RFS Advance Access published August 12, 2016

SRISK: A Conditional Capital Shortfall Measure of Systemic Risk

Christian Brownlees
Department of Economics and Business, Universitat Pompeu Fabra and Barcelona GSE

Robert F. Engle
Department of Finance, Stern School of Business, New York University

We introduce SRISK to measure the systemic risk contribution of a financial firm. SRISK measures the capital shortfall of a firm conditional on a severe market decline, and is a function of its size, leverage and risk. We use the measure to study top financial institutions in the recent financial crisis. SRISK delivers useful rankings of systemic institutions at various stages of the crisis and identifies Fannie Mae, Freddie Mac, Morgan Stanley, Bear Stearns, and Lehman Brothers as top contributors as early as 2005-Q1. Moreover, aggregate SRISK provides early warning signals of distress in indicators of real activity. (*JEL* C22, C23, C53, G01, G20)

Received June 7, 2011; accepted April 18, 2016 by Editor Geert Bekaert.

One of the lessons learned from the 2007–2009 financial crisis is that undercapitalization of large financial institutions can impose significant negative externalities on the real economy. When the economy is in a downturn, the bankruptcy of a firm cannot be absorbed by a stronger competitor. Obligations will spread throughout both the financial and real economy, and the natural functions of the financial sector will be curtailed. When the system is undercapitalized, it will no longer supply credit for ordinary everyday business, and the economy will suffer. Thus, a capital shortfall is dangerous for a firm and its bondholders, but it is also dangerous for the whole economy if it occurs just when the rest of the financial sector is undercapitalized.

We have benefited from discussions with Viral Acharya, Gianpiero Aielli, Matteo Barigozzi, Samantha Cook, Giuseppe Corvasce, Frank Diebold, Farhang Farazmand, Martin Hansen, Andrew Patton, Lasse Pedersen, José-Luis Peydró, Thomas Philoppon, Matthew Richardson, Simon Robertson, Clara Vega, and David Veredas. We would also like to thank for useful comments the Editor Geert Bekaert and two anonymous referees. This manuscript previously circulated with the title "Volatility, Correlation and Tails for Systemic Risk Measurement." Christian Brownlees acknowledges financial support from the Spanish Ministry of Science and Technology (Grant MTM2015-67304-P) and from the Spanish Ministry of Economy and Competitiveness, through the Severo Ochoa Programme for Centres of Excellence in R&D (SEV-2011-0075). Robert Engle thanks the Sloan Foundation, the National Science Foundation, and NYU Stern and Corporate and Individual Sponsors of the Volatility Institute for financial support. Send correspondence to Christian Brownlees, Universitat Pompeu Fabra, Ramon Trias Fargas 25-27, Office 20-2E10, 08005, Barcelona, Spain; telephone: (+34) 93 542 2750. E-mail: christian.brownlees@upf.edu.

doi:10.1093/rfs/hhw060

A number of contributions that focus on the analysis of 2007–2009 financial crisis have introduced theoretical models that formalize this intuition. Among others, Acharya *et al.* (2010) have developed a model in which the capital shortfall experienced by a financial firm when the financial system is undercapitalized generates negative externalities to the entire economy. In their framework, the vulnerability of the financial system arises because firms do not take into account the negative externality costs that they generate in a crisis. Firms that take excessive risk will face higher costs of capital from market participants but will not be charged for the externalities they impose on the real economy. The higher profit opportunities encourage others to also raise risk limits. This creates the need for appropriate tools for supervisors to measure the degree of undercapitalization a financial firm would experience, conditional on severe distress in the entire system.

These considerations motivate us to introduce an empirical methodology to measure the systemic risk contribution of financial firms. We introduce a measure called SRISK, defined as the expected capital shortfall of a financial entity conditional on a prolonged market decline. SRISK is a function of the size of the firm, its degree of leverage, and its expected equity loss conditional on the market decline, which we call Long Run Marginal Expected Shortfall (LRMES). The measure can readily be computed using balance sheet information and an appropriate LRMES estimator. SRISK is used to construct rankings of systemically risky institutions: Firms with the highest SRISK are the largest contributors to the undercapitalization of the financial system in times of distress. The sum of SRISK across all firms is used as an measure of overall systemic risk in the entire financial system. It can be thought of as the total amount of capital that the government would have to provide to bail out the financial system in case of a crisis.

We apply the SRISK methodology to analyze the systemic risk contribution of top financial firms between January 2005 and December 2012, with a special focus on the 2007–2009 financial crisis. SRISK delivers useful rankings of systemically risky firms at various stages of the financial crisis. In particular, the rankings identify Fannie Mae, Freddie Mac, Morgan Stanley, Bear Stearns, and Lehman Brothers as top systemic contributors as early as 2005-Q1. Aggregate SRISK tracks the evolution of the undercapitalization of the financial system throughout the crisis. The measure shows that the capitalization of the financial system began to erode in July 2007. Aggregate SRISK peaks following the demise of Lehman Brothers in September 2008 and (to a much lesser extent) following the worsening of the European sovereign debt crisis in June 2010 and October 2011. As of December 2012, SRISK signals that the financial system has not entirely healed since the beginning of the financial crisis. For an early report on SRISK, see Acharya, Engle, and Richardson (2012).

We carry out a number of predictive evaluation exercises to assess the usefulness of SRISK for real-time systemic risk monitoring. Between 2007 and 2009, the Federal Reserve Bank carried out several programs to provide capital to those financial firms that experienced a capital shortfall. A natural evaluation exercise for our methodology consists of assessing whether precrisis SRISK predicts the capital injections carried out by the Fed during the crisis. We address this question using the Bloomberg Loan Crisis Data database, a dataset containing details of such operations analyzed in a number of studies (as in Bayazitova, and Shivdasani 2012). Regression results show that SRISK is a significant predictor of the capital injections. The finding is robust to the inclusion of a number of controls including firm size and alternative capital shortfall indices.

The majority of systemic risk definitions proposed in the literature emphasize that systemic risk has negative spillover effects on the real economy. To this extent, we investigate whether aggregate SRISK provides early warning signals of worsening macroeconomic conditions. Specifically, we use predictive regressions of the future growth rates of industrial production and the unemployment rate on the growth rate of aggregate SRISK (analogously to Allen, Bali, and Tang 2012). The forecasting horizon of the regressions varies from 1 month to 12 months. Results show that an increase in SRISK predicts future declines in industrial production and increases in the unemployment rate, and that the predictive ability of aggregate SRISK is stronger at longer horizons. Prediction results are robust to the inclusion of a large set of alternative control predictors that includes systematic risk (measured as the volatility of the market), the SRISK measure computed for nonfinancial firms, an aggregate capital shortfall index computed from a structural Merton-type default risk model, the default spread, the term spread, and an index measuring the degree of activity of the housing market.

A number of additional checks are carried out to assess the robustness and sensitivity of our evidence. First, we are concerned with determining the extent to which SRISK measures a different dimension of risk that is not already captured by other indices. To do so, we compare the SRISK rankings with those provided by a number of firm characteristic and alternative risk measures. We find that the rank correlation between SRISK and these alternatives is positive in the majority of the cases, though of modest magnitude. Next, we investigate the sensitivity of SRISK to the choice of its tuning parameters. We find that the rankings are stable for reasonable ranges of their values. Last, we address the choice of the LRMES estimator for SRISK. We argue that systemic risk monitoring ought to be based on indices that are able to promptly adapt to rapidly changing market conditions. To this extent we investigate which LRMES estimator delivers an aggregate SRISK measure that cannot be anticipated by an alternative aggregate SRISK measure based on a different LRMES estimator. Results show that LRMES estimation based on the standard GARCH-DCC time series model strikes a good balance between prediction accuracy and model complexity.

This paper contributes to the literature on systemic risk measurement, and more precisely to the strand of the literature proposing market–based indices of systemic distress. Bisias *et al.* (2012) and Sylvain *et al.* (2016) contain surveys on this literature. The CoVaR of Adrian and Brunnermeier (2016) links the systemic risk contribution of a financial institution with the increase of the VaR of the entire financial system associated with that financial entity being under distress. Allen, Bali, and Tang (2012) propose a system–wide systemic risk index called CATFIN, which associates systemic risk to the VaR of the financial system. Huang, Zhou, and Zhu (2011) measure systemic risk as the marginal contribution of a financial firm to the distress insurance premium of the financial sector. A large number of contributions on market–based systemic risk measurement associate this risk with the degree of interdependence among financial firms, as in Hartmann, Straetmans, and de Vries (2006). Research in this strand of the literature includes, among others, the work of Billio *et al.* (2012); Ang and Longstaff (2013); Diebold and Yilmaz (2014); Hautsch, Schaumburg, and Schienle (2015); and Zhang, Schwaab, and Lucas (2014). The main difference between our proposal and the majority of market–based systemic risk indices, is that SRISK merges market and balance sheet information in order to construct a market–based measure of financial distress, which is the expected capital shortfall of a financial firm conditional on a systemic event. SRISK depends not only on equity volatility and correlation (or other moments of the equity return distribution), but also explicitly on the size and the degree of leverage of a financial firm.

Our contribution is also related to that of Acharya *et al.* (2010) who also propose a systemic risk measure, called Systemic Expected Shortfall (SES), which measures the conditional capital shortfall of a financial firm. Their estimation approach, however, is based on structural assumptions, and it requires observing a realization of the systemic crisis for estimation. Thus their methodology cannot be used for *ex-ante* measurement. Ignoring the look ahead bias of SES, our empirical analysis shows that SRISK has significantly higher predictive power than SES does. This paper is also related to Acharya, Engle, and Pierret (2014) who carry out a comparison between the capital shortfall estimates of systemic risk institutions provided by SRISK and regulatory stress tests (based on supervisory data). Their analysis shows that regulatory capital shortfalls measured relative to total assets provide similar rankings to SRISK for U.S. stress tests. On the contrary, rankings are substantially different when the regulatory capital shortfalls are measured relative to risk–weighted assets. Greater differences are observed in the European stress tests.

1. Systemic Risk Measurement

The objective of the SRISK methodology is to measure the capital shortfall a financial firm is expected to experience conditional on a systemic event. The SRISK calculation is analogous to the stress tests that are regularly applied to financial firms. However, here it is done with publicly available information only, making the index widely applicable and relatively inexpensive to implement.

1.1 Conditional capital shortfall

We are concerned with monitoring a financial system made up of N financial institutions. The variable we introduce to measure the distress of a financial firm is its capital shortfall, which is here taken as the capital reserves the firm needs to hold (because of regulation and/or prudential management) minus the firm's equity. Formally, we define the capital shortfall of firm i on day t as

$$\mathsf{CS}_{it} = k\mathsf{A}_{it} - \mathsf{W}_{it} = k(\mathsf{D}_{it} + \mathsf{W}_{it}) - \mathsf{W}_{it},$$

where W_{it} is the market value of equity, D_{it} is the book value of debt, A_{it} is the value of quasi assets, and k is the prudential capital fraction. In particular, in this work we set the prudential capital fraction k to 8%. The capital shortfall can be thought of as the negative of the working capital of the firm. When the capital shortfall is negative, i.e., the firm has a capital surplus, the firm functions properly. However, when this quantity is positive, the firm experiences distress.

We are concerned with predicting the capital shortfall of a financial entity in case of a systemic event. Different definitions of systemic event can be adopted. Here we define it as a market decline below a threshold C over a time horizon h. The justification for this choice comes from the model of Acharya *et al.* 2010, where the capital shortfall of a firm generates negative externalities if it occurs when the system is already in distress. In addition, in order to produce a meaningful stressed capital shortfall measure, we implicitly assume that the systemic event corresponds to a sufficiently extreme scenario. We denote the multiperiod arithmetic market return between period $t+1$ and $t+h$ as $R_{mt+1:t+h}$ and the systemic event as $\{R_{mt+1:t+h} < C\}$. In this work, we set the horizon h to 1 month (that is twenty-two periods) and the threshold C to -10%. We define SRISK as the expected capital shortfall conditional on a systemic event

$$\begin{aligned}\mathsf{SRISK}_{it} &= \mathrm{E}_t(\mathsf{CS}_{it+h} | R_{mt+1:t+h} < C),\\ &= k\mathrm{E}_t(\mathsf{D}_{it+h} | R_{mt+1:t+h} < C) - (1-k)\mathrm{E}_t(\mathsf{W}_{it+h} | R_{mt+1:t+h} < C).\end{aligned}$$

In order to compute this expectation, we further assume that in the case of a systemic event debt cannot be renegotiated, implying that $\mathrm{E}_t(\mathsf{D}_{it+h} | R_{mt+1:t+h} < C) = \mathsf{D}_{it}$. Using this assumption it follows that

$$\begin{aligned}\mathsf{SRISK}_{it} &= k\mathsf{D}_{it} - (1-k)\mathsf{W}_{it}(1 - \mathsf{LRMES}_{it}),\\ &= \mathsf{W}_{it}[k\mathsf{LVG}_{it} + (1-k)\mathsf{LRMES}_{it} - 1],\end{aligned} \tag{1}$$

where LVG_{it} denotes the quasi leverage ratio $(\mathsf{D}_{it} + \mathsf{W}_{it})/\mathsf{W}_{it}$ and LRMES_{it} is Long Run MES, the expectation of the firm equity multiperiod arithmetic return conditional on the systemic event, that is

$$\mathsf{LRMES}_{it} = -\mathrm{E}_t(R_{it+1:t+h} | R_{mt+1:t+h} < C),$$

where $R_{it+1:t+h}$ is the multiperiod arithmetic firm equity return between period $t+1$ and $t+h$. Formula (1) shows that SRISK is a function of the size of the firm, its degree of leverage, and its expected equity devaluation conditional on a market decline. SRISK is higher for firms that are larger, more leveraged, and with higher sensitivity to market declines. Note that, for simplicity, the dependence on the prudential ratio k, the threshold C, and the time horizon h is implicit in the SRISK notation

The SRISK measure of Equation (1) provides a point prediction of the level of capital shortfall a financial entity would experience in case of a systemic event. It is also interesting to define the $1-\alpha$ capital shortfall prediction interval conditional on the systemic event as

$$\left(\mathsf{CS}^{\alpha/2}_{it+h|t}, \mathsf{CS}^{1-\alpha/2}_{it+h|t}\right), \tag{2}$$

where

$$\mathsf{CS}^{q}_{it+h|t} = \mathsf{W}_{it}\left[k\,\mathsf{LVG}_{it} - (1-k)\,F^{-1}_{it+1:t+h|t}(q) - 1\right],$$

with $F_{it+1:t+h|t}(x)$ denoting the distribution function of the firm multiperiod return conditional on the systemic event.

We use the SRISK_{it} measure across all firms to construct a system–wide measure of financial distress. The total amount of systemic risk in the financial system is measured as

$$\mathsf{SRISK}_t = \sum_{i=1}^{N} (\mathsf{SRISK}_{it})_+ ,$$

where $(x)_+$ denotes $\max(x, 0)$. Aggregate SRISK_t can be thought of as the total amount of capital that the government would have to provide to bail out the financial system conditional on the systemic event. Notice that in the computation of aggregate SRISK we ignore the contribution of negative capital shortfalls (that is capital surpluses). In a crisis it is unlikely that surplus capital will be easily mobilized through mergers or loans. Thus, it will not necessarily be available to support failing firms.

Rather than reporting the SRISK measure it is often more insightful to report its percentage version. We define the percentage SRISK measure as

$$\mathsf{SRISK\%}_{it} = \frac{\mathsf{SRISK}_{it}}{\mathsf{SRISK}_t} \text{ if } \mathsf{SRISK}_{it} > 0,$$

and zero otherwise. SRISK% can be interpreted as a systemic risk share.

1.2 Long-run marginal expected shortfall

The computation of SRISK requires specifying a model for the market and firm returns that can be used to obtain estimators of the LRMES. A number of different specifications and estimation techniques can be used to obtain this prediction. In this work we construct LRMES predictions using a GARCH-DCC model Engle (2002, 2009). The GARCH-DCC methodology is widely used in financial time–series analysis because this class of models is able to capture well the stylized facts of the data.

Let the logarithmic returns of the firm and the market be denoted respectively as $r_{it} = \log(1+R_{it})$ and $r_{mt} = \log(1+R_{mt})$. We assume that conditional on the information set $\mathcal{F}_{t-1}$ available at time $t-1$, the return pair has an (unspecified) distribution $\mathcal{D}$ with zero mean and time–varying covariance,

$$\begin{bmatrix} r_{it} \\ r_{mt} \end{bmatrix} \Bigg| \mathcal{F}_{t-1} \sim \mathcal{D}\left(\mathbf{0}, \begin{bmatrix} \sigma_{it}^2 & \rho_{it}\sigma_{it}\sigma_{mt} \\ \rho_{it}\sigma_{it}\sigma_{mt} & \sigma_{mt}^2 \end{bmatrix}\right).$$

This approach requires specifying equations for the evolution of the time varying volatilities and correlation. We opt for the GJR-GARCH volatility model and the standard DCC correlation model (Glosten, Jaganathan, and Runkle 1993, Rabemananjara, and Zakoïan 1993, Engle 2002). The GJR-GARCH model equations for the volatility dynamics are

$$\sigma_{it}^2 = \omega_{Vi} + \alpha_{Vi}\, r_{it-1}^2 + \gamma_{Vi}\, r_{it-1}^2 I_{it-1}^- + \beta_{Vi}\, \sigma_{it-1}^2,$$

$$\sigma_{mt}^2 = \omega_{Vm} + \alpha_{Vm}\, r_{mt-1}^2 + \gamma_{Vm}\, r_{mt-1}^2 I_{mt-1}^- + \beta_{Vm}\, \sigma_{mt-1}^2,$$

with $I_{it}^- = 1$ if $\{r_{it} < 0\}$ and $I_{mt}^- = 1$ if $\{r_{mt} < 0\}$. The DCC specification models correlation through the volatility adjusted returns $\epsilon_{it} = r_{it}/\sigma_{it}$ and $\epsilon_{mt} = r_{mt}/\sigma_{mt}$

$$\text{Cor}\begin{pmatrix} \epsilon_{it} \\ \epsilon_{mt} \end{pmatrix} = R_t = \begin{bmatrix} 1 & \rho_{it} \\ \rho_{it} & 1 \end{bmatrix} = \text{diag}(Q_{it})^{-1/2}\, Q_{it}\, \text{diag}(Q_{it})^{-1/2},$$

where Q_{it} is the so-called pseudo correlation matrix. The DCC model then specifies the dynamics of the pseudo-correlation matrix Q_{it} as

$$Q_{it} = (1-\alpha_{Ci}-\beta_{Ci})S_i + \alpha_{Ci} \begin{bmatrix} \epsilon_{it-1} \\ \epsilon_{mt-1} \end{bmatrix} \begin{bmatrix} \epsilon_{it-1} \\ \epsilon_{mt-1} \end{bmatrix}' + \beta_{Ci}\, Q_{it-1},$$

where S_i is the unconditional correlation matrix of the firm and market adjusted returns. The model is typically estimated by a two–step QML estimation procedure. More extensive details on this modeling approach and estimation are provided in Engle (2009). In what follows we refer to this specification as GARCH-DCC for short.

LRMES is in general not available in closed form for this class of dynamic models. However, it is straightforward to implement a simulation based procedure to obtain exact LRMES predictions. The procedure consists of simulating a random sample of size S of h–period firm and market arithmetic returns conditional on the information set available on day t

$$\begin{bmatrix} R^s_{i\,t+1:t+h} \\ R^s_{m\,t+1:t+h} \end{bmatrix} \Bigg| \mathcal{F}_t \quad s=1,...,S.$$

These are computed by simulating a path of logarithmic returns of length h conditional on the information set on day t, computing the cumulative logarithmic return (which is the sum of the path) and then converting this into the arithmetic h–period return (by exponentiating and subtracting 1). The LRMES for day t is then calculated using the Monte Carlo average of the simulated arithmetic h–period returns,

$$\mathrm{LRMES}^{\mathrm{dyn}}_{it} = -\frac{\sum_{s=1}^{S} R^s_{i\,t+1:t+h} I\{R^s_{m\,t+1:t+h} < C\}}{\sum_{s=1}^{S} I\{R^s_{m\,t+1:t+h} < C\}}. \tag{3}$$

A detailed description of the simulation algorithm is provided in Appendix A. An appealing feature of the simulation–based procedure is that it also allows us to compute the capital shortfall prediction intervals of Formula (2) using the quantiles of the simulated returns. Notice that in the algorithm, the innovations are simulated by resampling the standardized residuals of the GARCH-DCC rather than relying on parametric assumptions. We point out that Duan and Zhang (2015) have introduced an efficient algorithm for the computation of LRMES based on bridge sampling.

For comparison purposes, in the empirical application, we also consider two alternative approaches to construct LRMES forecasts. The first one is based on a static bivariate normal model, and the second on a dynamic bivariate copula model.

In the static bivariate normal framework, the firm and market logarithmic returns are assumed to be iid from a bivariate normal distribution with zero mean. The market volatility, firm volatility, and correlation parameters are denoted respectively as σ_m, σ_i, and ρ. In this setting, LRMES can be simply approximated by

$$\mathrm{LRMES}^{\mathrm{stat}}_{it} = -\sqrt{h}\,\beta_i\,\mathrm{E}(r_{m\,t+1} | r_{m\,t+1} < c), \tag{4}$$

where $\beta_i = \rho_i \frac{\sigma_i}{\sigma_m}$ and

$$\mathrm{E}(r_{m\,t+1} | r_{m\,t+1} < c) = -\sigma_m \frac{\phi(c/\sigma_m)}{\Phi(c/\sigma_m)},$$

with $\phi(\cdot)$ and $\Phi(\cdot)$ denoting, respectively, the density and distribution of a standard normal, and $c = \log(1+C)/\sqrt{h}$. Reading from right to left, LRMES is the product of the one–period market expected shortfall (defined using logarithmic returns), market beta, and the square root of the forecast horizon. Importantly, note that even with a static model and normal shocks LRMES is an increasing function of market volatility. We note that Formula (4) has a negative approximation error and should be used for short–horizon prediction only.[1]

Finally, we also consider a more sophisticated nonlinear dynamic specification that models the nonlinear tail dependence of firm and market logarithmic returns using copulas. Different dynamic copula specifications have been proposed in the literature. In this work we resort to the dynamic bivariate copula model of Patton (2006). This class of models is appealing in that it focuses directly on modeling the joint tail dependence of the firm and market returns. We provide details of this alternative specification in Appendix B.

1.3 Discussion

A number of remarks on the SRISK methodology we propose are in order.

SRISK is a forward-looking, market-based measure of a firm's net worth incorporating the distribution of future assets conditional on a systemic event. An important characteristic of our measurement approach is that it merges together balance sheet and market information to estimate the conditional capital shortfall of a firm. The capital shortfall could be measured using solely the accounting value of assets and liabilities. On the contrary, the market value of the equity of the firm provides a market estimate of the future value of the firm, which may differ from the accounting value because the assets or liabilities are evaluated differently from the accounting figures, and also because the market value is forward looking and may take into account factors that have yet to occur. Naturally enough, the conditional capital shortfall measure proposed in this work makes a number of simplifying assumptions in order to deliver a measure that can be easily computed in practice. Among the possible extensions of the baseline model, one could think of using different values of the prudential capital ratio k for different types of institutions and/or types of assets. Also, one limitation of the measure that one has to bear in mind is that it does not employ off-balance sheet information, and to this extent it might not appropriately capture the true asset structure of a firm.

The value of the prudential capital ratio k that we use is based on the capital ratio maintained by well managed large financial institutions in normal times. For instance, a rough back of the envelope calculation shows that from summer 2009 to spring 2011 the prudential capital ratio used by Wells Fargo averaged around 10% whereas JPM was closer to 7%. In this work we use 8% for our analysis and show later in the robustness checks section that ranking results

[1] In the static bivariate normal case, the exact closed–form expression for LRMES is

$$\mathsf{LRMES}_{it}^{\mathsf{stat}} = -\exp\left\{\frac{h}{2}(\beta^2\sigma_m^2 + (1-\rho^2)\sigma_i^2)\right\} \frac{\Phi\left(\frac{\beta\log(1+C) - h\beta^2\sigma_m^2}{\sqrt{h}\beta\sigma_m}\right)}{\frac{1}{2} + \frac{1}{2}\mathrm{erf}\left(\frac{\beta\log(1+C)}{\sqrt{2}\sqrt{h}\beta\sigma_m}\right)} + 1.$$

where $\mathrm{erf}(\cdot)$ is the error function.

are substantially stable in a reasonable range of values of k. We acknowledge that there is a current debate on the optimal capital ratio and that in particular, Admati and Hellwig (2013) argue that the ratio should be much higher. Our results do not inform this debate except to show the consequences for capital shortfall.

As far as the choice of the systemic event parameters h and C is concerned, we emphasize that the systemic event used for the SRISK calculation should entail a sufficiently long-horizon h and extreme threshold loss C. Otherwise, when the horizon is short and the threshold is modest, the role of risk is dramatically reduced, and SRISK reflects the current capital shortfall of an institution rather than the stressed conditional capital shortfall. In this work we set the horizon h to a month in order to compare more naturally our methodology with other monthly frequency indicators of distress. By contrast, the empirical implementation of SRISK for systemic risk monitoring can be based on different choices of these parameters, and, in particular, it can be based on a longer horizon.

SRISK assumes the triggering systemic event of the financial crisis is a prolonged market decline. It is natural to associate the fragility of the financial system with the conditional capital shortfall that the industry would suffer in times of distress. Because of the extensive use of leverage made in the financial sector, this industry is particularly vulnerable to downward market movements. De Bandt and Hartmann (2002) report that many banking crises have occurred in conjunction with aggregate shocks or cyclical downturns. We do not make any assumptions about the direction of causality. Our calculation is on the expected value of one endogenous variable conditioned on the value of another. The most common interpretation is that if the financial sector is undercapitalized and cannot survive a substantial downturn in the economy, this can in and of itself precipitate such a down turn. The macrofinance underpinnings of this process are topics of current research but include the negative effects of asset sales and other forms of delevering and the failure to supply sufficient capital to the real economy. See, for example, Bernanke and Gertler (1989) and Kiyotaki and Moore (1997).

Our notion of systemic risk assumes that the capital shortfall of the financial system has spillover effects on the real economy. Generally speaking, most systemic risk definitions typically assume the existence of these types of linkages. Empirically, Hoggarth, Reis, and Saporta (2002) find that output losses incurred during banking crisis periods are large. Jordà, Schularick, and Taylor (2013) analyse nearly 200 recession episodes over a long historical span and across different countries and document that a stronger increase in financial leverage before a recession leads to deeper subsequent downturn in the economy. One of the main channels through which a capital shortfall in the financial sector spills over to the real economy is lending. If the financial system is capital constrained, the availability of credit will dry up. This will adversely constrain businesses and will end up negatively affecting output and unemployment. Ivashina and Scharfstein (2010) document evidence of a substantial reduction in lending activity during the 2007–2009 financial crisis that originated from the supply side.

Our methodology is close in spirit to the classic Merton–type structural approach that is at the core of credit risk models such as Moody's KMV. The key difference between that approach and ours is that we are concerned with measuring the distress a financial institution is going to suffer conditional on a systemic event which affects the entire system; whereas systemic risk indices proposed on the basis of Merton–type models such as Lehar 2005 focus on measuring the capital shortfall in case of a firm default. In our view the default of a single financial institution, if it occurs under usual market conditions, should, in principal, be absorbed by the system and does not lead necessarily to systemic threats.

The systemic risk measurement methodology put forward in this paper differs from a number of contributions in the literature. Because the work of, among others, Hartmann, Straetmans, and de Vries (2006), market-based measurement approaches often associate systemic risk with the probability of joint distress of a large proportion of firms in the financial system. However, in this work, we emphasize that systemic risk is determined by the capital shortfall generated by distressed institutions conditional on a systemic event. Our framework takes into account joint dependence among firms, as well as their size and the degree of leverage. Thus our framework is able to detect if a small number of large financial institutions pose systemic threats to the entire system.

The measurement approach proposed to compute conditional capital shortfalls is general and can be applied to other types of firms. However, nonfinancial firms are not expected to be as highly leveraged and vulnerable as financial firms are. Moreover, it is less clear through which channels the capital shortfall of a inancial firm would negatively affect the whole economy. In the prediction section of the paper, we investigate this question empirically by comparing (financial) SRISK with a version of the SRISK computed using only nonfinancial firms.

2. Data and Capital Shortfall Estimation

Our empirical analysis focuses on a panel of large U.S. financial firms. The panel contains all U.S. financial firms with a market capitalization greater than 5 bln USD as of the end of June 2007. The panel spans from January 3, 2000, to December 31, 2012, and is unbalanced in that not all companies have been trading continuously during the sample period. We obtain daily logarithmic returns and market capitalization from CRSP, and quarterly book value of equity and debt from COMPUSTAT. SIC codes are used to divide firms into four subindustry groups: Depositories (such as Bank of America and JP Morgan Chase), Broker-Dealers (Bear Stearns and Lehman Brothers), Insurance (AIG), and Others (non–depository institutions, and real estate, such Freddie Mac and

Fannie Mae). We make one exception to this rule for Goldman Sachs (GS). This firm should have been classified as Others on the basis of the SIC, but, instead, we include it with Brokers-Dealers. The full list of tickers and company names grouped by subindustry is reported in Table 1. The daily CRSP market value–weighted index return is used as the market index return.

2.1 SRISK computation

We compute SRISK each month for all firms in the panel from January 2003 to December 2012. SRISK is computed at the end of each month using all data available as of that date; therefore, all our subsequent results have no look-ahead bias. The computation of LRMES requires us to estimate the GARCH–DCC model for each firm in the panel. We estimate the specification by quasi–maximum likelihood using a recursive estimation scheme, that is, using all available information starting from January 3, 2000, up to the end of each month. We show selected quantiles of the parameter estimates of the GJR-GARCH and DCC models for each industry group over the full sample in Table 2. The dynamics of the firms in the panel do not have a strong degree of heterogeneity. The GJR–GARCH parameters do not fluctuate much, with the exception of the intercept, which is on average higher for Broker-Dealers and Others. The range of the asymmetric coefficient reaches more extreme values for Broker-Dealers, signaling higher sensitivity to large volatility increases in case of a drop of the stock. Over all, the point estimates are in line with the typical GJR-GARCH estimates, with slightly higher α's and γ's together with lower β's, implying a higher level of unconditional kurtosis. Turning to the DCC, parameters are again close to the typical set of estimates and, intercept aside, parameters are similar across groups. Broker-Dealers have the highest level of unconditional correlation, followed by Others, Insurance, and Depositories.

2.2 Alternative capital shortfall measures

In the empirical analysis, we compare SRISK with a set of alternative capital shortfall measures. We provide details on these alternative indices and their computation. Similarly to SRISK, these alternative measures are computed once a month for each firm in the panel from January 2003 to December 2012.

Acharya *et al.* (2010) propose a measure of systemic risk for ranking systemically risky firms called Systemic Expected Shortfall (SES). Like SRISK, SES measures the expected capital shortfall of an individual firm conditional on a substantial reduction of the capitalization of the system. The index is estimated from the data using a structural estimation approach. Under appropriate assumptions, SES is expressed as a linear combination of 1-day ahead MES and Leverage. The coefficients of the linear combination are then obtained by regressing 1-day ahead MES and Leverage on the equity arithmetic return of each financial institution observed during the crisis. The fitted values of this regression are used to compute realized SES, which can then be used for ranking purposes. In their work, one-step-ahead MES is estimated as the

Table 1
Tickers, company names, and financial industry groups

	Depositories (29)
BAC	Bank of America
BBT	BB&T
BK	Bank of New York Mellon
C	Citigroup
CBH	Commerce Bancorp
CMA	Comerica inc
HBAN	Huntington Bancshares
HCBK	Hudson City Bancorp
JPM	JP Morgan Chase
KEY	Keycorp
MI	Marshall & Ilsley
MTB	M & T Bank Corp
NCC	National City Corp
NTRS	Northern Trust
NYB	New York Community Bancorp
PBCT	Peoples United Financial
PNC	PNC Financial Services
RF	Regions Financial
SNV	Synovus Financial
SOV	Sovereign Bancorp
STI	Suntrust Banks
STT	State Street
UB	Unionbancal Corp
USB	US Bancorp
WB	Wachovia
WFC	Wells Fargo & Co
WM	Washington Mutual
WU	Western Union
ZION	Zion

	Others (22)
ACAS	American Capital
AMP	Ameriprise Financial
AMTD	TD Ameritrade
AXP	American Express
BEN	Franklin Resources
BLK	Blackrock
BOT	CBOT Holdings
CBG	C.B. Richard Ellis Group
CBSS	Compass Bancshares
CIT	CIT Group
CME	CME Group
COF	Capital One Financial
FITB	Fifth Third Bancorp
FNM	Fannie Mae
FRE	Freddie Mac
ICE	Intercontinental Exchange
JNS	Janus Capital
MA	Mastercard
LM	Legg Mason
NYX	NYSE Euronext
SEIC	SEI Investments Company
SLM	SLM Corp

	Insurance (34)
ABK	Ambac Financial Group
AET	Aetna
AFL	Aflac
AIG	American International Group
AIZ	Assurant
ALL	Allstate Corp
AOC	Aon Corp
WRB	Berkley Corp
BRK	Berkshire Hathaway
CB	Chubb Corp
CFC	Countrywide Financial
CI	CIGNA Corp
CINF	Cincinnati Financial Corp
CNA	CNA Financial corp
CVH	Coventry Health Care
FNF	Fidelity National Financial
GNW	Genworth Financial
HIG	Hartford Financial Group
HNT	Health Net
HUM	Humana
L	Loews
LNC	Lincoln National
MBI	MBIA
MET	Metlife
MMC	Marsh & McLennan
PFG	Principal Financial Group
PGR	Progressive
PRU	Prudential Financial
SAF	Safeco
TMK	Torchmark
TRV	Travelers
UNH	Unitedhealth Group
UNM	Unum Group
WLP	Wellpoint

	Broker-Dealers (10)
AGE	A.G. Edwards
BSC	Bear Stearns
ETFC	E-Trade Financial
GS	Goldman Sachs
LEH	Lehman Brothers
MER	Merrill Lynch
MS	Morgan Stanley
NMX	Nymex Holdings
SCHW	Schwab Charles
TROW	T. Rowe Price

The table reports the list of tickers and company names used in the SRISK analysis grouped by financial industry group.

Table 2
GARCH-DCC parameter estimates

		TARCH				DCC		
		σ	α	γ	β	ρ	α	β
Dep.	$q_{0.1}$	22.44	0.02	0.06	0.84	0.49	0.02	0.81
	$q_{0.5}$	26.86	0.04	0.09	0.91	0.63	0.04	0.94
	$q_{0.9}$	32.51	0.08	0.14	0.94	0.68	0.08	0.97
Ins.	$q_{0.1}$	22.11	0.01	0.06	0.84	0.39	0.01	0.90
	$q_{0.5}$	25.55	0.03	0.10	0.91	0.53	0.02	0.97
	$q_{0.9}$	33.36	0.08	0.15	0.95	0.67	0.05	0.99
Bro.-deal.	$q_{0.1}$	24.15	0.00	0.06	0.71	0.52	0.01	0.89
	$q_{0.5}$	28.31	0.02	0.10	0.93	0.69	0.03	0.96
	$q_{0.9}$	39.24	0.07	0.33	0.96	0.73	0.06	0.98
Other	$q_{0.1}$	24.77	0.00	0.05	0.89	0.46	0.01	0.86
	$q_{0.5}$	28.30	0.03	0.07	0.93	0.57	0.02	0.96
	$q_{0.9}$	31.84	0.06	0.11	0.94	0.73	0.07	0.99

The table reports the 10%, 50%, and 90% quantiles of the GJR-GARCH and DCC paramaters estimates dividided by subindustry group. The parameter estimates are obtained over the full sample, which spans January 2005 to December 2012.

sample average of the firm's equity arithmetic returns on the days in which the market return is lower than its 5% quantile. In order to account for time-variation, the average is computed using a rolling-window estimation scheme. Naturally enough, it is unclear how SES can be estimated in real time, because it requires observing a systemic crisis to infer the level of systemic risk of an institution. In what follows we produce SES estimates using the latest figures of 1-step ahead MES and Leverage available and the SES coefficients based on the estimation results carried out in Acharya *et al.* (2010). 1-day ahead MES is computed on the basis of a GARCH-DCC model.

Lehar (2005) makes an important contribution to the systemic risk literature by proposing to use a standard Merton-type default model to monitor the financial system (see also Gray, Merton, and Bodie 2007). Among other quantities, he introduces the capital Expected Shortfall (ES), which is defined as the amount of debt that cannot be covered by the assets in case of default. Moreover, he proposes the total sum of Expected Shortfalls, which we label here as TES, as an index of overall distress. We construct the ES and TES following closely the steps outlined in Lehar (2005) and using methods developed in Duan (1994) to carry out inference on the Merton model. We make one exception to his procedure only, which consists of estimating the shortfalls using daily data rather than monthly, using a 2-year rolling window.

In this work we emphasize that SRISK measures the systemic risk associated with the capital shortfall of the financial system. It is natural to ask whether SRISK may capture distress irrespective of which category of firms it is constructed from. To this extent, we construct a nonfinancial SRISK measure and we compare it with (financial) SRISK. We build the measure using all U.S. nonfinancial firms (SIC code larger than 5999 and smaller than 7000) with a market capitalization larger than 5 bln USD as of the end of June 2007.

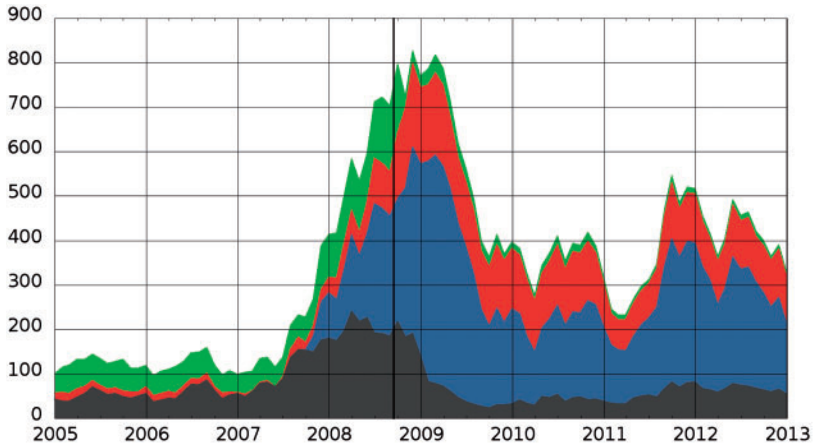

Figure 1
Aggregate SRISK by industry
The figure shows the plot of aggregate SRISK between January 2005 and December 2012. Aggregate SRISK is layered by financial industry group. The industry groups are (from top to bottom) Others, Insurance, Depositories, and Broker-Dealers. The solid vertical line marks the Lehman Brothers bankruptcy.

Nonfinancial SRISK is then constructed using the same steps used for the computation of (financial) SRISK, and in particular, we use the same values of the k, H, and C parameters.

3. The time-series and cross-section of SRISK

In this section we describe the time-series evolution and the cross-sectional composition of SRISK. In Figure 1 we display aggregate SRISK layered by financial industry group from January 2005 to December 2012,[2] whereas in Table 3 we report the SRISK% rankings of the most systemically risky financial institutions at the end of the first quarter of each year during the same period.

From January 2005 to July 2007, the total conditional capital shortfall is estimated to be close to 100 bln USD. Most of the shortage originates from the Broker-Dealers and Others sectors. This is mostly determined by the fact that these groups contained institutions with high levels of leverage and market beta. The main contributors in the Others group are Freddie Mac and Fannie Mae, which combined account for more than the 40% of aggregate SRISK. In the Broker-Dealers group, the top contributors are Morgan Stanley, Bear Stearns, and Lehman Brothers. It is important to stress that these five firms, which in different ways have all played important roles in the financial crisis, are identified as highly systemic as early as 2005-Q1.

[2] To see results for recent periods, please see the online source `http://vlab.stern.nyu.edu`.

Table 3
SRISK% rankings

2005-Q1			2006-Q1			2007-Q1			2008-Q1		
Ticker	SRISK%	SRISK%-PI	Ticker	SRISK%	SRISK%-PI	Ticker	SRISK%	SRISK%-PI	Ticker	SRISK%	SRISK%-PI
FNM	28.21	26.31 – 30.18	FRE	24.39	23.39 – 27.39	MS	23.46	20.72 – 26.46	C	16.56	14.85 – 18.46
FRE	21.42	19.59 – 23.97	MS	22.13	21.21 – 23.27	FRE	22.11	20.69 – 23.79	MER	9.54	8.90 – 10.24
MS	12.65	10.58 – 14.60	FNM	21.02	20.02 – 24.02	FNM	17.28	15.32 – 19.20	MS	9.05	8.24 – 9.89
BSC	9.17	8.86 – 9.46	BSC	9.13	8.81 – 9.48	BSC	13.05	12.34 – 13.69	FNM	8.91	8.19 – 9.59
LEH	6.14	5.27 – 6.98	MET	6.96	6.47 – 7.65	LEH	12.57	11.04 – 14.13	FRE	8.87	8.34 – 9.44
PRU	5.71	4.88 – 6.77	GS	5.35	4.78 – 5.93	MER	8.03	5.58 – 10.30	LEH	8.82	8.34 – 9.30
MER	5.64	4.33 – 6.74	LEH	4.88	4.05 – 5.73	GS	1.95	0.00 – 4.84	GS	7.88	7.12 – 8.75
MET	3.28	2.47 – 4.14	HIG	3.15	2.07 – 4.42	MET	1.34	0.00 – 2.87	BSC	5.28	5.26 – 5.30
GS	2.95	1.95 – 4.17	LNC	2.30	1.93 – 2.46	HIG	0.23	0.00 – 1.00	WB	3.94	3.07 – 4.88
HIG	2.77	2.25 – 3.33	PRU	0.68	0.59 – 0.79	AXP	0.00	0.00 – 0.00	WM	3.35	3.05 – 3.60

2009-Q1			2010-Q1			2011-Q1			2012-Q1		
Ticker	SRISK%	SRISK%-PI	Ticker	SRISK%	SRISK%-PI	Ticker	SRISK%	SRISK%-PI	Ticker	SRISK%	SRISK%-PI
C	17.50	17.14 – 17.85	C	23.22	21.24 – 26.29	BAC	26.62	23.97 – 29.63	BAC	23.30	21.43 – 25.45
BAC	14.14	12.98 – 15.27	AIG	20.81	20.62 – 21.00	C	17.49	15.65 – 19.62	C	17.88	16.61 – 19.67
JPM	13.58	11.67 – 15.57	BAC	10.70	6.10 – 15.24	MS	12.08	11.33 – 12.92	JPM	11.14	10.11 – 12.59
WFC	8.51	7.08 – 9.91	MS	10.16	9.77 – 10.67	MET	9.31	8.36 – 10.19	MET	9.45	8.94 – 9.74
AIG	7.96	7.86 – 8.04	PRU	5.29	5.02 – 5.47	PRU	7.76	7.17 – 8.27	MS	8.32	7.87 – 8.77
MS	4.44	3.96 – 4.93	HIG	5.18	5.03 – 5.33	HIG	6.59	6.35 – 6.89	GS	7.26	6.48 – 8.40
GS	4.27	3.53 – 5.07	MET	4.91	4.64 – 5.20	JPM	5.93	3.50 – 8.75	PRU	6.96	6.74 – 7.28
PRU	3.94	3.71 – 4.14	JPM	4.68	2.66 – 6.17	SLM	4.30	4.09 – 4.53	HIG	4.48	4.32 – 4.61
MET	3.63	3.15 – 4.06	SLM	3.32	3.11 – 3.54	LNC	3.20	3.05 – 3.36	LNC	2.78	2.69 – 2.90
HIG	2.68	2.61 – 2.74	LNC	2.40	2.28 – 2.51	GS	1.65	0.25 – 3.25	SLM	2.58	2.50 – 2.67

The table reports SRISK% rankings of the largest U.S. financial firms at the end of the first quarter of each year from 2005 until 2012: The tickers in the SRISK% top ten, the value of the SRISK% measure, and the SRISK% prediction interval (using a 90%–confidence level).

In July 2007, SRISK begins to increase as the implications of the subprime crisis become progressively more apparent. The increase is rather steady, with SRISK quadrupling in approximately 6 months. As SRISK grows its composition also begins to change. With the widening of the crisis, Depositories and Insurance become progressively more relevant systemic risk contributors. Large commercial banks, such as Citigroup, Bank of America, and JP Morgan, start rising up in the top ten with large shares of SRISK.

In September 2008 the crisis accelerates dramatically with the demise of Lehman Brothers, and SRISK peaks at approximately 800 bln USD. The top SRISK contributors are now Depositories and Insurance. For instance, in 2009-Q1, the SRISK top five is made up of Citigroup, Bank of America, JP Morgan, Wells Fargo, and AIG. Moreover, many past top systemic risk contributors disappear from the rankings because they have ceased to exist or have been nationalized. In March 2008 Bear Stearns is acquired by JP Morgan, while in September 2008 Lehman Brothers files for bankruptcy, and Freddie Mac and Fannie Mae are placed under conservatorship.

In March 2009 the financial system capitalization starts to heal, and Aggregate SRISK decreases as the market begins to rally. However, after an initial marked improvement, the recovery is sluggish. The slow recovery is also a consequence of the distress generated by the European sovereign debt crisis, which has strong spillover effects in the US, starting from the spring of 2010 and the summer of 2011. The SRISK rankings in this phase continue to be dominated by large Depositories without substantial changes in the composition of the top ten.

In December 2012 the capitalization of the financial system still looks substantially weaker than in the mid-2000's, and Bank of America and Citigroup account together for approximately 40% of the conditional capital shortfall of the financial system.

In order to give insights on the SRISK evolution of individual financial firms, in Figure 2, we display the SRISK time series of Citigroup, AIG, Goldman-Sachs, and Freddie Mac. The figure documents the shift in the systemic risk composition from Broker-Dealers and Others to Depositories and Insurance. Before July 2007 Goldman-Sachs and Freddie Mac have large capital shortfalls, whereas Citigroup and AIG are appropriately capitalized. After July 2007 conditional capital shortfalls begin to rise steadily; Citigroup and AIG become two of the most influential SRISK contributors, while Goldman-Sachs becomes a secondary contributor, and Freddie Mac disappears.

We compute the Herfindahl index associated with the SRISK% shares to measure the degree of systemic risk concentration in the system. We construct the index for each month between January 2005 and December 2012. Inspection of the series (not reported in the paper) conveys that SRISK is highly concentrated among a relatively small number of financial firms. For the majority of the sample period, in fact, the index is above 0.10, the value the index would take if the top-ten firms each held one-tenth of the total SRISK.

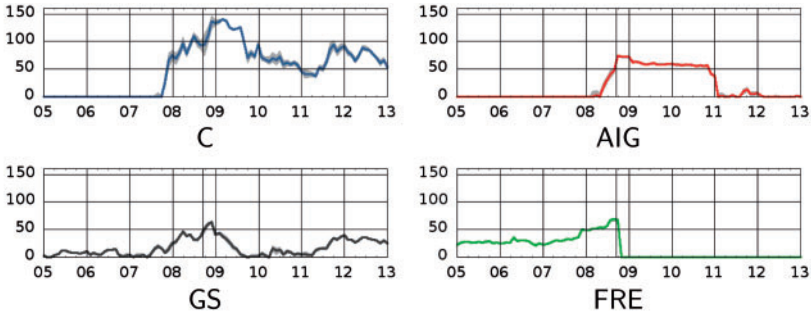

Figure 2
Firm SRISK
The figures show the plot of (the positive part of) SRISK for Citigroup (C), AIG (AIG), Goldman Sachs (GS), and Freddie Mac (FRE) between January 2005 and December 2012. The shaded area denotes the 90% capital shortage prediction interval. The solid vertical line marks the Lehman Brothers bankruptcy.

4. Predictive Power of SRISK

4.1 SRISK as a predictor of fed capital injections

The regulatory framework developed in the aftermath of the financial crisis puts special emphasis on identifying Systemically Important Financial Institutions (SIFIs) that can pose threats to the entire economy. In this work we identify such institutions as those firms that experience large capital shortfalls during times of severe market distress. From a regulatory perspective, this can be justified on the grounds that the firms with the largest capital shortfalls are those that will require the largest capital injections in case the supervisor decides to intervene to bail out the financial system following a systemic event.

These considerations suggest that a natural evaluation of our methodology consists of assessing if firm-specific SRISK predicts the realized Fed capital injections performed during the crisis to rescue the financial system. In fact, between 2007 and 2009, the Federal Reserve carried out several recapitalization programs, the most notable and extensive one being the Troubled Asset Relief Program (TARP).

We carry out this analysis using the Bloomberg Loan Crisis Data, a Bloomberg compiled dataset containing records of all financial firms that received capital injections from the Fed during the crisis. This dataset has been analyzed in Bayazitova and Shivdasani (2012), which provides a detailed assessment of the programs. Their study shows that government and firm incentives played a crucial role in the way the programs were implemented, and that the Fed injections are a useful, yet imperfect, proxy of the actual capital needs of the firms during the crisis.

We use a Tobit regression model to assess the significance of SRISK as a predictor of the Fed injections. Let CI_i^* denote the capital injection received by institution i during the crisis. We assume that the equation that determines the capital needs of firm i is

$$\log \mathsf{CI}_i^* = \alpha_0 + \alpha \log(1 + (\mathsf{SRISK}_i)_+) + \boldsymbol{\gamma}' \boldsymbol{x}_i + \epsilon_i \,, \tag{5}$$

where $\boldsymbol{x}_i$ is a vector of control explanatory variables and ϵ_i is a Gaussian random error term assumed to be uncorrelated with the regressors. We assume that the capital injection is carried out only if the amount to be injected is positive. This implies that the econometrician observes a censored version of $\log \mathsf{CI}_i^*$ defined as

$$\log \mathsf{CI}_i = \begin{cases} \log \mathsf{CI}_i^* & \log \mathsf{CI}_i^* > 0 \\ 0 & \text{otherwise} \end{cases} . \tag{6}$$

The model described in Equations 5 and 6 is a standard Tobit regression model that can be consistently estimated by maximum likelihood. We measure the Fed capital injection as the maximum level of firm borrowing after March 2008. Out of the ninety-five financial entities in our sample, only forty accessed the Fed programs after this date. Accordingly, predictor variables are computed using the latest data available before the end of March 2008. The set of control variables we consider are: subindustry group dummies; firm total assets, measured in logs; firm volatility, which is obtained from a GARCH model; firm equity fall from July 2007 relative to total assets; SES; and ES. We compute the equity fall starting from July 2007 because this date corresponds approximately to the peak in the equity valuations of the financial institutions in the panel.

Table 4 reports the estimation results of the Tobit model under different sets of restrictions. The table reports parameter estimates, as well as the pseudo R^2 of the regression. The baseline Tobit model, which only includes industry fixed effects, log assets, volatility, and equity fall, explains 18.2% of the variation of the capital injections. Augmenting the baseline model with SRISK increases the pseudo R^2 to 21.5% and delivers a significant positive estimate of the SRISK "elasticity," equal to 0.59. Using an alternative conditional capital shortfall measure such as SES or ES delivers analogous results; however, the improvement in terms of pseudo R^2 over the baseline is smaller. When SRISK, SES, and ES are included simultaneously in the Tobit regression, SRISK turns out to be the predictor with the strongest significance. Overall results convey that SRISK improves predicting the Fed capital injections observed during the crisis.

4.2 Aggregate SRISK as a predictor of macroeconomic distress

The majority of systemic risk definitions proposed in the literature emphasize that an increase in systemic risk can have negative spillover effects on the real economy. Building upon this notion, in this section, we use predictive regressions to show that aggregate SRISK provides early warning signals of distress in indicators of real activity. Particular attention is devoted to show that the predictive ability of SRISK is significant after controlling for other indices of financial distress, *inter alia*, market volatility.

Table 4
Fed capital injections and SRISK

	Fed Capital Injection					
Const	7.00***	−8.52*	−0.50	1.13	−3.74	5.96
	(1.211)	(4.612)	(4.883)	(5.308)	(5.409)	(5.297)
FE bro-deal	−9.74***	−8.23***	−8.08***	−7.90***	−7.95***	−7.78***
	(1.906)	(1.533)	(1.430)	(1.456)	(1.505)	(1.398)
FE insurance	−3.55	−1.84	−2.54	−0.97	−1.57	−1.72
	(2.507)	(2.506)	(2.366)	(2.435)	(2.505)	(2.396)
FE other	−11.99***	−9.35***	−8.81***	−9.28***	−8.87***	−8.62***
	(2.333)	(2.112)	(1.982)	(2.080)	(2.116)	(1.987)
Asset		1.58***	0.94***	0.95**	1.47***	0.74**
		(0.352)	(0.359)	(0.370)	(0.371)	(0.337)
Vol		−0.09	−0.17**	−0.26***	−0.21**	−0.34***
		(0.080)	(0.077)	(0.092)	(0.103)	(0.109)
Equity fall		7.33	7.17	8.71*	7.87	8.53*
		(5.037)	(4.788)	(5.082)	(5.060)	(4.870)
SRISK			0.59***			0.46**
			(0.164)			(0.207)
SES				6.76***		2.67
				(1.991)		(2.507)
ES					0.23**	0.20*
					(0.117)	(0.114)
$\widetilde{R}^2$	10.2%	18.2%	21.5%	21.1%	19.2%	22.9%

The table reports the Tobit regression results of the Fed capital injection after March 2008: Estimated coefficients, standard errors (in parenthesis) and pseudo $\widetilde{R}^2$ index. Asterisks are used to denote significance at standard significance levels (* = 0.10, ** = 0.05, and *** = 0.01).

A number of studies have attempted to shed light on this issue, among others Allen, Bali, and Tang (2012); Giglio, Kelly, and Pruitt (2015); and Brownlees *et al.* (2016). In particular, the work of Giglio, Kelly, and Pruitt (2015) reports that many systemic risk indicators proposed in the literature lack predictive power for downside macroeconomic risk. Let us note that Giglio, Kelly, and Pruitt (2015) include one-step-ahead MES (based on the methodology proposed in this work) as one of the candidate systemic risk measures but do not consider SRISK. In our view, MES should not be interpreted as a systemic risk measure, and it has different time-series properties in comparison to SRISK.[3] More generally, we believe that the findings of their paper should be interpreted with caution. In the main empirical exercise of their paper, the authors analyse the predictive power of systemic risk measures in the United States using a long historical sample that spans 1946 to 2011. This sample, however, contains only a few financial crises (1989-1991 Savings and Loan Crisis, 1998 LTCM Crisis and the 2007-2009 Great Financial Crisis). It is not surprising to find that systemic risk measures have limited predictive ability for macro downside risk in a sample in which few systemic crises have occurred. In fact, Hubrich and Tetlow (2015), for example, provide evidence that the linkages between financial frictions and the macroeconomy become relevant when the financial system is distressed and not operating normally.

[3] The Working Paper version of the same paper erroneously labelled one-step ahead MES as SRISK, which has created some confusion in the literature.

Here we focus on assessing if an increase in SRISK predicts future declines in industrial production and the unemployment rate. To this extent we employ an h-step-ahead predictive regression using monthly frequency data whose general form is given by

$$y_{t+h} = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, y_{t-i+1} + \sum_{i=1}^{p} \beta_i \, \Delta \log \mathsf{SRISK}_{t-i+1} + \boldsymbol{\delta}' \boldsymbol{x}_t + u_t \,, \tag{7}$$

where y_{t+h} denotes either the h-step-ahead monthly log change in industrial production or the h-step-ahead monthly change in the unemployment rate, $\Delta \log \mathsf{SRISK}_t$ is the monthly growth rate of aggregate SRISK, $\boldsymbol{x}_t$ is a vector of control predictor variables, and u_t is a random–error term assumed to be uncorrelated with the predictors. The set of control variables contains the S&P500 return; the default spread change, defined as the change in the difference of BAA and AAA rated corporate bonds; the term spread change, defined as the change in the difference of the 10-year T-bond and 1-month T-bill yields; and the percentage change in the number of new housing units started in the United States. The regression measures the change in economic conditions based on the change in the predictors h months before. By focusing on changes, the regression examines how new information can be used to predict changes in outcomes. The regression is run for different values of the predictive horizon h, ranging from 1 month to 12 months ahead. The number of lags p in the equation is set to three (a quarter). Parameters are estimated by least squares using data from January 2003 to December 2012, and standard errors are computed using the Newey-West HAC estimator.[4]

Table 5 contains detailed results for a subset of the predictive regressions using industrial production as the dependent variable. The table reports the estimated coefficients of Equation (7), together with robust standard errors and adjusted R^2 statistics for all forecasting horizons from 1 month to 12 months ahead. The table also reports the increment of the (standard) R^2 because of the inclusion of the lagged values of SRISK. The estimation results show that SRISK is negative and significant for the vast majority of forecasting horizons. SRISK is also the main predictor that contributes to long–horizon predictability, as lagged values of industrial production and the control predictors have significant estimates at short and medium horizons only. Overall, the estimation results convey that an increase in aggregate SRISK predicts a drop in future industrial production, which, judging from the increment of the R^2 statistic, has an economically meaningful magnitude.

We summarise the overall evidence of the predictive regression exercise in row (a) of Table 6. The left panel of the table shows results for industrial production, while the right panel shows results for the unemployment rate. The

[4] We set the number of lags in the Newey-West HAC formula equal to the optimal bandwidth formula provided in Newey and West (1987) plus the length of the horizon h of the predictive regression.

Table 5
SRISK predictive regressions

	Industrial Production											
Horizon	1	2	3	4	5	6	7	8	9	10	11	12
Const	0.052	0.044	0.025	0.071	0.071	0.073	0.076	0.076	0.104	0.117	0.120	0.132
	(0.057)	(0.049)	(0.075)	(0.074)	(0.087)	(0.096)	(0.122)	(0.100)	(0.112)	(0.098)	(0.110)	(0.087)
$SRISK_t$	0.564	−0.420	0.424	−0.663	0.167	−1.204*	−0.572	−0.359	−0.740	−1.683	−0.838*	−1.465**
	(0.381)	(0.312)	(0.448)	(0.412)	(0.335)	(0.637)	(0.512)	(0.343)	(0.720)	(1.175)	(0.449)	(0.587)
$SRISK_{t-1}$	−0.846*	0.217	−0.493	−0.085	−1.378*	−0.039	−0.024	−0.232	−1.472	−0.147	−1.048*	−0.956
	(0.489)	(0.394)	(0.305)	(0.339)	(0.728)	(0.382)	(0.338)	(0.680)	(1.063)	(0.389)	(0.544)	(0.669)
$SRISK_{t-2}$	−0.068	−0.240	−0.124	−1.323**	0.030	−0.233	−0.718	−1.415*	−0.511	−1.606***	−1.515*	−1.188
	(0.432)	(0.264)	(0.352)	(0.588)	(0.318)	(0.319)	(0.800)	(0.826)	(0.370)	(0.567)	(0.791)	(0.959)
IP_t	0.117	0.132**	0.289**	0.269**	0.217***	0.161***	0.038	0.083	0.071	−0.025	−0.040	−0.167*
	(0.096)	(0.060)	(0.124)	(0.111)	(0.080)	(0.051)	(0.088)	(0.065)	(0.066)	(0.077)	(0.090)	(0.094)
IP_{t-1}	0.278***	0.132**	0.199**	0.149	0.114	−0.090	0.068	−0.102	0.041	−0.004	−0.145	−0.041
	(0.089)	(0.065)	(0.093)	(0.143)	(0.094)	(0.114)	(0.106)	(0.071)	(0.088)	(0.105)	(0.090)	(0.083)
IP_{t-2}	0.235**	0.241***	0.022	0.059	−0.046	0.029	0.002	−0.051	−0.050	−0.111*	−0.015	−0.026
	(0.096)	(0.064)	(0.073)	(0.074)	(0.083)	(0.073)	(0.047)	(0.068)	(0.078)	(0.067)	(0.050)	(0.057)
CS_t	0.804**	1.453***	0.784**	0.384	0.796***	0.584	1.126***	0.479*	−0.065	0.042	0.234	0.253
	(0.385)	(0.202)	(0.322)	(0.292)	(0.197)	(0.496)	(0.297)	(0.291)	(0.472)	(0.411)	(0.315)	(0.457)
TE_t	−0.510	0.422***	−0.302	0.047	0.020	0.492**	0.358	0.880**	−0.185	0.511	0.623**	0.476
	(0.464)	(0.140)	(0.217)	(0.252)	(0.258)	(0.206)	(0.321)	(0.360)	(0.213)	(0.390)	(0.262)	(0.435)
$HOUSE_t$	0.010	0.013	−0.006	0.004	0.010	0.003	−0.008	−0.012	−0.001	−0.004	−0.012	0.005
	(0.009)	(0.008)	(0.009)	(0.007)	(0.007)	(0.009)	(0.012)	(0.008)	(0.012)	(0.011)	(0.012)	(0.014)
Ret_t	−0.915	2.299**	5.661***	0.560	1.111	3.346**	−0.712	3.163	−0.893	−0.452	−0.321	−0.113
	(1.640)	(1.109)	(1.730)	(3.262)	(1.928)	(1.432)	(1.796)	(1.993)	(1.573)	(1.397)	(1.236)	(1.191)
$\widetilde{R}^2$	22.0%	36.0%	32.0%	20.3%	14.8%	11.7%	0.6%	10.6%	1.2%	10.2%	11.1%	13.4%
ΔR^2	2.8%	0.7%	1.2%	6.0%	5.4%	3.7%	2.2%	6.1%	8.9%	12.9%	11.9%	12.2%

The table reports estimation results of the predictive regressions of Equation (7) for industrial production using a forecasting horizon ranging from 1 month to 12 months ahead. For each predictive horizon, the table reports estimated coefficients, robust standard errors, adjusted R^2, and the difference in the (standard) R^2 of the predictive regressions with and without SRISK. Asterisks are used to denote significance at standard significance levels (* = 0.10, ** = 0.05, and *** = 0.01).

Table 6
SRISK predictive regressions

		Industrial Production						Unemployment Rate					
		(1)			(2)			(1)			(2)		
	Horizon	F-test	F-test	Adj R^2	F-test	F-test	Adj R^2	F-test	F-Test	Adj R^2	F-test	F-test	Adj R^2
		SRISK	IP		SRISK	IP		SRISK	UR		SRISK	UR	
	1−3	12.75***	39.01***	21.5%	0.72	47.77***	29.6%	0.00	37.46***	20.3%	2.77*	50.60***	24.7%
(a)	4−6	14.84***	12.78***	15.3%	6.84***	6.12**	15.5%	4.15**	29.64***	17.8%	0.01	39.47***	27.1%
	7−9	6.32**	1.09	3.5%	4.53**	0.18	4.0%	9.85***	19.42***	13.4%	8.20***	15.55***	13.1%
	10−12	14.12***	3.65*	12.3%	14.35***	6.87***	11.5%	10.37***	6.79***	9.7%	7.32***	5.30**	11.0%
		SRISK	NF-SRISK		SRISK	NF-SRISK		SRISK	NF-SRISK		SRISK	NF-SRISK	
	1−3	0.70	9.47***	26.2%	0.12	6.91***	31.0%	0.95	3.38*	20.0%	3.28*	0.93	23.5%
(b)	4−6	11.45***	5.07**	16.3%	4.88**	3.62*	15.7%	1.76	2.20	18.2%	0.00	0.24	26.6%
	7−9	4.85**	6.20**	3.3%	4.12**	3.45*	3.5%	10.02***	3.36*	13.5%	9.20***	2.79*	13.1%
	10−12	13.30***	2.75*	11.9%	14.97***	2.16	11.8%	12.80***	2.02	9.3%	9.94***	0.74	10.3%
		SRISK	VIX		SRISK	VIX		SRISK	VIX		SRISK	VIX	
	1−3	2.82*	12.48***	28.9%	0.39	1.85	32.8%	0.99	3.32*	20.5%	3.54*	1.94	24.6%
(c)	4−6	9.03***	2.67	15.1%	6.36**	0.83	14.7%	0.52	9.48***	21.4%	0.01	0.01	26.6%
	7−9	5.61**	0.18	3.2%	5.23**	3.02*	3.5%	8.71***	0.28	12.5%	7.87***	2.43	12.6%
	10−12	13.25***	4.05**	11.8%	14.76***	3.32*	11.7%	8.94***	0.48	9.2%	8.28***	0.75	11.0%
		SRISK	TES		SRISK	TES		SRISK	TES		SRISK	TES	
	1−3	11.67***	20.92***	25.5%	0.81	2.44	29.8%	2.38	27.15***	28.5%	2.64	16.87***	29.3%
(d)	4−6	14.46***	40.33***	19.7%	7.37***	10.59***	17.7%	2.68	63.41***	27.7%	0.01	17.43***	29.2%
	7−9	5.49**	23.76***	7.7%	5.76**	19.27***	7.4%	9.82***	14.26***	15.3%	9.17***	7.42***	14.2%
	10−12	13.40***	2.10	10.2%	14.88***	1.80	9.2%	9.97***	12.88***	12.9%	8.74***	5.02**	11.4%

The table reports summary estimation results of the predictive regressions of industrial production growth rates (left panel) and the unemployment rate changes (right panel). Row (a) presents estimation results based on the model of Equation (7), whereas rows (b), (c), (d) report estimation results based on the model of Equation (8) where the additional predictor z_t is set to, respectively, nonfinancial SRISK, VIX, and TES. Columns (1) and (2) report estimation results based on the specifications with and without control predictors, respectively. The table reports the joint F-test for the significance of the SRISK coefficients across multiple horizons (1 to 3 months, 4 to 6 months, 7 to 9 months, and 10 to 12 months) in the different specifications. Moreover, the table shows the joint F-test for the significance of the dependent variable, nonfinancial SRISK, VIX and TES coefficients across the same multiple horizons, as well as the average adjusted R^2 across the same horizons. Asterisks are used to denote significance at standard significance levels (* = 0.10, ** = 0.05, and *** = 0.01).

table reports the F-tests for the joint significance of the SRISK coefficients as well as the F-tests for the joint significance of the lagged values of the dependent variable coefficients across multiple horizons (1 to 3 months, 4 to 6 months, 7 to 9 months, and 10 to 12 months).[5] The table also reports the average adjusted R^2 of the predictive regressions across the same horizons. Column (1) presents results based on the predictive regression model without control predictors, whereas Column (2) presents the results with controls.

Interestingly, the overall empirical evidence provided by the two macro–variables is analogous. The lagged growth rate of SRISK is generally significant and it contributes to improve forecasting ability, especially at longer horizons. After controlling for a larger number of control predictors, the short-term significance of the SRISK coefficients becomes weaker; however, the long-horizon significance of SRISK is unaffected. Lagged values of the dependent variables are significant at short horizons; but as the horizon increases predictability diminishes.

A number of robustness checks are carried out to investigate further the significance of the results. First, this paper associates systemic risk with the conditional capital shortfall of the financial system. To this extent, we investigate whether SRISK computed using nonfinancial firms shares similar properties. This allow us to assess if the forecasting ability of SRISK is driven by financial firms' "specialness" or if the measure captures distress irrespective of which category of firms it is applied to. Second, we investigate the relation between systemic and systematic risk. Here we measure systematic risk with the volatility of the market, as it is estimated by the VIX. As indices of systemic and systematic risk (such as volatility) are typically correlated, it is natural to ask if the predictive significance disappears after including a market volatility proxy. Last, we compare SRISK with an alternative measure of the aggregate capital shortfall in the system, that is TES. This also allows us to assess the role of the conditioning event from a predictive perspective. Figure 3 shows the time–series plot of the SRISK, nonfinancial SRISK, VIX and TES from January 2005 to December 2012. The correlation of the SRISK growth rates with the growth rates of inancial SRISK, VIX, and TES are 0.40, 0.33, and 0.24, respectively.

We consider an augmented version of the predictive regression of Equation (7)

$$y_{t+h}=\alpha_0+\sum_{i=1}^{p}\alpha_i\, y_{t-i+1}+\sum_{i=1}^{p}\beta_i\,\Delta\log \mathsf{SRISK}_{t-i+1}+\sum_{i=1}^{p}\gamma_i\, z_{t-i+1}+\boldsymbol{\delta}'\boldsymbol{x}_t+u_t\,, \quad (8)$$

where z_t denotes the growth rate of either nonfinancial SRISK, the VIX or TES. The model is estimated using the same steps outlined previously.

[5] The joint F-test across multiple horizons is carried out by stacking the predictive regressions in a SUR system. Parameter estimates are obtained by least squares, and robust standard errors are computed using the Newey-West HAC estimator with bandwidth equal to the optimal bandwidth formula provided in Newey and West (1987) plus the length of the maximum horizon h of the predictive regressions.

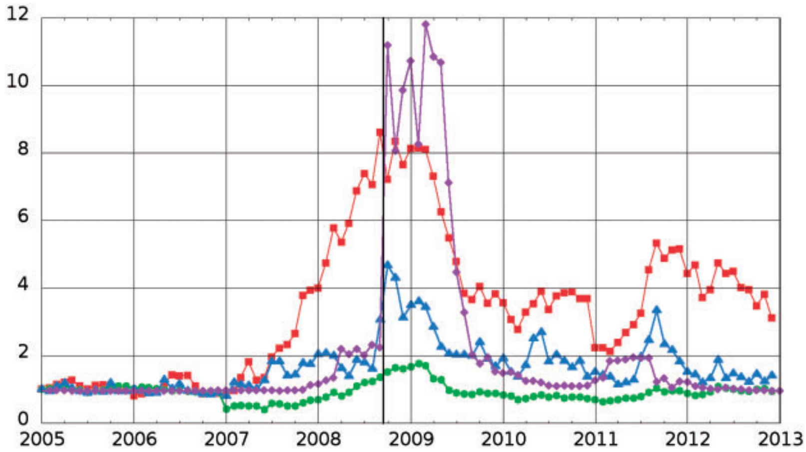

Figure 3
SRISK vis-à-vis nonfinancial SRISK, VIX, and TES
The figure shows the plot of aggregate (financial) SRISK (squares), aggregate nonfinancial SRISK (circles), VIX (triangles), and TES (diamonds) between January 2005 and December 2012. The series are normalized by the value of each series as of January 2005. The solid vertical line marks the Lehman Brothers bankruptcy.

We report summary results obtained from the predictive model of Equation (8) using nonfinancial SRISK, VIX, and TES, respectively, in row (b), (c), and (d) of Table 6. The left panel of the table reports results for industrial production, and the right panel those for the unemployment rate. Each row of the table reports the F-tests for the joint significance of the (financial) SRISK coefficients and the F-tests for the joint significance of the additional predictor coefficients across multiple horizons (1 to 3 months, 4 to 6 months, 7 to 9 months, and 10 to 12 months). The table also reports the average adjusted R^2 of the predictive regressions across the same horizons. Columns (1) and (2) show the estimation results, respectively, with and without controls.

Nonfinancial SRISK is strongly significant at short horizons for industrial production and has some weak significance for the unemployment rate when considering the regression model without control predictors. When considering the augmented specification with controls, most of its significance is substantially weakened. By contrast, (financial) SRISK is significant, and the inclusion of nonfinancial SRISK does not affect its long-horizon predictive ability. As far as the VIX is concerned, the results show that this indicator is strongly significant at short horizons for industrial production and medium horizons for the unemployment rate when considering the regression model without controls. However, most of its significance disappears and does not have a clear pattern once considering controls. SRISK is still significant at long horizons, even in this case. Finally, TES is significant across almost all horizons when considering the regression model without control predictors. Interestingly, after controls are included, most of its significance is still retained.

Table 7
SRISK% rank comparison

	Firm Characteristics				Risk Measures			
	Assets	Size	Debt	Leverage	SES	ES	LRMES	VOL
2005-Q1	0.20*	0.15	0.19*	0.29***	0.29***	0.08	0.37***	0.09
2006-Q1	0.15	0.17*	0.16	0.28***	0.28***	0.11	0.26**	−0.17
2007-Q1	0.19*	0.11	0.20*	0.30***	0.30***	0.04	0.24**	−0.18*
2008-Q1	0.08	0.00	0.14	0.09	0.09	0.04	0.14	0.15
2009-Q1	−0.07	0.06	−0.03	−0.03	−0.03	−0.15	0.09	0.01
2010-Q1	0.03	−0.01	−0.01	0.04	0.04	0.05	0.22**	−0.05
2011-Q1	0.33***	0.21**	0.35***	0.32***	0.32***	0.18*	0.29***	−0.01
2012-Q1	0.24**	0.18*	0.30***	0.35***	0.35***	0.34***	0.23**	0.28***

The table reports Spearman's correlation of SRISK with Assets, Equity, Debt, Leverage, SES, ES, LRMES, and Volatility at the end of the first quarter of each year from 2005 until 2012. Asterisks are used to denote significance at standard significance levels (* = 0.10, ** = 0.05, and *** = 0.01).

Again, SRISK is still significant at long–horizons, and its significance is robust to the inclusion of this indicator as well. It is important to emphasize that the inclusion of the alternative predictors does not contribute much to increasing the adjusted R^2 of the predictive regressions, especially at longer horizons.

5. Additional Robustness Checks

5.1 SRISK rankings comparison

In this section we compare the SRISK rankings with the ones obtained from a set of firm characteristic and alternative risk measures. The objective here is to assess how similar SRISK rankings are to the ones provided by these alternative indices. The firm characteristics we consider are assets, defined as the book value of assets; equity, defined as the market value of equity; debt, defined as the book value of debt; and leverage, defined as the ratio of the book value of debt to the market value of equity. The set of risk measures are SES, ES, LRMES, computed using Formula (3) on the basis of a GARCH-DCC model and taken in absolute value; and volatility, measured as the conditional standard deviation of firm returns estimated with a GJR-GARCH model. On each of the ranking dates of Table 3, we compute Spearman's correlation between the SRISK rankings and the rankings provided by the other indices. The indices are computed using the latest data available as of each date. Table 7 reports the results of the comparison. In general, Spearman's correlation between SRISK and the other indices is often significantly positive, but it never exceeds 0.40. The indices that have highest rank correlation are those that also enter in the SRISK formula, that is LRMES and leverage.

5.2 SRISK rankings sensitivity

In this section we assess the sensitivity of the SRISK rankings to the choice of the SRISK parameters and LRMES estimator. On each of the ranking dates of Table 3, we compute Spearman's correlation between the SRISK rankings obtained from our proposed approach and a number of modifications

Table 8
SRISK% rank sensitivity

	Alt. SRISK Params		Alt. LRMES Estimator	
	$k=10\%$	$C=20\%$	Static normal	Dynamic copula
2005-Q1	1.00***	0.98***	0.99***	0.99***
2006-Q1	0.99***	0.99***	0.99***	0.99***
2007-Q1	0.97***	0.90***	0.97***	0.97***
2008-Q1	0.80***	0.59***	0.74***	0.77***
2009-Q1	0.81***	0.61***	0.79***	0.89***
2010-Q1	0.92***	0.89***	0.75***	0.87***
2011-Q1	1.00***	0.87***	0.86***	0.88***
2012-Q1	1.00***	0.91***	0.99***	1.00***

The table reports Spearman's correlation of the default SRISK measure with SRISK indices computed using alternative choices of the SRISK parameters and alternative LRMES estimators at the end of the first quarter of each year from 2005 until 2012. The set of alternative SRISK parameters are $k=10\%$, and $C=-10$, $h=22$, and $k=8\%$, $C=-20\%$, and $h=22$. The set of alternative LRMES estimators is the one based on the static normal model and the dynamic copula model. Asterisks are used to denote significance at standard significance levels (* = 0.10, ** = 0.05, and *** = 0.01).

of the default settings. We consider: increasing the prudential capital ratio k to 10%, decreasing the systemic event threshold C to -20%, using the LRMES estimator based on the static normal model (using Formula 4), and using the LRMES estimator based on the dynamic copula model. The results of the comparison are reported in table 8. Overall, results show that the rank correlation is high and is above 0.90 in the majority of cases. As far as the choice of the SRISK parameters is concerned, detailed inspection of the results (not reported in the paper) shows that the companies at the low end of the rankings are quite sensitive to changes to k and C. However, the top positions are relatively stable for reasonable choices of these parameters.[6] It is straightforward to see from Equation (1) that SRISK increases when k increases or C decreases. However, in our dataset, the SRISK time–series profile and the SRISK rankings are not influenced excessively by the choice of these parameters. Looking at the different LRMES estimators, we note that the rankings based on the static normal and dynamic copula models are fairly similar to the ones provided by GARCH-DCC. Interestingly, ranking differences become more pronounced in the crisis period, especially the ones with the static normal model. This is because volatility and correlation dynamics become more hectic during a crisis, and the differences between the LRMES estimators become more pronounced, especially those between static and dynamic models.

5.3 SRISK timeliness

A supervisor performing real–time systemic risk monitoring is interested in using measures that promptly adapt to current market conditions. To this extent, we investigate here which LRMES estimator provides the most timely SRISK.

6 On the companion website we allow users to select their preferred choice of k and see how this affects rankings.

Table 9
SRISK timeliness

	Predictor					
Dependent	GARCH–DCC		Static normal		Dynamic copula	
GARCH–DCC			−0.13 (0.129)	4.02%	0.11 (0.162)	3.59%
Static normal	0.68*** (0.169)	13.03%			0.79*** (0.224)	10.59%
Dynamic copula	0.38** (0.180)	5.98%	−0.23 (0.190)	3.59%		

The table reports the results of the Granger causality test among the SRISK indices based on different LRMES estimators. For each pair of LRMES estimators (GARCH–DCC, static normal, and dynamic copula), the table reports the estimated β coefficient of Equation (9), its standard error, and the adjusted R^2 of the predictive regression. Asterisks are used to denote significance at standard significance levels (* = 0.10, ** =0.05, and *** =0.01).

We consider aggregate SRISK computed using three variants of the LRMES estimator: GARCH–DCC, static normal (based on 4), and dynamic copula. For each pair of LRMES estimators (A,B), we consider a Granger causality test based on the following predictive regression

$$\Delta \log \mathsf{SRISK}^A_{t+1} \;=\; \alpha_0 + \alpha \Delta \log \mathsf{SRISK}^A_t + \beta \Delta \log \mathsf{SRISK}^B_t + u_t, \qquad (9)$$

where $\Delta \log \mathsf{SRISK}^A_t$ and $\Delta \log \mathsf{SRISK}^B_t$ are the log growth rates of the aggregate SRISK based on estimators A and B, and u_t is an error term. We say that the SRISK measure based on LRMES estimator B leads the one based on estimator A if β is significantly different from zero. We carry out this test for each combination of LRMES estimators in order to determine the lead/lag relations among the different SRISK indices. We say that a LRMES estimator is timely if it provides an SRISK measure that is not lead by any other SRISK measure based on an alternative LRMES estimator. We estimate the coefficients of Equation (9) by least squares and compute robust standard errors using the Newey-West covariance estimator (using the standard plug–in formula for the bandwidth parameter). We report the results of the Granger causality test in Table 9. For each pair of estimators, the table reports the estimate of the β coefficient, its standard error, as well as the R^2 of the regression. The table shows that the SRISK indices based on the dynamic models (GARCH-DCC and dynamic copula) lead SRISK based on the static one. However, static LRMES based SRISK never leads the dynamic ones. The table also shows that GARCH–DCC leads the dynamic copula model; however, the significance is weak. Overall, the results convey that dynamic models, and the GARCH–DCC in particular, provide a timely SRISK measure.

6. Conclusions

The 2007–2009 financial crisis highlighted the need for better tools to measure systemic risk. In this paper we propose a systemic risk measure called SRISK that measures the expected capital shortfall of a financial institution conditional on a prolonged and severe market decline. SRISK is a function of the size, leverage and LRMES of the firm. The measure can be computed using balance-sheet data and an appropriate LRMES estimator. We use this methodology to analyze the systemic risk of top U.S. financial firms between 2005 and 2012. The SRISK analysis provides useful insights for monitoring the financial system, and, retrospectively, it captures several of the early signs of the crisis. Among other findings, we show that precrisis SRISK is a predictor of the capital injections performed by the Fed during the crisis and that an increase in aggregate SRISK provides an early warning signal of a decline in industrial production and an increase in the unemployment rate.

Appendix A. Simulation Algorithm for LRMES

This section describes the simulation based procedure we use to construct LRMES forecasts. Specifically, we are interested in computing the LRMES of firm i on period T at horizon h and conditional on a market decline equal to C,

$$\mathsf{LRMES}_{iT} = -\mathrm{E}_T(R_{i\,T+1:T+h} | R_{m\,T+1:T+h} < C).$$

In what follows we assume parameters to be known, while in practice, we use estimated parameters using all of the information available up to time T.

1. Construct the GARCH-DCC standardized innovations
$$\epsilon_{mt} = \frac{r_{mt}}{\sigma_{mt}} \text{ and } \xi_{it} = \left(\frac{r_{it}}{\sigma_{it}} - \rho_{it}\frac{r_{mt}}{\sigma_{mt}}\right) \Big/ \sqrt{1-\rho_{it}^2},$$
for each $t = 1, ..., T$. Note that by construction ϵ_{mt} and ξ_{it} are zero mean, unit variance, and cross–sectionally, as well as serially uncorrelated.
2. Sample with replacement $S \times h$ pairs of standardized innovations $[\xi_{it}, \epsilon_{mt}]'$. Use these to construct S pseudo samples of GARCH–DCC innovations from period $T+1$ to period $T+h$, that is
$$\begin{bmatrix} \xi^s_{i\,T+t} \\ \epsilon^s_{m\,T+t} \end{bmatrix}_{t=1,...,h} \qquad s = 1, ..., S.$$
3. Use the pseudo samples of GARCH–DCC innovations as inputs of the the DCC and GARCH filters, respectively, using as initial conditions the last values of the conditional correlation ρ_{iT} and variances σ^2_{iT} and σ^2_{mT}. This step delivers S pseudo samples of GARCH-DCC logarithmic returns from period $T+1$ to period $T+h$, conditional on the realized process up to time T, that is
$$\left.\begin{bmatrix} r^s_{i\,T+t} \\ r^s_{m\,T+t} \end{bmatrix}_{t=1,...,h} \right| \mathcal{F}_T \quad s = 1, ..., S.$$
4. Construct the multiperiod arithmetic firm return of each pseudo sample
$$R^s_{i\,T+1:T+h} = \exp\left\{\sum_{t=1}^{h} r^s_{i\,T+t}\right\} - 1,$$
and compute the multiperiod arithmetic market return $R^s_{m\,T+1:T+h}$ analogously.

5. Compute LRMES as the Monte Carlo average of the simulated multiperiod arithmetic returns conditional on the systemic event

$$\text{LRMES}_{iT} = -\frac{\sum_{s=1}^{S} R^s_{iT+1:T+h} I\{R^s_{mT+1:T+h} < C\}}{\sum_{s=1}^{S} I\{R^s_{mT+1:T+h} < C\}}.$$

Note that a number of algorithmic shortcuts can be implemented to reduce substantially the computational burden associated with the LRMES computation in large panels. The strategy we adopt is to draw first S market return samples and check which samples meet the systemic event condition. For each of these samples, we store the sequence of draws' dates. Then, for each individual firm, we sample directly the sequence of firm innovations corresponding to those dates. This speeds up the simulations, in that it avoids having to simulate and select paths for each firm/market return pair in the panel.

Appendix B. Time-Varying Copula Model

Several time-varying copula models have been introduced in the literature. Among other proposals, we consider the Dynamic Rotated Gumbel model put forward in Patton (2006). We choose this particular specification since Patton (2006) documents that it performs well empirically, relative to a set of alternative dynamic copula models. Let F_{mt} and F_{it} denote the conditional marginal cumulative distributions of market logarithmic returns r_{mt} and firm logarithmic returns r_{it}. In particular, in this work, we consider these to be the marginal conditional distributions implied by a GJR-GARCH model with (unspecified) marginal innovation distributions $\mathcal{D}_m$ and $\mathcal{D}_i$ (analogously to the GARCH-DCC presented in Section 1.2). We then define the uniform margins of the market and firm returns as

$$u_{mt} = F_{mt}(r_{mt}, \theta_m) \quad \text{and} \quad u_{it} = F_{it}(r_{it}, \theta_i),$$

that is the probability integral transformations of the returns series obtained from their marginal conditional distributions. Dynamic copula models specify a time–varying conditional copula function for the market and firm returns. This is equivalent to specifying a time–varying cumulative distribution function for the uniform margins

$$C_t(u_{mt}, u_{it}) = P_t(U_{mt} \le u_{mt}, U_{it} \le u_{it}).$$

The copula function allows to capture the time-varying dependence structure between the series. In particular, the rotated Gumbel copula uses one parameter to determine the degree of dependence in the lower tail. The distribution is defined as

$$C(u_{mt}, u_{it}|\delta_t) = u_{mt} + u_{it} - 1 + \exp\{-((-\log(1-u_{mt}))^{\delta_t} + (-\log(1-u_{it}))^{\delta_t})^{1/\delta_t}\},$$

where $\delta_t \in [1, \infty)$ is the parameter determining the degree of dependence. We assume the parameter evolves according to the following autoregressive equation

$$\delta_t = 1 + \left(\omega + \alpha \frac{1}{10} \sum_{\tau=1}^{10} |u_{mt} - u_{it}| + \beta \delta_{t-1}\right)^2.$$

Note that this formulation ensures δ_t is always greater than one, so that the copula distribution is well defined. Details on the estimation of the model and additional properties are provided in Patton (2006). In particular, the model is fitted by estimating the marginal models first and then by maximizing the copula likelihood using the fitted uniform margins.

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