Adj. R^2 (%)	*REAL*	Adj. R^2 (%)	*CSM*	Adj. R^2 (%)	*LOANINV*	Adj. R^2 (%)
n = 1	−0.012***	37.48	−0.014***	57.37	−0.013***	37.94	−0.005	39.87	−0.010***	19.78
	(−3.58)		(−3.81)		(−4.15)		(−1.39)		(−3.23)	
n = 2	−0.013***	31.85	−0.015***	51.80	−0.009**	23.55	−0.011**	26.06	−0.012***	13.83
	(−4.62)		(−3.89)		(−2.33)		(−2.49)		(−4.43)	
n = 3	−0.015***	29.27	−0.016***	51.01	−0.009**	20.32	−0.015***	25.64	−0.013***	13.28
	(−4.04)		(−3.91)		(−2.23)		(−3.06)		(−4.19)	
n = 4	−0.013***	29.21	−0.017***	50.30	−0.007*	20.48	−0.013**	24.25	−0.009**	15.5
	(−3.50)		(−4.17)		(−1.80)		(−2.52)		(−2.49)	
n = 5	−0.016***	27.82	−0.019***	46.50	−0.007**	19.28	−0.012***	24.47	−0.011***	15.25
	(−5.37)		(−4.69)		(−2.01)		(−2.89)		(−4.08)	
n = 6	−0.016***	27.51	−0.018***	45.65	−0.009**	18.61	−0.013***	25.45	−0.010***	14.28
	(−4.42)		(−3.42)		(−2.51)		(−3.63)		(−3.01)	
n = 7	−0.023***	27.25	−0.027***	45.64	−0.020***	19.37	−0.015***	24.02	−0.016***	15.77
	(−7.51)		(−6.03)		(−6.00)		(−3.37)		(−6.19)	
n = 8	−0.022***	26.79	−0.024***	44.98	−0.018***	19.81	−0.015***	21.90	−0.014***	15.24
	(−6.55)		(−5.50)		(−4.97)		(−2.98)		(−4.84)	
n = 9	−0.017***	25.20	−0.021***	40.79	−0.013***	19.15	−0.015***	21.9	−0.011***	13.75
	(−4.16)		(−4.31)		(−2.89)		(−3.16)		(−3.55)	
n = 10	−0.020***	23.38	−0.022***	43.16	−0.011***	16.58	−0.017***	22.14	−0.010***	12.43
	(−5.47)		(−4.58)		(−2.83)		(−3.62)		(−3.19)	
n = 11	−0.017***	20.54	−0.024***	37.18	−0.008*	15.01	−0.014***	25.71	−0.010***	11.24
	(−4.68)		(−4.62)		(−1.80)		(−2.81)		(−3.09)	
n = 12	−0.014***	25.34	−0.024***	39.26	−0.006	18.97	−0.008*	24.69	−0.007	16.35
	(−3.32)		(−3.62)		(−1.29)		(−1.69)		(−1.59)	

Entries report coefficient estimates from the predictive regressions: $Y_{t+n}=\alpha+\gamma CATFIN_t+\beta X_t+\sum_{i=1}^{12}\lambda_i Y_{t-i+1}+\varepsilon_{t+n}$, where Y_{t+n} is one of the five variables for the n-month-ahead aggregate lending activity: total loans and leases (*LOANS*), commercial and industrial loans (*BUS*), real estate loans (*REAL*), consumer loans (*CSM*), and total loans and investments (*LOANINV*). Newey and West's (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 denoted by *, **, and ***, respectively. For expositional purposes, the slope coefficients on the control variables, including twelve lags of the dependent variable, are suppressed. They are available upon request.

the commonly used financial ratios depicting the aggregate financial condition of the banking sector obtained from quarterly Call Report data. For example, *CATFIN* is significantly (at the 5% level or better) positively correlated with several ratios of loan losses, demonstrating that *CATFIN* increases when bank capital is impaired by asset devaluations. The correlation between *CATFIN* and Tier 1 regulatory capital is negative as expected because systemic risk is higher for undercapitalized banks but is insignificant at the 5% level. Further, the correlation between bank returns on assets and *CATFIN* is negative and significant at the 1% level, demonstrating that increases in *CATFIN* are indicative of reduced bank profitability. Finally, the positive correlation between *CATFIN* and the deposit ratio indicates that the availability of core deposits allows banks to take on additional systemic risk exposure. Thus, *CATFIN*'s predictive ability can be traced to its link to measures of the financial health of the banking sector, such as capital adequacy, loan losses, profitability, and liquidity.

As further validation of *CATFIN* as a measure of systemic risk, it is useful to note that the names of financial firms in the 1% tail of the return distribution over the period from January 2007 to December 2009 include AIG, Bear Stearns, Citicorp, Countrywide, Fannie Mae, Freddie Mac, Lehman Brothers, Merrill Lynch, and Washington Mutual. Indeed, Fannie Mae was one of the firms that most frequently contributed to systemic risk exposure, with eleven months in the 1% lowest tail of the return distribution over a time period ranging from December 1973 to August 2008, one month before it was placed into receivership by the U.S. government.

Finally, we examine the link between *CATFIN* and the health of financial firms using credit default swap (CDS) data. The CDS data are described in Section 2.4. Panel B of Table 8 presents the correlation matrix for our *CATFIN* measure and the standardized CDS data for each financial firm as well as the standardized CDS index. The correlations between *CATFIN* and the standardized values of credit default swaps are economically and statistically significant; they are in the range of 0.69 and 0.89, with p-values of less than 1%. The smallest correlation (0.69) between *CATFIN* and the standardized CDS is obtained for Citigroup, and the largest correlation (0.89) is obtained for Goldman Sachs. The correlation between *CATFIN* and the equally weighted CDS index (EWCDS) is about 0.83 and highly significant, thereby further demonstrating the link between *CATFIN* and the financial condition of the banking sector.

Consistent with our analysis of CDS spreads as indicators of downside risk in financial firms, we find that *CATFIN* is closely related to the volatility of returns in the financial sector. Section 5 of the online appendix uses both realized volatility and an AR(1)-GARCH(1,1) model to estimate the monthly conditional volatility of financial industry equity returns. Figure A4 of the online appendix plots the volatility of the cross-sectional distribution (i.e., the tail of the cross-sectional distribution is used to estimate *CATFIN*) against the

Table 8
Linking *CATFIN* to financial sector conditions

Panel A: Correlations between *CATFIN* and measures of the aggregate condition of the financial sector

Variable	Start Date	End Date	No. of Quarters	Corr. with *CATFIN*
Tier 1 scaled by total assets	3/31/2001	12/31/2008	32	−0.2891
Allowance for loans and leases scaled by total loans and leases	6/30/1986	12/31/2008	91	0.4940
Provision for credit loss scaled by net interest income	6/30/1986	12/31/2008	91	0.6260
Loans delinquent 90+ scaled by total loans and leases	9/30/1990	12/31/2008	74	0.2798
Nonaccrual debt and others scaled by total loans and leases	9/30/1990	12/31/2008	74	0.4581
Net income scaled by total assets	6/30/1986	12/31/2008	91	−0.4012
Total deposits scaled by total liabilities	6/30/1986	12/31/2008	91	0.2723

Panel B: Correlations between *CATFIN* and the standardized CDS

	EWCDS	BOA	CICN	GS	JPM	MS	WFC	AXP
CATFIN	0.8251	0.7153	0.6895	0.8886	0.8215	0.8019	0.7693	0.8025
EWCDS		0.9561	0.9429	0.9465	0.9791	0.8810	0.9739	0.9729
BOA (Bank of America)			0.9850	0.8184	0.9303	0.7232	0.9845	0.9188
CICN (Citigroup)				0.8046	0.9013	0.7281	0.9648	0.8889
GS (Goldman Sachs)					0.9243	0.9521	0.8610	0.9358
JPM (J.P. Morgan Chase)						0.8402	0.9622	0.9553
MS (Morgan Stanley)							0.7750	0.8424
WFC (Wells Fargo)								0.9310

Panel A provides the correlation coefficients between the *CATFIN* and commonly used financial ratios of the aggregate financial condition of the banking sector obtained from the quarterly Call Report database. Panel B presents the correlation matrix for the *CATFIN* and the CDS data for each financial firm and their equal-weighted average (EWCDS). The CDS data are from Bloomberg covering the period of January 2004–December 2009, and are standardized to have zero mean and unit standard deviation.

monthly realized and monthly GARCH volatility of financial industry returns (calculated as the value-weighted and equal-weighted returns of all financial firms). We find sample correlations between the cross-sectional distribution of financial sector returns (used for *CATFIN*) and realized (GARCH) volatility of 38.21% (57.29%) for the value-weighted returns and 47.43% (43.44%) for the equal-weighted returns, thereby further establishing the relationship between *CATFIN* and the systemic risk of the financial sector.

4.3 Uncertainty and the *CATFIN* measure

The first test of our conjecture that aggregate risk taking by financial institutions forecasts increased uncertainty uses the implied volatility of the European-style S&P 500 index options (*VIX*) as well as the implied volatility of the American-style S&P 100 index options (*VXO*) to proxy for uncertainty. *VIX* and *VXO* are the Chicago Board Options Exchange's (CBOE) implied volatility indices, and they provide investors with up-to-the-minute market estimates of expected future volatility by using real-time index option bid/ask quotes so that an increase in *VIX* and *VXO* is often used as a proxy for an increase in financial market uncertainty. To test whether *CATFIN* forecasts uncertainty, we run the n-month-ahead predictive regressions of *VIX* and *VXO* on *CATFIN*. Table A10 in the online appendix shows that when uncertainty is proxied by *VIX* and *VXO*, the slope coefficients on *CATFIN* are positive and highly significant for one month to six months ahead, thereby indicating that *CATFIN* forecasts uncertainty, as measured by financial market volatility.

As a second test of our conjecture that aggregate risk taking by financial institutions forecasts uncertainty, we rely on macroeconomic variables commonly used in the literature: (1) default spread (*DEF*), (2) term spread (*TERM*), (3) relative T-bill rate (*RREL*), (4) aggregate dividend yield (*DIV*), (5) the monthly growth rate of the U.S. industrial production (*INDP*), (6) the monthly inflation rate based on the U.S. consumer price index (*INF*), and (7) the monthly excess return on the value-weighted CRSP index (*MKT_RET*). We proxy for uncertainty about a macroeconomic variable with the time-varying conditional volatility based on the standard AR(1)-GARCH(1,1) model.

Once we estimate the monthly GARCH volatilities of the seven macroeconomic variables listed above, a proxy for uncertainty is defined as the average of these volatility measures denoted by *AVGVOL*. Then, we test the significance of a predictive relation between aggregate risk taking by financial institutions and uncertainty in the aggregate economy. Specifically, we run the n-month-ahead predictive regressions of *AVGVOL* on *CATFIN*. Table A10 shows that the coefficient on *CATFIN* is positive and statistically significant for one month to six months ahead. As a further robustness check, we compute the first principal component of the monthly conditional volatilities of the seven macroeconomic variables (denoted by *PCAVOL*) and use it as an alternative proxy for uncertainty. As presented in the last two columns of Table A10, when

PCAVOL is used to proxy for uncertainty, the coefficient of *CATFIN* is also positive and highly significant six months in the future.

4.4 A conditional asset pricing model with market and systemic risk

The Merton (1973) intertemporal capital asset pricing model (ICAPM) implies the following equilibrium relation between expected return and risk for any risky asset i:

$$\mu_i = A\sigma_{im} + B\sigma_{ix}, \tag{15}$$

where μ_i denotes the unconditional expected excess return on risky asset i, σ_{im} denotes the unconditional covariance between the excess returns on the risky asset i and the market portfolio m, and σ_{ix} denotes a $(1 \times k)$ row of unconditional covariances between the excess returns on the risky asset i and the k-dimensional state variables x. A is the relative risk aversion of market investors, and B measures the market's aggregate reaction to shifts in a k-dimensional state vector that governs the stochastic investment opportunity set. Equation (15) states that in equilibrium, investors are compensated in terms of expected return for bearing market risk and for bearing the risk of unfavorable shifts in the investment opportunity set.

Although in the original Merton (1973) model, the parameters of expected returns and covariances are all interpreted as constants, the ability to model time variation in expected returns and covariances permits use of time-varying parameters (see Bali and Engle 2010), resulting in the following conditional ICAPM model:

$$E\left[R_{i,t+1}|\Omega_t\right] = A \cdot Cov\left[R_{i,t+1}, R_{m,t+1}|\Omega_t\right] + B \cdot Cov\left[R_{i,t+1}, X_{t+1}|\Omega_t\right], \tag{16}$$

where $Cov\left[R_{i,t+1}, R_{m,t+1}|\Omega_t\right]$ measures the time-t expected conditional covariance between the excess returns on risky asset i and the market portfolio. A is the reward-to-risk ratio, interpreted as the Arrow-Pratt relative risk-aversion coefficient. $Cov\left[R_{i,t+1}, X_{t+1}|\Omega_t\right]$ measures the time-t expected conditional covariance between the excess returns on risky asset i and a state variable X, and the parameter B represents the price of risk for the state variable X.

Because economy-wide levels of uncertainty are related to aggregate risk taking in the financial sector, we use this to propose a conditional asset pricing model with market and systemic risk. We then test whether the conditional time-varying exposures of financial firms to market and systemic risk factors predict their future returns:

$$E\left[R_{i,t+1}|\Omega_t\right] = A \cdot Cov\left[R_{i,t+1}, R_{m,t+1}|\Omega_t\right] + B \cdot Cov\left[R_{i,t+1}, CATFIN_{t+1}|\Omega_t\right], \tag{17}$$

where the time-varying exposure of financial firm i to changes in the market portfolio is measured by the conditional covariance between the excess return on firm i and the excess return on the aggregate stock market, denoted by $Cov\left[R_{i,t+1}, R_{m,t+1}|\Omega_t\right]$, and the time-varying exposure of financial firm i to systemic risk is proxied by the conditional covariance between the excess returns on firm i and *CATFIN*, denoted by $Cov\left[R_{i,t+1}, CATFIN_{t+1}|\Omega_t\right]$.

In Equation (17), we assume that *CATFIN* is a measure of systemic risk in the financial sector, as we have shown its correlation with investment and lending decisions. If *CATFIN* is priced in the conditional ICAPM framework, it can be viewed as a factor that is correlated with innovations in investment opportunities, similar to Merton (1973) characterization of business cycle fluctuations.

To test whether the common slope coefficients $(A,\ B)$ on $Cov\left[R_{i,t+1}, R_{m,t+1}|\Omega_t\right]$ and $Cov\left[R_{i,t+1}, CATFIN_{t+1}|\Omega_t\right]$ are significantly positive, we first form ten value-weighted size portfolios of financial and nonfinancial firms. Then, following Bali and Engle (2010), we estimate the time-varying conditional covariances of portfolios' excess returns with the market and systemic risk factors using the dynamic conditional correlation (DCC) model of Engle (2002). Finally, we estimate the portfolio-specific intercepts $(\alpha_i,\ \alpha_m)$ and the common slope coefficients $(A,\ B)$ from the following panel regression:

$$R_{i,t+1} = \alpha_i + A \cdot Cov_t(R_{i,t+1}, R_{m,t+1}) + B \cdot Cov_t(R_{i,t+1}, CATFIN_{t+1}) + \varepsilon_{i,t+1}, \tag{18}$$

$$R_{m,t+1} = \alpha_m + A \cdot Var_t(R_{m,t+1}) + B \cdot Cov_t(R_{m,t+1}, CATFIN_{t+1}) + \varepsilon_{m,t+1},$$

where $Cov_t(R_{i,t+1}, R_{m,t+1})$ is the time-t expected conditional covariance between the excess return on portfolio i and the excess return on the market portfolio; $Cov_t(R_{i,t+1}, CATFIN_{t+1})$ is the time-t expected conditional covariance between the excess return on portfolio i and *CATFIN*; and $Var_t(R_{m,t+1})$ is the time-t expected conditional variance of excess returns on the market portfolio.[10]

Table 9 shows that the market risk-return coefficient (A) is positive and highly significant, implying a strongly positive link between expected return and market risk. For the value-weighted portfolios of financial firms, the risk-aversion coefficient is estimated to be $A = 4.28$ ($A = 3.94$) with the t-statistic of 3.27 (3.26) using $CATFIN^{VaR}$ ($CATFIN^{ES}$). As shown in Table 9, similar results are obtained for the nonfinancial firms as well; the risk-aversion coefficient is estimated to be $A = 3.89$ ($A = 2.21$) with the t-statistic of 3.65 (2.33) using $CATFIN^{VaR}$ ($CATFIN^{ES}$).

The results in Table 9 also indicate a significantly positive market price of systemic risk for financial and nonfinancial firms. Equity portfolios of

[10] Following Bali (2008) and Bali and Engle (2010), we estimate the system of equations in (18) using a weighted least squares method that allows us to place constraints on coefficients across equations. We compute the t-statistics of the parameter estimates accounting for heteroscedasticity and autocorrelation, as well as contemporaneous cross-correlations in the errors from different equations.

Table 9
Conditional ICAPM with market and systemic risk

	Financial Firms		Nonfinancial Firms	
	A	*B*	*A*	*B*
$CATFIN^{VaR}$	4.284***	2.616**	3.890**	2.695***
	(3.27)	(2.53)	(3.65)	(3.35)
$CATFIN^{ES}$	3.940***	2.696**	2.212**	2.106**
	(3.26)	(2.54)	(2.33)	(1.98)

This table reports the common slope estimates (A, B) from the following panel regression:

$$R_{i,t+1} = \alpha_i + A \cdot Cov_t\left(R_{i,t+1}, R_{m,t+1}\right) + B \cdot Cov_t\left(R_{i,t+1}, CATFIN_{t+1}\right) + \varepsilon_{i,t+1},$$

$$R_{m,t+1} = \alpha_m + A \cdot Var_t\left(R_{m,t+1}\right) + B \cdot Cov_t\left(R_{m,t+1}, CATFIN_{t+1}\right) + \varepsilon_{m,t+1},$$

where $Cov_t\left(R_{i,t+1}, R_{m,t+1}\right)$ is the time-t expected conditional covariance between the excess return on portfolio i and the excess return on the market portfolio, $Cov_t\left(R_{m,t+1}, CATFIN_{t+1}\right)$ is the time-t expected conditional covariance between the excess return on portfolio i and *CATFIN*, and $Var_t\left(R_{m,t+1}\right)$ is the time-t expected conditional variance of excess returns on the market portfolio. *CATFIN* is estimated using the 1% value-at-risk ($CATFIN^{VaR}$) and 1% expected shortfall ($CATFIN^{ES}$) of the cross-sectional return distribution of financial firms. The parameters and their t-statistics are estimated using the monthly excess returns on the market portfolio and the ten value-weighted size portfolios of financial and nonfinancial firms for the sample period from January 1973 to December 2009. The t-statistics are adjusted for heteroscedasticity and autocorrelation for each series and contemporaneous cross-correlations among the portfolios. Significance at the 5%, and 1% level is denoted by **, and ***, respectively.

financial firms that are highly correlated with systemic risk (proxied by *CATFIN*) carry a significant premium relative to portfolios that are uncorrelated or minimally correlated with *CATFIN*. The common slope coefficient on $Cov_t(R_{i,t+1}, CATFIN_{t+1})$ is estimated to be positive and highly significant for both measures of *CATFIN*; $B = 2.62$ ($B = 2.70$) with the t-statistic of 2.53 (2.54) using $CATFIN^{VaR}$ ($CATFIN^{ES}$). As reported in the last column of Table 9, similar findings are obtained for the nonfinancial firms as well. These results indicate that equity portfolios of financial and nonfinancial firms with higher sensitivity to increases in *CATFIN* are expected to generate higher returns next period.[11] The significantly positive slope coefficients on $Cov_t(R_{i,t+1}, CATFIN_{t+1})$ in the conditional ICAPM framework indicate that *CATFIN* plays a significant role for market participants and proxies for innovations in the investment opportunity set.

The interpretation of these findings is based on Merton (1973) original contribution. The main difference between the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) and Merton (1973) ICAPM is the "intertemporal hedging demand." The CAPM is built on an implausible assumption that investors care only about the mean and variance of single-period portfolio returns. However, in practice, investors make decisions

[11] Bekaert, Engstrom, and Xing (2009) investigate the relative importance of economic uncertainty and changes in risk aversion in the determination of equity prices. They focus on economic uncertainty proxied by the conditional volatility of dividend growth and find that both the conditional volatility of cash flow growth and time-varying risk aversion are direct determinants of equity returns. Since *CATFIN* can be viewed as a proxy for economic uncertainty, we find evidence of an indirect link between economic uncertainty and future returns via firms' exposures to the market and systemic risk factors.

for multiple periods and they revise their portfolio and risk management decisions over time based on the expectations about future investment opportunities. In Merton (1973) ICAPM, investors are concerned not only with the terminal wealth that their portfolio produces but also with the investment and consumption opportunities that they will have in the future. Hence, when choosing a portfolio at time t, ICAPM investors consider how their wealth at time $t+1$ might vary with future state variables. This implies that like CAPM investors, ICAPM investors prefer high expected return and low return variance, but ICAPM investors are also concerned with the covariances of portfolio returns with state variables that affect future investment opportunities.

Hence, one of the implications of our results is that *CATFIN* is a relevant state variable that affects the investment opportunity set of investors. In other words, when investing in financial and nonfinancial firms, investors care about the stocks' covariation with aggregate systemic risk affecting the investment and consumption opportunities that investors will have in the future. However, because nonfinancial firms' systemic risk exposure (*CATnonFIN*) does not affect future investment and consumption opportunities, it is not priced by investors. Because under the conditional ICAPM framework investors have intertemporal hedging demands, these results also suggest that the covariation of *CATFIN* with the stock returns provides a better hedging instrument than the covariation with *CATnonFIN*, explaining why *CATFIN* is priced in both the time series and cross-section of individual stocks.

5. Conclusion

We derive a measure of the financial system's systemic risk that can forecast macroeconomic downturns approximately six months 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. 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*) and expected shortfall (ES) of financial firms to measure aggregate systemic risk exposure. The *VaR* and ES measures are estimated using three approaches: (1) a parametric extreme value method using estimates of the generalized Pareto distribution (GPD); (2) a parametric estimate of the skewed generalized error distribution (SGED); and (3) a nonparametric approach. Our new systemic risk measure, denoted *CATFIN*, is constructed using an average of the three *VaR* and ES estimates. However, our results are robust to use of each of the individual *VaR* and ES measures and to estimation using both time-series and cross-sectional data.

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 nonfinancial 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 also show that the strong predictive power of *CATFIN* remains intact after controlling for leverage, firm size, past returns, business cycle variables, volatility, market beta, persistence in real economic activity, and bank interconnectedness in the financial sector, as well as the recently proposed microlevel measures of systemic risk.

We find that a high level of aggregate systemic risk, as measured by *CATFIN*, predicts declines in aggregate bank lending activity, as well as being correlated with measures of bank health, such as CDS spreads and financial ratios. We then test whether the conditional time-varying exposures of individual stocks to market and systemic risk factors predict their future returns. Since *CATFIN* is priced in the conditional ICAPM framework, it plays a significant role for market participants and proxies for innovations in the investment opportunity set. This provides additional evidence from an asset pricing perspective that aggregate risk taking in the banking sector measured by *CATFIN* is related to real economic activity.

We measure macroeconomic conditions using the Chicago Fed National Activity Index (CFNAI), but our results are robust to other measures of macroeconomic conditions, such as the growth rate of GDP and industrial production, unemployment rate, an NBER recession dummy variable, and alternative measures of real economic activity. Using an established recession cutoff value of the CFNAI, we determine an early warning critical value for *CATFIN* such that if the monthly value of *CATFIN* exceeds this out-of-sample critical value, there is an increased chance of macroeconomic decline. Thus, regulators can utilize readily available information to intervene expeditiously in order to prevent a financial crisis that has macroeconomic implications.

In addition to the evidence from the U.S. financial sector, we investigate the predictive ability of regional *CATFIN* for the GDP growth rates of the Asian countries and the European Union. The results indicate that the international regional *CATFIN* can significantly predict lower GDP growth rates of the European Union and the Asian countries eight and six months ahead, respectively. In other words, the predictive power of *CATFIN* is strong for international countries as well. The *CATFIN* model does suffer from the problem of false positives in that it may forecast recessions that never actually take place. However, even a false reading may be useful to regulators as a means of taking action when the economic cost of marginal systemic risk is high. Hence, the *CATFIN* measure can be used by international bank regulators in conjunction with microlevel systemic risk measures to calibrate regulatory limits and risk premiums on individual bank systemic risk taking.

References

Abel, A. B., and O. J. Blanchard. 1986. The Present Value of Profits and Cyclical Movements in Investment. *Econometrica* 54:249–73.

Acharya, V., D. Gale, and T. Yorulmazer. 2011. Rollover Risk and Market Freezes. *Journal of Finance* 66: 1177–209.

Acharya, V., L. Pedersen, T. Philippon, and M. Richardson. 2010. Measuring Systemic Risk. Working Paper, New York University.

Adrian, T., and M. K. Brunnermeier. 2009. CoVaR. Federal Reserve Bank of New York Staff Reports, No. 348, August.

Ang, A., and G. Bekaert. 2007. Stock Return Predictability: Is It There? *Review of Financial Studies* 20:651–707.

Artzner, P., F. Delbaen, J.-M. Eber, and D. Heath. 1999. Coherent Measures of Risk. *Mathematical Finance* 9:203–28.

Ashcraft, A. B. 2005. Are Banks Really Special? New Evidence from the FDIC-Induced Failure of Healthy Banks. *American Economic Review* 95:1712–30.

Bali, T. G. 2003. An Extreme Value Approach to Estimating Volatility and Value at Risk. *Journal of Business* 76:83–108.

———. 2007. A Generalized Extreme Value Approach to Financial Risk Measurement. *Journal of Money, Credit, and Banking* 39:1611–47.

———. 2008. The Intertemporal Relation between Expected Returns and Risk. *Journal of Financial Economics* 87:101–31.

Bali, T. G., and P. Theodossiou. 2008. Risk Measurement Performance of Alternative Distribution Functions. *Journal of Risk and Insurance* 75:411–37.

Bali, T. G., and R. F. Engle. 2010. The Intertemporal Capital Asset Pricing Model with Dynamic Conditional Correlations. *Journal of Monetary Economics* 57:377–90.

Bekaert, G., E. Engstrom, and Y. Xing. 2009. Risk, Uncertainty, and Asset Prices. *Journal of Financial Economics* 91:59–82.

Bekaert, G., M. Ehrmann, M. Fratzscher, and A. Mehl. 2011. Global Crises and Equity Market Contagion. Working Paper, Columbia University.

Bernanke, B. S. 1983. Nonmonetary Effects of the Financial Crisis in the Propagation of the Great Depression. *American Economic Review* 73:257–76.

Brunnermeier, M. K., G. N. Dong, and D. Palia. 2011. Banks Non-Interest Income and Systemic Risk. Working Paper, Princeton University.

Byoun, S., and Z. Xu. 2011. Product Market Competition during a Financial Crisis. Working Paper, Baylor University.

Campello M., J. R. Grahamb, and C. R. Harvey. 2010. The Real Effects of Financial Constraints: Evidence from a Financial Crisis. *Journal of Financial Economics* 97:470–87.

Carlson, M. A., T. B. King, and K. F. Lewis. 2008. Distress in the Financial Sector and Economic Activity. Federal Reserve Board Economics and Finance Discussion Paper No. 2008-43.

Chan-Lau, J. 2009. Regulatory Capital Charges for Too-Connected-To-Fail Institutions: A Practical Proposal. Working Paper, IMF.

DeBandt, O., and P. Hartmann. 2002. Systemic Risk: A Survey. In C. A. E. Goodhard and G. Illing, eds., *Financial Crisis, Contagion, and the Lender of Last Resort: A Book of Readings.* London: Oxford University Press.

Dixit, A. K., and R. S. Pindyck. 1994. Investment under Uncertainty. Princeton, NJ: Princeton University Press.

Duchin, R., O. Ozbas, and B. A. Sensoy. 2010. Costly External Finance, Corporate Investment and the Subprime Mortgage Credit Crisis. *Journal of Financial Economics* 97:418–35.

Embrechts, P., C. Kluppelberg, and T. Mikosch. 1997. Modelling Extremal Events for Insurance and Finance. Berlin: Springer.

Engle, R. F. 2002. Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroscedasticity Models. *Journal of Business and Economic Statistics* 20:339–50.

Espinosa-Vega, M. A., C. M. Kahn, and J. Sole. 2010. Systemic Risk and the Redesign of Financial Regulation. IMF Global Financial Stability Report, Chapter 2, April.

Fama, E. F., and K. R. French. 1992. Dynamic Conditional Correlation: The Cross-Section of Expected Stock Returns. *Journal of Finance* 46:427–66.

Froot, K. A., and J. C. Stein. 1998. Risk Management, Capital Budgeting and Capital Structure Policy for Financial Institutions: An Integrated Approach. *Journal of Financial Economics* 47:55–82.

Gorton, G., and P. He. 2005. Bank Credit Cycles. Working Paper, NBER Series No. 11363.

Gray, D., and A. A. Jobst. 2009. New Directions in Financial Sector and Sovereign Risk Management. *Journal of Investment Management* 8:22–38.

Hakkio, C. S., and W. R. Keeton. 2009. What Is It, How Can It Be Measured, and Why Does It Matter? *Economic Review Federal Reserve Bank of Kansas City* 94:5–50.

Hill, B. M. 1975. A Simple General Approach to Inference about the Tail of a Distribution. *Annals of Mathematical Statistics* 3:1163–74.

Hodrick, R. 1992. Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement. *Review of Financial Studies* 5:357–86.

Ivashina, V., and D. Scharfstein. 2010. Bank Lending during the Financial Crisis of 2008. *Journal of Financial Economics* 97:319–38.

Jermann, U., and V. Quadrini. 2009. Macroeconomic Effects of Financial Shocks. Working Paper, NBER Series No. 15338.

Kambhu, J., T. Schuermann, and K. J. Stiroh. 2007. Hedge Funds, Financial Intermediation, and Systemic Risk. *Economic Policy Review, Federal Reserve Bank of New York* 13:1–18.

Kashyap, A. K., and J. C. Stein. 2000. What Do a Million Observations on Banks Say About the Transmission of Monetary Policy? *American Economic Review* 90:407–28.

Kashyap, A. K., J. C. Stein, and D. W. Wilcox. 2000. Monetary Policy and Credit Conditions: Evidence from the Composition of External Finance. *American Economic Review* 83:78–98.

Kashyap, A. K., R. B. Berner, and C. A. Goodhart. 2011. The Macroprudential Toolkit. *IMF Economic Review* 59:145–61.

Kelly, B. 2011. Tail Risk and Asset Prices. Working Paper, University of Chicago.

Korinek, A. 2011. Systemic Risk-taking: Amplification Effects, Externalities, and Regulatory Responses. Working Paper, European Centrl Bank Series No. 1345.

Lemmon, M., and M. R. Roberts. 2010. The Response of Corporate Financing and Investment to Changes in the Supply of Credit. *Journal of Financial and Quantitative Analysis* 45:555–87.

Lintner, J. 1965. The Valuation of Risky Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *Review of Economics and Statistics* 47:13–37.

Longstaff, F. A. 2010. The Subprime Credit Crisis and Contagion in Financial Markets. *Journal of Financial Economics* 97:436–50.

Merton, R. C. 1973. An intertemporal Capital Asset Pricing Model. *Econometrica* 41:867–87.

Newey, W. K., and K. D. West. 1987. A Simple, Positive-Definite, Heteroscedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55:703–8.

Peek, J., and E. Rosengren. 2000. Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States. *American Economic Review* 90:30–45.

Pickands, J. I. 1975. Statistical Inference Using Extreme Order Statistics. *Annals of Statistics* 3:119–31.

Sharpe, W. F. 1964. Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *Journal of Finance* 19:425–42.

Shleifer, A., and R. W. Vishny. 2010. Unstable Banking. *Journal of Financial Economics* 97:306–18.

Shumway, T. 2010. The Delisting Bias in CRSP Data. *Journal of Finance* 52:327–40.

Tarashev, N., C. Borio, and K. Tsatsaronis. 2009. The Systemic Importance of Financial Institutions. *BIS Quarterly Review* September: 75–87.

Tong, H., and S.-J. Wei. 2008. Real Effects of the Subprime Mortgage Crisis: Is It a Demand or a Finance Shock? International Monetary Fund WP/08/186, July.