Systemic Risk in the Insurance Industry and Its Impact on the Economy

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Abstract

Systemic risk, defined as the risk that a failure of a large financial institution could lead to counterparty failures and could trigger adverse effects for the real economy, has been a priority for both academicians and policy-makers. The literature focuses on the measures and definition of systemic risk and on its impact on the financial sector with little or no attention given to the relationship between systemic risk and the real economy. In this paper, we investigate the link between the systemic risk in the insurance sector and the macro economy during the 2008 financial crisis. In particular, we test the predictive power of insurance companies' systemic risk of macroeconomic downturns using various measures of systemic risk constructed from daily returns for 169 insurance companies between 1988 and 2011. Our findings show that insurance systemic risk forecasts macroeconomic downturns three months into the future.

I. Introduction

An important sector of the U.S. financial system is the insurance industry. According to the Bureau of Economic Analysis, in 2014, insurance companies held $5.2 trillion of assets under management, employed around 2.5 million people in different capacities, and contributed about $450 billion to the U.S. gross domestic product representing 2.6% of total GDP. In 2015, insurance companies' total claims were $15.2 billion for property and casualty companies and $617 billion for life and health insurers. Therefore, insurance companies contribute to economic growth, both as financial intermediaries and as providers of risk transfer and loss payments. They foster national savings and allow the efficient management of risks facing individuals and businesses.

The 2008 financial crisis exposed important vulnerabilities in the financial sector. In the aftermath of the Great Recession, tremendous effort has been devoted to better understand the risks posed by financial institutions and their impact on the financial system. Policymakers passed the Dodd –Frank 2010 Act to prevent future financial crisis, establish a mechanism to orderly liquidate troubled financial institutions, and monitor systemic risk of banks and nonbank entities including insurance companies. During the financial crisis, few insurance companies were under the spotlight notably AIG one of the largest insurance companies. AIG had a sizable credit default swaps portfolio around $450 billion (Sundaram and Das 2016). As the real estate prices collapsed, AIG suffered catastrophic losses on its mortgage-backed securities. The U.S. government provided AIG with an $85 billion loan to prevent the company from failing and causing further distress to the economy.

Even though the insurance sector is not directly involved in lending, insurance companies are interconnected to the wider financial sector. They play the financial intermediation role as they invest premiums collected in financial assets such as equity, debt securities, and real estate. Insurance companies are one of the major institutional investors in debt securities. In fact, about sixty percent of the assets of insurance companies are invested in government and corporate bonds.

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Therefore, any disruption in corporate financing will lead businesses to cancel or delay capital investments and would result in reduction in production and loss of job creation. On another level, insurance companies, mainly property and casualty, provide insurance protections on vehicles and real estate. This protection is a prerequisite to financing approval, without it, individuals and businesses may not be able to secure the needed loans that would spur economic growth. Another specialty insurance segment, bond insurers, provides financial guaranty insurance that facilitates credit for financial institutions and municipalities. These local and state governments spend the borrowed money on capital improvement projects, and help local economies.

Given the contribution of the insurance industry to the U.S. economy and its interconnectedness to the wider financial markets, we explore the impact of the insurance systemic risk on the macro economy. Using daily return data for a sample of insurance companies, we construct two measures of systemic risk: the expected shortfall as defined by Artzner et al (2005) and financial volatility calculated as the within-month standard of the daily returns. We check for the predictive power of our systemic risk measures by forecasting out of sample following a methodology similar to Allen et al (2012). To measure economic activity, we use the Chicago Fed National Activity Index (CFNAI). We explore an alternative measure of economic activity: growth in industrial production (IP) to check the robustness of the results. We find that both measures of systemic risk forecast future macroeconomic activity declines up to the three months in advance.

The rest of the paper is organized as follows: Section 2 explores the literature review. Section 3 describes the dataset used in the empirical application. Section 4 discusses the estimation procedure. Section 5 summarizes the findings and presents concluding remarks.

II. Literature Review

Going back to the Great Depression of 1933, the economic crisis was attributed to failures in the financial system (Bernanke 1989). In the aftermath of the financial crisis of 2008, the literature focused on the measures and definition of systemic risk and its impact on the financial sector with little or no attention given to the relationship between systemic risk and the real economy initially. Since, a few studies have looked at the impact of systemic risk on the macro-economy. Most notably Allen, Bali, and Tang (2012) use an aggregate measure of systemic risk, CATFIN, an average of three variations of VaR, for financial firms using return data from January 1973-2009. Their aggregate measure of systemic risk was able to predict economic downturn up to six months in advance. The authors report that their results were robust to alternative measures of economic activities such as monthly growth in GDP, industrial production, and unemployment rate. Their work does not test for the systemic risk impact on the macro economy by industry in the financial sector.

Giglio, Kelly and Pruitt (2016) investigate the predictive power of systemic risk measures in forecasting macroeconomic downturns using European and U.S. data. Several measures of systemic risk have been proposed in the academic literature since the financial crisis of 2008. The purpose of these measures is to assess the contribution of each financial institution to the overall risk of a financial system. Giglio et al (2016) use a quantile regression model to estimate the predictive power of the different measures of systemic risk. The authors calculate nineteen different measures of systemic risk for financial institutions and measure macroeconomic shocks by the innovations in the industrial production index and CFNAI. The analysis shows that only a few systemic risk measures, financial volatility, CoVaR, MES, CATFIN proposed by Allen, Bali, and Tang (2012), have predictive power of macroeconomic downturns with financial volatility yielding the strongest results. The study fails to discern the results by industry within the wider financial sector.

The previous studies examine the impact of systemic risk of the entire financial system on the macro economy. Our contribution is to investigate the effect of insurance systemic risk on the broader economy and whether the insurance systemic risk measured with expected shortfall (ES) and financial volatility has any predictive power of economic downturns. Our findings will be useful to regulators and policymakers to tailor their efforts to individual industries instead of subjecting all financial institutions to the same set of regulations without regard to their uniqueness and specificities. The results will further enrich the debate over whether the insurance industry should remain state regulated or be subject to oversight by a federal regulatory entity.

III. Data

We use daily returns for insurance companies with SIC codes of 6331, 6311, and 6321 in order to estimate systemic risk. Our sample includes 169 insurance companies. The data was collected from the CRSP database. The sample period starts in January 1988 and ends in December 2011.

The literature on systemic risk examined a wide range of topics from measurement issues, determinants, and to out of sample predictive power. There is a wide range of systemic risk measures used in the literature. After the 2008 financial crisis a lot of systemic risk measures have been proposed and analyzed. Some of the common measures of systemic risk typically used in the literature are conditional (CoVaR), change in conditional VaR (ΔCoVaR), and marginal expected shortfall (MES) among many others. Giglio et al (2016) report that there is a strong correlation between these popular systemic risk measures; for example, the correlation between MES and CoVaR is 0.93 for their sample of financial institutions. Even though there is no consensus concerning the best measure of systemic risk, the Basel Committee starting 2016 recommends the use of the Expected Shortfall (ES).

For the purpose of this study, we estimate the systemic risk calculating the financial volatility and the Expected Shortfall (ES) methodology. The Expected Shortfall was first introduced by Artzner et al (1999) in order to overcome some of the drawbacks associated with using VaR as a risk measure. The financial volatility measure is calculated as the within –month standard deviation of daily equity returns of individual insurance companies.

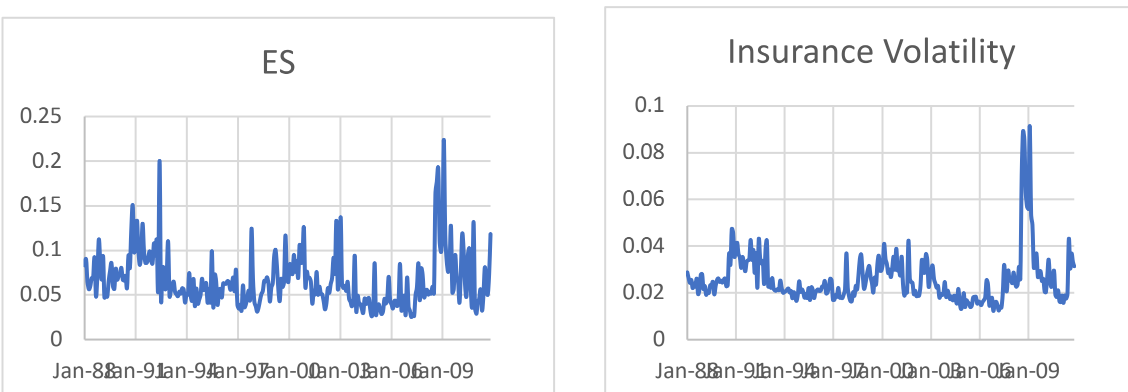
Following Artzner et al (1999) the ES measure is defined as the conditional expectation of the market loss conditional on the loss less than the α quantity that is the VaR as defined in equation (1). Therefore, we look at loss beyond the VaR level. We use a nonparametric kernel estimation of the tail expectations along the lines of Scaillet (2005) using the average of extreme returns beyond 5% VaR. Alternatively, using a 1% VaR we find qualitatively and quantitatively similar results.

$$ES_{\alpha}(R) = E[R \mid R \leq VaR_{\propto}(R)] \quad (1)$$

Where, ES is the expected shortfall, R represents the extreme return, and α is the probability.

Figure (1) plots the monthly ES and the financial volatility measure for our sample from January 1988 to December 2011. We notice an increase in the level of systemic risk as measured by the ES in 1992-1993, 2002-2003 and in periods of recession especially during the 2008-09 financial crisis. The estimated shortfall (ES) peaked during the period 1992-1993 where the insurance industry experienced turmoil on two fronts: the property liability companies suffered catastrophic losses due to Hurricane Andrew (1992) and life insurance companies experienced a contagion problem from the downfall of some large life insurers that invested heavily in junk bonds (Fenn & Cole 1994). These peak levels in the estimated shortfall are close to the levels reached during the financial crisis. Our second measure of systemic risk - financial volatility as measured by the monthly standard deviation of daily excess returns follows a similar pattern as the estimated shortfall. The highest level of volatility recorded occurs during the great recession.

Figure I Time Series of Systemic Risk Measures



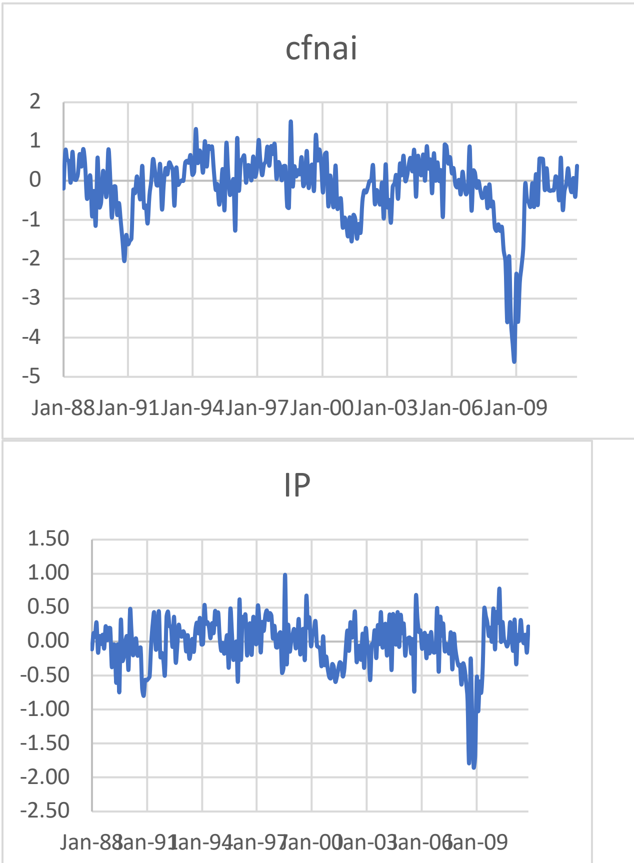
Panel (a) Insurance Estimated Shortfall Panel (b) Insurance Financial Volatility

IV. Model and Estimation

The recent financial crisis renewed the interest in the systemic risk of financial institutions. The role of insurance companies during the financial crisis is not well understood. On one hand, insurance companies may have proven to be resilient to economic downturns given the composition of their investment portfolio, investment grade bonds, and became a moderating factor during bad economic times. The products sold by insurance companies are prefunded and there were no disruptions in the supply of insurance during the crisis. Alternatively, they may have exacerbated the situation by failing to honor their obligations as they do not accurately predict their losses or invest in high-risk assets. Against these two competing hypotheses, we test whether insurance companies' systemic risk had any adverse impact on economic activity.

In the first step, we estimate the systemic risk (ES) as defined in equation (1). Then we apply our model in equation (2) to determine the impact of the insurance systemic risk on the economy. We measure economic activity through the Chicago Fed National Activity Index (CFNAI) which is a weighted average of 85 monthly economic indicators. By design, the CFNAI is constructed to have a mean value of zero and a standard deviation of one. Therefore, since economic activity tends to gravitate toward a trend, an index above zero means economic growth above the trend. Our second measure of economic activity is industrial production (IP) growth downloaded from the Federal Reserve of St Louis site.

Figure II Time Series of Economic Indicators



Panel (a) CFNAI Panel (b) Industrial Production Growth

Figure II shows a time series plot of CFNAI in panel (a), our proxy of economic activity. A positive index represents growth above a trend and a negative index is growth below trend. Clearly, the largest dip in economic activity occurred in 2008-2009 over the period covered by our sample. Usually the economic impact is preceded by the financial crisis. The industrial production growth follows the same pattern as the broader CFNAI index. The other peaks and troughs correspond to business cycles turning points in 1991 and 2001 as identified by the National Bureau of Economic Research.

Using this data set, we estimate the following regression:

$$Y_{t+n} = \propto + \beta SR_t + \sum_{i=1}^{12} \gamma_i Y_{t-i+1} + \varepsilon_{t+n} \qquad (2)$$

Where,

Y_t: the monthly Chicago Fed National Activity Index (CFNAI) and the Industrial Production growth (IP)

SR_t: monthly systemic risk; measured by estimated short fall and financial volatility

In our estimation, we allow up to 12 lags for our dependent variable in the specification model. The choice of the number of lags was determined by using AIC and SIC model selection criteria. We use Newey-West standard errors rather than the ones obtained from standard regression, as they are robust to the autocorrelation and heteroscedasticity. We do not try to identify the factors that forecast economic downturns our goal is simply to test the impact of insurance systemic risk on the wider economy. More precisely, we set out to test to what extent insurance systemic risk can predict macro-economic downturns.

Table I presents the results of the estimation of equation (2) using the estimated shortfall (ES) as measure of systemic risk and the two measures of economic activity: CFNAI and IP (industrial production growth).

Table I
Predictive Power of Estimated Shortfall

$$Y_{t+n} = \propto \ + \beta SR_t \ + \sum_{i=1}^{12} \gamma_i Y_{t-i+1} + \varepsilon_{t+n}$$

	CFNAI			IP		
N	β	t-stat	Adj.R^2	β	t-stat	Adj.R^2
1	-3.6899	-2.47***	0.6247	-0.0523	-4.92	0.7920
2	-3.3619	-2.05**	0.6032	-0.0473	-3.64	0.7991
3	-2.8016	-1.49	0.4913	-0.0540	-3.56	0.8053
4	-1.6452	-0.75	0.3713	-0.0328	-1.35	0.7946
5	-1.6655	-0.62	0.2859	-0.0180	-0.80	0.7938
6	-1.6036	-0.57	0.2295	0.0094	0.40	0.7918

The table reports the six-month ahead, the corresponding parameter estimate of (ES) t-statistics based on Newey West (1987) standard errors and the adjusted R^2
*10% significant, **5% significant, *** 1% significant

Table I shows that the coefficient estimates of the ES, our measure of systemic risk, are negative and significant at 5% or better up to three months in advance. From one to two months the coefficients of the CFNAI are negative as expected. The magnitude of the beta coefficients varies from -3.69 to -2.80, compared to Allen et al (2012) who find smaller beta coefficients and a longer forecasting period; their predictive window extends into six months. The adjusted R^2 values range from 62% to 23%. The alternative economic indicator, growth in industrial production, yields stronger results with a predictive window up to three months and a much stronger goodness of fit, adjusted R squared up to 80%.

Table II presents the results of the estimation of equation (2) using the financial volatility as measure of systemic risk and the two measures of economic activity: CFNAI and IP.

Table II

Predictive Power of Financial Volatility

$$Y_{t+n} = \propto \ + \beta SR_t \ + \sum_{i=1}^{12} \gamma_i Y_{t-i+1} + \ \varepsilon_{t+n}$$

	CFNAI			IP		
N	β	t-stat	Adj.R^2	β	t-stat	Adj.R^2
1	-19.1881	-3.96***	0.635	-0.3579	-4.92***	0.8035
2	-18.0776	-2.56**	0.613	-0.3166	-3.64***	0.8079
3	-16.5352	-2.15*	0.5006	-0.2598	-3.56***	0.8086
4	-9.6831	-1.14	0.3745	-0.1763	-1.89*	0.7966
5	-10.9897	-1.16	0.2903	-0.1663	-1.81*	0.7965
6	-5.9952	-0.64	0.2292	0.0943	-0.99	0.7928

The table reports the six-month ahead, the corresponding parameter estimate of financial volatility
t-statistics based on Newey West (1987) standard errors and the adjusted R^2
*10% significant, **5% significant, *** 1% significant

In order to check the robustness of our results, Table II shows the results with financial volatility, the within-month standard deviation of daily equity returns, as an alternative proxy for systemic risk. The results are stronger than with the estimated shortfall. The forecasting period extends to up to five months using industrial production growth as a measure of economic indicator and better goodness of fit as indicated by the adjusted R squared that ranges from 80% to 50%. Not surprisingly, the adjusted R squared declines at the longer forecasting horizon. The decline in goodness of fit is more pronounced using CFNAI as economic indicator.

The coefficients on the IP measure are smaller than those on CFNAI. This finding can be attributed to the fact that industrial production represents a small share of the economy and has been declining (20 % in 2016 according to the Federal Reserve Board). Moreover, the CFNAI is a much broader index than the IP meaure. Our results echo the findings of Giglio, Kelley and Pruitt (2016) who, among 19 different measures of systemic risk, find that financial volatility had the strongest predictive power to forecast macroeconomic shocks.

In summary, our measures of systemic risk of the insurance industry provides a predictive power to forecast a macroeconomic downturn up to three months. We believe that our results are important given that we only consider the insurance sector while Allen, Bali, and Yang (2012) include in their analysis the entire financial sector. This contradicts a long held belief by insurance advocates that insurance companies do not contribute to systemic risk but rather the industry, especially in times of economic hardships, is a source of security and stability and acts more as a moderating factor.

V. Conclusion

The financial crisis of 2008 put the spotlight on banks and their role in causing the great recession. The past recession highlighted the financial sector's role in the economy, specifically that a financial crisis can result in economic downturns. Academicians and policymakers wanted to understand bank risks to prevent future crises and in case of recurrence of financial crisis to limit their impact. The insurance sector represents a large segment of the financial sector. It plays an important role in the economy, providing individuals and businesses protection against potentially catastrophic consequences. Yet the financial crisis of 2008 revealed that at least some insurance entities like AIG contributed to the severity of the crisis.

Using a sample of insurance companies, we find that insurance systemic risk forecasts macroeconomic downturns three months into the future. Knowing to what extent insurance systemic risk affects the macro economy gives the appropriate regulatory authorities the ability to make proper policies to reduce economy's exposure to systemic risk. Whether the existing insurance regulatory system has the tools to deal of systemic risk is debatable. Currently, insurance companies are subject to the 1944 McCarran-Ferguson Act that gives the right to the states to regulate the insurance industry. State regulators, long focused on solvency and consumer complaints may not have the policy tools to manage systemic risk. As a result, The Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 established the Financial Stability Oversight Council (FSOC).

The FSOC's task is to identify systemically important bank and non-bank financial institutions (SIFI) whose potential collapse could lead to a systematic failure of the financial system. Among those institutions, the largest insurance companies such as MetLife, AIG, and Prudential were identified as SIFI. After a drawn out litigation battle, the FSOC removed MetLife and Prudential's systemic risk label. The FSOC's prerogative is to monitor only large financial institutions with at least $50 billion assets. The focus of oversight should not be limited to the largest insurers but also smaller insurance companies' failures may contribute to the instability of the financial system. Effective and efficient regulation requires monitoring insurance products that are highly correlated with the economy such as financial guarantees. Second, insurance state guaranty funds, which may encourage moral hazard, maybe redesigned similarly to the FDIC that requires prefunding and risk based premiums while monitoring excessive risk taking behavior by member institutions. Next, reinsurance arrangements should be subject to more scrutiny to avoid shadow insurance, a practice by some insurers to sell liabilities to unrated and unregulated reinsurance companies. Insurance companies rely on shadow insurance to reduce risk based capital requirements ultimately increasing risk. Therefore, measures at the state level in conjunction with the FSOC and the newly created Federal Insurance Office would modernize insurance regulation.

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