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Options-based systemic risk, financial distress, and macroeconomic downturns[☆]

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ABSTRACT

We extract an option-implied measure for systemic risk, the Systemic Options Value-at-Risk (SOVaR), from put option prices that can capture the buildup stage of systemic risk in the financial sector earlier than the standard systemic risk measures (SRMs). Our measure exhibits more timely early warning signals of main events around the global financial crisis than the main SRMs. SOVaR shows significant predictive power for macroeconomic downturns as well as future recessions up to one year ahead. Our results are robust to various specifications, breakdowns of financial sectors, and controlling for other main risk measures proposed in the literature.

1. Introduction

Because of the global financial crisis (GFC), systemic risk has become a high-priority regulatory issue that requires applicable macroprudential policy measures aimed at identifying the systemic contributions of banks. Systemic risk in the banking system has attracted the attention of financial researchers as well as regulators and policymakers worldwide and they proposed a number of systemic risk measures (SRMs). Further, macro- and micro-level measures are both widespread in the systemic risk literature.[1]

A large proportion of the SRMs proposed so far rely only on historical market information. Many researchers have advocated the introduction of early warning tools, claiming that stock market-based SRMs are timely and ex-ante indicators of systemic crisis events. Acharya et al. (2017) suggest that another way to estimate systemic risk measures might be the adoption of information

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[1] Bisias et al. (2012) undertake a validity study to examine the existing SRMs and identified 31 different quantitative measures in supervisory, research, and data categories.

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through the prices of out-of-the-money (OTM) equity options and insurance contracts against losses of individual firms when the system as a whole is in distress. In addition, Adrian and Brunnermeier (2016) argue that a measure of systemic risk should be able to capture the buildup phase of systemic risk.

In this paper, we expand into a new avenue of research for measuring systemic risk. We analyse information extracted from equity options prices, tracking investors' negative expectations related to the tail risk in the financial sector in a more timely manner. It is crucial for policymakers and regulators *to see* systemic risk when it builds up so that governments and institutions can minimize the ripple effect from company-level distress through targeted regulations and actions. It would also be useful to companies more widely since a timely warning about an increase in systemic risk, overall or for some business partners, may allow corporates to prepare for more turbulent times ahead.

We directly contribute to the development of systemic risk measures by proposing an options-based measure that is easily implementable, transparent, timely, and can be updated in real-time on a daily basis. We name our newly proposed SRM the *Systemic Options Value-at-Risk* – SOVaR. Our measure incorporates market participants' ex-ante expectations regarding future (negative) outcomes for any financial institution and its tail risk, and it can aid supervisors to design ex-ante interventions to reduce the number of defaults in the financial industry when a systemic crisis builds up or materializes.

Due to its characteristics, the SOVaR should improve the regulation and monitoring of financial firms as it can capture financial downturns in a timelier manner. Thus, our main research question is: *does the SOVaR perform better than the contemporaneous market-based SRMs in terms of predicting the main systemic risk events?* For the most representative days of the GFC,[2] we compare the early warning ability of the SOVaR with the three main SRMs, namely the $Exposure\text{-}\Delta CoVaR$ by Adrian and Brunnermeier (2016), the marginal expected shortfall (MES) by Acharya et al. (2017) and the $SRISK$ by Brownlees and Engle (2016). Furthermore, we also investigate whether SOVaR carries any predictive power in relation to macroeconomic indicators as well as recessions in the US, namely *does SOVaR predict future economic downturns and recessions?* The analysis based on the GFC shows that the SOVaR can anticipate financial distress well by capturing the buildup of systemic risk within the financial sector and it has strong predictability with respect to the real economy.[3]

The idea that options contain a superior set of information compared to the stock market has a long tradition see Manaster and Rendleman, 1982; Bhattacharya, 1987; Diltz and Kim, 1996. Information extracted from options prices has also been used to study price discovery in the options market compared to the stock market see Chakravarty et al., 2004; Patel et al., 2020; Hauser et al., 2022, options market efficiency see Chen et al., 2011, and option transactions see Hu, 2014.[4] This literature suggests that options price returns contain useful information that influences future stock returns e.g. Cremers and Weinbaum, 2010; Xing et al., 2010; Ruan, 2020.

Previous literature has also confirmed the greater information content of options-based risk measures when compared to those constructed from historical data from the stock market. Santa-Clara and Yan (2010) argue that the information extracted from options reflects the ex-ante risks analysed by options investors. Option prices are often used to measure the forward-looking volatility of the market see, e.g. Christensen and Prabhala, 1998; Whaley, 2009 which has also predictive power for stock index returns e.g. Bakshi et al., 2011. Studies have also focused their attention on the information implied in the tail of the price distribution to predict future market returns e.g. Bakshi et al., 2003; Bollerslev et al., 2015. In the risk management literature, Barone-Adesi et al. (2019) and Molino and Sala (2021) recently discuss the adoption of option market data as a valid alternative to the classical stock-based risk measures.

Moreover, given the high leverage as well as the downside protection achievable with options, we consider the options market as an ideal venue for informed trading. A large body of theoretical literature has suggested that informed investors may indeed migrate towards the options market for leverage purposes e.g. Boyer and Vorkink, 2014; Ge et al., 2016. In terms of option moneyness, some studies have demonstrated that the predictability of options is stronger for OTM options e.g. Cao et al., 2005; Pan and Poteshman, 2006; Ge et al., 2016. Chakravarty et al. (2004) argue that OTM options, being highly leveraged contracts, have the greatest level of predictability for the future dynamics of the underlying asset. Xing et al. (2010) present evidence that informed traders with negative news prefer to trade OTM put options. Thus, investors can purchase OTM put options to insure their positions in the event of a price crash see Kelly et al., 2016.

Our methodological framework focuses on the downside component of risk captured by OTM puts. In particular, our measure of systemic risk adopts prices for a range of OTM put options on financial stocks that provide a hedge against larger price drops in the next month. The newly proposed SOVaR is based on a quantile of current OTM put option log-returns, scaled by an option-implied beta. It is intrinsically related to the left tail risk information extracted from the OTM put options prices, reflecting expectations on future extreme firm price drops.[5] SOVaR is able to capture tail co-movement in advance, thus giving policymakers and supervisory authorities time to identify promptly possible crises, systemic market distress, and macroeconomic downturns.

[2] The list of events follows the Bank for International Settlements (BIS)'s 78th and 79th annual reports see BIS, 2008, 2009, and it also incorporates those analysed in Kelly et al. (2016).

[3] Allen et al. (2012b) propose a measure of catastrophic risk in the financial sector (CATFIN) that uses both value-at-risk (VaR) and expected shortfall (ES) methods, while Giglio et al. (2016) introduce a systemic risk indicator that uses dimension reduction estimators that are applied to 19 measures of systemic risk in the US. In our empirical analysis, we also compare the predictive ability of our SOVaR measure against them.

[4] Other studies also found substantial empirical support for the presence of informed investors in the options market with respect to trading ahead of the announcements of earnings or corporate news e.g. Roll et al., 2010; Augustin et al., 2022, and of the leveraged buyouts (Acharya and Johnson, 2010).

[5] This tool differs from other studies that measure bank default probabilities or systemic risk based on the interconnectedness and network spillovers between financial institutions; see Billio et al., 2012 for relevant studies. In the area of financial networks, Baruník et al. (2022) develop a forward-looking monitoring tool that uses stock option prices to characterize the asymmetric network connectedness of investors' fears.

Lastly, our study is also anchored in the financial economics literature that has advocated the importance of the predictive power of systemic risk measures with respect to macroeconomic and uncertainty indicators see Allen et al., 2012a; Giglio et al., 2016; Danielsson et al., 2016; Caporin et al., 2022. In fact, shocks to large banks and their failures can cause either simultaneous or subsequent macroeconomic fluctuations which represent a financial dislocation with large and far-reaching consequences see Bartram et al., 2007. An option implied measure of systemic risk based on individual firms' OTM puts can identify in advance information about future firms' idiosyncratic distress that can be useful in predicting macroeconomic downturns transmitted via the equity channel.

The main results of this study show that the proposed SOVaR does predict the main market downturns and financial distress in the sample period by up to one month sooner than conventional SRMs. This result could be interpreted as indicative of the buildup of financial distress. We find substantial empirical evidence that the SOVaR predicts a greater level of systemic risk than the three SRMs at the inception and in the midst of the GFC. A great proportion of our non-parametric statistical tests confirm the superiority of the SOVaR over the other three main SRMs. The strength of a good early warning tool for systemic risk should increase steadily as the relevant negative systemic event approaches and should decrease rapidly when coming close to a positive systemic risk event. We show that the SOVaR behaves in this manner while standard SRMs do not. In addition, we highlight that systemic risk evolves differently for different financial sectors and that refining the SOVaR provides improved information at the sector levels. In particular, this study shows that the SOVaR for the depositories is the best indicator of systemic risk events during the GFC. We corroborate our results by showing that the SOVaR is also predictive of future macroeconomic downturns and recessions by up to one year. In addition, we conduct several robustness checks that control for other well-known measures of risk in the literature and an out-of-sample analysis, and we find that the predictive power of our measure still holds.

The remainder of this paper is organized as follows: in Section 2, we provide detailed descriptions of the derivation of the SOVaR, our data, and our hypotheses. Section 3 presents the empirical results of the comparison and testing between the SOVaR and the three leading SRMs for the whole financial system. Section 5 shows the comparison and testing of the sub-industries by the SOVaR. Section 6 presents the empirical results for predicting macroeconomy downturns while Section 7 concludes the study. Further results and robustness checks are reported in the paper Appendix.

2. Measuring and testing options-based systemic risk

In this section, we introduce the options-based SRM (SOVaR), describe the options data adopted in the study, and discuss the testing procedure applied to compare the SOVaR with the other three SRMs around the main events of the GFC.

2.1. Introducing SOVaR

The SOVaR is computed from OTM put options prices of individual financial institutions that are often used to capture the tail risk of the underlying asset. OTM put options are excellent predictors of price reversals and can convey more information on when stock prices are expected to drop see Chen et al., 2011. Similarly, Xing et al. (2010) state that investors choose OTM puts to express their worries about possible future negative jumps as they become more expensive before large negative jumps. OTM put options are also often used to capture downside risk and investors' ex-ante perception of tail risk of the underlying asset see Gao et al., 2019. Bank investors have long been concerned with tail risk, and the 2007–2009 financial crisis only heightened this concern see Cohen et al., 2014.

In addition, Kelly et al. (2016) point out that during the 2007–2009 financial crisis, the basket of individual bank options exceeded the cost of the index options. This divergence was more pronounced for OTM put options, while the OTM call spread remained largely unchanged in all sectors during the crisis. Bai et al. (2019) recently revisit these conclusions and argue that equity dynamics specified endogenously exhibit a leverage effect that would naturally increase the probability that future stock prices will reach very low values (including zero) that will enhance the value of OTM put options by fattening the left tail of the distribution. This effect is much stronger for puts on individual stocks than for puts on the index, thus increasing the basket-index spread.

Building on this argument, since expected cash flows $E[\max(0, K - S_T)]$ of put options with strike K increase when there is a larger likelihood of very low values for S_T, our framework for measuring systemic risk from option prices intuitively should benefit from the rise in put option prices in anticipation of systemic crises. Thus, to capture the options buyer expectations of such downside (tail) risk we consider the daily log-returns of the bid price of OTM puts for every financial institution in the sample, where we fix the maturity at a one-month (1M) horizon, as: $log(Put_{t,1M}) - log(Put_{t-1,1M})$.[6]

An increase in the put option price reflects an expectation for the underlying asset to drop in value. Thus, when the stock put price changes it reflects changes in investors' expectations about that stock at the option maturity T, which is one month in our calculations. In particular, the put price will move up when the market sentiment and investors' expectations go more negative

[6] As an alternative estimation following previous literature on implied risk measures, we also compute our measures by adopting mid-quotes e.g. Bakshi et al., 2003; Buss and Vilkov, 2012; Martin, 2017. Such estimation would take into account the whole set of market participants information. For instance, when measuring implied volatility measures (SVIX), Martin (2017) reassuringly found that during periods of extreme stress, the results are very similar with the lower bound being high at all horizons whether mid or bid prices are used. In addition, Eraker and Osterrieder (2018) state that for measures working with OTM and left tail, the use of mid quote reflects a lower bound in the estimation. We find that, everything else being equal, the estimations based on bid price or bid–ask spreads are highly correlated, with a correlation above 96%, therefore the results of the paper are robust to the choice of options price.

towards a worse economic condition (e.g., market downturn or financial distress) at maturity T. Conversely, a decreasing put price might signal investors' beliefs of better economic conditions for that stock at maturity T.

The evolution of the pricing kernel, defined generically as $q_{t,T}/p_{t,T}$ (where $q_{t,T}$ is the probability density function under the risk-neutral measure and $p_{t,T}$ is the probability density function under the physical measure) over time deserves some mentioning in this context. The mismatch of backward-looking subjective and forward-looking risk-neutral distributions of asset returns was suggested in the literature as a possible cause of pricing kernel puzzle.

Recent research into the pricing kernel highlights the importance of information encapsulated in the option market data e.g. Cuesdeanu and Jackwerth, 2018; Barone-Adesi et al., 2020.[7] Even though this previous research assumes that the option-implied information might not be fully mapped into physical measures, the consensus appears to suggest that this bias varies with the time horizon in consideration e.g. Busch et al., 2011; Molino and Sala, 2021 and one can show that the pricing kernel converges to 1 as the time to maturity decreases.[8]

While we do not make any assumptions about the direction of causality, our aim is to propose a SRM for an individual institution's exposure to a system-wide distress. Therefore, we first investigate the directions of systemic risk in the existing market-based SRMs as they are directional by definition. They may be used to estimate an increase in the systemic risk of the market given that a single institution is in distress, or the focus can be on how much a particular institution's risk increases given that the whole financial system is in distress.[9] The $SRISK$ and the MES capture the direction of systemic risk from a market-wide systemic event to the particular institution. In particular, they are respectively defined as the expected capital shortfall of a financial entity i conditional on a prolonged market decline, and as the expected shortfall of a firm i during the 5% worst market outcomes. In order to preserve the same directionality, we also compare SOVaR with the $Exposure - \Delta CoVaR$ developed in Adrian and Brunnermeier (2016).[10] For an overview of the calculations for each of the market-based SRMs, see Appendix A.

Hence, we consider estimating the components of our systemic risk measure from price series of put options that are contingent on a firm's equity stock S. Our SOVaR measure is defined as:

$$SOVaR^{i}_{q,t} = \beta^{i|\mathcal{M}}(VaR^{P^i|\mathcal{M}}_{q,t} - VaR^{P^i|\mathcal{M}}_{50,t}) \tag{2}$$

where the $VaR^{P_i}_{q,t}$ is calculated with filtered historical simulation from the bootstrapped distribution of OTM put option returns ($r_t = log(Put^i_{t,1M}/Put^i_{t-1,1M})$) for company i over a one year (252 days) rolling window.[11] This method relies on first collecting standardized returns from the historical sample of option price series and then scale these returns by the current volatility. Then these adjusted option prices returns are used as innovations in a conditional variance model for projecting future options prices variance and price levels, as described in the seminal paper by Barone-Adesi et al. (1999). The method is generic in the sense that any conditional variance model can be used. We adopt a simple GARCH(1,1) variance model in our main analysis.[12] For more details on the steps, please see Appendix B. This procedure will avoid the well-known problems related to plain historical simulation estimation of VaR that during highly volatile market conditions risk is underestimated, as pointed out by Vlaar (2000).

This is the idea behind the construction of our option-implied systemic risk measure. By comparing the quantile risk measures of the put options' returns, we can measure when the OTM puts move farther out that can be used as a signal for a firm's systemic riskiness. Thus, the direction of the risk for the underlying stock of a firm and the corresponding put option prices are the opposite. In other words, when the tail risk increases, the stock prices decreases while the put option price increases. Following the Basel's recommendation, the SOVaR is estimated with a 97.5% confidence level.[13] Hence, at the 97.5% confidence level, it follows that

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7 For instance, Cuesdeanu and Jackwerth (2018) used forward looking information only and confirm under a newly proposed test the existence of a U-shaped pricing kernel in S&P500 options data. More recently, Barone-Adesi et al. (2020) combine historical stock returns and option market data through the Dirichlet Process with precision parameter calibrated to the amount of trading activity in deep-out-of-the-money options. They construct an option-adjusted pricing kernel and show on the S&P 500 Index from 2002 to 2015 that the option-adjusted pricing kernel is consistently monotonically decreasing, regardless of the level of volatility.

8 If Ψ_t is the current expected payoff of a primitive contingent claim then it follows that

$$\Psi_t = e^{r_t T} q_{t,T} \cdot 1 = e^{R_t T} p_{t,T} \cdot 1 \tag{1}$$

Thus, in a complete and arbitrage-free economy the risk-neutral price grows at the current risk-free rate, r_t, whereas the physical price grows at the current risk-adjusted risk-free rate, R_t. Then, as the time to maturity T goes to zero, both quantities converge to the same state price density, S_t and therefore the pricing kernel becomes 1, while conversely, when T increases the pricing kernel is $\frac{q_{t,T}}{p_{t,T}} = \exp((R_t - r_t)T)$ and the divergence between $q_{t,T}$ and $p_{t,T}$ increases at the rate $(R_t - r_t)T$. We would like to thank an anonymous referee for useful discussions around this point.

9 The importance of the direction of the conditioning can be illustrated with the following example. Consider a financial institution i, which returns are subject to substantial idiosyncratic noise. A distress to the entire financial system would likely increase the systemic risk of institution i. At the same time, the systemic risk of the entire financial system conditioned on this particular institution being in distress would not be necessarily impacted, due to the large idiosyncratic component of the returns. In this example any SRM would send wrong signal about systemicity since a market wide systemic event is highly likely to increase the systemic risk of institution i.

10 Without loss of generality we refer to $Exposure - \Delta CoVaR$ as $\Delta CoVaR$, henceforth.

11 We generate paths of a 1 million bootstrap samples of OTM put options returns. Results are quantitatively and qualitatively similar compared to those based on a 100,000 bootstraps distribution.

12 As a robustness check, we also adopt methods based on different GARCH models and EWMA. We find that the correlation between the resulting systemic risk measures ranges from a minimum of 95.3% for insurance to a max of 97.5% for depositories. Therefore the proposed SOVaR measures are robust to the choice of the conditional variance model adopted.

13 The choice of the 2.5% shortfall probability is consistent with risk management practices and it provides a fair characterization of extreme movements in the left-tail of the conditional loss distribution without targeting probability close to the distribution boundary limits. The choice of the 50% quantile is also standard in risk management and systemic risk calculation, representing a proxy for the median state of the economy in a non-stressed market condition. Moreover, $VaR^{P^i|\mathcal{M}}_{50,t}$, which represents the expected loss at the median state, so in the absence of a distress, is usually equal to zero in our data-set.

$VaR_{q,t}^{P^i|\mathcal{M}}$ corresponds to the tail of risk and an enlargement of the difference $VaR_{q,t}^{P^i|\mathcal{M}} - VaR_{50,t}^{P^i|\mathcal{M}}$ from one period to another means an increase in systemic risk.[14]

Therefore, SOVaR is then based on a quantile of the bootstrapped distribution of the current OTM put option prices log-returns, reflecting the market view for events up to one month ahead, and it is scaled by a directional beta from the market (denoted here by $\mathcal{M}$) to the firm. The beta measure we adopt is an option-implied beta over the coming month as provided by Buss and Vilkov (2012).[15] This provides us with a reasonable proxy of implied stock risk matching the information in the option-implied value-at-risk differential. In this way we are able to reconstruct the $\Delta CoVaR$ systemic risk measure in Adrian and Brunnermeier (2016) but on an option-implied basis. The implied betas are reported for 445 out of 500 stocks in the S&P 500 from options prices and are calculated with the formula:

$$\beta_t^{i|\mathcal{M}} = \frac{\sigma_{i,t}^{Q} \sum_{j=1}^{N} w_j \sigma_{j,t}^{Q} \rho_{ij,t}^{Q}}{(\sigma_{M,t}^{Q})^2}, \tag{3}$$

where $\sigma_{i,t}^{Q}$ are the implied volatilities of the options of individual firm i. The $\sigma_{M,t}^{Q}$ is the implied volatility of the S&P 500, and the implied correlations $\rho_{ij,t}^{Q}$ are based on the fitting of the expected correlation under an objective measure and calibrated for an unknown parameter α_t which is identified as a closed form. For a comprehensive description of the computation of the implied correlations see Driessen et al., 2009; Buss and Vilkov, 2012. We adopt the betas by using a one-month duration that matches the one-month horizon of our implied systemic risk measure.

Another possible formula to estimate an implied CAPM beta (β) is to replace Eq. (2) with the following by French et al. (1983):

$$\beta_{t,FGK}^{i|\mathcal{M}} = \rho_{i\mathcal{M},t} \times \frac{\widetilde{\sigma_t^i}}{\widetilde{\sigma_t^{\mathcal{M}}}} \tag{4}$$

where $\rho_{i\mathcal{M},t}$ is, in our case, the correlation at time t between the stock and the market OTM put returns of firm i, while $\widetilde{\sigma_t^i}$ and $\widetilde{\sigma_t^{\mathcal{M}}}$ are the implied volatilities at t for firm i and the market, respectively.[16]

2.2. Data

We consider the main US financial institutions included in the S&P 500. The benchmark sample we adopt to estimate both the stock market-based and options-based SRMs is in line with the one by Brownlees and Engle (2016). Since the SRMs used in this study are based on public market data, we do not consider financial firms: (i) which are not publicly listed or have become de-listed, (ii) for which market data are not available, and (iii) with not enough available observations (at least 1-year of daily observations). The sample is divided into four financial industry groups as follows: 23 firms in the depositories, 27 in insurance, 13 in other financials, and 8 in broker-dealers for a total of 71.[17] The list of companies within the four financial industry groups is reported in Table C.1 in Appendix C.

Daily options prices and information are collected from OptionMetrics. We select OTM puts with a maturity of around one month by selecting option contracts with maturities ranging between 23 and 37 days that average one month at expiration, which is similar to the CBOE VIX approach. Next, we rollover our options sample when contracts exit this maturity range. We select OTM puts with deltas strictly larger than −0.5. We also apply the following filters to remove options with (i) bid prices equal to zero, (ii) implied volatility missing data, (iii) missing delta data or (iv) zero open interest. If more than one option contract is available, we select the one with a greater delta. Stock prices and market capitalizations are collected from Bloomberg. Data covers the period January 2000 to December 2020.

In order to have a full pairwise comparison among the SRMs used in this paper, we match the options for each financial institution in our sample with the ones for which implied betas are provided in the dataset of Buss and Vilkov (2012). We match the CRSP database (stocks sorted by PERMCO) and the tickers in OptionMetrics for our financial sector firms. This matching results in a panel from January 2000 to December 2020, that is unbalanced since not all firms have traded continuously during the sample period. However, it is large enough to test around the main financial distress events of the GFC and to conduct our empirical predictive analysis.

Our main risk measure, SOVaR, is the product of two components, which account for two risk sources, namely institutions' risk in isolation ($VaR_{q,t}^{P^i|\mathcal{M}} - VaR_{50,t}^{P^i|\mathcal{M}}$) and institutions' risk due to co-movement ($\beta_t^{i|\mathcal{M}}$). The scatter plot in Fig. 1 points out that the two SOVaR components measure two different but equally important dimension of systemic risk.[18] When focusing on the correlation of the two components of SOVaR we do not observe any pattern. Hence, applying financial regulation solely based on a single risk component of an institution in isolation might not be sufficient to insulate the financial sector against systemic risk.

[14] We have also estimated our SOVaR with more and less extreme confidence levels, namely 99% and 95%, and the measure estimation and the empirical results are qualitatively and quantitatively similar. For instance, the SOVaR of the whole financial system estimated at the 97.5% and 95% confidence level are 98.9% correlated.

[15] We thank Grigory Vilkov for kindly sharing the option-implied betas at: http://www.vilkov.net/index.html.

[16] We are also aware of an additional method for computing implied betas from Chang et al. (2012), but this method produces a more noisy and almost flat risk-return relation as well as worse performance in predictability compared to both the other implied betas see Buss and Vilkov, 2012.

[17] Due to the greater number of variables required to compute the $SRISK$, we cannot estimate this measure for the following financial firms because of unavailable data: Bear Stearns, Lehman Brothers, Safeco, Synovus Financial, Torchmark, and Wachovia. Hence, we consider a sample made of 65 (instead of 71) financial firms for the computation of $SRISK$.

[18] A detailed breakdown for each sector is in Fig. D.3 in Appendix D.

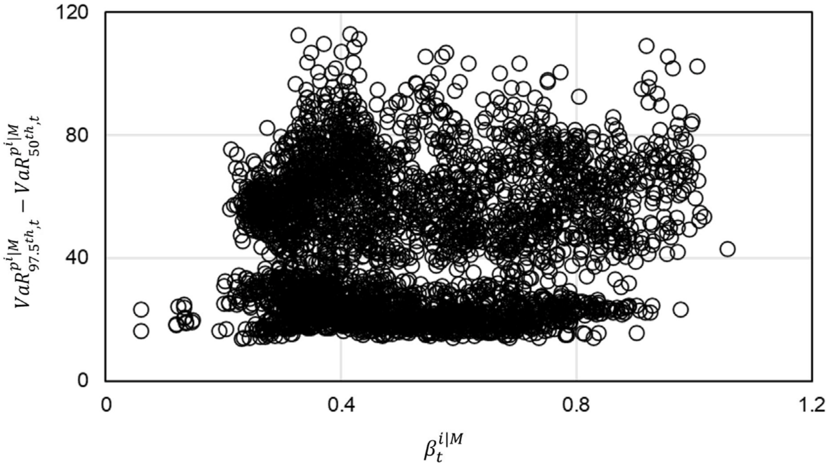

Fig. 1. SOVaR components: $\beta_t^{i|\mathcal{M}}$ and $VaR^{P^i|\mathcal{M}}_{q,t} - VaR^{P^i|\mathcal{M}}_{50,t}$.

Notes: This scatter plot shows the correlation between the two components of SOVaR. Institutions' risk in isolation is measured by the difference $VaR^{P^i|\mathcal{M}}_{q,t} - VaR^{P^i|\mathcal{M}}_{50,t}$ (y-axis), whereas institutions' co-movement is measured by $\beta_t^{i|\mathcal{M}}$ (x-axis). Time-series are estimated from January 2000 to December 2020, at the daily frequency.

Following equity option prices over time, we construct a time series of the $SOVaR_{97.5^{th},i}$ for each financial firm and industry group included in our sample. In order to compute the SOVaR of a financial sector, we build an equity-weighted option portfolio of the firms classified in the specific financial industry group and calculate the corresponding $VaR_{q,t}$ and equity-weighted $\beta_t^{i|\mathcal{M}}$ to be applied at time t.[19]

2.3. Testing SOVaR and market-based SRMs around the main GFC events

In this subsection, we present the statistical tests that we use to compare the three main market-based SRMs with the SOVaR around the main events of the GFC. Our main focus regarding the choice of the events to test is on the GFC being the period during which share prices of major US financials collapsed and which included the failures of several large financial institutions, most emblematic and with far-reached consequences, Lehman Brothers. Moreover, starting in July 2007, Bear Stearns liquidated two hedge funds that invested in various types of mortgage-backed securities. In August 2007, the American Home Mortgage Investment Corporation filed for Chapter 11 bankruptcy protection and BNP Paribas, France's largest bank, halted redemption on three investment funds.

In order to have a full pairwise comparison between the measures, we normalize the SRMs for the financial system, each financial industry group, and each financial firm with the formula:

$$Normalized - SRM_i = \frac{SRM_i - min(SRM_i)}{max(SRM_i) - min(SRM_i)} \times 100 \tag{5}$$

where SRM_i denotes the SRM under analysis; that is, $\Delta CoVaR$, MES, $SRISK$, and SOVaR, respectively, while the $min(SRM_i)$ and $max(SRM_i)$ are the minimum and maximum values of the corresponding time series. The normalized SRMs and the SOVaR take values between zero and one for the period from January 2000 to December 2020.[20]

Taking the depositories, insurance, other financials, and broker dealers sectors into consideration, we start by testing the normalized systemic contribution of the SOVaR compared to the normalized systemic contributions of the other SRMs during the key systemic events of the GFC. To test whether the systemic contribution is greater for the SOVaR, we use the Kolmogorov–Smirnov (KS) bootstrap test enhanced by Abadie (2002) who introduced a resampling method that the research has found to be superior to

[19] When defining SOVaR for the financial sector and industry groups, $VaR_{q,t}$ is calculated using an equity-weighted options' portfolio of the financial sector or of the firms classified in the specific financial industry group, where the daily changes of the options' portfolio value are: $\sum_{i=1}^{N} MktCap_{i,t} \times [log(Put_{i,t,1M}) - log(Put_{i,t-1,1M})] / \sum_{i=1}^{N} MktCap_{i,t}$. As for market-based SRMs, being the market capitalization the maximum loss related to a single firm i at time t, it is used to build equity-weighed portfolios that proxy the financial sector or industry groups also for our measure based on OTM put options data (SOVaR). At time t, the market capitalization represents also the maximum profit (loss) an investor with a long (short) position can realize at time of the settlement of that put option. We do not use the volume of options trading to construct our measures because volume is a flow variable related to the liquidity of trade and our systemic risk measure is centred on the future value of stock derived from current option prices.

[20] It is important to note that by normalizing the SRMs through Eq. (5), we do not affect the distribution or the shape of the SRMs time-series. In particular, the maximum (minimum) value of each time-series will correspond to one (zero) and will occur on the same date of its non-normalized maximum (minimum) value. The entire set of non-normalized results is available from the authors upon request.

the standard KS test because of the Durbin problem see Durbin, 1973. The KS test compares the cumulative distribution functions (CDFs) instead of considering estimates sensitive to outliers. It has been showed that the KS test dominates many other solutions, see for instance the simulation results in Barrett and Donald (2003). Moreover, the non-parametric nature of this test does not require any assumptions to be made about the distribution of the SRMs.

Table C.2 in Appendix C presents the date t and description of these key systemic events. We adopt the BIS's 78th and 79th annual reports to track the GFC key events see BIS, 2008, 2009; Kelly et al., 2016. The KS test statistic for each sample is given by:

$$D_{mn} = \sqrt{\left(\frac{mn}{m+n}\right)} sup_x |S_m(x) - T_n(x)| \tag{6}$$

where $S_m(x)$ and $T_n(x)$ are the CDFs of the SRM related to two different populations, and m and n represent the size of the two samples, respectively.

In order to test our first hypothesis, we first compare the normalized SOVaR of the financial system, each financial industry group, and each financial firm in our sample to the normalized stock market-based SRMs. This comparison is based on the month preceding the key systemic events at time t ($t-28 : t$). By definition of the point in time style SRM, measures like $\Delta CoVaR$, MES, and $SRISK$ should fully capture these events when they occur at time t. A greater value associated with the SOVaR would indicate the superior power of this measure to gauge systemic risk. Given their option-implied nature, one-month maturity options encapsulate the market participants' expectations about the price development of the underlying assets one month later.

To see how early on the SOVaR may outperform the SRMs, we also test our hypotheses by lagging the SOVaR to the period $t-h-28 : t-h$ by $h = 7$, 14, 21, and 28 days. In this case, we compare the normalized lagged SOVaR for the financial system, each financial industry group, and each financial firm in our sample with the normalized point in time SRMs without any lag that is calculated over the period $t-28 : t$. If the systemic risk level of the SOVaR and its lagged version is greater than the SRMs for time t, then they indicate that it has greater information content in its early warning compared to the SRMs. The null and alternative hypotheses are defined as follows:

$$H_0 : SOVaR_{t-h-28:t-h} \leq SRM_{t-28:t} \tag{7}$$

$$H_1 : SOVaR_{t-h-28:t-h} > SRM_{t-28:t} \tag{8}$$

The failure to reject the null (7) means that the early warning signal of the contemporaneous SRMs is greater than the one from the SOVaR for $h = 0$, 7, 14, 21, and 28.

3. Options-based vs stock market-based SRMs

3.1. The magnitude of systemic risk

Fig. 2 displays the SOVaR and the SRMs for the entire financial system.[21] Following the studies by Adrian and Brunnermeier (2016) and Brownlees and Engle (2016), we look closely at some of the major dates covered by our sample period in order to measure the magnitude of this risk and the response of both types of measures to the two main crises and events related to them. The dates considered are: (1) the freezing of BNP Paribas' funds on August 9, 2007; (2) the Lehman Brothers bankruptcy on September 15, 2008; (3) the start of the European debt crisis on May 9, 2009; (4) the agreement between the Greek government and the IMF for the first bailout package of €110 billion on May 2, 2010; and (5) the peak of 44.21% reached by the Greek 10-year bond yields on March 9, 2012.

The SOVaR appears to anticipate the main systemic events of the GFC. In particular, the time-series patterns of the SOVaR clearly point to the beginning of the GFC before the three SRMs that do not start to signal an increased systemic risk until after the bankruptcy of Lehman Brothers (2). The SOVaR fully captures the market turmoil caused by BNP Paribas in 2007 (1) and reaches its peak efficacy with the bankruptcy of Lehman Brothers (2), while the SRMs lag behind.

Fig. 2 shows that SOVaR reacts immediately, with two peaks, to the first main event of the GFC, while the SRMs increase their values more smoothly once the historical stock market prices deteriorate. Therefore, they maintain higher estimates for a longer period (2009 – 2010). A similar conclusion is reached regarding events (3) and (5). The SOVaR adjusts its level with the ebbs and flows of market information while the SRMs need some time to recognize the systemic risk that potentially may have blurred the decision process from a financial stability point of view. In addition, event (4) is a positive systemic risk event in that the IMF found a solution to the Greek debt problem. Because the SOVaR indicates a rapid decrease in systemic risk, it anticipates once again this event. The evolution of the SOVaR versus the other three SRMs vis-a-vis event (4) indicates that our proposed measure works well for both negative and positive systemic risk events. The high level of SOVaR in 2013 may suggest some false positive signalling. We explain this peak when we drill down our analysis at the sector level in Section 5. A final remark is that during the Covid-19 pandemic it is only SOVaR that decreased rapidly towards the end of 2020, investors realizing that the impact on the economy was not as bad as thought while the other measures, except the $SRISK$, were more conservative in their evolution.

[21] For an overview of the summary statistics for the systemic risk estimates of the US financial system and the financial industry groups, see Table C.3 in Appendix C.

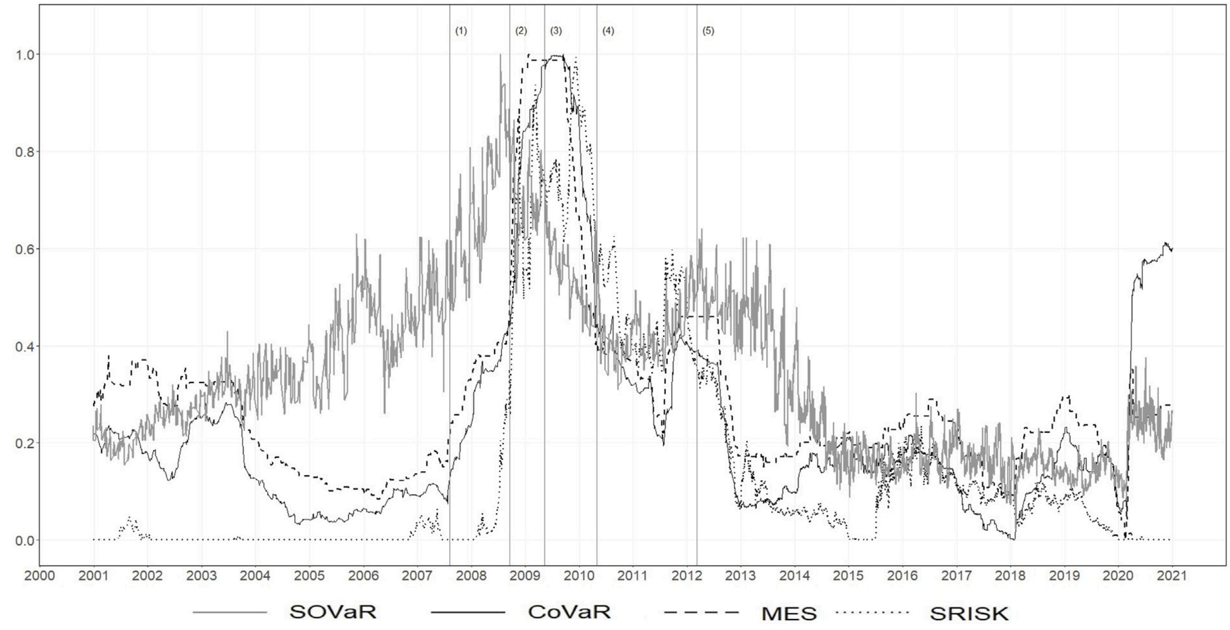

Fig. 2. Systemic risk of US financial system: SOVaR vs. stock market-based SRMs.
Notes: This figure shows the time series of the SOVaR and the stock market-based SRMs of the US financial system. The vertical lines denote: (1) the freezing of BNP Paribas funds on August 9, 2007; (2) the Lehman Brothers bankruptcy on September 15, 2008; (3) the start of the European debt crisis on May 9, 2009; (4) the agreement between the Greek government and the IMF for the first bailout package of €110 billion on May 2, 2010; and (5) the peak of 44.21% reached by the Greek 10-year bond yields on March 9, 2012. Time-series are estimated from January 2000 to December 2020, at the daily frequency.

By early 2016, global stock markets were affected by negative economic reports from China which caused panic selling, as well as by the Brexit vote in the UK in mid-2016. SOVaR reflects these events in a timely manner. The Covid-19 period is characterized by an almost harmonized behaviour of the measures showing a significant abrupt increase of SOVaR. The harmonized increase of systemic risk could be explained by the exogenous nature of the pandemic that affected financial markets' risk assessments and models, exposing them to a greater number of common exogenous risk factors that exacerbated their interdependencies and heighten systemic risk.[22]

As a robustness check, we also change the SOVaR by replacing the implied beta in Eq. (2) with the implied beta computed as in Eq. (4). We denote the options-based SRM computed from the implied beta by French et al. (1983) as $SOVaR_{Beta-FGK}$. We present the corresponding plot in Figs. D.2 in Appendix D where we compare the market-based SRMs with the aggregate $SOVaR_{Beta-FGK}$. The $SOVaR_{Beta-FGK}$ leads to estimates that are both quantitatively and qualitatively similar to the original SOVaR as the two series share a correlation of 0.88%.

3.2. SOVaR as an early warning tool for systemic risk

In this subsection, we carry out non-parametric tests to assess whether SOVaR performs better than the other SRMs. Table 1 presents the KS statistics and the associated bootstrapped significance level under the null hypothesis (7) for the dominance test. This test shows whether SOVaR has a greater systemic level (at time t) and early warning information content (at time $t-h$, with $h \neq 0$) than the SRMs. Therefore, we lag (with $h = 0$, 7, 14, 21, and 28) the SOVaR. The failure to reject the null hypothesis (7) would mean that: (i) with $h = 0$, SOVaR does not contain any additional systemic information compared to the other SRMs; and (ii) with $h = 7$, 14, 21, and 28, the SOVaR does not anticipate any systemic event that should peak under the SRMs at time t with no lag ($h = 0$).

[22] In order to build up on the discussion of Section 2, to better understand the difference between a stock- and an option-based systemic risk measure in our context, we plot the difference between the SOVaR, as the option-implied systemic risk measure, and the three stock-based SRMs computed under the physical measure, namely the $\Delta CoVaR$, MES, and $SRISK$ in Fig. D.1 in the paper Appendix D. We observe that the distance between the set of series is not constant and it varies according to the financial market state. The gap between the two sets of risk measures is usually larger and negative after recessions (e.g. 2001–2003, 2010–2012), while tighter during calmer periods (e.g. 2005–2007, 2013–2015). We find a positive difference (i.e. SOVaR above stock-based measures) usually associated with positive market trends (e.g. 2005–2007) where the SOVaR anticipates potential financial sector distresses and is able to capture in a prompter manner possible negative outlooks. Conversely, we find that the SOVaR is below the stock-based measures in the aftermath of recessions (e.g. dot-com bubble, GFC) as options investors may expect a quicker recovery period.

Table 1
Dominance test results during the key events of the GFC.

	H_0: $SOVaR_{t-h-28:t-h} \leq \Delta CoVaR_{t-28:t}$					H_0: $SOVaR_{t-h-28:t-h} \leq MES_{t-28:t}$					H_0: $SOVaR_{t-h-28:t-h} \leq SRISK_{t-28:t}$				
	$h = 0$	$h = 7$	$h = 14$	$h = 21$	$h = 28$	$h = 0$	$h = 7$	$h = 14$	$h = 21$	$h = 28$	$h = 0$	$h = 7$	$h = 14$	$h = 21$	$h = 28$
Aug 9th 2007	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***
Sept 14th 2007	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***
Mar 16th 2008	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***
July 15th 2008	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***
Sept 17th 2008	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***
Oct 13th 2008	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***
Dec 11th 2008	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***
Mar 5th 2009	0.32$^{\bullet}$	0.32$^{\bullet}$	0.32$^{\bullet}$	0.32$^{\bullet}$	0.32$^{\bullet}$	0.21$^{\bullet}$	0.21$^{\bullet}$	0.30$^{\bullet}$	0.22$^{\bullet}$	0.20$^{\bullet}$	0.30$^{\bullet}$	0.22$^{\bullet}$	0.20$^{\bullet}$	0.22$^{\bullet}$	0.20$^{\bullet}$
May 21st 2009	0.00$^{\bullet}$	0.00$^{\bullet}$	0.00$^{\bullet}$	0.00$^{\bullet}$	0.00$^{\bullet}$	0.00$^{\bullet}$	0.00$^{\bullet}$	0.00$^{\bullet}$	0.00$^{\bullet}$	0.00$^{\bullet}$	0.00$^{\bullet}$	0.00$^{\bullet}$	0.00$^{\bullet}$	0.00$^{\bullet}$	0.00$^{\bullet}$

Notes: This table presents the results of the Kolmogorov–Smirnov bootstrap test for the financial system that aims to determine whether: (i) the CDFs of the SOVaR are greater than the ones for $\Delta CoVaR$, MES, and $SRISK$ (columns: 2 to 6, 7 to 11, and 12 to 16, respectively) for the aggregate financial system during the key events in the GFC. The hypotheses tested are stated in the headers of the table. The columns contain the test statistics. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively; while, $^{\bullet}$ indicates a statistically significant inverse relation.

For the entire financial system, Table 1 provides evidence that the SOVaR is more successful in anticipating the systemic risk events than the $\Delta CoVaR$, MES, and $SRISK$. In addition, we show how SOVaR is successful in satisfying a key requirement stated by Zhang et al. (2015), namely offering information compared to other risk measures, and signalling something not already known to supervisors and regulators which complements conventional drivers of systemic risk. More importantly, the results show that our new measure not only has an improved systemic information content at time t, but it is also successful in anticipating 7 out of 9 of the main systemic events of the GFC compared to the SRMs. In particular, because the CDFs of the SOVaR are higher than those for the other SRMs, they show that the SOVaR was signalling a greater systemic risk for the entire financial system 28 days earlier than the SRMs.

The relation between the SOVaR and the SRMs with few exceptions is inverted in the closing episodes of the crisis. In particular, from March 5, 2009 to May 21, 2009, the CDFs of $\Delta CoVaR$, MES and $SRISK$ are higher than those of the SOVaR. We interpret this result as investors having a positive expectation of a recovery in the financial markets also due to central bank actions through a liquidity buffer channel e.g. Sedunov, 2021. Specifically, the Federal Reserve injected liquidity into key credit markets on November 12, 2008 (around 1,570US billion), that reached an historical maximum level on January 21, 2009 (around 440US billion). The Fed's debt through the purchase of mortgage-backed securities exceeded 1,000US billion on November 25, 2008 for the first time and decreased below this threshold only in September 2011.[23] In addition, on December 16, 2008, the Federal Open Market Committee decreased the target federal funds rate (FFR) to a range of 0 to 0.25% from the previous level of 1.00% (October 29, 2008). The FFR remained at those levels until December 17, 2015, when it raised the rate to a range of 0.25 to 0.50%.[24] These actions are depicted in Fig. 2 that also shows that the SRMs maintained a peak from mid-2009 to mid-2010 while the SOVaR decreased its value after mid-2009, which is actually identified as the end of the GFC (BIS, 2009).

4. In-sample and out-of-sample SOVaR predictability

From a practical perspective, the computation of risk measures is impacted by two major challenges, that ultimately determine the risk measure that is selected to operate with. First, most financial institutions are exposed to many risk factors. For example, in the Management Discussion and Analysis section of its annual report, Goldman Sachs indicates that its VaR model includes 70,000 market factors. Secondly, financial institutions have many positions that involve non-linear exposures to the market factors. The need to capture such non-linear exposures often dictates the VaR methodology that will be used. The number of relevant factors may vary over time and different investors may consider different number of market factors at a given point in time.[25] Selecting the relevant factors is still one of the cornerstones of modern finance.[26] Using options available on stocks provides a shortcut to extract the information on what options traders expect about the underlying stock of a given firm in the near future, therefore providing a synthetic view of several market factors affecting the firm.

Moreover, one may argue that stock-market based SRMs can be more easily predicted or replicated by common set of factors as performed in Adrian and Brunnermeier (2016) with respect to the $\Delta CoVaR$. To support the above discussion, we conduct a similar exercise, adopting a set of common financial and macroeconomic factors and we show that SOVaR can also be predicted by these lagged factors both in-sample and out-of-sample up to one year in advance. We first present the regression results for

23 This time series is available at: https://www.clevelandfed.org/our-research/indicators-and-data/credit-easing.aspx.
24 These data are available at: https://www.federalreserve.gov/monetarypolicy/openmarket.htm.
25 We would like to thank an anonymous referee for useful discussions around this point.
26 Feng et al. (2020) considered 150 factors over a 30 years period and highlight the issue of model selection mistakes.

Table 2
Predicting SOVaR with institutions' characteristics and financial variables.

	Horizon			
	(1)	(3)	(6)	(12)
Loan-to-Deposit	−0.083***	−0.079***	−0.084***	−0.017
	(0.013)	(0.013)	(0.013)	(0.016)
Price-to-Book	−0.481	−1.036*	−0.493	−3.122***
	(0.632)	(0.607)	(0.640)	(1.293)
Leverage	0.019*	0.010	0.018*	0.059***
	(0.009)	(0.023)	(0.009)	(0.028)
VaR	0.240***	0.272***	0.238***	0.104***
	(0.039)	(0.040)	(0.041)	(0.049)
3M Yield Change	0.408***	0.030	0.361	5.761***
	(0.161)	(0.701)	(0.706)	(0.945)
Term Spread Change	2.715*	5.705***	2.620	4.894**
	(1.603)	(1.653)	(1.672)	(1.997)
Ted Spread	4.525***	4.097***	4.601***	3.477***
	(1.107)	(1.142)	(1.125)	(1.394)
Credit Spread Change	3.205***	4.790***	3.134***	0.837
	(1.118)	(1.155)	(1.187)	(1.421)
S&P 500 Returns	2.304	6.013	2.302	6.312
	(4.438)	(4.579)	(4.488)	(5.935)
VIX Index	0.120***	0.077	0.118	0.197**
	(0.041)	(0.083)	(0.082)	(0.102)
SPXF Returns	−3.207**	−6.850	3.287	−2.268
	(1.600)	(9.903)	(9.753)	(12.117)
SKEW	−0.126*	−0.084	−0.127*	−0.113*
	(0.069)	(0.072)	(0.070)	(0.092)
USDEU	2.791***	2.231***	2.798***	2.535***
	(0.390)	(0.403)	(0.402)	(0.486)
SPX Volume	−0.001	−0.002**	−0.001	−0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Intercept	15.355	11.931	19.262*	25.305*
	(10.815)	(11.194)	(10.981)	(13.507)
Obs	239	237	234	228
Adj. R^2	0.807	0.796	0.741	0.713

Notes: This table presents the results of the predictive multiple regressions in which a series of institutions characteristics and financial variables are adopted in order to predict the future levels of SOVaR. The predictive horizons are 1, 3, 6, and 12 months and the regressions are run from January 2000 to December 2019 (the Covid period is excluded from our analysis). The frequency of the independent variables as well as SOVaR is monthly. Coefficients, standard errors (in parentheses) and Adj. R^2s are reported. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

SOVaR on lagged financial and macroeconomic factors. The same factors are then used to build an in-sample and out-of-sample SOVaR predictors. The exercise is conducted at a monthly frequency due to the frequency of the banks' financial characteristics. Among characteristics, we select the loan-to-deposit ratio, the price-to-book ratio, and the leverage ratio. These are collected from Bloomberg together with each bank's market capitalization used to weight these variable to create an aggregate monthly series.

Among other financial factors, we select the put options market equity loss (VaR) also taken as the weighted average for all banks in our sample, the 3-month yield change, the term spread change, the TED spread, the credit spread change, the S&P 500 market returns, the real estate excess return, the equity volatility (CBOE VIX index), the S&P financial sector index returns, the CBOE SKEW index, the Baker and Wurgler (2006) investors' sentiment index,[27] the USD-EUR exchange rate, and the S&P total options volume. The financial variables data are collected either from Bloomberg or OptionMetrics. We then run the following predictive regression for a forecast horizon $h = 1, 3, 6, 12$ months:

$$\text{SOVaR}_{t+h} = \beta_0 + \beta_X \ X_t + \beta_{Mkt} \ Mkt_t + \epsilon_t \tag{9}$$

where SOVaR is our dependent variable to be forecasted, X is a matrix including the weighted average of bank characteristics, Mkt is a matrix including financial market variables, and ϵ is an error term. Table 2 shows the regression results.

We find that the selected factors predict well the future SOVaR with adjusted R^2 being close to 80% at the 1- and 3-month horizons, while equal to 74% and 71% at the 6- and 12-month horizon, respectively. This decrease in the adjusted R^2 may be because some of the selected factors (e.g. Loan-to-Deposit, Credit Spread Change) lose their predictive ability at the annual horizon.

[27] The investor sentiment index is collected from http://people.stern.nyu.edu/jwurgler/.

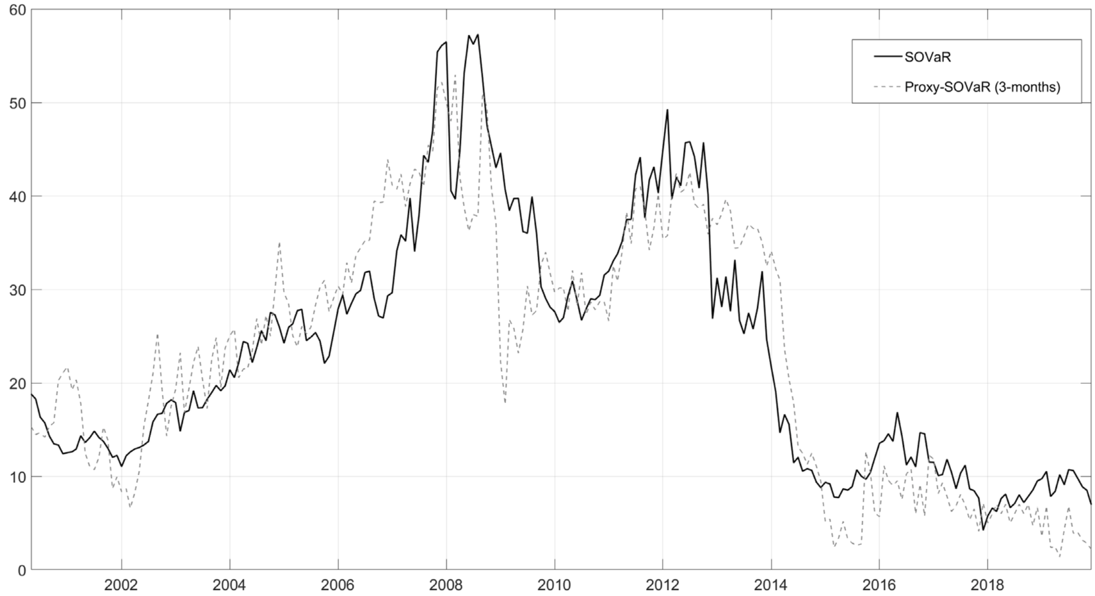

Fig. 3. Time-series of historical-$SoVaR$ and proxy-$SoVaR$.
Notes: This figure shows the time series of the original $SoVaR$ for all financial industries at a monthly frequency and the estimated $SoVaR$ that we denote *proxy*–SOVaR, which we estimated in-sample from January 2000 to December 2009 and the out-of-sample *forward*–SOVaR from January 2010 onwards.

Overall, we show that SOVaR is closely related to and can be predicted by exploiting the information enclosed in common financial institutions' characteristics, financial market or options-based market factors. The predicted SOVaR at each horizon h is then denoted as *proxy*–SOVaR and given by the following equation:

$$proxy - \text{SOVaR}_{t+h} = \widehat{\beta_0} + \widehat{\beta_X}\ X_t + \widehat{\beta_{Mkt}}\ Mkt_t \tag{10}$$

This equation is estimated in-sample from 2000 to 2009 and out-of-sample from 2010 onwards. We plot the comparison between the original SOVaR and the *proxy*–SOVaR at the 3-month horizon in Fig. 3.

We also construct a forward-$\Delta CoVaR$ for the aggregate financial sector that only adopts the financial and macroeconomic factors as in the predictive exercise in Adrian and Brunnermeier (2016). We forecast the $\Delta CoVaR$ in a 1-month to 1-year horizon. We also conduct a non-parametric test with respect to these series around the main events of the GFC, and the results show that the SOVaR also anticipates the forward-$\Delta CoVaR$.[28]

5. Options-based systemic risk at the industry and firm level

5.1. The SOVaR at the industry level

Following a similar structure as in Section 3, we show here the predictive magnitude of the SOVaR for each of the four financial industries and the test to empirically compare it to the other SRMs. Fig. 4 compares the SOVaR with the SRMs for the four financial industries considered in our analysis. The four groups react differently to financial market downturns. While the depositories are the main protagonists during the GFC, insurance companies, broker-dealers and other financials reach extreme SOVaR values also before and after the GFC, signalling a higher sensitivity to increased volatility, as investors start to expect a drop in stock prices. Such sub-industry heterogeneous behaviour is also found when studying the correlations between institutions' risk in isolation ($VaR_{q,t}^{P^i|\mathcal{M}} - VaR_{50,t}^{P^i|\mathcal{M}}$) and the $\beta_t^{i|\mathcal{M}}$ which vary from 0.03 for insurances to 0.24 for broker-dealers (see Fig. D.3 in Appendix D).

The buildup in SOVaR for the insurance sector since the end of 2004 to the peaks observed in 2005 and 2006 may be because of the increased frequencies of hurricanes. For the first time since 1886 three hurricanes (Charley, Frances, and Jeanne) hit the same state, Florida, in 2004 alone. Florida was also partially hit by hurricane Ivan that had started in Alabama. For 2004, Swiss Re estimated total economic losses of $56 billion and total insurance losses of $27 billion. If policymakers had followed SOVaR over

[28] Due to the monthly frequency of the predictive regression, we interpolate the series to daily and we test them around the main events of the GFC. The results are available from the authors on request.

that period, then the insurance industry would have been better prepared to face the impact of hurricane Katrina in 2005. That storm caused more than $160 billion in damage and led to a reduction of 29% in the population of New Orleans between the fall of 2005 and 2011. The similar high systemic risk period observed for this sector's SOVaR between 2013 and 2014 may be due to the problems caused by fires. Our measure captures some of the recent years' mounting physical toll of climate change in fires, flooding and hurricanes. These findings may reflect a tight link between the insurance industry and intensifying climate change related insurance risk. Our SOVaR calculations confirm the necessity of action for regulators focusing on climate risk in the global financial system.

The sector of other financials includes most credit card companies and hence covers many consumer finance companies. The systemic risk for consumers as captured by SOVaR has been very high during the dot.com era and building up rapidly post 2003. It reached very high levels in 2005, 2006, 2007, and 2008. The broker-dealers sector represents investment banks. There was an increase in SOVaR starting mid-2002 that could be associated with the introduction of Sarbanes–Oxley regulation and its peak reached exactly with the Lehman Brothers bankruptcy. According to Brownlees and Engle (2016), from January to mid-July of 2005, a great part of the capital shortfall originated from the broker-dealers and other financials sectors that contained institutions with high levels of leverage and market beta.[29] The firms in these two subsectors all played important roles in the financial crisis that was reflected by a high systemic risk identified as early as the first quarter of 2005, as reflected in Fig. 4.

When looking at the depositories sector, the SOVaR evolution indicates a buildup phase between 2006 with a first peak just before the Lehman collapse in 2008. Then, the SOVaR for this sector stayed high through 2009 because of the European sovereign crisis but it fell very fast in the second half of 2009 because it anticipated the IMF solution in event (4) in the figure. But the other SRMs were producing high false positives. This buildup phase was followed by another one in 2011 preceding the announcement of the Greek sovereign-debt yield spike in 2012 after which it and the other SRMs decreased back to historically low levels that could be attributed to the increased level of regulations in financial markets.

Considering the financial industries, Table D.1 in Appendix D confirms the evidence that the SOVaR succeeds in anticipating the systemic risk events in the period from August 9, 2007, to December 11, 2008, (October 13, 2008) compared to the $\Delta CoVaR$ (MES and $SRISK$). The only exception was the broker-dealers effectiveness ended on December 11, 2008, for the $\Delta CoVaR$. In addition, for the financial industries we detect an almost inverse relation between SOVaR and the SRMs when approaching the closing episodes of the crisis, with only a few exceptions. Overall, we can say that SOVaR announces the increased possibility of an event while the other SRMs announce that such an event had already occurred.

We employ the SOVaR as an early warning system and not as a crisis forecasting tool. Thus, we are not concerned here about false positives and false negatives because the role of SOVaR is not to predict event occurrence. The evolution of our SOVaR measure can be divided into three regimes. A benign period is associated with SOVaR values below 0.4. The buildup stage can be mapped to values between 0.4 and 0.6 and high levels of systemic risk are indicated by SOVaR values larger than 0.6. These three different regimes can be followed in the individual sectors analysed in Fig. 4. It is interesting to notice that for Broker-Dealers the systemic risk measure dropped abruptly after the Lehman Brothers bankruptcy on September 15, 2008, while the Other Financials sector it continued to stay above 0.6 for a very long period, declining rapidly later on in the aftermath of the subprime crisis.

Also for the SOVaR at the industry level, as a robustness check, we replace the SOVaR measures with the ones estimated with the implied beta computed as in Eq. (4), namely the $SOVaR_{Beta-FGK}$ for the four financial sub-sectors. We present the corresponding plots in Fig. D.4 in Appendix D where we compare the market-based SRMs with the industry $SOVaR_{Beta-FGK}$. This comparison, once again, leads to estimates that are both quantitatively and qualitatively similar to the original SOVaR with the two set of series sharing a correlation that ranges from a minimum of 0.80 for the insurance sector to a maximum of 0.91 for other financials.

5.2. The impact of Dodd–Frank Act on SOVaR

On July 21, 2010, the US Congress enacted the Dodd–Frank Wall Street Reform and Consumer Protection Act (DFA) to reorganize the financial regulatory system. Its main focus was on the banking sector — depositories and broker-dealers. The act introduced the Financial Stability Oversight Council (FSOC) and the Office of Financial Research to identify threats to the financial stability of the US, monitor and address systemic risks posed by large financial firms, and it gave the Federal Reserve new powers to regulate systemically important institutions (see also Freixas and Rochet (2013)). The main provision of this act was to restrict banks from making certain kinds of speculative investments (Volcker Rule).

Unlike banks, insurance and other financial firms do not play a role in the monetary or payment systems and their activities are usually viewed as being safer than those of banks, as they rely on longer-term liabilities and a strong operating cash flow (Bernal et al., 2014). For this reason, these two industry groups were not the primary target of the DFA that explains the results of high levels of systemic risk as measured by the SOVaR in the previous section in the corresponding plots in Fig. 4.

We employ our systemic risk measure extracted from options prices to test the reactions of the SOVaR and the SRMs to the enactment of the DFA. In particular, we use the Wilcoxon signed rank sum test for paired data to test whether the systemic risk level as captured by the four SRMs decreased after July 21, 2010. We consider various window lengths of h equal to 7, 14, 21, and 28 days. The Wilcoxon test is applied to the following hypotheses:

$$H_0 : SRM_{i,t-h-1:t-1} \leq SRM_{i,t:t+h-1} \tag{11}$$

[29] For instance, among the main contributors in the broker-dealers subsector were Morgan Stanley, Bear Stearns, and Lehman Brothers.

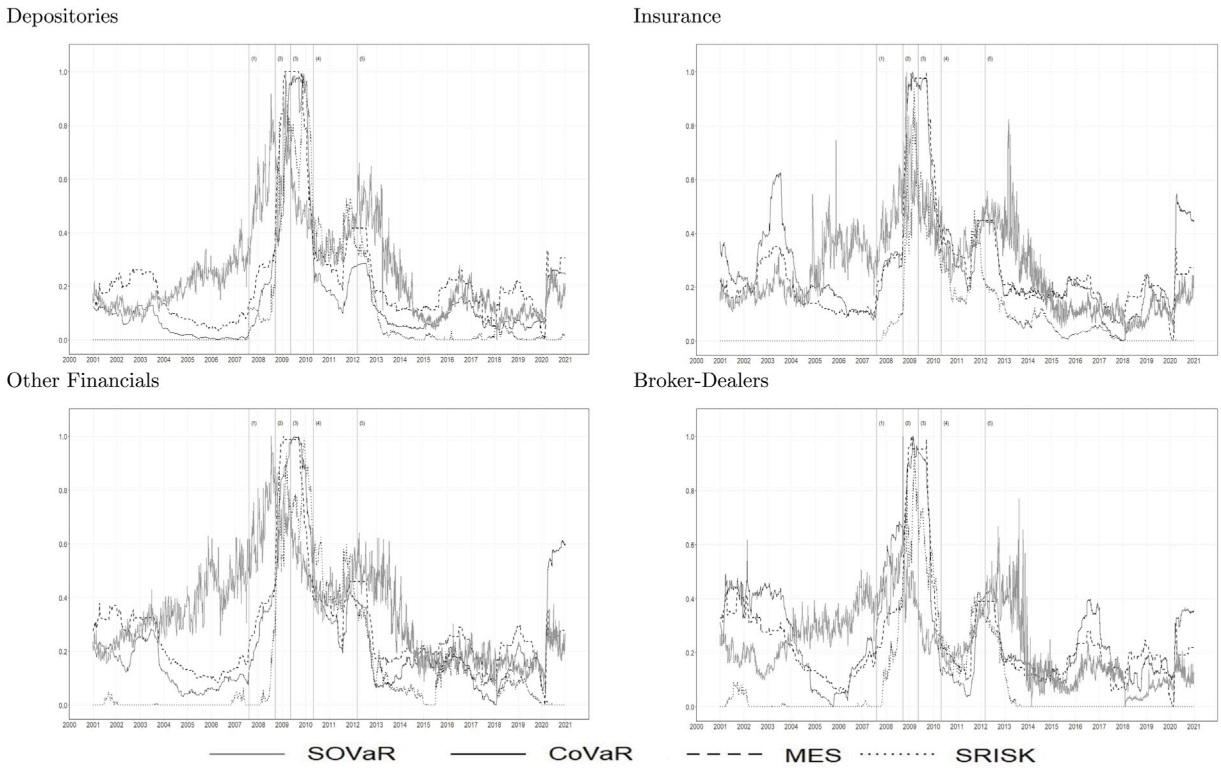

Fig. 4. Systemic risk of US financial industries: SOVaR vs. stock market-based SRMs.
Notes: This figure shows the time series of the SOVaR and the stock market-based SRMs of the US depositories, insurance, broker-dealers, and other financials industries. The vertical lines denote (1) the freezing of BNP Paribas funds on August 9, 2007; (2) the Lehman Brothers bankruptcy on September 15, 2008; (3) the start of the European debt crisis on May 9, 2009; (4) the agreement between the Greek government and the IMF for the first bailout package of €110 billion on May 2, 2010; and (5) the peak of 44.21% reached by the Greek 10-year bond yields on March 9, 2012. Time-series are estimated from January 2000 to December 2020, at the daily frequency.

$$H_1 : SRM_{i,t-h-1:t-1} > SRM_{i,t:t+h-1} \tag{12}$$

where i indicates the financial system or industry group studied. The failure to reject the null hypothesis (11) means that the systemic risk level of the financial system or sector under analysis did not decrease after the enactment of the DFA. The results are given in Table 3.

For the entire financial system, the null hypothesis is rejected at the 5% (1%) significance level only for SOVaR and $\Delta CoVaR$ at h = 7, 14, 21 and 28 (28, $\Delta CoVaR$). The results related to MES and $SRISK$ are not significant for any h. An interesting finding is that $\Delta CoVaR$ has the same results for each industry group that means a high correlation among the financial industry groups captured by this measure; however, this is not true for the SOVaR. The null hypothesis is rejected only for depositories and broker-dealers that were subject to DFA.

5.3. The SOVaR at the firm level

In this subsection, we report the SOVaR evolution for four firms from our sample. Fig. 5 illustrates that the SOVaR for Citigroup, JP Morgan Chase, StateStreet and Wells Fargo & Co was on a steep ascending path and breaking the 0.4 threshold well in advance of the Lehman collapse in 2008. The SOVaR for all companies also dropped a lot quicker post Lehman Brothers collapse although it remained high coming close to the European sovereign debt crisis. Our systemic risk monitoring tool helps investors in all companies, not only the GSIBs, to anticipate and manage the systemic risk buildup phase.

To gain more evidence, we test hypothesis (7) for each financial institution in our sample. Table 4 provides the percentage of the cases in which we reject the null hypothesis at the 1% significance level. The CDFs of the SOVaR are higher than the SRMs from a minimum of 53.96% (October 13, 2008, with h = 21 and 28) to a maximum of 100%, from August 9, 2007, to October 13, 2008. The results in Table 4 show statistically significant superior systemic and early warning information content at the individual

Table 3
Wilcoxon signed rank sum test around the enactment of the Dodd–Frank Act.

H_0: $SRM_{i,t-h-1:t-1} \leq SRM_{i,t:t+h-1}$					
		$SOVaR$	$\Delta CoVaR$	MES	$SRISK$
All Financial Industries	h = 7	−2.1539**	−2.1539**	0.0000	−0.4023
	h = 14	−2.1539**	−2.1539**	0.0000	−0.4023
	h = 21	−2.1539**	−2.1539**	0.0000	−0.4023
	h = 28	−2.1765**	−2.6601***	0.0000	−0.0981
		$SOVaR$	$\Delta CoVaR$	MES	$SRISK$
Depositories	h = 7	−2.1539**	−2.1539**	0.0000	−0.4023
	h = 14	−2.1539**	−2.1539**	0.0000	−0.4023
	h = 21	−2.1539**	−2.1539**	0.0000	−0.4023
	h = 28	−1.8627*	−2.6601***	0.0000	−0.1871
		$SOVaR$	$\Delta CoVaR$	MES	$SRISK$
Insurance	h = 7	−0.9468	−2.1539**	0.0000	−0.6745
	h = 14	−0.9468	−2.1539**	0.0000	−0.6745
	h = 21	−0.9468	−2.1539**	0.0000	−0.6745
	h = 28	−0.4451	−2.6601***	0.0000	−0.4451
		$SOVaR$	$\Delta CoVaR$	MES	$SRISK$
Others	h = 7	0.0000	−2.1539**	0.0000	0.0000
	h = 14	0.0000	−2.1539**	0.0000	0.0000
	h = 21	0.0000	−2.1539**	0.0000	0.0000
	h = 28	0.0000	−2.6601***	0.0000	0.0000
		$SOVaR$	$\Delta CoVaR$	MES	$SRISK$
Broker-Dealers	h = 7	−2.6601***	−2.1539**	0.0000	−0.6745
	h = 14	−2.6601***	−2.1539**	0.0000	−0.6745
	h = 21	−2.6601***	−2.1539**	0.0000	−0.6745
	h = 28	−2.0635**	−2.6601***	0.0000	−0.7245

Notes: This table presents the results of the Wilcoxon signed rank sum test for the financial industries. We test whether the level of systemic risk h-days after the enactment of the Dodd–Frank act on July 21, 2010 is greater than the same h-days before. The hypothesis tested is H_0: $SRM_{t-h-1:t-1} \leq SRM_{t:t+h-1}$, with h = 7, 14, 21, and 28 days. The failure to reject this hypothesis means that according to the particular SRM_i with i = SOVaR $\Delta CoVaR$, MES, or $SRISK$, the systemic risk level of the financial system (or sector) did not decrease after the enactment of the Dodd–Frank act. The columns contain the test statistics. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

firm level for the SOVaR. From December 11, 2008, to May 21, 2009, the relation between the SOVaR and the SRMs is reversed at the individual firm level in most of the cases. In particular, the null hypothesis is rejected between 0% to 33.33% of times. These results confirm that investors had positive expectations of a recovery for the financial firms at the end of the GFC.

As an additional test, we also rank the financial firms during the 21 days preceding the collapse of Bear Stearns, Bank of America's announcement of its purchase of Merrill Lynch, and the Lehman Brothers' bankruptcy on March 16 and September 14 and 15 of 2008, respectively. The SOVaR ranked Bear Stearns first on the day before its collapse (second during the preceding four days); while the $\Delta CoVaR$ ranked it fifth and sixth up to its collapse, and the MES ranked it tenth two days before the event and then ranked it seventh. At the time of Bank of America's announcement of purchasing Merrill Lynch, the SOVaR, $\Delta CoVaR$, MES, and $SRISK$ ranked this bank on average as seventh, tenth, twentieth, and thirtieth. Lastly, the SOVaR ranked Lehman Brothers first 22 days before its bankruptcy. The MES started ranking Lehman Brothers as a systemically riskier bank only seven days before its bankruptcy; while the $\Delta CoVaR$ ranked it second 21 days before the last listing day of this bank. Overall, the results presented in this subsection show that the SOVaR is able to fully gauge systemic risk during the key events of the GFC and to outperform the stock market-based SRMs of $\Delta CoVaR$, MES, and $SRISK$.

6. Options-based systemic risk and macroeconomic downturns

After showing the usefulness of the SOVaR as an early warning tool for financial distress, we now investigate whether the SOVaR can also predict future macroeconomic fluctuations. While the majority of the empirical studies on systemic risk has focused on measuring distress in financial markets, only a few have attempted to shed light on this issue e.g. Allen et al., 2012a; Giglio et al., 2016; Brownlees and Engle, 2016; Caporin et al., 2022. 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. Studies have detected distress in the financial system as an important amplification factor with respect to adverse fundamental shocks which can result in more severe downturns in the macroeconomy see Bartram et al., 2007. Conversely, the absence of financial distress does not necessarily lead to a macroeconomic boom e.g. Mendoza, 2010; Giglio et al., 2016. We use predictive regressions to show whether the SOVaR provides early warning signals of distress in the real economic activity as well as of recessions.

Table 4
Success ratio of SOVaR during key dates of the GFC.

	H_0: $SOVaR_{t-h-28:t-h} \leq SRM_{i,t-28:t}$				
	$h = 0$	$h = 7$	$h = 14$	$h = 21$	$h = 28$
August 9th, 2007					
$\Delta CoVaR$	92.06%	92.06%	92.06%	92.06%	90.47%
MES	87.30%	87.30%	87.30%	87.30%	82.53%
$SRISK$	100.00%	100.00%	100.00%	100.00%	100.00%
September 14th, 2007					
$\Delta CoVaR$	98.41%	98.41%	98.41%	93.65%	93.65%
MES	85.71%	85.71%	85.71%	80.95%	79.36%
$SRISK$	100.00%	100.00%	100.00%	100.00%	100.00%
March 16th, 2008					
$\Delta CoVaR$	85.71%	85.71%	85.71%	85.71%	82.53%
MES	76.19%	76.19%	76.19%	76.19%	66.67%
$SRISK$	100.00%	100.00%	100.00%	100.00%	100.00%
July 15th, 2008					
$\Delta CoVaR$	79.36%	79.36%	79.36%	74.60%	74.60%
MES	66.67%	66.67%	66.67%	66.67%	61.90%
$SRISK$	100.00%	100.00%	100.00%	100.00%	100.00%
September 17th, 2008					
$\Delta CoVaR$	74.60%	74.60%	74.60%	66.67%	66.67%
MES	73.01%	73.01%	73.01%	73.01%	69.84%
$SRISK$	95.23%	95.23%	95.23%	95.23%	95.23%
October 13th, 2008					
$\Delta CoVaR$	69.84%	69.84%	69.84%	69.84%	68.25%
MES	60.31%	60.31%	60.31%	53.96%	53.96%
$SRISK$	77.77%	77.77%	77.77%	74.60%	66.67%
December 11th, 2008					
$\Delta CoVaR$	28.57%	28.57%	28.57%	19.04%	19.04%
MES	0.00%	0.00%	0.00%	0.00%	0.00%
$SRISK$	14.28%	14.28%	14.28%	14.28%	14.28%
March 5th, 2009					
$\Delta CoVaR$	28.57%	28.57%	19.04%	15.87%	14.28%
MES	0.00%	0.00%	0.00%	0.00%	0.00%
$SRISK$	11.11%	11.11%	11.11%	11.11%	11.11%
May 21st, 2009					
$\Delta CoVaR$	0.00%	0.00%	0.00%	0.00%	0.00%
MES	0.00%	0.00%	0.00%	0.00%	0.00%
$SRISK$	33.33%	33.33%	33.33%	33.33%	33.33%

Notes: This table presents the success ratio of the SOVaR at the 1% significance level in identifying riskier financial firms during the key events of the GFC. The hypotheses tested are stated in the header of the table. The test adopted is the Kolmogorov–Smirnov bootstrap test.

We use the following monthly macroeconomic indicators: the Aruoba–Diebold–Scotti Business Conditions Index (ADS) see Aruoba et al., 2009, the US industrial production (IP) growth rate, and the Chicago Fed National Activity Index (CFNAI).[30] Following the standard practice in the literature, we aggregate our measures at a monthly frequency to match the macroeconomic indicators we predict. We start by running this regression model:

$$\text{Macro}_{t+h} = \beta_0 + \beta_{SOVaR}\ SOVaR_t + \epsilon_t \tag{13}$$

where $h \in \{1, 3, 6, 9, 12\}$. The results with respect to macroeconomic indicators up to one year are presented in Table 5.

The SOVaR shows strong predictive power with respect to all three macroeconomic indicators up to one year in advance. The regressions' performance, measured by the adjusted R^2 statistic, is increasing with the predicting horizon being the highest at the 9-month horizon, and equal to 11.8% (15.6%) when predicting ADS (CFNAI). For the IP monthly growth rate, we observe a monotonic increasing adjusted R^2 with the predicting horizon, being equal to 6.6% at the 12-month horizon. The regressions' coefficients are negative for any horizon and with respect to all three indicators. Thus, an increase in the SOVaR indicates worsening macroeconomic

[30] The ADS Business Condition Index tracks the real business conditions at a high frequency and is based on economic indicators. It is collected from: https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index. The IP measures the real output for all the facilities in the US and is collected from https://fred.stlouisfed.org/series/INDPRO. The CFNAI tracks the overall economic activity and the inflationary pressure and is computed as a weighted average of 85 monthly indicators. It is collected from: https://www.chicagofed.org/publications/cfnai/index.

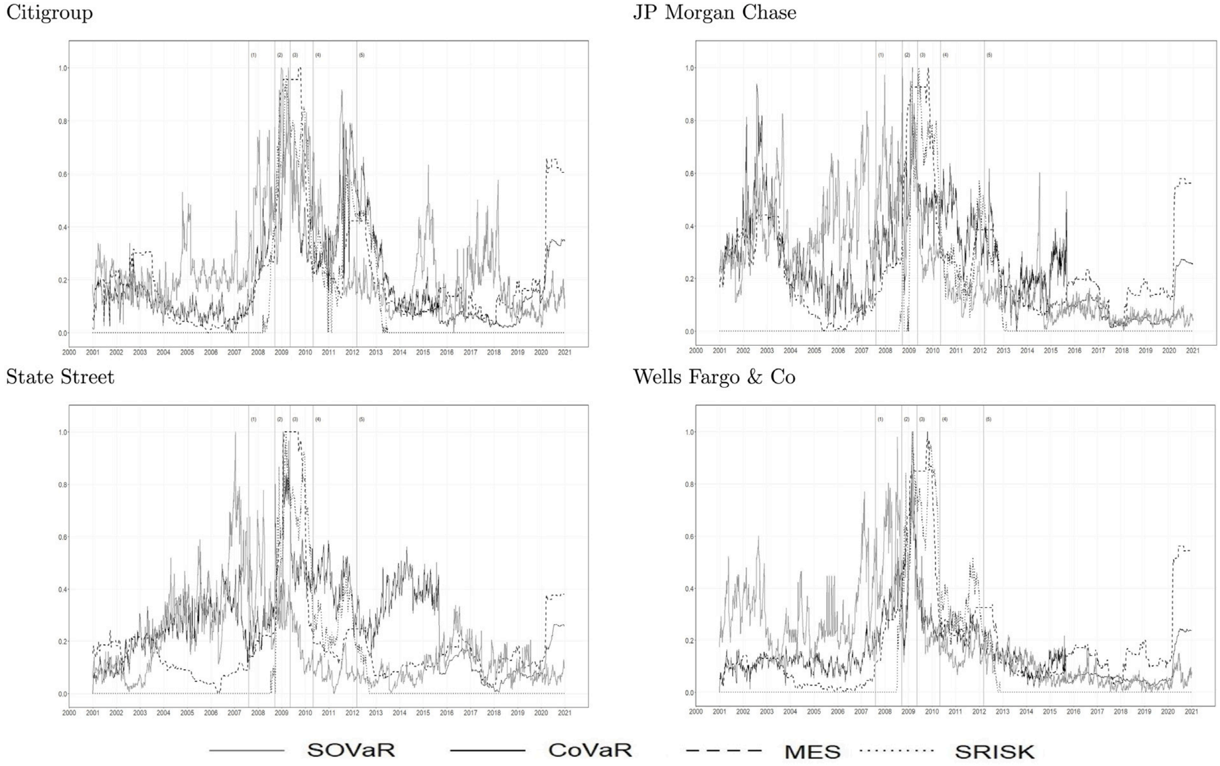

Fig. 5. Systemic risk at firm level: SOVaR vs. stock market-based SRMs.
Notes: This figure shows the time series of the SOVaR and the stock market-based SRMs of Citigroup, JP Morgan Chase, State Street and Wells Fargo & Co. The vertical lines denote (1) the freezing of BNP Paribas funds on August 9, 2007; (2) the Lehman Brothers bankruptcy on September 15, 2008; (3) the start of the European debt crisis on May 9, 2009; (4) the agreement between the Greek government and the IMF for the first bailout package of €110 billion on May 2, 2010; and (5) the peak of 44.21% reached by the Greek 10-year bond yields on March 9, 2012. Time-series are estimated from January 2000 to December 2020, at the daily frequency.

conditions consistent with the rationale behind the SRMs. Overall, the SOVaR has predictive ability that spans the whole 12-month horizon, hence being a timely systemic risk monitoring tool.[31]

6.1. Controlling for stock market-based systemic risk measures

To further check the predictive ability of SOVaR we explore whether it provides additional information that predicts macroeconomic downturns on top of other selected measures of risk. Therefore, we repeat the predictive exercises in the previous section by extending the covariate information set with $\Delta CoVaR$, MES, and $SRISK$ as well as the CATFIN by Allen et al. (2012b) and the partial quantile regression (PQR) estimator by Giglio et al. (2016), respectively.[32] CATFIN is based on non-parametric and parametric approaches, and it uses both the VaR and the ES methods. It is then constructed as an average of the three VaR and ES measures. The parametric distributions used to estimate the 1% VaR and ES are the generalized Pareto distribution (GPD) and the skewed generalized error distribution (SGED). The non-parametric methods are measured as cut-off points for the left tail minus one percentile of the monthly excess returns for the VaR and as an average of the extreme financial firms' returns beyond the 1% non-parametric VaR. The PQR estimator is computed aggregating 19 measures of systemic risk and financial market distress. We

[31] As a robustness check we conduct the same bivariate exercise adopting ATM-puts based on the SOVaR. The empirical findings are similar directionally, but weaker with respect to the predictive power. This result confirms that the SOVaR that is based on the OTM put options captures tail risk performs better in terms of real economic predictability. This is also found in line with Gao et al. (2019) stating that implied volatility of OTM options is higher than that of ATM options for most assets, suggesting that average investors are concerned about extreme downside movements of these assets.

[32] We thank the authors for making the CATFIN and the PQR series publicly available at https://sites.google.com/a/georgetown.edu/turan-bali/ and https://sites.google.com/view/stefanogiglio/data-code.

Table 5
Bivariate SOVaR Predictive Results.

	Dependent variable: ADS				
	h = 1	h = 3	h = 6	h = 9	h = 12
SOVaR	−0.013***	−0.015***	−0.018***	−0.019***	−0.018***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Adj. R^2	0.061	0.075	0.117	0.118	0.111
Obs	239	237	234	231	228
	Dependent variable: IP				
	h = 1	h = 3	h = 6	h = 9	h = 12
SOVaR	−0.051**	−0.058**	−0.070***	−0.084***	−0.096***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Adj. R^2	0.019	0.024	0.035	0.050	0.066
Obs	239	237	234	231	228
	Dependent variable: CFNAI				
	h = 1	h = 3	h = 6	h = 9	h = 12
SOVaR	−0.019***	−0.021***	−0.025***	−0.025***	−0.025***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Adj. R^2	0.086	0.108	0.152	0.156	0.147
Obs	239	237	234	231	228

Notes: This table presents the predictive results for the SOVaR with respect to the selected macroeconomic indicators: ADS, IP, and CFNAI that are estimated through Eq. (13). The model is run from January 2000 until December 2019, at a monthly frequency. The results are reported for predictive horizons equal to 1, 3, 6, 9, and 12 months along with the coefficients, standard errors (in parentheses), and adjusted R^2. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

also control for the SVIX (1-month, mid-price) proposed by Martin (2017) in order to obtain valuable information from the index option prices as well as a direct proxy for the equity premium in our regressions.[33]

We now run the multiple regression models including each of the above risk measures:

$$\text{Macro}_{t+h} = \beta_0 + \beta_{SOVaR}\ SOVaR_t + \beta_{RM}\ \text{RM}_t + \epsilon_t \tag{14}$$

where RM stays now for each risk measure we adopt as a control: $\Delta CoVaR$, MES, SRISK, CATFIN. We also include all of them jointly (RMs). The time period of the analysis is from January 2000 until December 2019, as to avoid the pandemic period, at a monthly frequency. We control also for other two risk measures, namely PQR and SVIX, however the analysis period which includes them goes only until December 2011. All results are reported in Tables 6 to 8.

Once again, there is evidence that the SOVaR is a strong predictor of the future level of the ADS Business Condition Index up to one year in advance, even when we control for $\Delta CoVaR$, MES, $SRISK$, and SVIX. When we control for CATFIN or PQR, the SOVaR is still able to predict future ADS from 3-month up to one year in advance. The predictive power of the SOVaR is also preserved, up to one year in advance, after controlling for all risk measures (RMs) at the same time.

The SOVaR shows predictive power also for the growth rate of industrial production, even after controlling for the other SRMs. The PQR is a strong predictor for shorter term horizons, but it does not lessen the predictive ability of the SOVaR for longer horizons. We find similar results when controlling for SVIX. When we control for the all the SRMs, the SOVaR still shows a predictive ability for future levels of IP, especially from the 3-month horizon onwards. For the CFNAI indicator, we confirm the strong predictive power of the SOVaR up to one year ahead even after controlling for $\Delta CoVaR$, MES, $SRISK$, and SVIX. There is empirical evidence that PQR is a strong predictor of CFNAI up to one year ahead (e.g. Giglio et al., 2016), but the SOVaR still remains statistically significant from 3-month up to one year ahead confirming its important role in the macroeconomic environment. Overall, even though the literature finds that measures such as the CATFIN and the PQR are strong predictors of macroeconomic conditions, the predictive power of the SOVaR still holds when we control for them. The SOVaR predicts macroeconomic conditions indicators up to one year ahead, even after controlling for all of the information available in the SRMs jointly.

Overall, the findings of this section confirm our hypothesis that the SOVaR is a valid predictive tool for macroeconomic downturns and changes in the real economy. In general, the findings show that the information content of SOVaR exhibits strong predictive power both in the short and also in the long run, hence it is a valid candidate to be a more timely predictive tool than the stock market-based SRMs and is also more timely than a forward-looking risk measure such as the SVIX.[34]

[33] We thank Ian Martin for publicly sharing the SVIX data on his website http://personal.lse.ac.uk/martiniw/.

[34] As a further robustness check, we replace the SVIX control in all the regressions with the well-known VIX index and with the 1month, bid-prices of SVIX, respectively. The strong predictive power of the SOVaR still holds. Moreover, we also replace the SVIX with another forward-looking proxy of financial distress

Table 6
Multiple SOVaR Predictive Results: ADS.

	h = 1	h = 3	h = 6	h = 9	h = 12
SOVaR	−0.007**	−0.011***	−0.018***	−0.020***	−0.021***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$\Delta CoVaR$	−0.145***	−0.081***	−0.007	0.042	0.076***
	(0.024)	(0.026)	(0.026)	(0.026)	(0.025)
Adj. R^2	0.179	0.109	0.114	0.124	0.140
Obs	239	237	234	231	228
SOVaR	−0.003	−0.009***	−0.013***	−0.016***	−0.018***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
CATFIN	−0.030***	−0.028***	−0.014***	−0.008**	0.001
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Adj. R^2	0.315	0.306	0.175	0.131	0.107
Obs	239	237	234	231	228
SOVaR	−0.007**	−0.010***	−0.019***	−0.021***	−0.022***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
MES	−0.146***	−0.082***	0.004	0.049**	0.072***
	(0.020)	(0.022)	(0.022)	(0.022)	(0.022)
Adj. R^2	0.227	0.125	0.114	0.133	0.148
Obs	239	237	234	231	228
SOVaR	−0.009**	−0.015***	−0.024***	−0.027***	−0.027***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
SRISK	−0.024***	0.002	0.030***	0.044***	0.050***
	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)
Adj. R^2	0.085	0.071	0.159	0.215	0.238
Obs	239	237	234	231	228
SOVaR | RMs	−0.008***	−0.012***	−0.021***	−0.024***	−0.026***
	(0.009)	(0.009)	(0.011)	(0.011)	(0.013)
Adj. R^2	0.456	0.470	0.410	0.406	0.306
Obs	239	237	234	231	228
SOVaR	−0.005	−0.011**	−0.023***	−0.029***	−0.031***
	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
PQR	6.190***	5.229***	3.448***	2.086***	1.266*
	(0.544)	(0.596)	(0.647)	(0.686)	(0.724)
Adj. R^2	0.501	0.401	0.308	0.252	0.216
Obs	143	141	138	135	132
SOVaR	−0.011***	−0.017***	−0.029***	−0.034***	−0.035***
	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
SVIX	−1.262***	−0.959***	−0.404***	0.104	0.279*
	(0.120)	(0.136)	(0.151)	(0.153)	(0.154)
Adj. R^2	0.461	0.314	0.205	0.202	0.218
Obs	143	141	138	135	132

Notes: This table presents the predictive multiple regression results for the SOVaR for the ADS Business Condition Index estimated through Eq. (14). We control for $\Delta CoVaR$, MES, SRISK, CATFIN, as well as for all of them jointly (RMs). The coefficients for all RMs are omitted for the sake of space. We also control for PQR and SVIX (until 2011). The results are reported for predictive horizons equal to 1, 3, 6, 9, and 12 months and for the coefficients, standard errors (in parentheses), and adjusted-R^2. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

6.2. Options-based systemic risk and recession

In this section we check the predictive power or the SOVaR with respect to a dummy variable for a NBER recession period in the US.[35] For the NBER variable, we use a probit regression as follows:

$$Prob(\text{NBER}_{t+h} = 1) = \Phi\left(\beta_0 + \beta_{SOVaR}\ SOVaR_t\right) \tag{15}$$

and insurance demand against financial market downturns in the case of a borrower's default, namely the credit default swap index (CDX) collected from IHS Markit database. Also in this case, the predictive ability of SOVaR holds with respect to any horizon and any macroeconomic indicator. All these additional results are available from the authors upon request.

[35] The NBER dummy tracks recession (1) and expansion (0) periods and is available at https://fred.stlouisfed.org/series/USREC.

Table 7
Multiple SOVaR Predictive Results: IP.

	h = 1	h = 3	h = 6	h = 9	h = 12
SOVaR	−0.001	−0.006**	−0.007**	−0.008**	−0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$\Delta CoVaR$	−0.052**	−0.010	0.034	0.056**	0.071***
	(0.024)	(0.025)	(0.024)	(0.024)	(0.024)
Adj. R^2	0.016	0.016	0.015	0.027	0.044
Obs	239	237	234	231	228
SOVaR	−0.001	−0.002	−0.006**	−0.007**	−0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
CATFIN	−0.126***	−0.175***	−0.050	−0.014	0.042
	(0.034)	(0.033)	(0.035)	(0.035)	(0.035)
Adj. R^2	0.054	0.109	0.016	0.015	0.044
Obs	239	237	234	231	228
SOVaR	−0.001	−0.003	−0.008**	−0.008**	−0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
MES	−0.057***	−0.019	0.034	0.057***	0.062***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Adj. R^2	0.028	0.003	0.018	0.036	0.046
Obs	239	237	234	231	228
SOVaR	−0.003	−0.006*	−0.011***	−0.012***	−0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
SRISK	−0.044	0.112	0.275***	0.328***	0.327***
	(0.083)	(0.083)	(0.081)	(0.081)	(0.081)
Adj. R^2	0.006	0.017	0.054	0.072	0.075
Obs	239	237	234	231	228
SOVaR | RMs	−0.002	−0.006**	−0.009***	−0.010***	−0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Adj. R^2	0.097	0.202	0.121	0.123	0.069
Obs	239	237	234	231	228
SOVaR	−0.001	−0.006	−0.013**	−0.016***	−0.018***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
PQR	3.993***	2.768***	1.476**	0.586	0.322
	(0.553)	(0.603)	(0.631)	(0.648)	(0.666)
Adj. R^2	0.276	0.148	0.090	0.073	0.079
Obs	143	141	138	135	132
SOVaR	−0.006	−0.009*	−0.015***	−0.018***	−0.020***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
SVIX	−0.612***	−0.539***	−0.139	0.246*	0.229
	(0.128)	(0.130)	(0.139)	(0.139)	(0.140)
Adj. R^2	0.145	0.127	0.060	0.089	0.096
Obs	143	141	138	135	132

Notes: This table presents the predictive multiple regression results for the SOVaR for the industrial production (IP) growth rate estimated through Eq. (14). We control for $\Delta CoVaR$, MES, SRISK, CATFIN, as well as for all of them jointly (RMs). The coefficients for the all RMs are omitted for the sake of space. We also control for PQR and SVIX (until 2011). The results are reported for predictive horizons equal to 1, 3, 6, 9 and 12 months and for the coefficients, standard errors (in parentheses), and adjusted-R^2. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

where Φ is the standard Gaussian cumulative distribution function, NBER is the dummy recession variable, and $h \in \{1, 3, 6, 9, 12\}$. The results are reported in the first panel of Table 9. We observe that the SOVaR is a strong predictor of recessions up to one year ahead and can explain about 9.5% to 13.3% of the future probability of recessions in the next month and next year, respectively. The coefficients' sign is positive, hence an increase in the SOVaR leads to a higher probability of recession in the next horizon h.

Lastly, we perform the same exercise as in Eq. (14) with respect to the NBER recession variable running the following:

$$Prob(\text{NBER}_{t+h} = 1) = \Phi\left(\beta_0 + \beta_{SOVaR}\ SOVaR_t + \beta_{RM}\ \text{RM}_t\right) \tag{16}$$

Table 8
Multiple SOVaR Predictive Results: CFNAI.

	h = 1	h = 3	h = 6	h = 9	h = 12
SOVaR	−0.011***	−0.016***	−0.023***	−0.026***	−0.027***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\Delta CoVaR$	−0.182***	−0.115***	−0.034	0.019	0.062**
	(0.028)	(0.029)	(0.030)	(0.030)	(0.030)
Adj. R^2	0.220	0.159	0.153	0.153	0.160
Obs	239	237	234	231	228
SOVaR	−0.005	−0.010***	−0.018***	−0.021***	−0.023***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
CATFIN	−0.376***	−0.303***	−0.193***	−0.121***	−0.037
	(0.035)	(0.038)	(0.040)	(0.041)	(0.043)
Adj. R^2	0.379	0.297	0.226	0.182	0.146
Obs	239	237	234	231	228
SOVaR	−0.009**	−0.016***	−0.024***	−0.026***	−0.028***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
MES	−0.178***	−0.103***	−0.017	0.027	0.061**
	(0.023)	(0.025)	(0.025)	(0.025)	(0.025)
Adj. R^2	0.261	0.164	0.150	0.156	0.165
Obs	239	237	234	231	228
SOVaR	−0.012***	−0.020***	−0.028***	−0.032***	−0.033***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
SRISK	−0.358***	−0.055	0.209**	0.370***	0.464***
	(0.101)	(0.102)	(0.099)	(0.098)	(0.097)
Adj. R^2	0.129	0.106	0.164	0.202	0.223
Obs	239	237	234	231	228
SOVaR | RMs	−0.010***	−0.017***	−0.025***	−0.029***	−0.031***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Adj. R^2	0.467	0.412	0.396	0.367	0.298
Obs	239	237	234	231	228
SOVaR	−0.008	−0.017***	−0.030***	−0.034***	−0.037***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)
PQR	7.013***	5.478***	4.259***	3.238***	1.928**
	(0.658)	(0.737)	(0.750)	(0.784)	(0.843)
Adj. R^2	0.475	0.349	0.342	0.304	0.243
Obs	143	141	138	135	132
SOVaR	−0.015***	−0.024***	−0.037***	−0.041***	−0.042***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)
SVIX	−1.562***	−0.956***	−0.521***	−0.044	0.235
	(0.135)	(0.167)	(0.176)	(0.180)	(0.182)
Adj. R^2	0.514	0.263	0.234	0.214	0.222
Obs	143	141	138	135	132

Notes: This table presents the predictive multiple regression results for the SOVaR for the Chicago Fed National Activity Index (CFNAI) estimated through Eq. (14). We control for $\Delta CoVaR$, MES, SRISK, CATFIN, as well as for all of them jointly (RMs). The coefficients for all RMs are omitted for the sake of space. We also control for PQR and SVIX (until 2011). The results are reported for predictive horizons equal to 1, 3, 6, 9, and 12 months and for the coefficients, standard errors (in parentheses), and adjusted-R^2. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

where now we control for each of the selected systemic risk measures, $\Delta CoVaR$, MES, $SRISK$, CATFIN, all of them together (RMs), and also PQR and SVIX for a shorter time period, with $h \in \{1, 3, 6, 9, 12\}$. The results of the probit regression are reported in Table 9.

Overall, this subsection further confirms that even when we control for the other RMs, the SOVaR out-performs the $\Delta CoVaR$, MES, $SRISK$ and CATFIN when it comes to signal future recession periods. SOVaR is still found to be significant in predicting future recessions even when we control for all of them jointly (RMs). We find that SOVaR is also still found to be significant

Table 9
Multiple SOVaR Predictive Results: NBER.

	h = 1	h = 3	h = 6	h = 9	h = 12
SOVaR	0.008***	0.008***	0.009***	0.010***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Pseudo R^2	0.095	0.100	0.142	0.150	0.133
SOVaR	0.005***	0.006***	0.009***	0.010***	0.010***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
$\Delta CoVaR$	0.064***	0.041***	0.008	−0.016	−0.028**
	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)
Pseudo R^2	0.205	0.143	0.140	0.153	0.150
SOVaR	0.004**	0.004***	0.006***	0.008***	0.009***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
CATFIN	0.105***	0.104***	0.081***	0.034**	0.005
	(0.015)	(0.015)	(0.015)	(0.016)	(0.017)
Pseudo R^2	0.247	0.250	0.231	0.162	0.129
SOVaR	0.005***	0.006***	0.009***	0.011***	0.011***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
MES	0.057***	0.037***	0.005	−0.021**	−0.029***
	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
Pseudo R^2	0.214	0.149	0.139	0.163	0.161
SOVaR	0.006***	0.007***	0.011***	0.013***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
SRISK	0.009**	0.002	−0.011***	−0.020***	−0.022***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Pseudo R^2	0.109	0.097	0.170	0.249	0.254
SOVaR| RMs	0.006***	0.007***	0.010***	0.012***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Pseudo R^2	0.358	0.352	0.445	0.471	0.365
SOVaR	0.004*	0.006**	0.010***	0.013***	0.013***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
PQR	−2.183***	−2.164***	−1.926***	−1.076***	−0.826**
	(0.293)	(0.292)	(0.291)	(0.321)	(0.339)
Pseudo R^2	0.324	0.335	0.356	0.244	0.203
SOVaR	0.007***	0.008***	0.013***	0.015***	0.015***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
SVIX	0.416***	0.350***	0.243***	−0.052	−0.142*
	(0.065)	(0.067)	(0.070)	(0.072)	(0.073)
Pseudo R^2	0.270	0.222	0.218	0.183	0.190

Notes: This table presents the predictive regression results for the SOVaR for the NBER recession dummy estimated through the bivariate probit model in Eq. (15) (first panel) and through the multiple probit model in Eq. (16) thereafter. In the multiple regressions, we control for each one of the risk measures, $\Delta CoVaR$, MES, SRISK, CATFIN, as well as for all of them jointly (RMs). The coefficients for all RMs are omitted for the sake of space. We also control for PQR and SVIX (until 2011). The results are reported for horizons equal to 1, 3, 6, 9, and 12 months and for the coefficients, z-stat (in parentheses), and pseudo- R^2. For the number of observations, please see Table 6. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

when we control for PQR and SVIX, with stronger predictive ability especially at longer horizons. This finding uncovers important complementary information shared by the different measures for predicting recessions.

6.3. Options-based systemic risk and out-of-sample predictability

In this subsection, we also check the out-of-sample predictive power of the SOVaR with respect to three macroeconomic indicators ADS, IP and CFNAI. We compute the regression forecast as:

$$\widehat{Macro}_{t+h} = \widehat{\alpha}_t + \widehat{\beta_{RM}} RM_t + Macro_t \tag{17}$$

Table 10
SOVaR Out-of-Sample Predictability: Adj. MSFE.

	h = 1	h = 3	h = 6	h = 9	h = 12
			ADS		
SOVaR	2.98***	2.22**	1.52*	1.96**	2.19**
$\Delta CoVaR$	0.73	−1.67	−1.77	−1.43	−0.22
MES	0.50	−0.08	−1.21	−1.17	0.41
SRISK	−0.99	−0.83	−1.62	−2.26	−2.33
CATFIN	1.89**	1.46*	1.22	2.25**	2.98***
			IP		
SOVaR	0.60	0.35	0.92	1.49*	1.54*
$\Delta CoVaR$	0.87	0.72	0.15	−0.26	−0.66
MES	0.83	0.87	0.74	0.17	−0.31
SRISK	0.70	0.91	1.28*	1.29*	0.67
CATFIN	0.79	0.78	0.73	0.64	0.51
			CFNAI		
SOVaR	4.10***	4.68***	3.89***	3.95***	4.27***
$\Delta CoVaR$	0.38	−0.21	−0.11	0.04	2.11**
MES	1.67**	2.47***	1.27*	1.17	3.50***
SRISK	0.83	1.77**	0.01	−0.78	−0.78
CATFIN	4.15***	4.31***	4.01***	4.92***	5.82***

Notes: This table presents the out-of-sample predictability results for the SOVaR and the other SRMs. The in-sample period is from 2000 to 2009, and out-of-sample estimation period is from 2010 to 2019. We report the Clark and West (2007) MSFE-adjusted statistics. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

where $\hat{\alpha}_t$, and $\widehat{\beta_{RM}}$ are the OLS estimates of α and βs, respectively, from the beginning of the sample until month t, and $Macro_t$ is an autoregressive process of lag 1. The RM is one of the systemic risk measures we test that contains the SOVaR, $\Delta CoVaR$, MES, $SRISK$, and CATFIN. The forecast horizons, h, are equal to 1, 3, 6, 9, and 12 months.

We are interested in testing whether the regression with the SOVaR achieves predictive power as good as or stronger than the predictive regressions including the other RMs. To test whether or not the predictive regression produces a significant improvement in the mean squared forecast error (MSFE), we report the Clark and West (2007) MSFE-adjusted statistic that tests the null hypothesis that the benchmark MSFE is less than or equal to the predictive regression's MSFE against the alternative hypothesis that the benchmark MSFE is greater than the predictive regression's MSFE which corresponds to $H_0 : R^2_{OS} \leq 0$ against $H_A : R^2_{OS} > 0$. The sample is split into an in-sample period (from 2001 to 2009) and an out-of-sample evaluation forecast period (from 2010 to 2019). Also in this analysis we exclude the pandemic period. The natural forecast benchmark we consider is an autoregressive process, namely the previous lag of the dependent variable. We report the results in Table 10 for the macroeconomic indicators.

The results from Table 10 show that the SOVaR achieves good out-of-sample forecast performance, especially with respect to CFNAI and ADS, at all forecasting horizons, with adjusted MSFE that is significantly less than the benchmark MSFE. SOVaR also achieves a better out-of-sample performance for the IP growth rate, superior to the majority of the other $SRMs$, but only at the 9- and 12-month horizons.[36]

6.4. Options-based financial industries systemic risk predictability

In this subsection, we continue the investigation of the predictive power of the SOVaR by drilling down to the four financial industries in our sample: depositories, insurance, others financial, and broker-dealers. In today's globalized and financialized economy, the breakdown of companies other than depositors, such as insurance firms, broker-dealers, non-depository institutions, and real estate, may also have a critical impact on the real economy see Bernal et al., 2014. In order to check this impact, we run regressions in order to gauge the impact of the financial sub-sectorial SOVaR on the future level of macro variables, that is ADS, CFNAI, IP growth, and also future recessions. We run the same equation as in (13) where the independent variable is now the SOVaR for each of the four financial industries. For the impact on recessions as a binary variable, a probit model is applied. The results are reported in ref tables Tables D.2 and D.3 in Appendix D for the bivariate and multiple predictive regressions, respectively.[37]

[36] The same exercise has been performed with respect to PQR and SVIX. However, due to the different time period availability we tested the out-of-sample predictive power of SOVaR against PQR and SVIX by choosing an in-sample period from 2001 to 2009 and the remaining two years as out-of-sample. The results show SOVaR performing as well as PQR and SVIX with respect to IP, while outperforming them with respect to ADS and CFNAI. The results are available from the authors on request.

[37] In this predictive exercise we only control for the corresponding financial industry market-based SRMs for which we are able to compute corresponding financial industry systemic risk measures, namely $\Delta CoVaR$, MES and $SRISK$ and still denote them as RMs.

Starting with the bivariate analysis in Table D.2, we observe that the SOVaR for depositories industry plays a key role in predicting macro variables as well as future recessions up to one year in advance as indicated by the high performance that is measured by the regression adjusted R^2. The SOVaR of the insurance and other financials sub-sectors also show good predictability for all indicators, however with lower adjusted R^2s compared to the depositories SOVaR. The SOVaR of broker-dealers is mainly able to predict future IP growth rate up to one year ahead, whereas all the other indicators mainly at longer horizons. Further, we repeat the same predictive exercise while controlling for all the other $SRMs$ together ($\Delta CoVaR$, MES, $SRISK$, and CATFIN) in Table D.3. We observe that the SOVaR is still statistically significant after controlling for all the other $SRMs$ jointly. Hence, we confirm the usefulness of the SOVaR in predicting future macroeconomic indicators also when considered at the financial sub-sector level, especially when computed from depositories.

7. Conclusion

We propose an option-implied SRM that is constructed from financial institutions' OTM put options. Our methodology is easily replicable and it can be applied in real-time on a daily basis by any company. Moreover, being extracted from OTM put options, SOVaR is closely linked to the investors' perception of future downside tail risk in the financial system. Our study shows the connection between the use of OTM puts on financial stocks and the identification of systemic risk in the financial sector. Relying on firms with traded equity options we propose a generic methodology that is applicable to every sector from which the next systemic crisis may originate and affect the economy.

In relation to the US economy, we find that the SOVaR can capture and signal buildups of systemic risk and financial distress in a more timely manner compared to other stock-based measures. Focusing on the GFC, non-parametric tests show that SOVaR is able to signal financial market distress in advance in contrast to standard stock market-based SRMs. In addition, SOVaR can predict economic downturns and recessions up to 12 months in advance. Our results also hold when we control for other measures of risk already proposed in the literature. The SOVaR for depositories is found to be the most informative in predicting macroeconomic indicators and recessions. The proposed monitoring tool can be useful to regulators, supervisory authorities, policymakers and investors, in turbulent and uncertain times.

To conclude, together with the most recognized market-based SRMs, the SOVaR could be used as a useful monitoring tool to prevent substantial financial disruptions in banking and other financial services necessary for stable economic growth. Despite its ease in the estimation, SOVaR is robust to changes in methodology, successfully delivering strong predictive empirical results, over-performing standard market-based SRMs, hence serving as a convenient and more timely alternative to complement the existing systemic risk measures. This study aims to stimulate a line of research that looks at the advantages of adopting options when measuring systemic risk, predicting financial distress and macroeconomic downturns.

Appendix A. Market-based systemic risk measures

This section details the methodologies implemented to estimate the three main stock market-based SRMs used in this paper, namely, the $\Delta CoVaR$ by Adrian and Brunnermeier (2016), the MES developed by Acharya et al. (2017), and the $SRISK$ introduced by Brownlees and Engle (2016).

A.1. Definition of CoVaR

Adrian and Brunnermeier (2016) introduced the conditional value-at-risk ($CoVaR$) to analyse risk transmissions from an individual financial institution to another or to the equity market as a whole. In particular, the $CoVaR$ is defined as the conditional value-at-risk of the equity market conditional on a financial institution i being in a particular state. The main measure $\Delta CoVaR$ is estimated as the difference between the $CoVaR$ conditional on the distress of institution i and the $CoVaR$ conditional on the median state of the same.

We denote by $q\% - VaR_{q,i}$:

$$Pr(X_i \leq VaR_{q,i}) = q\% \tag{18}$$

where X_i is institution i's *"return loss"* for which the $VaR_{q,i}$ is defined. $CoVaR_q^{S\&P500|C(X_i)}$ is defined as the VaR of the equity market conditional on some event $C(X_i)$ of institution i. The event C is defined as an event equally likely across institutions. Usually C is defined as institution i's loss being at or above its $VaR_{q,i}$ level. $CoVaR_q^{S\&P500|C(X_i)}$ is implicitly defined by the $q\%$-quantile of the conditional probability distribution:

$$Pr(X^{S\&P500|C(X_i)} \leq CoVaR_q^{S\&P500|C(X_i)}) = q\% \tag{19}$$

The $\Delta CoVaR$ of the equity market conditional on institution i being under distress is computed as follows:

$$\Delta CoVaR_q^{S\&P500|i} = CoVaR_q^{S\&P500|X_i=VaR_{q,i}} - CoVaR_q^{S\&P500|X_i=VaR_{50^{th},i}} \tag{20}$$

We use quantile regression to estimate the $\Delta CoVaR$. In particular, following the approach of Adrian and Brunnermeier (2016), we estimate the following quantile regression:

$$X_{q,S\&P500} = \alpha_q + \beta_q X_{q,i} \tag{21}$$

where $X_{q,S\&P500}$, and $X_{q,i}$ denote the equity market and institution i's return losses, respectively. Using the predicted value of $X_i = VaR_{q,i}$, we get the $CoVaR_{q,i}$ measure as follows:

$$CoVaR_{q,i} = VaR_q^{S\&P500|X_i=VaR_{q,i}} = \hat{\alpha}_q + \hat{\beta}_q VaR_{q,i} \tag{22}$$

where $VaR_{q,i}$ is the q%-quantile of institution i's losses.

Based on Eq. (20), the $\Delta CoVaR_{q,i}$ is estimated as:

$$\Delta CoVaR_{q,i} = CoVaR_{q,i} - CoVaR_q^{S\&P500|X_i=VaR_{50^{th},i}} = \hat{\beta}_q(VaR_{q,i} - VaR_{50^{th},i}) \tag{23}$$

For each financial institution and industry group included in our sample, we estimate the $\Delta CoVaR_{95^{th},i}$.[38]

In order to ensure consistency among the three SRMs used in this study, we compute the $\Delta CoVaR$ by conditioning institution i's losses on the financial system being in crisis. The $Exposure - \Delta CoVaR$ formula proposed by Adrian and Brunnermeier (2016), at critical level q, for company i that is part of the system $\mathcal{M}$ is calculated with the formula:

$$\Delta CoVaR^i_{q,t} = b_q^{i|\mathcal{M}}(VaR^{i|\mathcal{M}}_{q,t} - VaR^{i|\mathcal{M}}_{50,t}) \tag{24}$$

where this measure reflects the individual institution's exposure to system-wide distress. This measure is comparable from a directional calculation point of view with MES and SRISK.

A.2. Definition of MES

Acharya et al. (2017) developed the marginal expected shortfall (MES) as a measure to estimate the marginal contribution of each financial institution to systemic risk. The MES is defined as the expected shortfall of an institution in the tail of the aggregate sector's loss distribution by considering the expected shortfall (ES) defined as $ES_q = E[R|R \leq VaR_q]$ as a measure of firm-level risk. The focus on the ES is motivated by the fact that asymmetric yet very risky bets may not produce a large VaR. By decomposing the bank's return R into:

$$R = \sum_i y_i r_i \tag{25}$$

where r_i is the return of each firm i and y_i its weight, from (25) the ES can be written as:

$$ES_q = \sum_i y_i E[r_i|R \leq VaR_q] \tag{26}$$

The MES^i_a is then: $\frac{\partial ES_q}{\partial y_i} = E[r_i|R \leq VaR_q] \equiv MES^i_q$

The MES can be interpreted as each bank's losses when the system (S&P 500, in our case) is in a tail event. We estimate the MES with $q\% = 5\%$, as in Acharya et al. (2017), and use daily equity returns. This measure estimates the equal-weighted average return of any given firm (R^i) for the q% worst days of the market returns (R^m):

$$MES^i_{q\%} = \frac{1}{\#days} \sum R^i_t \tag{27}$$

A.3. Definition of SRISK

Brownlees and Engle (2016) proposed the $SRISK$ to measure the systemic risk contribution of an institution to a system made up of N financial institutions. For each institution i at time t the *Capital Shortfall* is formally defined as:

$$CS_{i,t} = kA_{i,t} - W_{i,t} \tag{28}$$

with $A_{i,t} = D_{i,t} + W_{i,t}$. It is possible to rewrite (28) as:

$$CS_{i,t} = k(D_{i,t} + W_{i,t}) - W_{i,t} \tag{29}$$

where $W_{i,t}$ is the market capitalization, $D_{i,t}$ is the book value of debt, $A_{i,t}$ is the value of quasi assets, and k is the prudential capital fraction equal to 8%.[39]

Brownlees and Engle (2016) defined the $SRISK$ as the expected capital shortfall conditional on a systemic event, which is defined as the market return between period $t+1$ and $t+h$ (h is 22 here) that is below a threshold C which is equal to 10%.

$$SRISK_{i,t} = E_t(CS_{i,t+h}|R_{m,t+1:t+h} < C) \tag{30}$$

Combining (29) and (30) gives:

$$SRISK_{i,t} = E_t(D_{i,t+h}|R_{m,t+1:t+h} < C) - (1-k)E_t(W_{i,t+h}|R_{m,t+1:t+h} < C) \tag{31}$$

[38] In order to estimate $\Delta CoVaR$ of a financial industry group, we build an equity-weighted portfolio of the firms classified in the specific industry group.

[39] Engle et al. (2015) explained that due to differences in accounting standards between European and other banks, European banks should use a capital ratio of $k = 5.5\%$, which approximately corresponds to a capital ratio of 8% in the other banking systems.

The authors assumed that in case of a systemic event, debt cannot be renegotiated. This assumption means that $E_t(D_{i,t+h}|R_{m,t+1:t+h} < C) = D_{i,t}$ and consequently:

$$SRISK_{i,t} = kD_{i,t} - (1-k)W_{i,t}(1 - LRMES_{i,t}) \tag{32}$$

Introducing the quasi leverage ratio $LVG^c_{i,t} = \frac{D_{i,t}+W_{i,t}}{W_{i,t}}$ the formula (32) becomes:

$$SRISK_{i,t} = W_{i,t}[kLVG_{i,t} + (1-k)LRMES_{i,t} - 1] \tag{33}$$

The term $LRMES_{i,t}$ is defined as the long run marginal expected shortfall. It represents the expected fractional loss of the financial firm in a crisis when the market index (S&P 500, in our case) declines significantly in a 6-month period. Specifically, it is calculated as:

$$LRMES_{i,t} = 1 - exp(log(1-d) \times \beta_{i,t}) \tag{34}$$

where d is the 6-month crisis threshold for the market index decline in which the default value is 40%, and $\beta_{i,t}$ is the firm's beta coefficient.[40] By default, the crisis threshold for the market decline is set to be 40%, which is consistent with the estimates of the $LRMES$ with simulation as explained in Brownlees and Engle (2016).[41]

A system-wide measure of financial distress that measures the total amount of systemic risk in the financial system is:

$$SRISK_t = \sum_{i=1}^{N} max(SRISK_{i,t}, 0) \tag{35}$$

Appendix B. Filtered historical simulation approach

For simplicity, we exemplify the steps when the GARCH(1,1) is applied to option prices returns. This model is underpinned by the dynamics equations:

$$r_t = \mu r_{t-1} + \varphi\varepsilon_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim N(0, h_t) \tag{36}$$

$$h_t = \omega + \alpha(\varepsilon_{t-1} - \lambda)^2 + \beta h_{t-1} \tag{37}$$

The key is to "make" the residuals almost i.i.d and for that we divide the residual ε by its corresponding daily volatility estimate

$$e_t = \frac{\varepsilon_t}{\sqrt{h_t}} \tag{38}$$

The projections of possible future values of option prices are determined by going iteratively period by period ahead. First, draw a standardized residual scaled by the deterministic volatility forecast one period ahead $u_{t+1} = e_1\sqrt{h_{t+1}}$ and use it to get the one day option price forecast

$$p_{t+1} = p_t \exp\left(\mu r_t + \varphi z_t + z_{t+1}\right) \tag{39}$$

Generating volatilities for following periods is achieved by the recursive replacement of scaled residuals into (37). The volatility dynamics is encapsulated into the equation:

$$h_{t+j} = (\omega + \alpha(z_{t+j-1} - \lambda)^2 + \beta h_{t+h-j}), \qquad j \geq 2 \tag{40}$$

For more details on the original methodology, please see the seminal paper by Barone-Adesi et al. (1999).

Appendix C. GFC event timeline and data description

See Tables C.1–C.3.

[40] A comprehensive description of the methodology is provided at: https://vlab.stern.nyu.edu/docs/srisk/MES.

[41] Acharya et al. (2012) used another approximation of the $LRMES$, which is still consistent with the estimates of the same term through simulation. In particular, the authors define the $LRMES$ as $1 - exp(-18 \times MES_{i,t})$, where the MES is the one day loss expected if market returns are less than 2%.

Table C.1
Tickers, company names, and financial industry groups.

Depositories (23)	
BAC	Bank of America
BBT	BB&T
BK	Bank of New York Mellon
CITI	Citigroup
CMA	Comerica inc
HBAN	Huntington Bancshares
HBCK	Hudson City Bancorp
JPM	JP Morgan Chase
KEY	Keycorp
MI	Marshall & Ilsley
MTB	M & T Bank Corp
NCC	National City Corp
NTRS	Northern Trust
PBCT	Peoples United Financial[a]
PNC	PNC Financial Services
RF	Regions Financial
SNV	Synovus Financial
STI	Suntrust Banks
STT	State Street
USB	US Bancorp
WB	Wachovia[a]
WFC	Wells Fargo & Co
ZION	Zion
Other Financials (13)	
AMP	Ameriprise Financial
AXP	American Express
BEN	Franklin Resources
BLK	Blackrock[a]
CME	CME Group
COF	Capital One Financial
FITB	Fifth Third Bancorp
ICE	Intercontinental Exchange[a]
JNS	Janus Capital
MA	Mastercard[a]
LM	Legg Mason
NYX	NYSE Euronext[a]
SLM	SLM Corp
Insurance (27)	
AFL	Aflac
AIG	American International Group
AIZ	Assurant[a]
ALL	Allstate Corp
AON	Aon Corp
BKH	Berkshire Hathaway[a]
CB	Chubb Corp
CFC	Countrywide Financial
CI	CIGNA Corp
CINF	Cincinnati Financial Corp
CVH	Coventry Health Care
GNW	Genworth Financial
HIG	Hartford Financial Group
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	Travellers
UNH	Unitedhealth Group
UNM	Unum Group
Broker-Dealers (8)	
BSC	Bear Stearns
ETFC	E-Trade Financial
GS	Goldman Sachs
LEH	Lehman Brothers
MER	Merrill Lynch
MS	Morgan Stanley
SCHW	Schwab Charles
TROW	T. Rowe Price

Notes: This table presents the list of tickers and company names included in our analysis. The list is sorted by financial industry group.
[a]Indicates companies not included in the analysis because of data availability.

Table C.2
Global Financial Crisis: key events for testing options-based systemic risk.

Date – t	Description of the testing period – $t-h-28:t$
2007	
9th August	Markets wake up to mortgage problems and credit spills over when French bank BNP Paribas and other issuers of asset-backed commercial paper encounter problems rolling over outstanding volumes, and large investment funds freeze redemptions after citing an inability to value their holdings.
14th September	Northern Rock, the UK's fifth-largest mortgage lender, suffers the first run on a British bank since 1866, after being forced to approach the Bank of England for a loan facility to replace money market funding. To face this credit crunch, the chancellor Alistair Darling is forced to step in with liquidity support for the bank, which will fall into state ownership in February, 2008.
2008	
16th March	J.P. Morgan Chase agreed to pay USD10 a share to buy Bear Stearns. The agreement is facilitated by the Federal Reserve System (FED) that agreed to offer a USD29 billion credit line to J.P. Morgan Chase.
15th July	This period is characterized by three key events. On June 4, Moody's and Standard & Poor's take negative rating actions on monoline insurers MBIA and Ambac. These ratings created fears about valuation losses on securities insured by these companies. On July 13, the US authorities announce plans for backstop measures supporting Fannie Mae and Freddie Mac that include purchases of agency stock. Finally, on July 15, the US Securities and Exchange Commission issues an order restricting "naked short selling".
17th September	This period is characterized by four key events. On September 7, the US government is forced to bail out Fannie Mae and Freddie Mac. On September 15, Bank of America agreed to by Merrill Lynch for USD50 billion. Panic breaks out in markets across the world as Lehman Brothers Holdings Inc files for Chapter 11 bankruptcy protection. The next day the FED is forced into an USD85 billion bailout of American International Group. Finally, on September 17, the Halifax Bank of Scotland is bought by Lloyds TSB, and J.P. Morgan Chase and Goldman Sachs come under threat.
13th October	This period is includes five key events. On September 29, FTSE 100 falls 15%; while, the MSCI World index falls 6% during the day. The UK mortgage lender Bradford & Bingley is nationalized; banking and insurance company Fortis receives a capital injection from three European governments; German commercial property lender Hypo Real Estate secures a government-facilitated credit line; troubled US bank Wachovia is taken over; the proposed Troubled Asset Relief Program (TARP) is rejected by the US House of Representatives. The next day, Dexia financial group receives a government capital injection; moreover, European governments announce a guarantee safeguarding all deposits, covered bonds and senior and subordinated debt of their main banks. On October 3, the US Congress approves the revised TARP. On the 8th, major central banks undertake a coordinated round of policy rate cuts; while, the UK authorities announce support and capital injections for UK-incorporated banks. Finally, on October 13, major central banks jointly announce the provision of unlimited amounts of US dollar funds to ease tensions in money markets.
11th December	Three key events: On November 15, the G20 countries plan joint efforts to enhance cooperation, restore global growth and reform the world's financial systems. On November 25, the FED creates a USD200 billion facility to extend loans against securitizations backed by consumer and small business loans; in addition to USD500 billion for purchases of bonds and mortgage-backed securities issued by US housing agencies. On December 11, the US government announce the world's largest economy is shrinking, just before the FED cuts interest rates to a 0% lower bound, the lowest in history.
2009	
5th March	The Bank of England launches a programme worth about USD100 billion that is aimed at outright purchases of private sector assets and government bonds over a 3-month period; moreover, it cuts the bank rate to 0.5%, its lowest level ever (until the post-Brexit vote emergency cut).
21st May	This period includes three key events. On May 7, the ECB's Governing Council decides in principle that the Euro-system will purchase euro-denominated covered bonds; the US authorities publish the results of their stress tests and identify 10 banks with an overall capital shortfall of USD75 billion that will be covered chiefly through additions to common equity. Two days after, the European debt crisis kicks off. On May 21, Standard and Poor's ratings service lowers its outlook on UK sovereign debt from stable to negative because of support to the nation's banking system.

Notes: This table presents the key events of the Global Financial Crisis, which have been used to test the early warning information content of the options-based systemic risk measures.

Table C.3
Descriptive statistics of the US financial sector and industries' systemic risk.

	SOVaR					
	Mean	Median	Std. dev.	Min	Max	N. obs
All Financial Industries	20.30	15.42	12.56	0.97	61.89	3678
Depositories	22.90	17.43	15.23	1.70	95.51	3678
Insurance	21.83	16.93	13.65	0.93	89.32	3678
Others	22.23	18.34	11.83	0.98	70.39	3678
Broker-Dealers	27.67	22.31	18.48	0.02	134.73	3678
	$\Delta CoVaR$					
	Mean	Median	Std. dev.	Min	Max	N. obs
All Financial Industries	2.36	1.81	1.53	0.90	9.56	3678
Depositories	3.37	2.41	3.17	0.89	19.24	3678
Insurance	1.40	1.14	0.82	0.26	4.78	3678
Others	1.64	1.33	1.12	0.40	6.05	3678
Broker-Dealers	3.05	2.47	1.49	0.90	9.11	3678
	MES					
	Mean	Median	Std. dev.	Min	Max	N. obs
All Financial Industries	2.78	2.43	1.76	0.36	10.87	3678
Depositories	2.85	2.46	2.06	0.41	12.03	3678
Insurance	2.36	1.99	1.61	0.12	9.74	3678
Others	2.70	2.37	1.63	0.13	9.85	3678
Broker-Dealers	3.21	2.81	1.89	0.36	10.87	3678
	$SRISK$					
	Mean	Median	Std. dev.	Min	Max	N. obs
All Financial Industries	23699.49	6357.73	46446.42	0.00	279565.50	3678
Depositories	7247.09	308.25	16339.61	0.00	85370.64	3678
Insurance	8603.66	1160.15	16647.83	0.00	11882.30	3678
Others	5275.94	2389.72	8428.35	0.00	42918.28	3678
Broker-Dealers	2572.79	23.63	6050.37	0.00	37074.17	3678

Notes: This table presents the descriptive statistics of the US financial industries' systemic risk. The options-based systemic risk is measured with SOVaR; while the stock market-based systemic risk is measured with $\Delta CoVaR$, MES, and $SRISK$. The columns (2–7) show the average, median, standard deviation, minimum value, maximum value, and number of observations.

Appendix D. Additional SOVaR results

In this section we present additional SOVaR results. First, we show the difference between the SOVaR measure and the stock-based systemic risk measures (Fig. D.1). Second, we show the SOVaR plots when the beta implied measure is replaced with the (French et al., 1983) beta approach (Fig. D.2). Then we depict some plots with the sub-sector components of the SOVaR (Figs. D.4 and D.3) and other empirical results at the sub-sector level (Tables from D.1 to D.3).

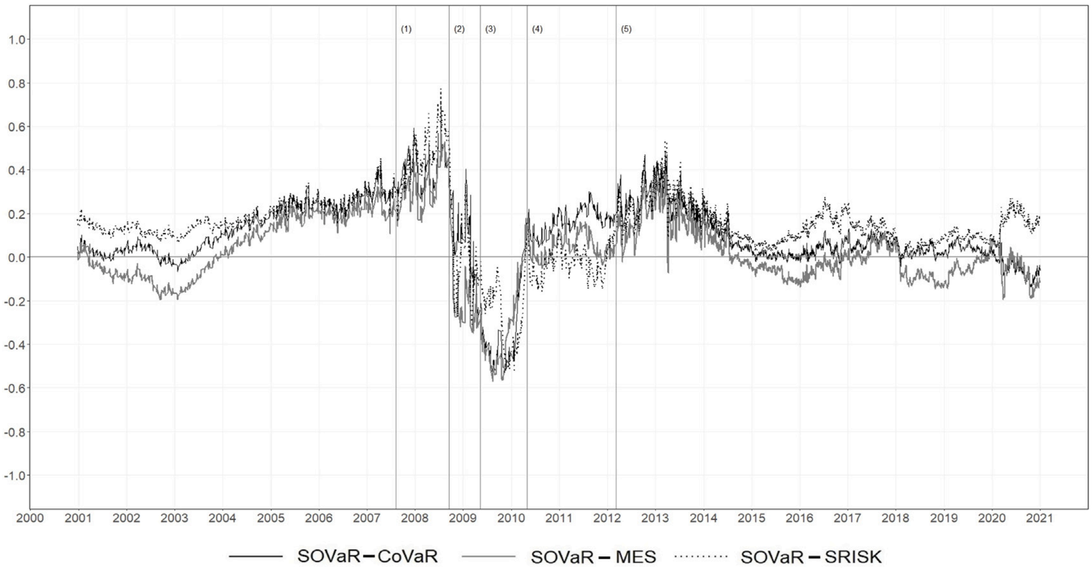

Fig. D.1. SOVaR vs. stock-market based systemic risk measures.
Notes: This plot shows the difference between our SOVaR and one of the three other stock-market based systemic risk measures, namely $\Delta CoVaR$, MES, and $SRISK$. The vertical lines denote: (1) the freezing of BNP Paribas funds on August 9, 2007; (2) the Lehman Brothers bankruptcy on September 15, 2008; (3) the start of the European debt crisis on May 9, 2009; (4) the agreement between the Greek government and the IMF for the first bailout package of €110 billion on May 2, 2010; and (5) the peak of 44.21% reached by the Greek 10-year bond yields on March 9, 2012. Time-series are estimated from January 2000 to December 2020, at the daily frequency.

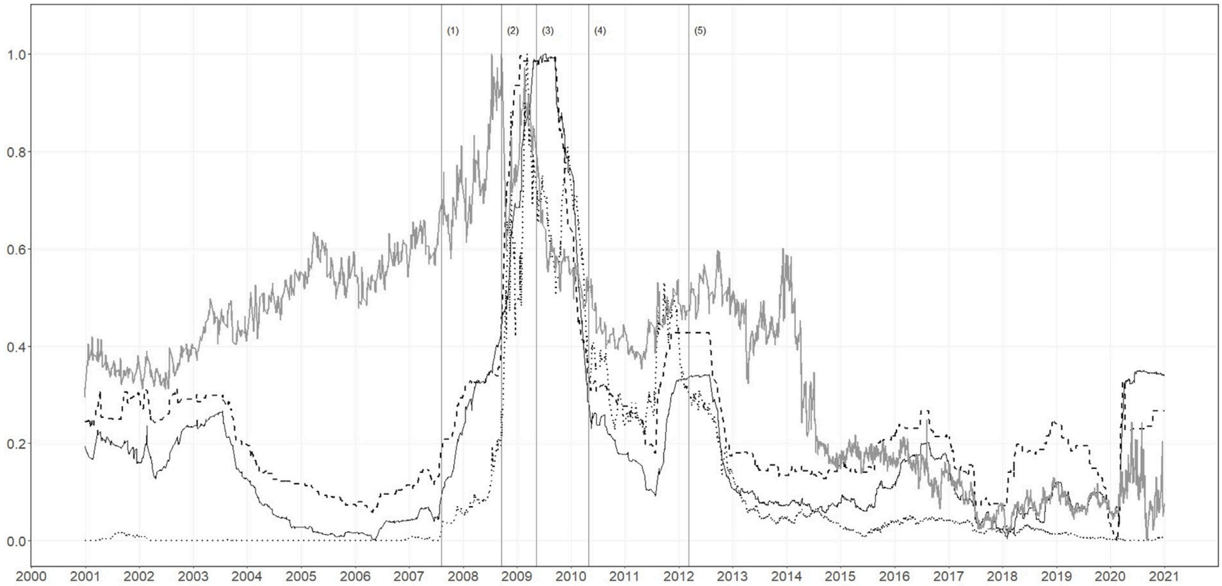

Fig. D.2. Systemic risk of US financial system: $SOVaR_{Beta-FGK}$ vs stock market-based systemic risk measures.
Notes: The figure shows the time series of the SOVaR computed from the implied *Betas* by French et al. (1983) and the SRMs for the US financial system. The vertical lines denote: (1) the freezing of BNP Paribas funds on August 9, 2007; (2) the Lehman Brothers bankruptcy on September 15, 2008; (3) the start of the European debt crisis on May 9, 2009; (4) the agreement between the Greek government and the IMF for the first bailout package of €110 billion on May 2, 2010; and (5) the peak of 44.21% reached by the Greek 10-year bond yields on March 9, 2012. Time-series are estimated from January 2000 to December 2020, at the daily frequency.

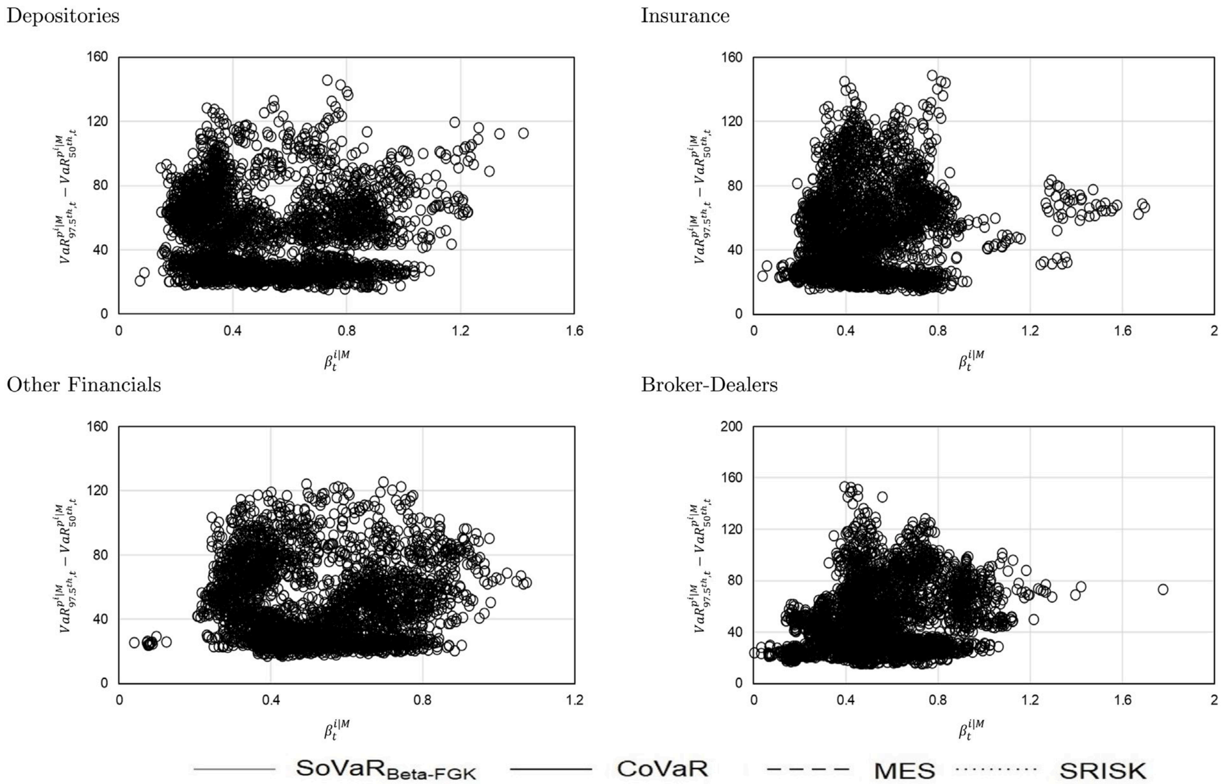

Fig. D.3. SOVaR components of US financial industries: $\beta_t^{i|\mathcal{M}}$ and $VaR_{q,t}^{P^i|\mathcal{M}} - VaR_{50,t}^{P^i|\mathcal{M}}$.
Notes: This scatter plot shows the correlation between the two components of SOVaR for the financial industries. Institutions' risk in isolation is measured by the difference $VaR_{q,t}^{P^i|\mathcal{M}} - VaR_{50,t}^{P^i|\mathcal{M}}$ (y-axis), whereas institutions' co-movement is measured by $\beta_t^{i|\mathcal{M}}$ (x-axis). Time-series are estimated from January 2000 to December 2020, at the daily frequency.

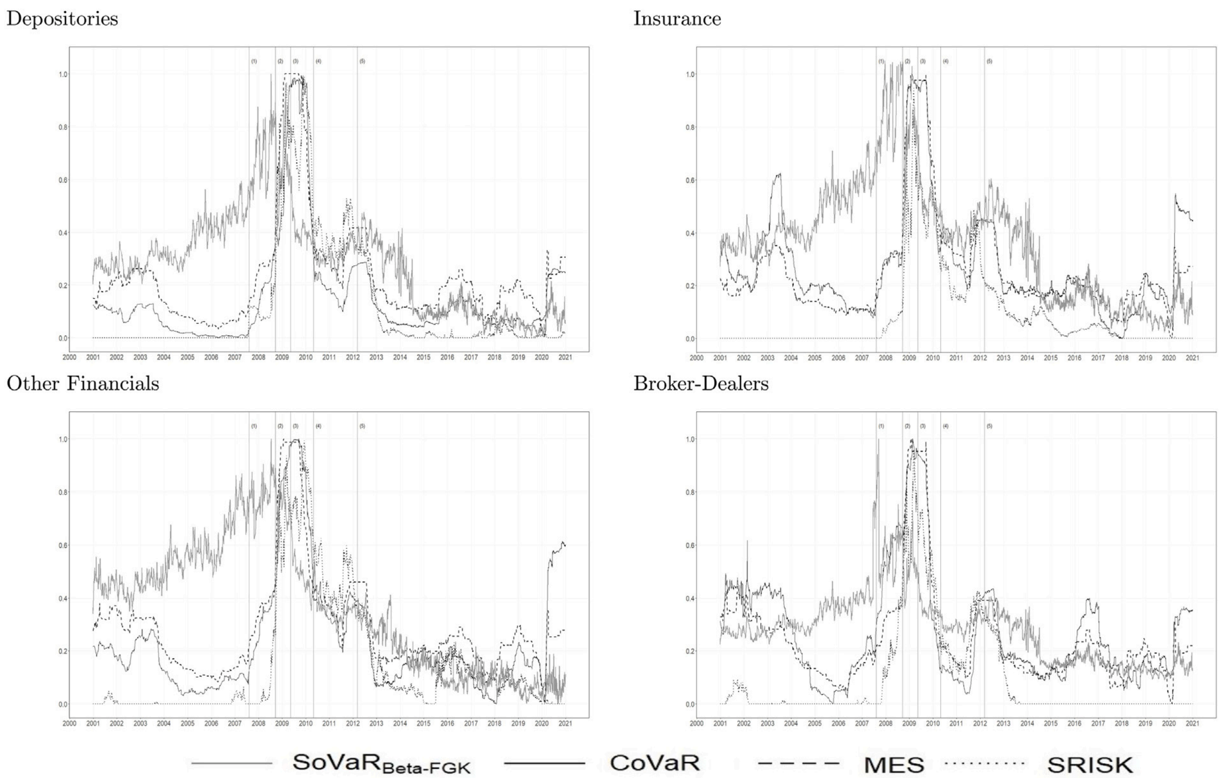

Fig. D.4. Systemic risk of US financial industries: $SOVaR_{Beta-FGK}$ vs stock market-based systemic risk measures.
Notes: The figure shows the time series of the SOVaR computed from the implied $Betas$ by French et al. (1983) and the SRMs of the US depositories, insurance, broker-dealers, and other financials industries. The vertical lines denote: (1) the freezing of BNP Paribas funds on August 9, 2007; (2) the Lehman Brothers bankruptcy on September 15, 2008; (3) the start of the European debt crisis on May 9, 2009; (4) the agreement between the Greek government and the IMF for the first bailout package of €110 billion on May 2, 2010; and (5) the peak of 44.21% reached by the Greek 10-year bond yields on March 9, 2012. Time-series are estimated from January 2000 to December 2020, at the daily frequency.

Table D.1
Dominance test results during the key events of the GFC.

	H_0: $SOVaR_{t-h-28:t-h} \leq \Delta CoVaR_{t-28:t}$					H_0: $SOVaR_{t-h-28:t-h} \leq MES_{t-28:t}$					H_0: $SOVaR_{t-h-28:t-h} \leq SRISK_{t-28:t}$				
	$h = 0$	$h = 7$	$h = 14$	$h = 21$	$h = 28$	$h = 0$	$h = 7$	$h = 14$	$h = 21$	$h = 28$	$h = 0$	$h = 7$	$h = 14$	$h = 21$	$h = 28$
August 9th, 2007															
Depositories	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Insurance	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Others	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Broker-Dealers	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
September 14th, 2007															
Depositories	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Insurance	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Others	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Broker-Dealers	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
March 16th, 2008															
Depositories	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Insurance	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Others	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Broker-Dealers	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
July 15th, 2008															
Depositories	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Insurance	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Others	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Broker-Dealers	0.917***	0.636**	0.636**	0.636**	0.583**	0.417	0.364	0.364	0.583**	0.818***	1.000***	1.000***	1.000***	1.000***	1.000***
September 17th, 2008															
Depositories	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Insurance	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Others	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Broker-Dealers	0.809***	0.809***	0.727***	0.727***	0.727***	0.833***	0.750***	0.750***	0.750***	0.607**	1.000***	1.000***	1.000***	1.000***	0.857***
October 13th, 2008															
Depositories	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Insurance	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Others	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Broker-Dealers	0.667**	0.636**	0.636**	0.583**	0.455*	0.667**	0.636**	0.636**	0.583**	0.273•	1.000***	1.000***	1.000***	1.000***	1.000***
December 11th, 2008															
Depositories	0.818***	0.809***	0.727***	0.727***	0.727***	0.000•	0.000•	0.000•	0.000•	0.000•	0.100•	0.100•	0.000•	0.000•	0.000•
Insurance	0.900***	0.900***	0.818***	0.818***	0.455*	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•
Others	0.818***	0.709***	0.636**	0.636**	0.636**	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•
Broker-Dealers	0.100•	0.091•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•
March 5th, 2009															
Depositories	0.000•	0.000•	0.000•	0.000•	0.000•	0.009•	0.000•	0.000•	0.000•	0.000•	0.273•	0.100•	0.000•	0.000•	0.000•
Insurance	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•
Others	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•
Broker-Dealers	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•
May 21st, 2009															
Depositories	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•
Insurance	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•
Others	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•
Broker-Dealers	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•	0.000•

Notes: This table presents the results, for the financial industries, of the Kolmogorov–Smirnov bootstrap test that determines whether: (i) the CDFs of the SOVaR are greater than the one for $\Delta CoVaR$, MES, and $SRISK$ (columns: 2 to 6; 7 to 11; and, 12 to 16, respectively) for each financial industry during key events of the GFC listed in Table C.2. The hypotheses tested are stated in the headers of the table. The failure to reject the null hypothesis means that the SOVaR is not greater than $\Delta CoVaR$, MES, and $SRISK$ (columns: 2 to 6; 7 to 11; and, 12 to 16, respectively). The columns contain the test statistic. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively; while, • indicates a statistically significant inverse relation.

Table D.2
Bivariate Financial Industries SOVaR Predictive Results.

	Dependent variable: ADS					*Dependent variable: CFNAI*				
	h = 1	h = 3	h = 6	h = 9	h = 12	h = 1	h = 3	h = 6	h = 9	h = 12
SOVaR Dep	−0.011***	−0.012***	−0.016***	−0.017***	−0.018***	−0.015***	−0.017***	−0.021***	−0.023***	−0.023***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Adj. R^2	0.063	0.078	0.136	0.157	0.170	0.088	0.111	0.176	0.209	0.207
SOVaR Ins	−0.010***	−0.011***	−0.013***	−0.014***	−0.014***	−0.014***	−0.016***	−0.019***	−0.018***	−0.020***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Adj. R^2	0.033	0.044	0.068	0.073	0.072	0.057	0.070	0.099	0.092	0.108
SOVaR Others	−0.012***	−0.014***	−0.018***	−0.020***	−0.021***	−0.016***	−0.019***	−0.023***	−0.025***	−0.028***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Adj. R^2	0.038	0.054	0.090	0.111	0.133	0.053	0.075	0.112	0.131	0.163
SOVaR BD	−0.001	−0.002	−0.005**	−0.009***	−0.011***	−0.002	−0.003	−0.008***	−0.011***	−0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Adj. R^2	0.001	0.002	0.019	0.052	0.089	0.002	0.001	0.026	0.060	0.093
	Dependent variable: IP					*Dependent variable: NBER*				
	h = 1	h = 3	h = 6	h = 9	h = 12	h = 1	h = 3	h = 6	h = 9	h = 12
SOVaR Dep	−0.037*	−0.040**	−0.041**	−0.046**	−0.062***	0.006***	0.006***	0.008***	0.008***	0.009***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adj. R^2	0.008	0.008	0.016	0.019	0.039	0.098	0.106	0.165	0.189	0.199
SOVaR Ins	−0.050**	−0.052**	−0.057**	−0.066***	−0.073***	0.006***	0.006***	0.007***	0.007***	0.006***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adj. R^2	0.016	0.018	0.022	0.030	0.038	0.065	0.072	0.094	0.091	0.071
SOVaR Others	−0.059**	−0.062**	−0.069***	−0.081***	−0.095***	0.007***	0.008***	0.010***	0.011***	0.011***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.027)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Adj. R^2	0.017	0.019	0.025	0.035	0.050	0.074	0.082	0.133	0.159	0.168
SOVaR BD	−0.038**	−0.033*	−0.039**	−0.042**	−0.059***	0.001	0.002*	0.004***	0.005***	0.006***
	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adj. R^2	0.006	0.008	0.011	0.012	0.027	0.001	0.007	0.043	0.081	0.113

Notes: This table presents the bivariate predictive results for the SOVaR constructed for the four financial sub-industries, namely, SOVaR Dep, SOVaR Ins, SOVaR Others, and SOVaR BD for depositories, insurance, other financials and broker-dealers, respectively. The predictive horizons are equal to 1, 3, 6, 9, and 12 months. The results are reported for the selected macroeconomic indicators, ADS, IP, CFNAI, and the NBER recession dummy. The coefficients, standard errors (in parentheses) and adjusted R^2s are reported for the OLS regression. A probit model is run for the NBER dummy variable, and pseudo-R^2s are reported. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table D.3
Multiple Financial Industries SOVaR Predictive Results.

	Dependent variable: ADS					*Dependent variable: CFNAI*				
	h = 1	h = 3	h = 6	h = 9	h = 12	h = 1	h = 3	h = 6	h = 9	h = 12
SOVaR Dep| RMs	−0.011***	−0.016***	−0.024***	−0.027***	−0.027***	−0.013***	−0.020***	−0.029***	−0.033***	−0.032***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Adj. R^2	0.338	0.242	0.262	0.314	0.316	0.321	0.226	0.258	0.310	0.299
SOVaR Ins| RMs	−0.006*	−0.011***	−0.017***	−0.020***	−0.021***	−0.009*	−0.015***	−0.021***	−0.023***	−0.026***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Adj. R^2	0.234	0.199	0.157	0.168	0.215	0.242	0.192	0.145	0.149	0.218
SOVaR Others| RMs	−0.008**	−0.012**	−0.017***	−0.020***	−0.023***	−0.011**	−0.011**	−0.022***	−0.025***	−0.029***
	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Adj. R^2	0.372	0.251	0.168	0.184	0.172	0.354	0.220	0.141	0.144	0.128
SOVaR BD| RMs	0.002	0.002	−0.002	−0.007***	−0.013***	0.003	0.002	−0.003	−0.010***	−0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Adj. R^2	0.362	0.280	0.261	0.212	0.195	0.380	0.314	0.247	0.180	0.159
	Dependent variable: IP					*Dependent variable: NBER*				
	h = 1	h = 3	h = 6	h = 9	h = 12	h = 1	h = 3	h = 6	h = 9	h = 12
SOVaR Dep| RMs	0.039**	0.038**	0.031	−0.033*	−0.065***	0.007***	0.007***	0.011***	0.014***	0.014***
	(0.018)	(0.018)	(0.019)	(0.019)	(0.020)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adj. R^2	0.340	0.351	0.325	0.288	0.267	0.266	0.205	0.250	0.383	0.393
SOVaR Ins| RMs	0.019	0.015	−0.002	−0.025	−0.045**	0.004***	0.006***	0.009***	0.010***	0.009***
	(0.017)	(0.016)	(0.017)	(0.018)	(0.019)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adj. R^2	0.544	0.570	0.547	0.497	0.447	0.159	0.127	0.175	0.205	0.181
SOVaR Others| RMs	−0.010	−0.012	−0.020	−0.036*	−0.053***	0.006***	0.007***	0.010***	0.011***	0.012***
	(0.021)	(0.020)	(0.020)	(0.020)	(0.019)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Adj. R^2	0.378	0.436	0.476	0.494	0.528	0.360	0.291	0.273	0.312	0.314
SOVaR BD| RMs	−0.038***	−0.031**	−0.023*	−0.024*	−0.035**	−0.001	0.001	0.003***	0.005***	0.007***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adj. R^2	0.427	0.477	0.493	0.482	0.472	0.404	0.319	0.230	0.211	0.227

Notes: This table presents the multiple predictive results for the SOVaR constructed for the four financial sub-industries, namely, SOVaR Dep, SOVaR Ins, SOVaR Others, and SOVaR BD for depositories, insurance, other financials and broker-dealers, respectively. The predictive horizons are equal to 1, 3, 6, 9, and 12 months. The results are reported for the selected macroeconomic indicators, ADS, IP, CFNAI, as well as the NBER recession dummy. Controls variables are $\Delta CoVaR$, MES, and $SRISK$ for the corresponding financial industries taken jointly (RMs). The coefficients, standard errors (in parentheses) and adjusted R^2s are reported for the OLS regression. A probit model is run for the NBER dummy variable, and pseudo-R^2s are reported. The coefficients of the controls are not reported for the sake of space. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

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