SenSR: A Sentiment-based Systemic Risk Indicator

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August 2016

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The media influence our perception of reality and, since we act on those perceptions, reality is in turn affected by the media. News is a rich source of information, but, in addition, the sentiment (i.e., the tone of financial news) tells us how others perceive the financial system and how that perception changes.

In this paper we propose a new indicator of the systemic risk in the global financial system. We call it SenSR: Sentiment-based Systemic Risk Indicator. This measure is constructed by dynamically aggregating the sentiment in news about systemically important financial institutions (SIFIs).

We test the SenSR for its ability to indicate or even forecast systemic stress in the financial system. We compare its performance to other well-known systemic risk indicators, as well as with macroeconomic fundamentals. We find that SenSR anticipates other systemic risk measures such as SRISK or VIX in signaling stressed times. In particular, it leads other systemic risk measures and macroeconomic indicators by as long as 12 weeks.

1. Introduction

Since the latest financial crisis, the issue of systemic risk has captured the attention of academics, regulators and other finance practitioners. Many sources and measures of systemic risk have been suggested and investigated (for a good review on this topic see, e.g., Benoit, Colliard, Hurlin, and Perignon (2015)). One strand of research investigates (by means of e.g., network analysis) how systemic risk arises from decisions of a particular financial institution, how risk spreads to other institutions and how it produces high volatility and losses for the whole financial system. Other studies use these results to construct market-wide measures of systemic risk, the most famous example being SRISK, introduced by V-LAB (Engle and Brownlees (2015)). SRISK is computed (per company, country, continent or worldwide) as the expected capital shortfall conditional on a market decline of 10%. It can be interpreted as the amount of capital required from regulators to save a company or a region in case of a systemic crash event. Engle and Brownlees (2015) show that SRISK provides an early warning signal for regulators, identifying Morgan Stanley, Bear Stearns and Lehman Brothers as top contributors to systemic risk pre-crisis, establishing SRISK as a useful predictor variable for declines in macroeconomic indicators (such as industrial production and the unemployment rate), particularly for longer horizons (9-12 months).

In this paper, we look at the systemic risk from the media sentiment standpoint. The influence of media on our perception of reality (and hence, on the reality itself) cannot be underestimated. The tone of news, or its sentiment, is often just as important as the actual information conveyed by the news. When we characterize elusive concepts such as "the state of the economy" or "the health of the financial system," we should realize that the socioeconomic reality is the result of human behavior and interactions. Based on the available information and our opinions, we form our own perception of the reality whereupon we act. In this way the loop is closed and the reality is driven by our perception of it. Our perception of the reality is strongly influenced by the media: The availability of information is related to the media attention, and the media bias about a certain topic strongly influences our opinion. As a result, the news and the media not only can change our perception of the reality – it can change reality itself. A great example of this is the UK referendum about leaving the EU, where not truthful, objective information but "news value"-driven (hysterical) and often biased media had a great influence on many voters, resulting in a momentous change of the reality for the UK and the rest of the world.

Similarly, when news and media are overwhelmed by a negative sentiment about the financial system, i.e., when the general feeling is that the financial system is not stable, agents in the financial markets act in ways that increase volatility (for example, by trading, or withdrawing bank deposits) and as a result can destabilize the financial system.

Our systemic risk indicator – which we call SenSR (for Sentiment-based Systemic Risk) – is based on the aggregated sentiment in news about major players in the global financial system: the so-called Systemically Important Financial Institutions (SIFIs). These institutions have the capacity to single-handedly destabilize the financial system, due to their exceptional size and central role. So the health of the financial system as a whole is largely determined by how "healthy" these institutions are (or at least whether we perceive them as being stable and healthy). Many measures of systemic risk are based on "hard," i.e., quantifiable, measures of these institutions' financial health, such as their leverage, creditworthiness, capitalization or amount of money they can lose in case of a market crash. We will look at them from another perspective, i.e., whether these institutions are perceived as "healthy" or "solid" by the media and, hence, by most of the players in the financial markets (and the public as a whole). We will quantify this perception by the sentiment (i.e., the tone) of news about them.

Previously, there have been only a few attempts to study the relationship between sentiment and proposed risk indicators. For example, Barone-Adesi, Mancini, and Shefrin (2012) use a behavioral version of pricing kernel theory for constructing optimism and overconfidence indices. Another example is the paper of Smales (2014), who investigates relationships between a company's perceived credit risk, measured as Credit Default Swap (CDS) spread, and the sentiment in news articles relevant to that company. His analysis confirms the hypothesis that credit risk increases with negative news. Another finding there, relevant to our work, is that there are spillover effects from news about large systematically important banks to regional and global CDS spreads.

The news sentiment data used for SenSR is obtained from the Thomson Reuters News Analytics (TRNA) engine: an artificial intelligence engine which reads and interprets (in real time) all the news that hits the Reuters newswire. We consider all news items that are relevant for systemically important financial institutions (banks, but also large insurance companies, investment funds and asset managers). Individual companies' news sentiment scores are aggregated weekly, where we also take into account the relevance and novelty of the news items as well as their republications by different news publishers. Subsequently, company-specific weekly scores are again aggregated across all systemically important financial institutions and asset managers, to obtain the resulting indicator. This aggregation procedure gives rise to several variants of SenSR, obtained by weighting the news sentiment scores by alternative bank-related measures such as market value (i.e., the company's size), its total debt or leverage. We find that weighting the news sentiment by either debt or by leverage provides the strongest signal of systemic stress. The details of SenSR construction are given in the next section.

We observe a long period of high overall positive sentiment from 2003 to 2007. The picture starts to change in early 2007, with an increasing trend in negative sentiment, which peaks in the first months of 2009. We also see increasing negative sentiment in 2011-2012, which corresponds to the European sovereign debt crisis. Our historical data period ends in the beginning of 2016; however, it would be extremely interesting to see the effect of the UK's referendum on leaving the EU (aka Brexit) on our indicator of systemic risk. We expect to report on this in the near future.

We conduct a number of tests on our systemic risk measure. First, we test for Granger causality between SenSR and other systemic risk indicators (such as LIBOR-OS spread, VIX and SRISK). We find that SenSR Granger-causes all these established risk measures at different time lags – up to 12 weeks. This means that SenSR tells us about the increased risk in the financial system up to 12 weeks before other systemic risk measures start to pick up on it.

We also investigate the relationships between SenSR, other risk measures and macroeconomic variables such as GDP, industrial production, unemployment rate, money supply and S&P 500 returns. We again test for causality and study the impulse response functions, to compare the predictive value of SenSR against other systemic risk measures. Our tests show that a substantial increase in SenSR is followed by significant effects in macroeconomic data, and that these effects are much larger for SenSR than for other risk measures such as SRISK.

In all, we find that SenSR tells us something about the health of the financial system that other risk measures do not, and it does it with a significant time advantage. This shows that perception about systemic risk matters a great deal: The signals obtained from "soft" sources such as new and media sentiment add invaluable information to the traditional, "hard" measures of risk.

2. SenSR construction

Our systemic risk indicator is based on the sentiment in news about systemically important financial institutions (SIFIs). We identify systemically important banks and insurers, following the definition of the Board of Financial Stability.[1] Additionally, we identify the 15 largest asset managers as also being systemically important. The complete list of the financial institutions we consider is in the Appendix.

The news sentiment data is obtained from Thomson Reuters News Analytics (TRNA) database. TRNA uses sophisticated natural language processing algorithms to interpret (in real time) all news that hits the Reuters newswire, for its relevance to a large number of stocks (and commodities), novelty and, most importantly, sentiment.

The database's most important contents, available for each news item (and the ones that we use for constructing SenSR), are:

- **Relevance score:** number between zero and one indicating how relevant a news item is for a particular company or commodity.
- **News sentiment scores (positive, neutral or negative):** also numbers between zero and one, that sum up to one. These scores can be interpreted as probabilities that the content of the news item is positive, neutral or negative for a particular company or commodity.
- **Novelty score** is expressed as the number of news items with a similar content that appeared previously to the current news item. This measure is available for different time spans (12 hours, 24 hours, 3 days, 5 days, 1 week).

Furthermore, the database contains a wealth of other information, such as story time and date, headline, source, genre, links to other news items and so on.

For each of the financial institutions that we consider, we aggregate the news sentiment scores on a weekly basis. In the aggregation process, we weight the sentiment scores by the relevance score for that news item and assign higher weights to more novel news items.

As an illustration, Figure 1 depicts the aggregated weekly sentiment scores for HSBC Holdings plc, from 2003 to 2014, and shows that the weekly bank-specific sentiment is quite noisy. Therefore, we use a filtering procedure which extracts a meaningful signal from the noisy data.

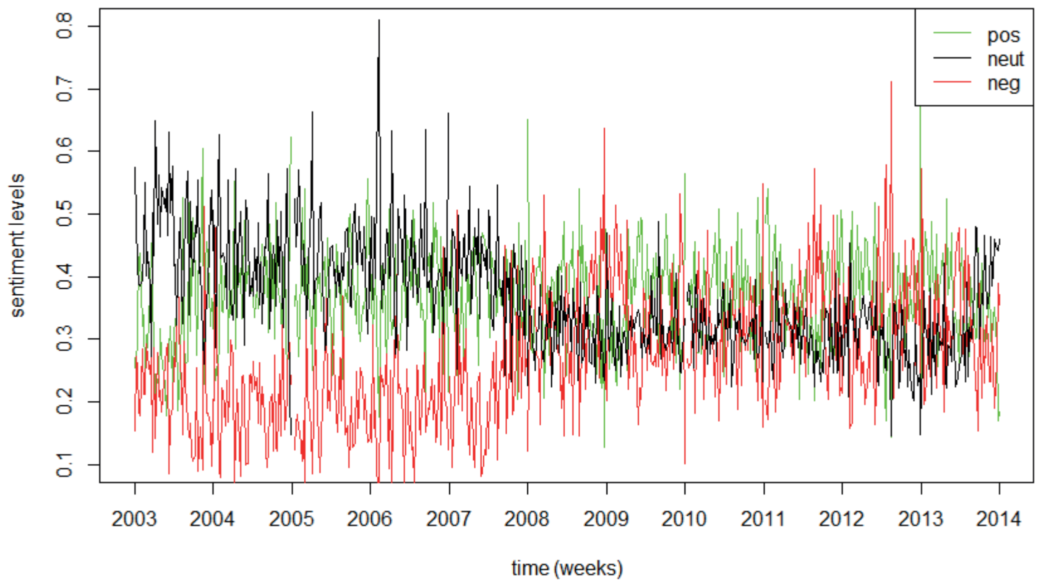

Figure 1: Example of Non-Filtered News Sentiment Probabilities (Company: HSBC).

1 http://www.fsb.org/

We consider the news sentiment scores from TRNA as noisy observations of the actual but unobserved news sentiment. For both observed and unobserved sentiments, we postulate the so-called Local Level model, which is a particular form of a state space model. Denote the unobserved state as μ_t and the observed signal as y_t. Following Borovkova and Mahakena (2015), we define the *Local News Sentiment Level (LNSL) model* as

$$y_{t+1} = \mu_t + \epsilon_t, \qquad \epsilon_t \sim \mathcal{NID}(0, \sigma_\epsilon^2) \tag{1}$$

$$\mu_{t+1} = \mu_t + \eta_t, \qquad \eta_t \sim \mathcal{NID}(0, \sigma_\eta^2) \tag{2}$$

The first equation is called the observation equation and the second one – the state equation, which describes the evolution of the true unobserved news sentiment, in our model assumed to be a random walk. Although the state μ_t is not observed, the Kalman Filter, applied to the LNSL model, can deduce the actual states from the noisy observations. In this filtering process, the unobserved state is updated each time a new observation comes.

The series of the Kalman-filtered sentiments for HSBC Holdings plc is shown in Figure 2, which is much less noisy than the figure above.

Figure 2: Example of Kalman-Filtered News Sentiment Probabilities (Company: HSBC).

Our systemic risk indicator – SenSR – is constructed from these filtered news sentiment probabilities for all financial institutions in our sample. When working with TRNA sentiment scores, the so-called *net sentiment* is often used, which is the difference between the positive and negative sentiment scores. Here we use a version of it, given by (for bank i at time t)

$$p_{i,t}^{net} = (p_{i,t}^{pos} - p_{i,t}^{neg})(1 - p_{i,t}^{neu}), \tag{3}$$

where $p^{pos,neu,neg}$ are the Kalman-filtered sentiment probabilities.

Next, using some appropriate bank-related weights $w_{i,t}$, we aggregate all company- specific sentiment scores into one number, which is our systemic risk indicator:

$$SenSR_t = \sum_{i=1}^{N} w_{i,t} p_{i,t}^{net}, \tag{4}$$

where N is the number of financial institutions we consider.

Here we consider four different weighting schemes (and thus four versions of SenSR): the company's market capitalization, the net debt (total debt – common equity), the leverage ratio (total debt/total assets) and a combination of market capitalization and leverage ratio. All weights are relative, i.e., normalized to sum up to one. The historical series of SenSR for all four weighting schemes is shown in Figure 3.

Figure 3: Historical SenSR. Black: market value weights, blue: leverage, red: market value and leverage, orange: debt.

Note that we show here the SenSR values relative to its value on January 1, 2003, i.e., in the beginning of our sample. In this way we can see, for example, that at the height of the financial crisis of 2007-2008, SenSR was three times higher than in the beginning of 2003, and during the European sovereign crisis of 2011-2012 – even four times higher. We also can observe that, although all four versions of SenSR move in unison, the version which uses debt-based weights seems to give the strongest signal of distress in the financial system.

Our SenSR indicator can be computed for different regions as well as globally – for its regional values see Figure 4. This figure clearly shows, for example, the higher magnitude of the European debt crisis in Europe than in the US.

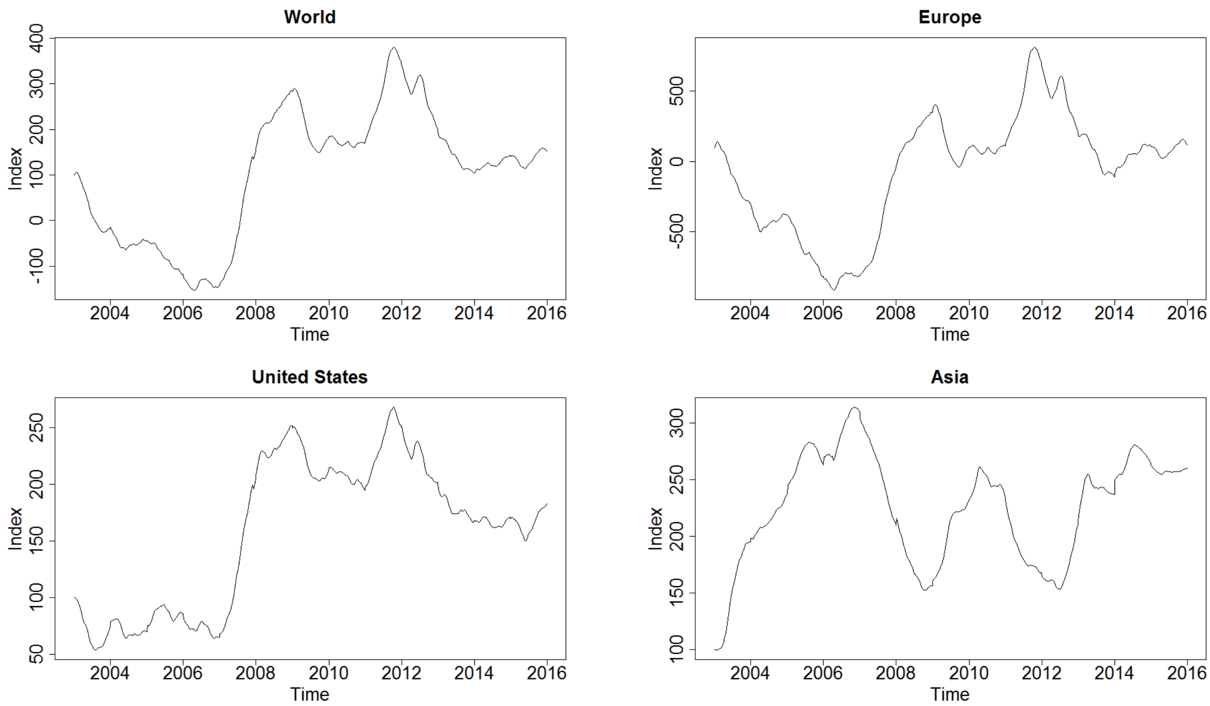

Figure 4: Historical SenSR for different regions.

3. Testing SenSR performance

We test how our systemic risk measure performs in comparison to other ones. For this analysis we focus on the SRISK, introduced by Engle and Brownlees (2015), the Volatility Index for the S&P 500 – VIX – developed by Brenner and Galai (1989) and the LIBOR-OIS spread, which is the difference between the interbank borrowing rate (LIBOR) and Overnight Indexed Swap rate (OIS). All these measures have been used to assess the "health" of the financial system.

The LIBOR-OIS spread indicates the systemic stress in the monetary markets, Thornton (2009). This spread is considered a proxy of a bank's belief about the likelihood of a default of another competitor. The VIX index represents the market's expected volatility for the next 30 days on the US stock market, and is often referred to as the "fear index." The SRISK, computed and published by V-LAB at at New York University (NYU), is a systemic risk measure computed as the expected capital shortfall, i.e., the amount of money required from the regulators to save a company, country or a region in case of a systemic crash event (represented by 10% fall in stock markets). The SRISK, just like SenSR, is computed for different regions and also on a global scale.

Figure 5 depicts SenSR together with all these risk measures and shows that the SenSR is the closest to SRISK – not surprisingly, as both indicators are specifically designed to monitor systemic risk. Both measures start rising early in 2007, whereas the collapse of Lehman Brothers occurred only in September 2008. From the first graph it also appears that SenSR is slightly ahead of SRISK during the entire historical period. Comparing VIX and SenSR, we can see that VIX starts rising slightly in 2007, but peaks only with the Lehman crisis. The LIBOR-OIS spread first peaks in 2007, with the liquidity crisis, but moves back to previous levels for a short time, before the collapse of Lehman. The LIBOR-OIS spread does not react to the Euro crisis. SenSR, in contrast, reaches its peak during this period, even though the systemic impact of the events of 2008 is arguably larger. Our explanation for this is an increase in crashophobia after the 2007-2008 crisis. Besides this graphical comparison, we also perform the so-called *Granger causality test* to study the causal relations between SenSR and other risk measures. This test establishes whether including past values of variable X into a linear predictive model (autoregression) for variable Y helps making better predictions of Y. In other words, it tells us whether past values of X contain useful information about future values of Y, that is not contained in Y's own past history.

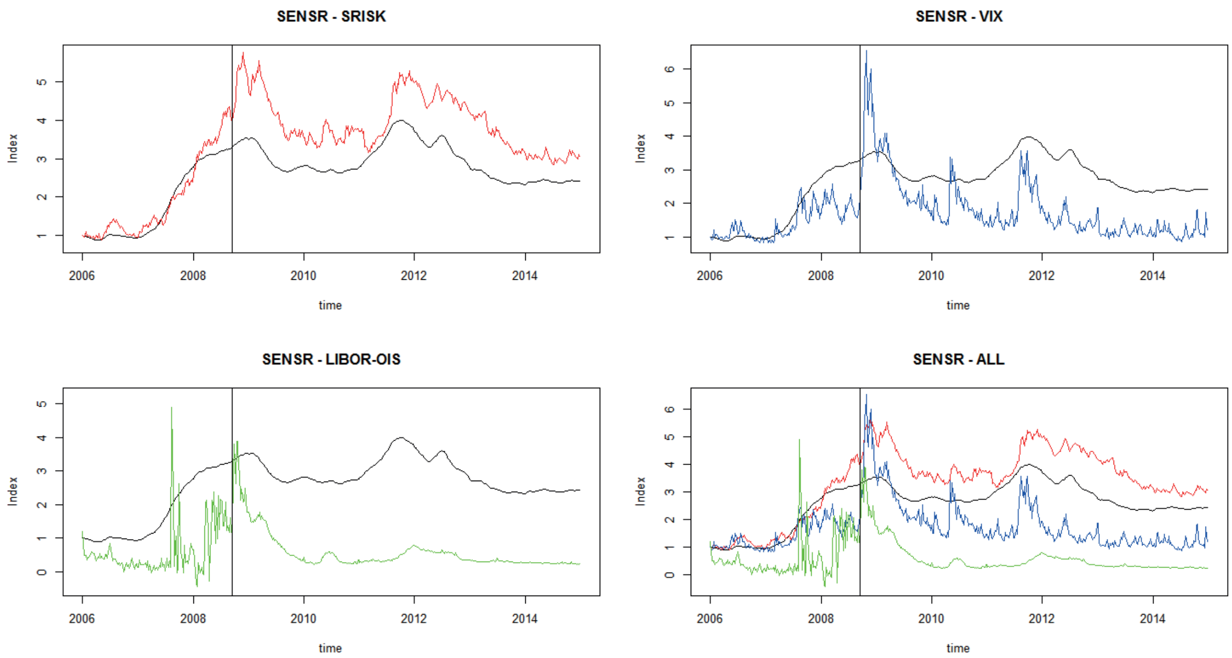

Figure 5: SenSR compared to other systemic risk indicators.

Furthermore, we also analyze causal relationships between SenSR and macroeconomic measures such as stock market indices (S&P 500 and the Euro Stoxx 50), US and EU GDP, unemployment rate, industrial production and central banks' money supply (whose increase can be seen as a sign of instability in the financial system and economy as a whole). Finally, we use the so-called *impulse response functions* (IRF) to study the response of macro and risk measures to a large increase (impulse) in SenSR, in a multivariate framework.

Granger causality between SenSR, SRISK (world and US versions), VIX and LIBOR-OIS spread is tested in a bivariate setting, using weekly data. Table 1 presents the p-values that correspond to the null hypothesis of no Granger causality, at various lags and up to 12 weeks, for the debt-weighted SenSR. We can see that, for SenSR as the explanatory variable, we reject this null hypothesis at all lags and at a high confidence level, for VIX and SRISK (meaning that SenSR does Granger-cause VIX and SRISK), but not for LIBOR-OIS spread. This means, for instance, that if we observe a rise in SenSR, this will help us to predict a subsequent rise in other risk measures such as SRISK or VIX. Remarkably, the lag in this information advantage extends to 12 weeks. The leverage-weighted SenSR performs identically to the debt-weighted one, hence the corresponding p-values are not shown. Market cap-based weights do not lead to such a good performance, with fewer Granger causality relationships observed (for brevity, we did not include the corresponding p-values – these can be provided upon request). So we suggest to use either a debt- or leverage-weighted version of SenSR.

Lags	VIX	US-SRISK	World SRISK	LIBOR-OIS
1	0.001	0.000	0.000	0.706
2	0.002	0.000	0.000	0.643
3	0.002	0.000	0.000	0.529
4	0.002	0.000	0.001	0.575
5	0.001	0.000	0.000	0.457
6	0.000	0.000	0.000	0.418
7	0.000	0.001	0.000	0.398
8	0.001	0.000	0.000	0.313
9	0.001	0.000	0.000	0.296
10	0.000	0.007	0.003	0.107
11	0.000	0.008	0.009	0.134
12	0.002	0.009	0.002	0.119

Table 1: Granger Causality Test: p-values for $\text{SenSR}_{\text{Debt}}$ against other risk measures.

For comparison, we present the results of the Granger causality test of global SRISK as the explanatory variable for SenSR, VIX and LIBOR-OIS. The corresponding p-values are given in Table 2 (the performance of US SRISK is similar and hence, not shown). Contrary to SenSR, SRISK does not seem to Granger-cause VIX, LIBOR-OIS or any of the versions of SenSR (except Market Cap-based SenSR at short lags).

Interestingly, we find that VIX significantly Granger-causes SRISK (both US and global), but not any version of SenSR or LIBOR-OIS spread – the corresponding p-values are shown in Table 3. We found that LIBOR-OIS spread does not cause any other risk measures at any lags, and hence the corresponding p-values are not shown.

Lags	SenSR M-Cap	$\text{SenSR}_{\text{Lev}}$	$\text{SenSR}_{\text{Debt,}}$	SenSR M+L	VIX	LIBOR-OIS
1	0.011	0.567	0.603	0.033	0.247	0.288
2	0.051	0.438	0.988	0.031	0.360	0.175
3	0.076	0.396	0.978	0.035	0.367	0.350
4	0.092	0.441	0.999	0.071	0.470	0.114
5	0.085	0.399	1.000	0.052	0.631	0.330
6	0.161	0.074	0.340	0.128	0.665	0.246
7	0.167	0.076	0.341	0.094	0.615	0.263
8	0.200	0.091	0.432	0.154	0.668	0.316
9	0.140	0.070	0.450	0.118	0.601	0.354
10	0.145	0.073	0.403	0.121	0.592	0.295
11	0.161	0.077	0.371	0.150	0.604	0.257
12	0.128	0.085	0.368	0.157	0.625	0.233

Table 2: Granger Causality Test: p-values for SRISK against other risk measures.

Lags	SenSR m	SenSR (lev)	SenSR	SenSR m+l	US-SRISK	W-SRISK	LIBOR-OIS
1	0.436	0.713	0.194	0.449	0.037	0.000	0.417
2	0.284	0.191	0.046	0.288	0.031	0.001	0.416
3	0.374	0.147	0.087	0.316	0.103	0.001	0.104
4	0.446	0.153	0.108	0.412	0.017	0.002	0.115
5	0.304	0.155	0.149	0.415	0.030	0.000	0.091
6	0.464	0.273	0.257	0.431	0.018	0.001	0.047
7	0.441	0.337	0.345	0.334	0.030	0.000	0.084
8	0.470	0.223	0.134	0.410	0.022	0.001	0.078
9	0.498	0.286	0.222	0.349	0.014	0.004	0.076
10	0.498	0.189	0.143	0.361	0.007	0.001	0.071
11	0.445	0.206	0.174	0.313	0.008	0.001	0.077
12	0.457	0.245	0.188	0.332	0.009	0.005	0.079

Table 3: Granger Causality Test: p-values for VIX against other risk indicators.

To summarize, we find strong Granger causality relations between SenSR and other risk indicators, with debt- or leverage-based SenSR showing the best predictive results. These causality relations are one-sided, meaning that SenSR contains new information about future developments of other risk indicators (SRISK, VIX) that is not incorporated in their own past history, but not the other way around.

Next, we test for Granger causality between the risk indicators and the macroeconomic variables, in a multivariate setting. As macroeconomic data is published monthly, we also aggregate the SenSR into a monthly measure. Using these monthly data, we estimate a vector autoregression model of order 12, where we include all risk and macro variables, and test for the Granger causality.

Table 4 shows p-values for the Granger causality test of $SenSR_{MktCp}$ on macroeconomic variables (both US and EU). This version of SenSR is best at explaining the stock market (at shorter lags) and unemployment (at medium lags), but there is also some evidence for causality relations with GDP (at 1 month lag) and money supply. If we separate the US and EU, we see similar results plus stronger causality relationships of SenSR with the local unemployment rate and industrial production.

Lags	GDP	Unemployment	Industrial Pro.	Money Supply	Stock Market
1	0.074*	0.331	0.228	0.451	0.003***
2	0.231	0.584	0.165	0.058*	0.007***
3	0.530	0.364	0.173	0.215	0.028**
4	0.349	0.049**	0.131	0.244	0.066*
5	0.541	0.032**	0.111	0.358	0.055*
6	0.831	0.026**	0.197	0.190	0.064*
7	0.792	0.072*	0.279	0.270	0.090*
8	0.731	0.077*	0.353	0.139	0.074*
9	0.213	0.125	0.429	0.125	0.088*
10	0.393	0.149	0.416	0.145	0.268
11	0.306	0.157	0.383	0.123	0.257
12	0.458	0.183	0.409	0.088*	0.202

Table 4: Granger Causality Test: p-values for SenSR Marketcap against macro data.

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Table 5 shows the results for $SenSR_{Lev}$ (for the US). We observe significant evidence for causality of this version of SenSR on the money supply and S&P 500 at short lags; the EU case (not shown) has stronger causality relationships of SenSR with EU unemployment and, again, EU stock market at short lags.

Lags	GDP	Unemployment	Industrial Prod.	Money Supply	Stock Market
1	0.056*	0.288	0.219	0.486	0.004***
2	0.279	0.460	0.117	0.045**	0.034**
3	0.462	0.599	0.107	0.060*	0.094*
4	0.354	0.180	0.069*	0.027**	0.198
5	0.568	0.070*	0.095*	0.037**	0.197
6	0.613	0.103	0.129	0.030**	0.236
7	0.562	0.194	0.401	0.053*	0.357
8	0.648	0.223	0.551	0.015**	0.363
9	0.140	0.313	0.642	0.034**	0.442
10	0.263	0.537	0.313	0.037**	0.757
11	0.068*	0.623	0.390	0.034**	0.705
12	0.100*	0.612	0.410	0.017**	0.635

Table 5: Granger Causality Test: p-values for SenSR leverage against US macro data.

Lags	GDP	Unemployment	Industrial Prod.	Money Supply	Stock Market
1	0.298	0.498	0.829	0.163	0.016**
2	0.503	0.966	0.928	0.067*	0.001***
3	0.672	0.950	0.791	0.082*	0.020**
4	0.464	0.674	0.755	0.086*	0.025**
5	0.605	0.507	0.729	0.137	0.027**
6	0.447	0.701	0.771	0.169	0.015**
7	0.446	0.712	0.892	0.081*	0.014**
8	0.506	0.669	0.938	0.135	0.061*
9	0.488	0.611	0.731	0.082*	0.026**
10	0.642	0.410	0.693	0.086*	0.041**
11	0.622	0.365	0.749	0.084*	0.039**
12	0.649	0.415	0.820	0.053*	0.039**

Table 6: Granger Causality Test: p-values for World-SRISK against macro data.

A similar analysis for SRISK shows significant evidence that it Granger-causes S&P 500 and Money Supply. The causality relation between SRISK and Money Supply is not a coincidence: Recall that SRISK reflects the expected capital shortfall conditional on a systemic risk event.

We also tested for Granger causality of VIX and LIBOR-OIS spread on macro data – for brevity, we do not present the p-values, but only summarize our findings. As other researchers have documented earlier, VIX appears to Granger-cause S&P 500 and Euro Stoxx 50, as well as has some causality effects on US Money Supply and both EU and US industrial production (at lags of 3 to 6 months). For LIBOR-OIS spread, we found fewer causality relationships – only on GDP and unemployment at high lags (8 to 12 months). This somewhat confirms its reputation as a measure of economic distress.

It is interesting to see that different forms of SenSR explain different macroeconomic data: Size-weighted SenSR is most closely related to unemployment and the stock market, while debt and leverage versions of it contain more information about money supply. All versions of SenSR Granger-cause GDP and the stock market at short lags, while no reverse causality relations (macro on SenSR) were found. Overall, we conclude that SenSR seems to outperform the other risk indicators in its ability to add forecasting power for macroeconomic data.

Finally, we present the results on the impulse response functions of macroeconomic indicators to SenSR. Figure 6 shows the effects of a one-standard-deviation increase (impulse) in $SenSR_{Debt}$ on the macroeconomic data. The confidence intervals are obtained by the wild bootstrap method of Hafner and Herwartz (2009), to account for possible (auto)correlations and heteroscedasticity.

We find a negative effect of GDP, which is significant after the second lag (i.e., second month). Furthermore, the effect of SenSR on the unemployment rate is positive and significant also after the second lag. The industrial production also responds negatively to a shock in SenSR, but is just slightly significant on the 5% level after the third lag. Money supply response positive on SenSR, but results are not significant. The S&P 500 responds negatively and this response is highly significant from the second lag. We believe that the reason in this delayed response in all macro variables to the increase in SenSR (approximately two months) is the fact that the macroeconomic variables are published with at least one month delay, by which time the effect of systemic stress has already penetrated the economy.

We compare the impulse response functions on the same macro variables but for SRISK. The results can be seen in Figure 7. Overall, the picture is similar to SenSR. The response of the GDP on an impulse of SRISK is negative and in terms of significance comparable to SenSR. The unemployment rate rises following the shock in SRISK; in fact, this response is significant already in the second lag (whereas for SenSR it is significant from the third lag onward). The effect of SRISK on the industrial production is negative and highly significant already in the first lag. The effect on the money supply is positive, but not significant. In contrast to SenSR, the response of the S&P 500 is not significant – this is not surprising, as SenSR measures media sentiment which is directly related to stock market sentiment and, hence, stock prices.

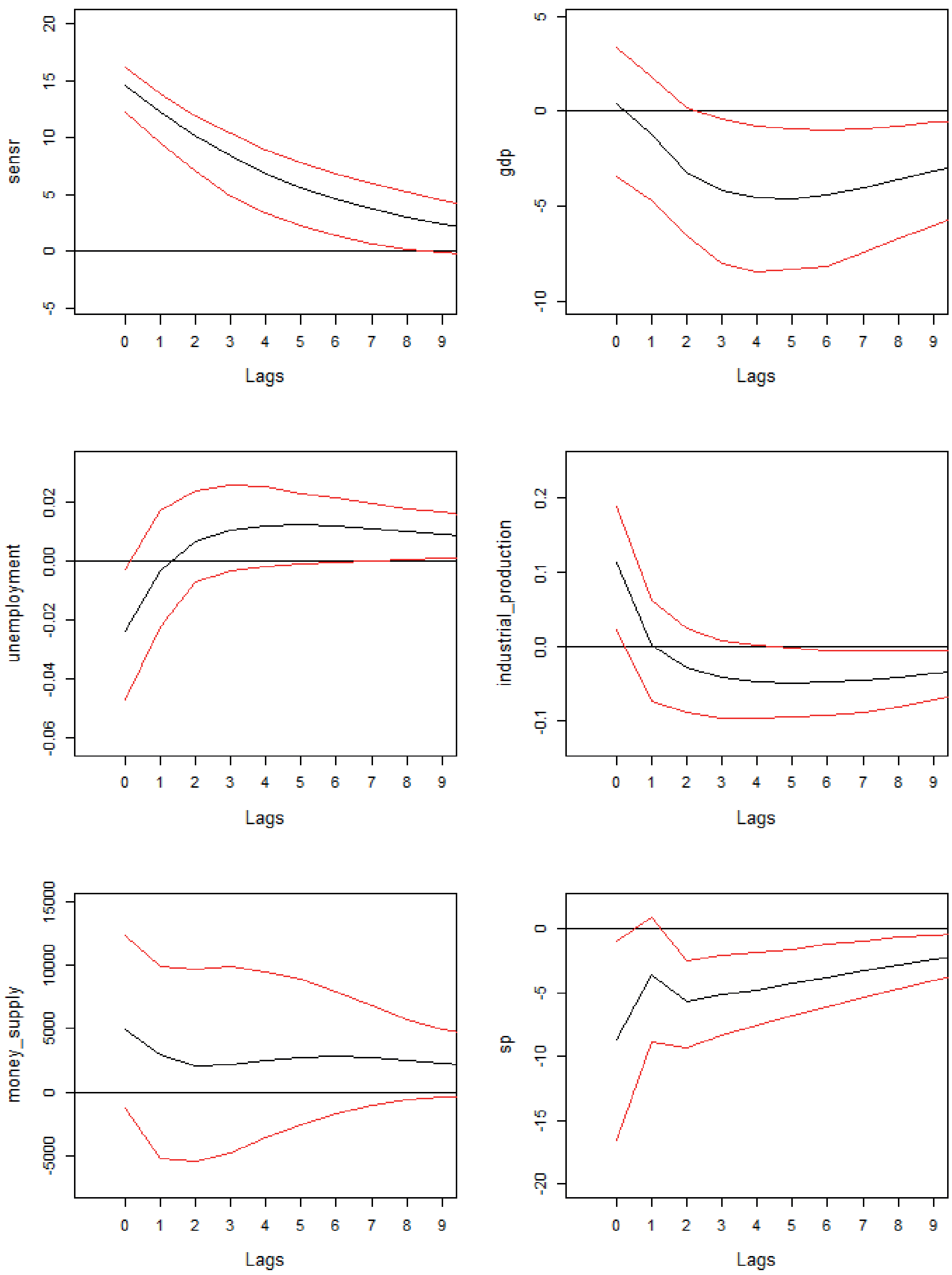

Figure 6: Impulse response function: SenSR on US Macro Data for VAR(1)

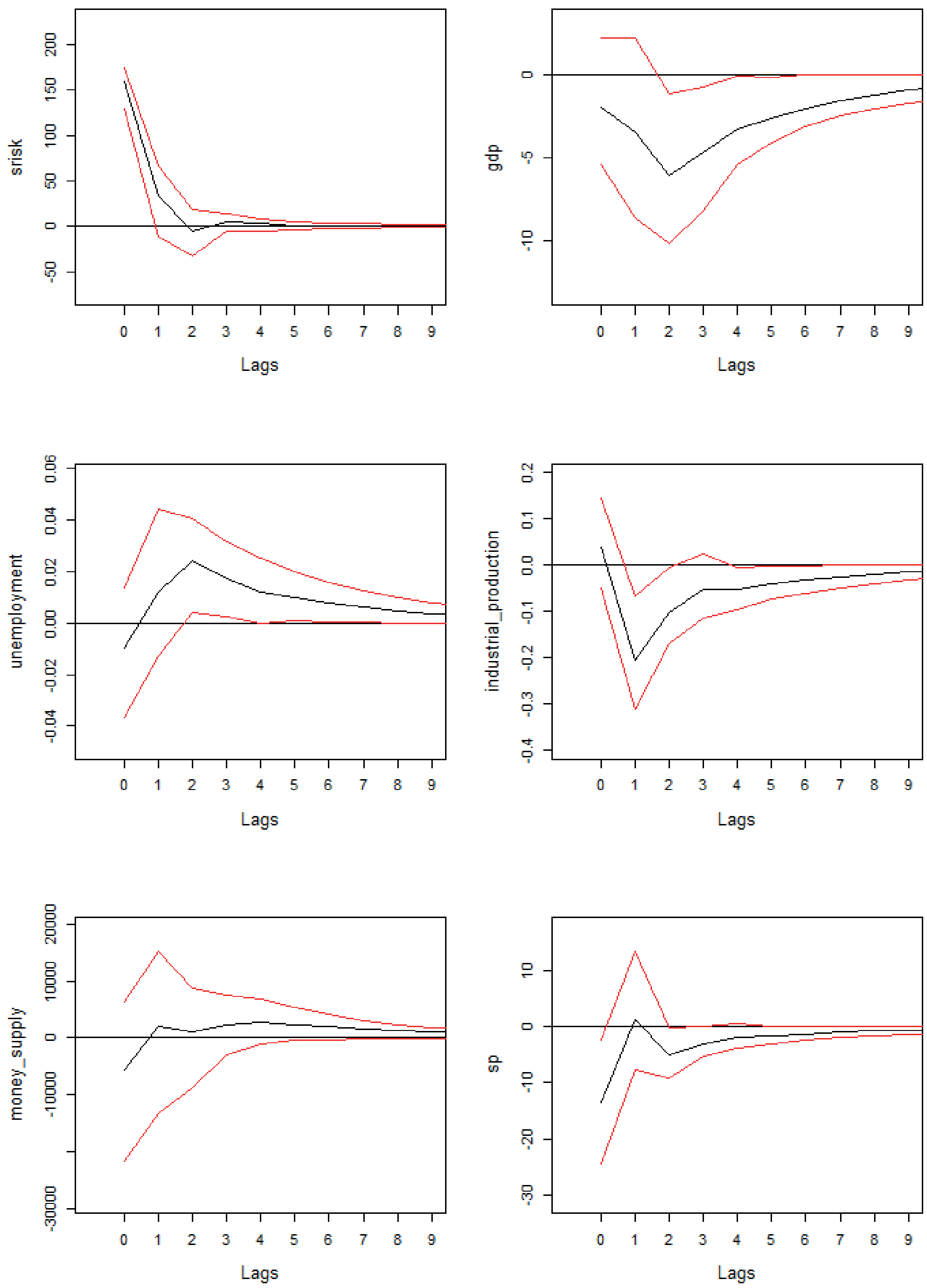

Figure 7: Impulse response function: SRISK global on US Macro Data for VAR(1)

4. Concluding remarks

In this paper we studied systemic risk from the news sentiment standpoint. Using Thomson Reuters News Analytics (TRNA) and Kalman filtering of TRNA sentiment, we introduced a new sentiment-based systemic risk index SenSR, which is a weighted sentiment score of financial institutions that are considered systemically important (SIFIs).

With the help of vector autoregression (VAR) models, we analyzed the behavior of SenSR with respect to other systemic risk measures and macroeconomic indicators. We investigated the impulse response functions and possible Granger causality relations. We find strong evidence that SenSR contains significant new information about systemic risk, not contained in other systemic risk indicators. In the multivariate setting, we find that SenSR provides improved predictions of macroeconomic indicators several months ahead, even when other systemic measures are taken into account. In all, we find that SenSR provides an early warning signal of systemic distress, and that this information advantage extends to at least 12 weeks.

5. References

Barone-Adesi, G., L. Mancini, and H. Shefrin (2012). Sentiment, asset prices, and systemic risk.

Benoit, S., J.E. Colliard, C. Hurlin, and C. Perignon (2015). Where the risks lie: A survey on systemic risk.

Borovkova, S. and D. Mahakena (2015). News, volatility and jumps: the case of natural gas futures. *Quantitative Finance*, 1217–1242.

Brenner, M. and D. Galai (1989). New financial instruments for hedging changes in volatility. *Quantitative Finance,* 61–64.

Engle, R.F. and C.T. Brownlees (2015). SRISK: A conditional capital shortfall measure of systemic risk.

Hafner, C.M. and H. Herwartz (2009). Testing for linear vector autoregressive dynamics under multivariate generalized autoregressive heteroskedasticity. *Statistica Neerlandica* 63 (3), 294–323.

Smales, L. (2014). News sentiment and measures of bank credit risk. *27th Australasian Finance and Banking Conference 2014 Paper*.

Thornton, D. L. (2009). What the LIBOR-OIS spread says? *Economic SYNOPSES*.

Appendix

List of SIFIs with descriptive statistics

Company	Observations	Pos. Sent.	Neut. Sent.	Neg. Sent.
Aegon N.V.	7546	0.397260	0.282708	0.320031
Agricultural Bank of China	2657	0.327816	0.370066	0.302117
Allianz SE	19965	0.360146	0.295729	0.344123
American International	35194	0.284053	0.306390	0.409556
Assicurazioni Generali S.p.A.	11310	0.387798	0.284273	0.327927
Aviva plc	33358	0.390368	0.440497	0.169134
AXA S.A.	14882	0.377818	0.375850	0.246331
Bank of America	73489	0.296940	0.305877	0.397181
Bank of China	5210	0.341728	0.360283	0.297988
Bank of New York Mellon	16465	0.340864	0.374588	0.284547
Barclays	95991	0.335577	0.428129	0.236292
BBVA	15877	0.409492	0.289673	0.300834
Bear Stearns	9455	0.300609	0.283404	0.415986
BlackRock	11652	0.367302	0.300158	0.332539
BNP Paribas	24434	0.334053	0.300034	0.365912
China Construction Bank	3569	0.319273	0.349840	0.330886
Citigroup	90212	0.301731	0.303495	0.394772
Commerzbank	18407	0.317050	0.299784	0.383165
Credit Suisse	31388	0.323743	0.291717	0.384538
Deutsche Bank	62689	0.316211	0.381004	0.302784
Dexia	6709	0.307878	0.299605	0.392516
Goldman Sachs	68291	0.316827	0.294551	0.388620
Groupe Crédit Agricole	15384	0.344201	0.275109	0.380688
HSBC	73796	0.313415	0.382170	0.304413
Ind. & Com. Bank	5957	0.352620	0.339992	0.307386
ING Bank	15579	0.377223	0.309410	0.313365
JP Morgan Chase	78555	0.300238	0.315513	0.384248
Lehman Brothers	16959	0.302657	0.299441	0.397900
Lloyds Banking Group	36816	0.328442	0.370018	0.301539
Merrill Lynch	23314	0.313504	0.318529	0.367966
MetLife, Inc.	11338	0.331660	0.388367	0.279972
Mitsubishi UFJ FG	13206	0.342180	0.262569	0.395250
Mizuho FG	12015	0.312377	0.278594	0.409027
Morgan Stanley	50166	0.308627	0.326301	0.365070
Nordea	7643	0.351972	0.297741	0.350286
Ping An Insurance (Group)	4333	0.333224	0.338998	0.327776
Prudential Financial, Inc.	10091	0.381511	0.388345	0.230142
Prudential plc	22567	0.364681	0.403750	0.231568
Royal Bank of Scotland	40745	0.334810	0.299932	0.365256
Santander	819	0.320075	0.455667	0.224257
Société Générale	20208	0.318864	0.275506	0.405628
Standard Chartered	21328	0.357400	0.322600	0.319998
State Street	9959	0.315125	0.388557	0.296316
Sumitomo Mitsui FG	10247	0.338997	0.288238	0.372763
UBS	17305 21	0.291867	0.262497	0.445635
UniCredit Group	25020	0.358724	0.278360	0.362915
Wells Fargo	33062	0.301507	0.359764	0.338728

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