SRISK:
A Conditional Capital Shortfall Index for Systemic Risk Measurement

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Abstract

This paper introduces the SRISK index to measure the systemic risk contribution of a financial firm. The index associates systemic risk to the capital shortfall a financial institution is expected to experience conditional on a severe market decline. SRISK is a function of the firm's size, its degree of leverage and its expected equity loss conditional on a market downturn. The sum of SRISK across all firms is used to measure the degree of undercapitalization of the whole financial system. We use SRISK to analyze the systemic risk of top US financial firms between January 2005 and December 2012, with a focus on the financial crisis. Results show that the methodology provides useful rankings of systemically risky firms at various stages of the crisis. In particular, SRISK rankings identify Fannie Mae, Freddie Mac, Morgan Stanley, Bear Stearns and Lehman Brothers as top systemic contributors as early as 2005-Q1. Moreover, we show that pre–crisis SRISK is a significant predictor of the capital injection received by the Fed during the crisis, and that an increase in aggregate SRISK is an early warning signal of a drop in industrial production and a hike in the unemployment rate.

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This manuscript previously circulated with the title "Volatility, Correlation and Tails for Systemic Risk Measurement". The systemic risk analysis of the top US financial institutions based on the methodology of this paper is reported on the Vlab (`http://vlab.stern.nyu.edu/`) and updated weekly. Acknowledgments are at the back of the paper. All mistakes are ours.

1 Introduction

One of the lessons learned from the 2007–2009 US financial crisis is that undercapitalization of large financial institutions can impose significant negative externalities to the real economy. When the economy is in a downturn, the bankruptcy of a firm cannot be absorbed by a stronger competitor and obligations will spread throughout both the financial and real economy as 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 collapse. Thus, a capital shortfall is dangerous for the firm and for its bondholders, but it is dangerous for the whole economy if it occurs just when the rest of the financial sector is undercapitalized.

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, Pedersen, Philippon, and Richardson (2010) develop 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. For instance, when the volatility of returns is low (e.g. from mid–2004 to mid–2007), risk is low, optimal leverage is high, and therefore firms can take excessive leverage. 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 an index called SRISK that is 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 index can readily be computed using balance sheet information and an appropriate LRMES estimator. The SRISK index 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 index 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 US 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 index shows that the capitalization of the financial system began to erode in July 2007. Aggregate SRISK peaks with 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, the index signals that the financial system has not entirely healed since the beginning of the financial crisis.

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 US 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 pre–crisis 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 recently analyzed in a number of studies (cf 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 (cf 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 over 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 index computed for non–financial 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 US housing market.

A number of additional checks are carried out to judge the robustness and sensitivity of our empirical 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 low in general. 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 a timely aggregate SRISK index, that is an aggregate SRISK index that cannot be anticipated by an alternative aggregate SRISK index based on a different LRMES estimator. Results show that the LRMES estimation approach based on the standard GARCH–DCC time series model strikes the best 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, Flood, Lo, and Valavanis (2012) contains a recent survey of over thirty systemic risk indices. The CoVaR of Adrian and Brunnermeier (2011) links the systemic risk contribution of a financial institution with the increase of the VaR of the entire financial system which is associated with that financial entity being under stress. Using a structural Merton–type model for default risk, Lehar (2005) defines the capital Expected Shortfall (ES) of a firm in case of default as a systemic risk measure (see also Gray, Merton, and Bodie, 2007). The fundamental difference between these approaches and SRISK lies in the choice of the systemic event. We associate systemic risk to a capital shortfall conditional on the entire market being in distress rather than one individual firm being insolvent or nearly insolvent. Traditionally, a large number of contributions on market–based systemic risk measurement associate this risk with the degree of interdependence among financial firms and the probability of joint distress in the financial sector. An early influential paper that puts forward this notion is Hartmann, Straetmans, and de Vries (2006). Contributions in this area typically differentiate themselves on the definition of the interdependence measure adopted and choice of the estimation approach. Research in this strand of the literature includes, among others, the work of Billio, Getmansky, Lo, and Pellizzon (2012), Andrew and Longstaff (2013), Diebold and Yilmaz (2014) Hautsch, Schaumburg, and Schienle (2014), and Zhang, Schwaab, and Lucas (2014). Several other significant contributions on market–based systemic risk measurement have also been proposed. Allen *et al.* (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. Finally, our contribution is also related to that of Acharya *et al.* (2010) who also propose a systemic risk index, called Systemic Expected Shortfall (SES), that measures the conditional capital shortfall of a financial firm. However, their estimation approach is based on structural assumptions and 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, the empirical analysis shows that SRISK has significantly higher predictive power than SES.

The rest of the paper is organized as follows. Section 2 introduces the SRISK methodology. Section 3 presents the panel of US financial firms analyzed in this work and details the empirical estimation of SRISK for the dataset. Section 4 describes the time series evolution and cross–sectional rankings of SRISK. Section 5 contains the results of the predictive analysis of the SRISK index. Section 6 carries out a number of additional robustness and sensitivity checks. Concluding remarks follow in Section 7.

2 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.

2.1 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 prudential management minus the firm's equity. We define the capital shortfall of firm i on day t as

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

where $\mathsf{W}_{i\,t}$ is the market value of equity, $\mathsf{D}_{i\,t}$ is the book value of debt, $\mathsf{A}_{i\,t}$ is the value of quasi assets and k is the prudential capital fraction. The capital shortfall can be thought of as minus the working capital of the firm. When the capital shortfall is negative, i.e., the firm has a capital surplus, the firm functions properly. On the other hand, 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. Also, in order to produce a meaningful stressed capital shortfall measure, we implicitly assume that the systemic event entails a sufficiently long horizon h and extreme threshold loss C. We denote the (arithmetic) multi–period market return between period $t+1$ and $t+h$ as $R_{m\,t+1:t+h}$ and the systemic event as $\{R_{m\,t+1:t+h} < C\}$. We define SRISK as the expected capital shortfall conditional on a systemic event

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

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

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

where $\mathsf{LVG}_{i\,t}$ denotes the leverage ratio $(\mathsf{D}_{i\,t} + \mathsf{W}_{i\,t})/\mathsf{W}_{i\,t}$ and $\mathsf{LRMES}_{i\,t}$ is Long Run MES, the expectation of the firm equity multi–period return conditional on the systemic event, that is

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

where $R_{i\,t+1:t+h}$ is the multi–period 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. The index is higher for firms that are larger, more leveraged and with higher tail dependence. 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 index 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 $1-\alpha$ conditional capital shortfall prediction interval as

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

where

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

with $F_{i\,t+1:t+h|t}(x)$ denoting the distribution function of the firm multi–period return conditional on the systemic event. Prediction intervals are useful in that they incorporate the uncertainty implied by the return distribution. Among others, Danielsson, James, Valenzuela, and Zer (2014) have recently emphasized the importance of using systemic risk diagnostics that also account for model implied uncertainty.

We use the $\mathsf{SRISK}_{i\,t}$ index across all firms to construct a system wide index of financial distress. The total amount of systemic risk in the financial system is measured as

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

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 be necessarily available to support failing firms.

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

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

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

2.2 Discussion

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

First, the index calculation is similar to the stress tests that are regularly applied to financial firms. However, here it is done with only publicly available information making the index widely applicable and relatively inexpensive to implement.

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 other hand, 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.

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 the empirical implementation of this paper we set the horizon h equal to one month and the threshold C to -10%. We set the horizon to a month in order to compare more naturally our methodology with other monthly frequency indicators of distress. On the other hand, 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.

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.

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. One of the main channels through which a capital shortfall in the financial sector spill overs to the real economy is lending. If the financial system is capitally 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. On the other hand, systemic risk indices proposed on the basis of Merton–type models like 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. Since the work of, among others, Hartmann *et al.* (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. On the other hand, 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 substantially large financial institutions pose systemic threats to the entire system, while measures of dependence like equity return (tail) correlation might to fail to do so.

The conditional capital shortfall index 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 k for different types of institutions and/or types of assets. Another limitation of the measure 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 measurement approach proposed to compute conditional capital shortfall is general and can be applied to other types of firms as well. However, non–financial firms are not expected to be as highly leveraged and vulnerable as financial firms. Moreover, it is less clear through which channels the capital shortfall of a non–financial industry 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 non–financial firms.

2.3 Long Run Marginal Expected Shortfall

The computation of the SRISK index requires specifying a model for the market and firm returns that can be used to obtain estimators of LRMES. A number of different models and estimation techniques can be used to compute this prediction. In this section we briefly review a number of approaches and put forward best practices.

A first MES estimation approach relies on static historical methods that are popular in the risk management literature. Assume that the compound equity returns of the firm and the market are iid from a zero mean, bivariate normal distribution. That is, let $r_{i\,t} = \log(1 + R_{i\,t})$, $r_{m\,t} = \log(1 + R_{m\,t})$ and

$$\begin{bmatrix} r_{i\,t} \\ r_{m\,t} \end{bmatrix} \sim \mathcal{N}\left(\mathbf{0}, \begin{bmatrix} \sigma_i^2 & \rho_i\sigma_i\sigma_m \\ \rho_i\sigma_i\sigma_m & \sigma_m^2 \end{bmatrix}\right) .$$

In this setting, LRMES can be approximated by

$$\mathsf{LRMES}^{\mathsf{stat}}_{i\,t} = \sqrt{h}\,\beta_i\,\mathsf{ES}^{\mathsf{stat}}_{t+1|t}\ , \tag{3}$$

where $\beta_i = \rho_i \frac{\sigma_i}{\sigma_m}$ and $\mathsf{ES}^{\mathsf{stat}}_{t+1|t}$ is the market expected shortfall, which is defined as

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

with $\phi(\cdot)$ and $\Phi(\cdot)$ denote 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–step ahead expected shortfall, systematic risk and the square root of the forecast horizon. Notice that even with a static model and normal shocks LRMES is an increasing function of market volatility. Let us emphasize that the formula in equation (3) has an error which is due to the fact that we are approximating MES using compound returns rather than arithmetic returns. In particular, the formula (3) has a negative approximation error and provides more extreme negative LRMES values.

LRMES predictions can also be obtained using dynamic time series models. There is an extensive literature documenting evidence of nonlinear dynamic dependence in financial returns time series, namely time varying volatility and correlation. To this extent, we consider a dynamic time series model for the firm and market compound returns where, 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. That is,

$$\left[\begin{array}{c} r_{i\,t} \\ r_{m\,t} \end{array}\right] \Bigg| \mathcal{F}_{t-1} \sim \mathcal{D}\left(\mathbf{0}, \left[\begin{array}{cc} \sigma^2_{i\,t} & \rho_{i\,t}\sigma_{i\,t}\sigma_{m\,t} \\ \rho_{i\,t}\sigma_{i\,t}\sigma_{m\,t} & \sigma^2_{m\,t} \end{array}\right]\right) .$$

This approach requires specifying equations for the evolution of the time varying volatilities and correlation. We opt for the TARCH volatility model and DCC correlation model (Rabemananjara and Zakoïan, 1993; Engle, 2002), benchmark specifications that are typically hard to out–perform out–of–sample. The TARCH model equations for the volatility dynamics are

$$\begin{aligned}
\sigma^2_{m\,t} &= \omega_{m\,G} + \alpha_{m\,G}\, r^2_{m\,t-1} + \gamma_{m\,G}\, r^2_{m\,t-1} I^-_{m\,t-1} + \beta_{m\,G}\, \sigma^2_{m\,t-1}\,, \\
\sigma^2_{i\,t} &= \omega_{i\,G} + \alpha_{i\,G}\, r^2_{i\,t-1} + \gamma_{i\,G}\, r^2_{i\,t-1} I^-_{i\,t-1} + \beta_{i\,G}\, \sigma^2_{i\,t-1}\,,
\end{aligned}$$

with $I^-_{i\,t} = 1$ if $\{r_{i\,t} < 0\}$ and $I^-_{m\,t} = 1$ if $\{r_{m\,t} < 0\}$. The DCC specification models correlation through the volatility adjusted returns $\epsilon_{i\,t} = r_{i\,t}/\sigma_{i\,t}$ and $\epsilon_{m\,t} = r_{m\,t}/\sigma_{m\,t}$

$$\mathsf{Cor}\begin{pmatrix} \epsilon_{i\,t} \\ \epsilon_{m\,t} \end{pmatrix} = R_t = \begin{bmatrix} 1 & \rho_{i\,t} \\ \rho_{i\,t} & 1 \end{bmatrix} = \mathrm{diag}(Q_{i\,t})^{-1/2}\, Q_{i\,t}\, \mathrm{diag}(Q_{i\,t})^{-1/2}\,,$$

where $Q_{i\,t}$ is the so–called pseudo correlation matrix. The DCC model then specifies the dynamics of the pseudo–correlation matrix $Q_{i\,t}$ as

$$Q_{i\,t} = (1 - \alpha_C - \beta_C) S_i + \alpha_C \begin{bmatrix} \epsilon_{i\,t-1} \\ \epsilon_{m\,t-1} \end{bmatrix} \begin{bmatrix} \epsilon_{i\,t-1} \\ \epsilon_{m\,t-1} \end{bmatrix}' + \beta_C\, Q_{i\,t-1},$$

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 typically 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 the h–period firm and market (arithmetic) returns conditional on the information set available on day t

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

where S denotes the number of simulations. The LRMES for day t is then calculated using the Monte Carlo average of the simulated returns,

$$\mathsf{LRMES}^{\mathsf{dyn}}_{i\,t} = \frac{\sum_{s=1}^{S} R^{s}_{i\,t+1:t+h} I\{R^{s}_{m\,t+1:t+h} < C\}}{\sum_{s=1}^{S} I\{R^{s}_{m\,t+1:t+h} < C\}}. \tag{4}$$

The details of the simulation algorithm are provided in the Appendix. 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 conditional quantiles of the simulated returns. The GARCH–DCC model bundled with the simulation procedure to compute LRMES is our preferred method to compute SRISK that we employ in the empirical analysis.

A computationally appealing approximation of the LRMES analogous to formula (3) is

$$\mathsf{LRMES}^{\mathsf{apx}}_{i\,t} = \sqrt{h}\,\beta_{i\,t+1}\,\mathsf{ES}^{\mathsf{apx}}_{t+1|t}\ , \tag{5}$$

where $\beta_{i\,t+1} = \rho_{i\,t+1}\frac{\sigma_{i\,t+1}}{\sigma_{m\,t+1}}$ and

$$\mathsf{ES}^{\mathsf{apx}}_{t+1|t} = \mathrm{E}_t(r_{m\,t+1}|r_{m\,t+1} < c) = \sigma_m \mathrm{E}_t(\epsilon_{m\,t+1}|\epsilon_{m\,t+1} < c/\sigma_{m\,t+1})\ ,$$

with $c = \log(1+C)/\sqrt{h}$ and $\epsilon_{m\,t+1} = r_{m\,t+1}/\sigma_{m\,t+1}$. It is important to stress that this approximation is more accurate when the conditional distribution of the returns is normal, and the volatility and correlation dynamics are highly persistent and smooth.[1] Diebold, Hickman, Inoue, and Schuermann (1998) warn about obtaining multi–period forecasts by rescaling by the square root of the forecast horizon as it is done in formula (5). In particular, the rescaling amplifies the effect of short term fluctuations.

Several other modeling strategies can be pursued to obtain LRMES predictions. Among others, we mention time varying copula models proposed by 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 the

[1]A GARCH process defined as $r_t = \sqrt{\sigma_t^2}z_t$ with $z_t \sim \mathcal{N}(0,1)$ and $\sigma_t^2 = \omega + \alpha r_{t-1}^2 + \beta\sigma_{t-1}^2$ is said to be persistent if $\alpha+\beta$ is close to unity and smooth if α is close to zero. Analogous definitions can be made for the TARCH and DCC models.

Appendix. Section 6 contains a comparison of alternative LRMES estimation methods for SRISK analysis.

3 Data and Capital Shortfall Estimation

Our empirical analysis focuses on a panel of large US financial firms. The panel contains all US financial firms with a market capitalization greater than 5 bln USD as of the end of June 2007. The panel spans between January 3, 2000 and December 31, 2012 and is unbalanced in that not all companies have been trading continuously during the sample period. We extract daily returns and market capitalization from CRSP, and quarterly book value of equity and debt from COMPUSTAT. SIC codes are used to divide firms into 4 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, real estate, like 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.

[INSERT TABLE 1 ABOUT HERE]

3.1 SRISK Computation

We compute SRISK each month for all firms in the panel from January 2003 to December 2012. Similar to other risk measures such as Value–at–Risk or Expected Shortfall, the practical implementation of SRISK requires setting a number of parameters, namely the prudential capital fraction k, the systemic market decline threshold C and its horizon h. We set the prudential fraction k to 8% and consider a $C = -10\%$ market drop over a month ($h = 22$). 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.

3.2 Alternative Capital Shortfall Measures

Our empirical analysis compares SRISK with alternative capital shortfall measure proposed in the literature. We provide here 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 one–day ahead MES and Leverage. The coefficients of the linear combination are then obtained by regressing MES and Leverage on the equity 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. Naturally enough, it is unclear how SES can be estimated in real time, as 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 one–step ahead MES and Leverage available and the SES coefficients based on the estimation results carried out in Acharya *et al.* (2010). MES is computed on the basis of a GARCH–DCC model.

Lehar (2005) makes an important contribution on systemic risk analysis by proposing to use a standard Merton–type default model to monitor the financial system. 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 two year rolling window.

4 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, while in table 2 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 MES. 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.

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 six 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, like Citigroup, Bank of America and JP Morgan, start rising up in the top ten with large shares of SRISK.

In September 2008 the crisis reaches its climax 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 as 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 US financial system.

[INSERT FIGURE 1 AND TABLE 2 ABOUT HERE]

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 while 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.

[INSERT FIGURE 2 ABOUT HERE]

Last, in figure 3 we show the degree of systemic risk concentration in the financial system. The figure displays the value of the Herfindahl index constructed using the SRISK% shares for each month between January 2005 and December 2012. From January 2005 until December 2006 SRISK is highly concentrated in a few companies only, namely Freddie Mac, Fannie Mae, Lehman Brothers, Bear Stearns and Morgan Stanley. Starting from the first months of 2007, the concentration of SRISK progressively decreases as the crisis unwinds and the majority of financial institutions suffer capital shortfalls. After the peak of the crisis SRISK concentration begins to raise again, without reaching, however, the pre–crisis levels. For the majority of the sample period, the Herfindahl index is above 0.10, the value the index would take if the top ten firms each held one tenth of the total SRISK. Overall, the picture conveys that SRISK is highly concentrated among a relatively small number of financial firms throughout the sample period.

[INSERT FIGURE 3 ABOUT HERE]

5 Predictive Power of SRISK

In this section we carry out a number of predictive exercises to show that SRISK indices are able to provide useful predictive signals for systemic risk monitoring.

5.1 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 which 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 notorious 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 recently 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

$$\log \mathsf{CI}_i^* = \alpha_0 + \alpha \log(1 + (\mathsf{SRISK}_i)_+) + \boldsymbol{\gamma}' \boldsymbol{x}_i + \epsilon_i \; , \tag{6}$$

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. Note that we transform SRISK using $\log(1 + x)$ rather than $\log(x)$ as the indicator can be zero. The set of control variables contains sub–industry group dummies, the log firm total assets, SES and ES. 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

$$\log \mathsf{CI}_i = \begin{cases} \log \mathsf{CI}_i^* & \log \mathsf{CI}_i^* > 0 \\ 0 & \text{otherwise} \end{cases} . \tag{7}$$

The model described in equations 6 and 7 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 95 financial entities in our sample only 40 accessed the Fed programs after this date. Accordingly, predictor variables are computed using the latest data available before the end of March 2008.

Table 3 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 and log assets, explains 16.8% of the variation of the capital injections. Augmenting the baseline model with SRISK increases the pseudo R^2 to 20% and delivers a significant positive estimate of the SRISK "elasticity", equal to 0.47. Using an alternative conditional capital shortfall measure like SES delivers analogous results; however, the improvement in terms of pseudo R^2 over the baseline is smaller. ES on the other hand does not have significant predictive power. When SRISK, SES and ES are included in the Tobit regression in the fully unrestricted model, only SRISK turns out to be significant. Overall results convey that SRISK improves predicting the Fed capital injections observed during the crisis.

[INSERT TABLE 3 ABOUT HERE]

5.2 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.

Specifically, 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

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

where y_t denotes either the growth rate of industrial production or the change in the unemployment rate, $\Delta \log \mathsf{SRISK}_t$ is the 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 ten year T-bond and one month T-bill yields; and the percentage change in the number of new housing units started in the US. 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). Model 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.

Table 4 contains the estimation results of the predictive regression under different sets of restrictions. The left panel shows the results for industrial production while the right panel shows results for the unemployment rate. Interestingly, overall the two macro variables provide similar empirical evidence. Column (1) presents the estimation results of the baseline predictive regression containing lagged values of the dependent variable only. The column reports the F–test for the joint significance of the lagged dependent variable coefficients as well as the adjusted R^2. These estimation results show that, at short horizons, lagged values of the dependent variables are significant; but as the horizon increases predictability diminishes. Column (2) presents the estimation results of the predictive regression containing lagged values of the dependent variable together with lagged growth rate of aggregate SRISK. The column reports the F–test for the joint significance of the SRISK coefficients and the adjusted R^2. The lagged growth rate of SRISK is generally significant and it contributes to improve forecasting ability especially over longer horizons. Finally, column (3) reports the estimation results of the fully unrestricted model, which are the F–test for the joint significance of the SRISK coefficients and the adjusted R^2. After controlling for a larger number of control predictors, the short term significance of the SRISK coefficients becomes weak; however, the long horizon significance of SRISK is unaffected. Overall, the estimation results show that an increase in aggregate SRISK has significant long horizon predictive power, which, judging from the adjusted R^2, has an economically meaningful magnitude.

[INSERT TABLE 4 ABOUT HERE]

A number of robustness checks are carried out to further investigate the significance of the results. First, this paper associates systemic risk with the conditional capital shortfall of the financial system. Thus, we investigate whether the SRISK index computed for non–financial firms would share similar properties. We construct non–financial SRISK following the same steps used for the computation of (financial) SRISK using all US non–financial firms with a market capitalization larger than 5 bln USD as of the end of June 2007. 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 index of the aggregate capital shortfall in the system, that is TES. This also allows us to assess what is the role of the conditioning event from a predictive perspective.

Figure 4 shows the time series plot of the SRISK, non–financial SRISK, VIX and TES from January 2005 to December 2012. The correlation of the SRISK growth rates with the growth rates of non–financial SRISK, VIX and TES are 0.40, 0.33 and 0.24, respectively.

[INSERT FIGURE 4 ABOUT HERE]

In order to carry out these additional robustness checks, we consider an augmented version of the predictive regression in equation (8)

$$y_{t+h} = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, y_{t-i+1} + \sum_{i=1}^{p} \beta_i \, \Delta \log \mathsf{SRISK}_{t-i+1} + \sum_{i=1}^{p} \gamma_i \, z_{t-i+1} + \boldsymbol{\delta}' \boldsymbol{x}_t + u_t \; , \tag{9}$$

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

Table 5 reports results of the model in equation (9) using non–finacial SRISK as the additional predictor z_t. Again, the left panel reports results for industrial production and the right panel those for the unemployment rate. Columns (1) and (2) show the estimation results of equation (9) with and without control predictors, respectively. Each column displays the F–test for the joint significance of the SRISK coefficients, the F–test for the joint significance of the non–financial SRISK coefficients and the adjusted R^2. Non–financial SRISK is significant at a few different horizons when considering the regression model without control predictors; however, most of its significance disappears once considering the fully unrestricted specification. On the other hand, (financial) SRISK is significant and the inclusion of non–financial SRISK does not affect its long horizon predictive ability.

Table 6 reports results of the model in equation (9) using the VIX as additional predictor. The table is structured as table 5. The results show that VIX is significant at short horizons for industrial production and medium horizons for the unemployment rate when considering the regression model without control predictors. However, most of its significance disappears and does not have a clear pattern once considering the fully unrestricted specification. SRISK on the other hand is still significant at long horizons.

Finally, we augment the predictive regression in equation (9) with the growth rates of TES, and report estimation results in table 7. Again, the table has the same layout of table 5. Interestingly, TES is significant at short to medium horizons when considering the regression model without control predictors. After controlling for a large set of control predictors part of its significance disappears but it still significantly improves medium horizon predictive ability. Again, SRISK is still significant at long horizons and its significance is robust to the inclusion of the indicator.

[INSERT TABLES 5, 6 AND 7 ABOUT HERE]

Overall, the predictive regression exercise conveys that the SRISK index provides significant long run predictability that is not captured by other indices of financial distress.

6 Additional Robustness Checks

A number of additional robustness checks are carried out to assess our empirical evidence.

6.1 SRISK Rankings vs Alternative Indices

One of the objectives of the SRISK methodology is to rank financial firms according to how much they contribute to systemic risk. In this section we compare the SRISK rankings to the ones constructed using common firm characteristic and alternative risk measures in order to determine to what extent SRISK captures a different dimension of risk. 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 (4) on the basis of a GARCH–DCC model; and Volatility, measured as the conditional standard deviation of firm returns estimated with a TARCH volatility model. We compare rankings by computing Spearman's correlation between the SRISK rankings and the rankings provided by the other indices at the end of the first quarter of each year between 2005 and 2012. On each ranking date, all the indices are computed using the latest data available.

Table 8 reports the results of the comparison. In general, Spearman's correlation between SRISK and the other indices is low. The variable that provides the highest rank correlation on average is LRMES; however, the rank correlation between the variables is never higher than 0.37. It is important to point out that the rank correlation with SES and ES is in one instance even mildly negative. Lastly, we point out that the rank correlation with the indices increases in the latter part of the sample. As the crisis widens, all the risk rankings provided by the different indices converge.

[INSERT TABLE 8 ABOUT HERE]

6.2 SRISK Sensitivity

In this section we assess the sensitivity of the results to the choice of the SRISK parameters and LRMES estimator, in particular, the choice of the SRISK parameters k and C as well as the choice of the estimator for LRMES. To this extent, we consider again Spearman's correlation between the cross–sectional rankings between the standard SRISK estimator used in the main analysis and the SRISK estimator obtained using $k = 10\%$, $C = -20\%$. Moreover, we consider the rank correlation of SRISK computed using alternative LRMES estimators. We consider static LRMES based on the analytical approximation, dynamic LRMES based on the GARCH–DCC model using the analytical approximation and the dynamic copula model using (exact) simulation.

We report the results in table 9. Results show that in general the rank correlation is high and is above 0.90 in the majority of cases. It is straightforward to see from equation (1) that increasing k or $-C$ increases the SRISK index: the stricter the capital requirements and/or the more extreme the threshold of the systemic event, the larger the capital shortfall. It is important to stress that the overall time series profile of SRISK is unaffected by the choice of k and C and that typically the increments across series in the panel are of comparable magnitude. Detailed inspection of the results shows that the companies at the very 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 the parameters.[2] Interestingly, the choice of the estimator plays a marginally smaller role in the SRISK rankings. Overall, the results convey that SRISK rankings are fairly stable for reasonable choices of the SRISK parameters and LRMES estimator.

[INSERT TABLE 9 ABOUT HERE]

6.3 SRISK Timeliness

The evidence of the previous section shows that from a systemic risk ranking perspective the choice of the LRMES estimator plays a marginal role. This would suggest that the

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

SRISK computation can be carried out with a static rather than a dynamic model. On the contrary, in this section we argue that the LRMES estimator based on dynamic models provide more timely signals.

A supervisor performing real time monitoring is interested in using a systemic risk index that is able to adapt promptly to current market conditions. To this extent, we assess which LRMES estimator provides the most timely SRISK index by carrying out the following exercise. We consider aggregate SRISK computed using four variants of the LRMES estimator: static model using the analytical approximation of LRMES, dynamic GARCH–DCC model using (exact) simulation (our suggested choice), dynamic GARCH–DCC model using the analytical approximation, and dynamic copula model using (exact) simulation. For any two distinct LRMES estimators A and B, we consider a Granger causality test based on the following predictive regression

$$\Delta \log \mathsf{SRISK}^{A}_{t+h} \quad = \quad \alpha_0 + \alpha \Delta \log \mathsf{SRISK}^{A}_{t} + \beta \Delta \log \mathsf{SRISK}^{B}_{t} + u_t \, ,$$

where $\Delta \log \mathsf{SRISK}^{A}_{t}$ and $\Delta \log \mathsf{SRISK}^{B}_{t}$ are the log growth rates of the aggregate SRISK index based on estimators A and B, and u_t is an error term assumed to be uncorrelated with the predictors. We say that the SRISK index based on LRMES estimator A is anticipated by the one based on LRMES estimator B if β is significantly different from zero. We carry out this test for each combination of LRMES estimators in order to determine which estimator delivers an aggregate SRISK index whose future changes cannot be anticipated. We perform the exercise for different forecast horizons h ranging from 1 month to 6 months

We report the results of the Granger causality test in table 10. We only report the results of the static LRMES and dynamic GARCH–DCC LRMES based on simulations. The table shows that the SRISK based on the dynamic GARCH–DCC model anticipates changes in the SRISK based on the static one. On the other hand, static LRMES based SRISK never anticipates dynamic GARCH–DCC based SRISK. The other comparisons (not reported) provide analogous evidence. Static LRMES based SRISK is anticipated by dynamic LRMES based SRISK indices. On the other hand, none of the dynamic approaches dominates the others.

[INSERT TABLE 10 ABOUT HERE]

7 Conclusions

The 2007-2009 financial crisis highlighted the need for better tools to measure systemic risk. In this paper we propose a systemic risk index 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, the leverage and the LRMES of the firm. The index 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 pre-crisis 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.

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A Appendix

A.1 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,

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

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

$$\epsilon_{m\,t} = \frac{r_{m\,t}}{\sigma_{m\,t}} \text{ and } \xi_{i\,t} = \left(\frac{r_{i\,t}}{\sigma_{i\,t}} - \rho_{i\,t}\frac{r_{m\,t}}{\sigma_{m\,t}}\right) \Big/ \sqrt{1-\rho_{i\,t}^2} \ ,$$

   for each $t = 1, ..., T$. Note that by construction $\epsilon_{m\,t}$ and $\xi_{i\,t}$ are zero mean, unit variance and cross–sectionally as well as serially uncorrelated.

2. Sample with replacement $S \times h$ pairs of standardized innovations $[\epsilon_{m\,t}, \xi_{i\,t}]'$. Use these to construct S pseudo samples of GARCH-DCC innovations from period $T+1$ to period $T+h$, that is

$$\left[\begin{array}{c} \epsilon^s_{m\,T+t} \\ \xi^s_{i\,T+t} \end{array}\right]_{t=1,...,h} \qquad s = 1, ..., S \ .$$

3. Feed the pseudo samples of GARCH–DCC innovations into the DCC and GARCH filters respectively using as initial conditions the last values of the conditional correlation $\rho_{i\,T}$ and variances $\sigma^2_{m\,T}$ and $\sigma^2_{i\,T}$. This step delivers S pseudo samples of GARCH-DCC returns from period $T+1$ to period $T+h$ conditional on the realized

process up to time T, that is

$$\left[\begin{array}{c} r^s_{m\,T+t} \\ r^s_{m\,T+t} \end{array}\right]_{t=1,\dots,h} \Bigg| \mathcal{F}_T \quad s = 1, ..., S\ .$$

4. Construct the multi–period 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 multi–period arithmetic market return $R^s_{m\,T+1:T+h}$ analogously.

5. Compute LRMES as the Monte Carlo average of the simulated multi–period returns conditional on the systemic event

$$\mathsf{LRMES}_{i\,T} = \frac{\sum_{s=1}^{S} R^s_{i\,T+1:T+h} I\{R^s_{m\,T+1:T+h} < C\}}{\sum_{s=1}^{S} I\{R^s_{m\,T+1:T+h} < C\}}.$$

Note that a number of algorithmic shortcuts can be implemented to substantially reduce 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.

A.2 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 (2004) and 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 $F_{m\,t}$ and $F_{i\,t}$ denote the conditional marginal cumulative distributions of market returns $r_{m\,t}$ and firm returns $r_{i\,t}$. In particular, in this work we consider these to be the marginal conditional distributions implied by a TARCH model with (unspecified) marginal innovation distributions $\mathcal{D}_m$ and $\mathcal{D}_i$ (analogously to the GARCH–DCC presented in Section 2.3). We then define the uniform margins of the market and firm returns as

$$u_{m\,t} = F_{m\,t}(r_{m\,t}, \theta_m) \quad \text{and} \quad u_{i\,t} = F_{i\,t}(r_{i\,t}, \theta_i),$$

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

$$C_t(u_{m\,t}, u_{i\,t}) = P_t(U_{m\,t} \leq u_{m\,t}, U_{i\,t} \leq u_{i\,t}).$$

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

$$C(u_{m\,t}, u_{i\,t}|\delta_t) = u_{m\,t} + u_{i\,t} - 1 + \exp\{-((-\log(1-u_{m\,t}))^{\delta_t} + (-\log(1-u_{i\,t}))^{\delta_t})^{1/\delta_t}\},$$

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

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

Note that this formulation ensures that 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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Table 1: Tickers, Company Names, Financial Industry Groups

Depositories (29)		Insurance (34)		Broker-Dealers (10)		Others (22)	
BAC	Bank of America	ABK	Ambac Financial Group	AGE	A.G. Edwards	ACAS	American Capital
BBT	BB&T	AET	Aetna	BSC	Bear Stearns	AMP	Ameriprise Financial
BK	Bank of New York Mellon	AFL	Aflac	ETFC	E-Trade Financial	AMTD	TD Ameritrade
C	Citigroup	AIG	American International Group	GS	Goldman Sachs	AXP	American Express
CBH	Commerce Bancorp	AIZ	Assurant	LEH	Lehman Brothers	BEN	Franklin Resources
CMA	Comerica inc	ALL	Allstate Corp	MER	Merrill Lynch	BLK	Blackrock
HBAN	Huntington Bancshares	AOC	Aon Corp	MS	Morgan Stanley	BOT	CBOT Holdings
HCBK	Hudson City Bancorp	WRB	W.R. Berkley Corp	NMX	Nymex Holdings	CBG	C.B. Richard Ellis Group
JPM	JP Morgan Chase	BRK	Berkshire Hathaway	SCHW	Schwab Charles	CBSS	Compass Bancshares
KEY	Keycorp	CB	Chubb Corp	TROW	T. Rowe Price	CIT	CIT Group
MI	Marshall & Ilsley	CFC	Countrywide Financial			CME	CME Group
MTB	M & T Bank Corp	CI	CIGNA Corp			COF	Capital One Financial
NCC	National City Corp	CINF	Cincinnati Financial Corp			FITB	Fifth Third Bancorp
NTRS	Northern Trust	CNA	CNA Financial corp			FNM	Fannie Mae
NYB	New York Community Bancorp	CVH	Coventry Health Care			FRE	Freddie Mac
PBCT	Peoples United Financial	FNF	Fidelity National Financial			ICE	Intercontinental Exchange
PNC	PNC Financial Services	GNW	Genworth Financial			JNS	Janus Capital
RF	Regions Financial	HIG	Hartford Financial Group			MA	Mastercard
SNV	Synovus Financial	HNT	Health Net			LM	Legg Mason
SOV	Sovereign Bancorp	HUM	Humana			NYX	NYSE Euronext
STI	Suntrust Banks	L	Loews			SEIC	SEI Investments Company
STT	State Street	LNC	Lincoln National			SLM	SLM Corp
UB	Unionbancal Corp	MBI	MBIA				
USB	US Bancorp	MET	Metlife				
WB	Wachovia	MMC	Marsh & McLennan				
WFC	Wells Fargo & Co	PFG	Principal Financial Group				
WM	Washington Mutual	PGR	Progressive				
WU	Western Union	PRU	Prudential Financial				
ZION	Zion	SAF	Safeco				
		TMK	Torchmark				
		TRV	Travelers				
		UNH	Unitedhealth Group				
		UNM	Unum Group				
		WLP	Wellpoint				

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

Table 2: 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 US financial firms at the end of the first quarter of each year starting from 2005 until 2012. The table reports the tickers in the SRISK% top ten, the value of the SRISK% index and the SRISK% prediction interval (using a 90% confidence level).

Table 3: Fed Capital Injections and SRISK

	Fed Capital Injection					
Const	7.00*** (1.211)	−9.74** (3.867)	−5.67 (3.705)	−7.58** (3.841)	−9.47** (3.880)	−5.64 (3.721)
FE bro-deal	−9.74*** (1.906)	−8.37*** (1.524)	−8.40*** (1.451)	−8.36*** (1.491)	−8.35*** (1.515)	−8.40*** (1.450)
FE insurance	−3.55 (2.507)	−2.76 (2.145)	−4.75** (2.165)	−4.07* (2.215)	−3.38 (2.317)	−4.92** (2.285)
FE other	−11.99*** (2.333)	−8.87*** (1.899)	−8.85*** (1.786)	−9.20*** (1.870)	−8.92*** (1.891)	−8.87*** (1.795)
Asset		1.48*** (0.328)	1.01*** (0.328)	1.18*** (0.344)	1.45*** (0.329)	1.01*** (0.334)
SRISK			0.47*** (0.160)			0.46** (0.217)
SES				3.39** (1.717)		−0.06 (2.509)
ES					0.07 (0.092)	0.02 (0.101)
$\widetilde{R}^2$	10.2%	16.8%	20.0%	18.8%	16.9%	20.0%

The table reports the Tobit regression results of the Fed capital injection after March 2008. The table reports 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).

Table 4: SRISK Predictive Regressions

	Industrial Production						Unemployment Rate					
Model	(1)		(2)		(3)		(1)		(2)		(3)	
Horizon	F-test Ind. Prod	Adj. R^2	F-test SRISK	Adj. R^2	F-test SRISK	Adj. R^2	F-test Un. Rate	Adj. R^2	F-test SRISK	R^2	F-test SRISK	Adj. R^2
1	25.93***	17.9%	0.87	19.9%	0.04	22.6%	38.03***	24.6%	0.03	23.5%	1.74	26.7%
2	35.29***	23.3%	6.58**	26.3%	0.36	36.7%	30.95***	22.0%	0.00	20.2%	1.68	24.9%
3	29.93***	21.7%	2.60	22.2%	0.03	32.3%	30.38***	21.7%	0.35	21.0%	0.53	27.6%
4	19.54***	15.8%	10.88***	23.3%	5.89**	21.2%	23.87***	18.7%	0.82	20.0%	0.63	32.1%
5	7.24***	6.3%	6.93***	14.8%	2.22	15.6%	24.36***	19.1%	3.27*	19.6%	0.03	28.1%
6	4.08**	2.6%	8.33***	10.7%	2.13	13.2%	14.54***	10.5%	3.85*	11.6%	0.08	20.1%
7	1.60	-0.9%	4.13**	0.5%	2.05	0.7%	13.44***	10.2%	4.76**	12.5%	3.19*	15.2%
8	0.74	-1.1%	7.96***	5.1%	3.81*	11.2%	7.29***	5.3%	8.67***	11.1%	6.25**	9.3%
9	0.01	-2.4%	7.84***	4.4%	6.66**	0.7%	6.70**	4.5%	15.90***	16.0%	12.63***	14.2%
10	0.37	-1.5%	14.51***	10.8%	12.22***	9.7%	3.37*	2.6%	14.13***	13.6%	7.98***	11.1%
11	1.03	-1.7%	14.86***	10.9%	13.08***	11.6%	2.49	2.0%	20.20***	17.4%	12.96***	21.9%
12	1.29	-1.6%	23.17***	16.2%	16.12***	14.4%	0.75	-2.3%	11.69***	6.8%	8.04***	9.1%

The table reports estimation results of the predictive regressions of the industrial production growth rates (left panel) and the unemployment rate changes (right panel) using a forecasting horizon ranging from 1 month to 12 months ahead. Columns (1) to (3) report results of the model in equation (8) under different sets of restrictions. Column (1) displays results of the restricted model using only lagged values of the dependent variable. Column (2) displays results of the restricted model using lagged values of the dependent variable and lagged growth rate of aggregate SRISK. Column (3) displays results of the unrestricted model. Column (1) shows the F–test for the joint significance of the dependent variable coefficients and adjusted R^2. Column (2) and column (3) show the F–test for the joint significance of the aggregate SRISK coefficients and adjusted R^2. Asterisks are used to denote significance at standard significance levels (*=0.10, **=0.05 and ***=0.01).

Table 5: SRISK Predictive Regressions: Financial vs Non–financial SRISK

	Industrial Production						Unemployment Rate					
	(1)			(2)			(1)			(2)		
Horizon	F-Test SRISK	F-Test NF SRISK	Adj R^2	F-Test SRISK	F-Test NF SRISK	Adj R^2	F-Test SRISK	F-Test NF SRISK	Adj R^2	F-Test SRISK	F-Test NF SRISK	Adj R^2
1	0.34	9.17***	26.2%	0.54	6.00**	26.7%	0.50	0.97	22.9%	1.62	0.01	25.1%
2	1.06	4.92**	29.6%	0.00	1.44	36.7%	0.20	1.33	19.6%	1.46	0.07	23.5%
3	0.26	3.65*	26.1%	0.00	0.38	32.0%	0.19	3.29*	21.4%	1.01	0.44	27.0%
4	4.40**	2.36	23.5%	2.97*	1.64	21.0%	0.01	2.48	21.1%	0.91	0.45	31.6%
5	1.63	3.46*	15.7%	0.74	1.62	14.7%	0.70	2.67	20.5%	0.00	0.27	28.2%
6	1.70	6.64**	15.0%	0.32	4.50**	16.5%	0.61	2.70	12.0%	0.00	0.30	18.5%
7	0.59	3.47*	1.5%	0.51	2.46	0.5%	1.33	2.18	14.1%	1.52	1.47	16.8%
8	2.73	2.61	6.2%	1.52	2.58	12.9%	3.72*	1.80	11.0%	3.04*	2.36	9.8%
9	3.31*	1.29	2.7%	3.48*	1.62	-0.8%	8.08***	0.92	15.0%	7.65***	1.29	13.4%
10	7.92***	0.68	10.2%	7.95***	1.55	10.3%	8.01***	0.97	13.1%	5.93**	0.41	10.0%
11	10.22***	0.31	10.8%	9.74***	0.76	13.3%	11.49***	1.43	17.2%	9.23***	0.71	21.1%
12	15.33***	0.39	15.3%	11.96***	0.39	13.0%	6.17**	0.73	7.0%	5.78**	0.25	9.4%

The table reports estimation results of the predictive regressions of the industrial production growth rates (left panel) and the unemployment rate changes (right panel) on aggregate financial and non–financial SRISK using a forecasting horizon ranging from 1 month to 12 months ahead. Columns (1) and (2) show the results of the predictive model of equation (9) with and without control predictors. For each model we report the F-test for the joint significance of the (financial) aggregate SRISK coefficients, the F–test for the joint significance of the non–financial aggregate SRISK coefficients, and the adjusted R^2. Asterisks are used to denote significance at standard significance levels (*=0.10, **=0.05 and ***=0.01).

Table 6: SRISK Predictive Regressions: Systemic vs Systematic Risk

	Industrial Production						Unemployment Rate					
	(1)			(2)			(1)			(2)		
Horizon	F-Test SRISK	F-Test VIX	Adj R^2	F-Test SRISK	F-Test VIX	Adj R^2	F-Test SRISK	F-Test VIX	Adj R^2	F-Test SRISK	F-Test VIX	Adj R^2
1	0.00	2.92*	29.8%	0.15	0.15	31.4%	0.61	1.93	23.0%	1.89	0.91	26.4%
2	1.76	4.61**	31.2%	0.43	0.63	36.1%	0.40	2.89*	20.3%	1.56	0.21	22.9%
3	0.57	5.06**	26.8%	0.18	0.95	32.1%	0.05	3.75*	21.6%	0.81	1.33	29.2%
4	6.64**	0.85	22.3%	4.86**	0.00	19.7%	0.10	7.62***	23.9%	1.53	0.02	34.3%
5	3.82*	0.40	15.9%	2.40	1.07	15.6%	0.30	7.18***	23.4%	0.01	0.07	25.9%
6	4.52**	2.88*	12.5%	2.15	0.03	13.8%	1.22	3.84*	14.9%	0.24	0.16	18.3%
7	2.13	0.43	-0.8%	1.91	0.08	-1.9%	4.61**	0.00	13.1%	4.99**	0.86	16.8%
8	6.39**	0.04	5.5%	4.51**	0.51	9.8%	10.03***	1.17	9.9%	7.14***	3.09*	9.7%
9	10.03***	2.09	4.4%	9.10***	3.66*	3.8%	15.14***	0.52	14.3%	12.24***	1.85	14.7%
10	17.96***	3.42*	11.3%	13.95***	6.26**	13.1%	10.83***	0.02	11.1%	8.06***	2.06	11.3%
11	14.14***	0.05	10.0%	12.56***	0.06	11.2%	12.09***	5.27**	20.4%	11.31***	3.02*	24.2%
12	19.97***	0.09	14.6%	15.12***	0.56	13.1%	8.63***	0.39	9.0%	9.03***	0.04	10.5%

The table reports estimation results of the predictive regressions of the industrial production growth rates (left panel) and the unemployment rate changes (right panel) on aggregate SRISK and VIX using a forecasting horizon ranging from 1 month to 12 months ahead. Columns (1) and (2) show the results of the predictive regression model of equation (9) with and without control predictors. For each model we report the F-test for the joint significance of the aggregate SRISK coefficients, the F–test for the joint significance of the VIX coefficients, and the adjusted R^2. Asterisks are used to denote significance at standard significance levels (*=0.10, **=0.05 and ***=0.01).

Table 7: SRISK PREDICTIVE REGRESSIONS: SRISK VS TES

	Industrial Production						Unemployment Rate					
	(1)			(2)			(1)			(2)		
Horizon	F-Test SRISK	F-Test TES	Adj R^2	F-Test SRISK	F-Test TES	Adj R^2	F-Test SRISK	F-Test TES	Adj R^2	F-Test SRISK	F-Test TES	Adj R^2
1	0.22	2.50	23.2%	0.00	0.60	23.7%	0.85	10.26***	28.9%	1.73	5.82**	29.6%
2	3.75*	8.93***	30.6%	0.25	0.39	35.3%	0.44	12.97***	27.7%	1.19	7.49***	28.2%
3	1.35	5.51**	25.7%	0.12	1.10	32.5%	0.24	22.86***	34.3%	0.57	12.04***	35.1%
4	6.79**	6.70**	27.1%	5.18**	4.66**	24.6%	0.01	18.96***	31.7%	0.45	5.12**	33.7%
5	4.89**	5.38**	19.7%	2.94*	2.73	16.9%	0.91	16.61***	31.0%	0.00	3.07*	32.7%
6	5.32**	7.36***	16.0%	2.02	2.94*	15.1%	1.79	11.00***	18.9%	0.10	2.07	19.8%
7	2.07	6.13**	5.2%	2.04	2.98*	2.4%	2.78*	6.46**	17.3%	3.43*	2.88*	16.7%
8	5.53**	6.52**	10.2%	4.91**	5.56**	14.4%	6.17**	3.34*	12.7%	6.91**	4.69**	11.8%
9	6.28**	1.87	5.9%	7.74***	4.18**	5.0%	13.05***	1.77	15.4%	13.24***	2.24	13.6%
10	12.31***	0.15	8.0%	11.23***	0.20	6.8%	10.18***	2.77*	13.5%	7.24***	1.53	9.9%
11	12.19***	0.28	8.6%	12.27***	0.21	9.4%	15.15***	3.54*	18.6%	12.12***	0.19	19.7%
12	19.78***	0.12	14.1%	15.40***	0.01	11.8%	8.32***	2.30	9.2%	7.76***	0.07	8.7%

The table reports estimation results of the predictive regressions of the industrial production growth rates (left panel) and the unemployment rate changes (right panel) on aggregate SRISK and TES using a forecasting horizon ranging from 1 month to 12 months ahead. Columns (1) and (2) show the results of the predictive regression model of equation (9) with and without control predictors. For each model we report the F-test for the joint significance of the aggregate SRISK coefficients, the F–test for the joint significance of the TES coefficients, and the adjusted R^2. Asterisks are used to denote significance at standard significance levels (*=0.10, **=0.05 and ***=0.01).

Table 8: 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	0.14	0.37	0.09
2006-Q1	0.15	0.17	0.16	0.28	0.28	0.23	0.26	-0.17
2007-Q1	0.19	0.11	0.20	0.30	0.30	0.24	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	0.11	0.22	-0.05
2011-Q1	0.33	0.21	0.35	0.32	0.32	0.30	0.29	-0.01
2012-Q1	0.24	0.18	0.30	0.35	0.35	0.35	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 starting from 2005 until 2012.

Table 9: SRISK% Rank Sensitivity

	Alt. SRISK Params		Alt. LRMES Estimator		
	$k = 10\%$	$C = 20\%$	S+A	D+A	C+S
2005-Q1	1.00	0.98	0.99	0.98	0.99
2006-Q1	0.99	0.99	0.99	0.99	0.99
2007-Q1	0.97	0.90	0.97	1.00	0.97
2008-Q1	0.80	0.59	0.74	0.84	0.77
2009-Q1	0.81	0.61	0.79	0.84	0.89
2010-Q1	0.92	0.89	0.75	0.88	0.87
2011-Q1	1.00	0.87	0.86	0.95	0.88
2012-Q1	1.00	0.91	0.99	0.99	1.00

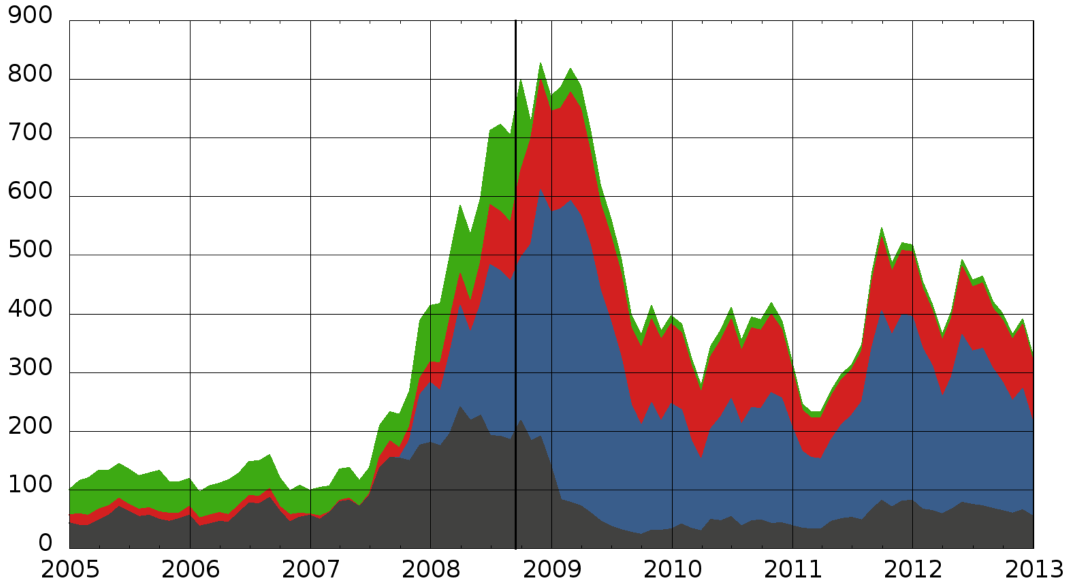
The table reports Spearman's correlation of the default SRISK index with SRISK indices computed using alternative choices of the SRISK parameters and alternative LRMES estimators at the end of the first quarter of each year starting from 2005 until 2012. The set of alternative SRISK parameters are $k = 10\%$, $C = -10$, $h = 22$ and $k = 8\%$, $C = -20\%$, $h = 22$. The set of alternative LRMES estimators are static model LRMES using the analytical approximation (S+A), dynamic GARCH–DCC LRMES using approximation (D+A) and dynamic copula LRMES using (exact) simulation (C+S).

Table 10: SRISK Timeliness

Lag	Static → Dynamic	Dynamic → Static
1	−0.99	4.00***
2	0.47	0.95
3	1.14	−1.41
4	0.41	−0.45
5	−0.91	1.35
6	−0.64	−0.17

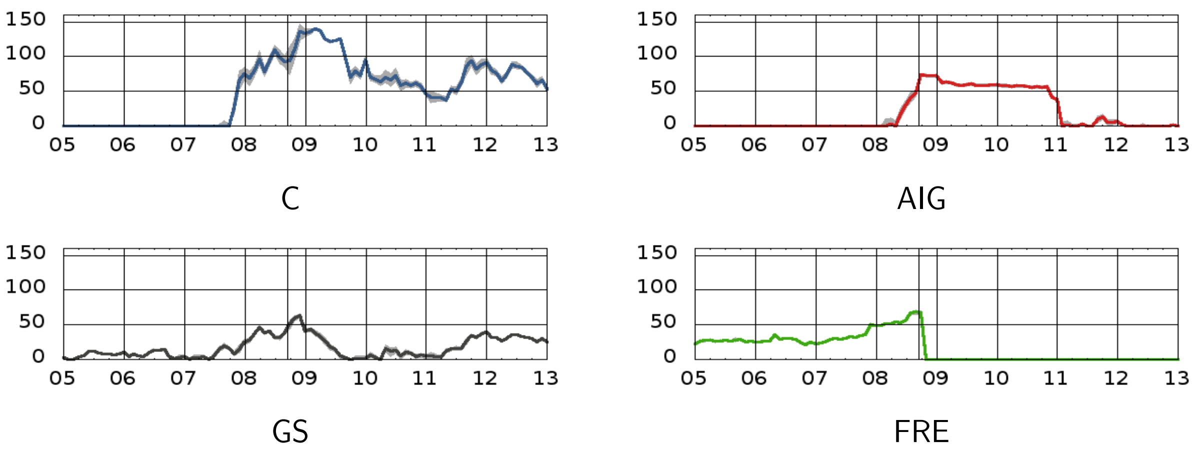
The table reports the results of the timeliness Granger causality tests for a predictive horizon ranging from 1 month to 6 months. The table reports the test statistic for the null hypothesis that SRISK based on dynamic LRMES is anticipated by SRISK using static LRMES (first column), and for the null hypothesis that SRISK constructed from static LRMES is anticipated by SRISK using dynamic LRMES (second column). Asterisks are used to denote significance at standard significance levels (*=0.10, **=0.05 and ***=0.01).

Figure 1: Aggregate SRISK by Industry



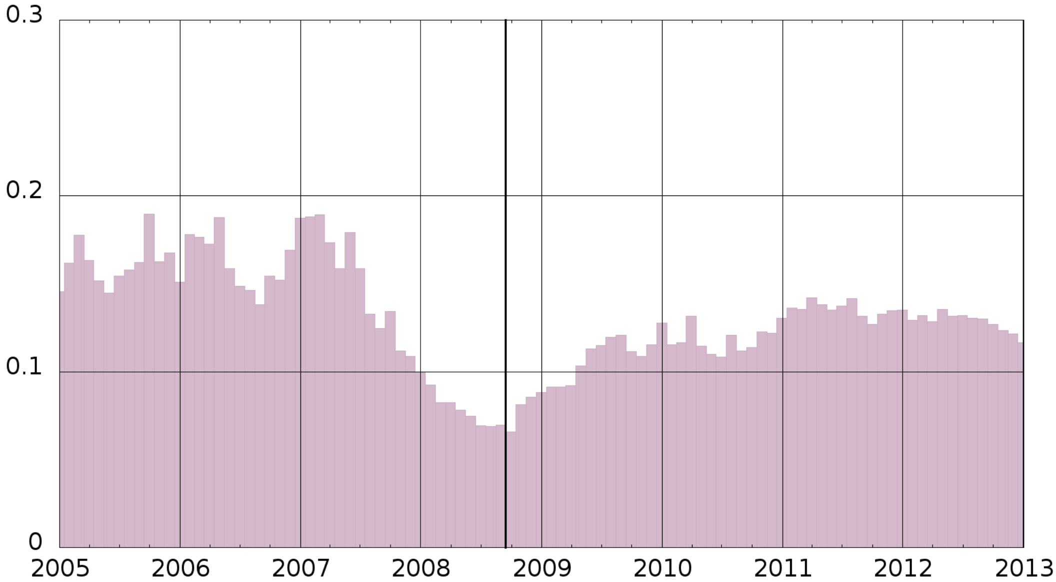
The figure shows the plot of aggregate SRISK between January 2005 and December 2012. Aggregate SRISK is layered by financial industry group. The industry groups are (from top to bottom) Others, Insurance, Depositories and Broker-Dealers. The solid vertical line marks the Lehman Brothers bankruptcy.

Figure 2: Firm SRISK



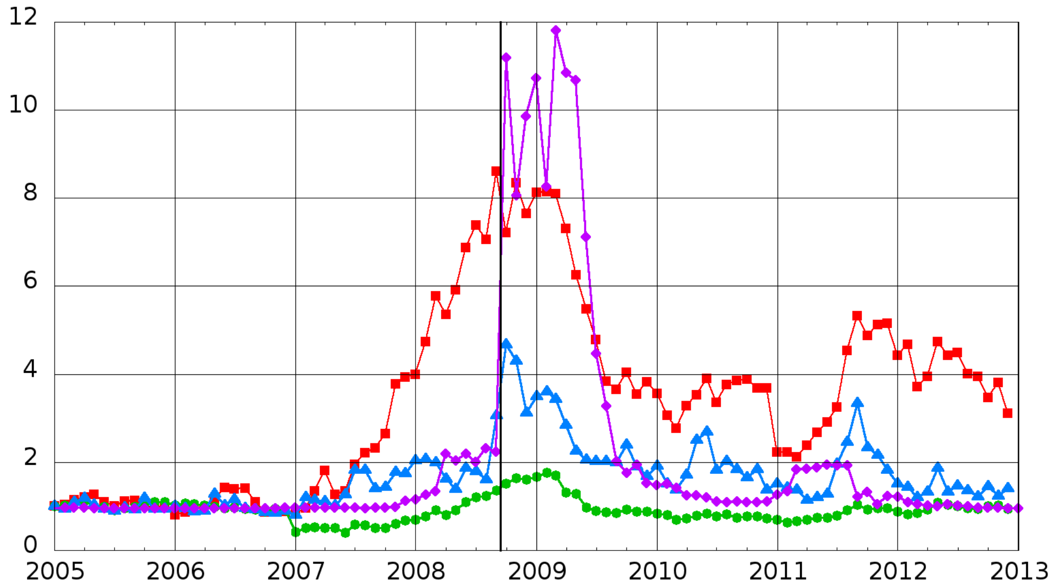
The figures show the plot of (the positive part of) SRISK for Citigroup (C), AIG (AIG), Goldman Sachs (GS) and Freddie Mac(FRE) between January 2005 and December 2012. The shaded area denotes the 90% capital shortage prediction interval. The solid vertical line marks the Lehman Brothers bankruptcy.

Figure 3: SRISK Concentration



The figure shows the plot of the SRISK% Herfindahl concentration index between January 2005 and December 2012. The solid vertical line marks the Lehman Brothers bankruptcy.

Figure 4: SRISK vis-à-vis Non–financial SRISK, VIX and TES



The figure shows the plot of aggregate (financial) SRISK (squares), aggregate non–financial 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.