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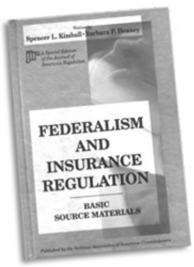

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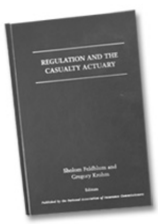

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CDS Spreads, Systemic Risk and Global Systemically Important Insurers Designations

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Abstract

After the recent court case overturning the Financial Stability Oversight Council (FSOC)'s systemic importance designation of MetLife, the public raises awareness about the robustness of the identification methodology for global systemically important insurers (G-SIIs). As the G-SII identification framework proposed by the International Association of Insurance Supervisors (IAIS) lacks empirical support and relies heavily on historical accounting data, we examine how systemic risk measures constructed from credit default swaps (CDS) data, which are market-consistent and forward-looking, can supplement the IAIS' identification framework. Using a dataset of insurers' CDS spreads between 2011 and 2015, we construct three different kinds of systemic risk measures (i.e., MES^{CDS}, networks of CDS spreads and absorption ratio) and assess the G-SII designation results announced by the Financial Stability Board (FSB). We find that: 1) the systemic risk of designated G-SIIs is, on average, higher than other insurers, suggesting that the IAIS' G-SII identification methodology is, in general, sound and effective; 2) reinsurers should fall within the IAIS' G-SII assessment exercise, as some of them generate more systemic risk than the designated G-SIIs;

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and 3) given the non-negligible litigation risk from the designated G-SIIs, the regulators should consider supplementing their G-SII identification methodology with CDS-based systemic risk measures to substantiate their designation decisions in court.

1. Introduction

> *"…… the Final Determination (of MetLife as systemically important) hardly adhered to any standard when it came to assessing MetLife's threat to U.S. financial stability…… This Court cannot affirm a finding that MetLife's distress would cause severe impairment of financial intermediation or of financial market functioning…… This Court finds that the Final Determination was arbitrary and capricious."*
>
> *Extract of judgment from the court case MetLife, Inc. v. Financial Stability Oversight Council, 2016, regarding MetLife's challenge to the regulator's decision to designate MetLife as systemically important.*

The issue of identifying global systemically important insurers (G-SIIs) is controversial. From the industrial perspective, there is no consensus among practitioners as to which insurers are systemically important. For example, MetLife was designated by the Financial Stability Oversight Council (FSOC) as systemically important in 2014 and subsequently challenged that decision in federal court (MetLife, 2017). In March 2016, the court ruled in MetLife's favor and overturned MetLife's designation. The judge opined that the identification process should involve assessment of MetLife's likelihood to experience financial distress, as well as the cost of the designation to MetLife's business (Dayen, 2017). In addition, U.S. President Donald Trump also considers that the designation process needs to be improved and signed an executive order to review the designation process in April 2017 (Chiglinsky and Harris, 2017).

From the academic perspective, the G-SII identification methodology proposed by the International Association of Insurance Supervisors (IAIS) lacks empirical support. According to the IAIS' proposal (IAIS, 2016), the calculation of systemic importance score is based on five categories of indicators: 1) size (5%); 2) global activity (5%); 3) interconnectedness (49%); 4) asset liquidation (36%); and 5) substitutability (5%). Based on the systemic importance score and the regulators' assessments, the Financial Stability Board (FSB) designates a list of insurers as G-SIIs on an annual basis. However, Weiβ and Mühlnickel (2014) find empirical evidence against the argument that global activity and substitutability contribute to insurers' systemic risk. Instead, based on a sample of listed U.S. insurers, they find that insurer's size is the primary driver of systemic risk. Their conclusion is clearly against the exceptionally low weighting (5%) assigned by the IAIS to the size indicator in the calculation of systemic importance score. The inclusion of global activity and substitutability indicators in the calculation is not appropriate as well. In addition, Bierth *et al.* (2015)'s empirical study reveals that insurers' contribution to systemic risk is mainly driven by their leverages. Surprisingly, the indicators proposed by the IAIS do not cover leverage at all.

A relevant question to the G-SII identification framework is why and how insurers are systemically risky. Although many academic studies show that insurers, in general, generate less systemic risk than banks (e.g., Billio *et al.*, 2012; Chen *et al.*, 2013; Bierth *et al.*, 2015), we cannot conclude insurers are not systemically risky. In fact, the channels through which insurers generate systemic risk have been well-documented in literature. For example, Eling and Pankoke (2014) argue that the nontraditional activities of insurers, such as financial guarantees and credit default swaps (CDS), are likely to be sources of systemic risk. Cummins and Weiss (2014) suggest that insurers' non-insurance activities, such as derivatives trading, are likely to generate systemic risk. Thimann (2014) concludes that insurers cause systemic risk by assuming the role of financial intermediary and investor, and Niedrig (2015) finds that the interconnectedness between banks and insurers is driven by insurers' investment in bank bonds. A more recent study by Bobtcheff *et al.* (2016) suggests that the surrender option of insurance policies is a source of systemic risk, as earlier findings of Russell *et al.* (2013) reveal that macroeconomic variables are correlated with surrender rates.

From the industry perspective, the regulators also do not preclude the possibility that insurers are able to generate systemic risk. For example, the study by the European Systemic Risk Board (ESRB, 2015) concludes that insurers generate systemic risk by: 1) participating in nontraditional and non-insurance activities; 2) causing procyclicality in asset allocation and pricing of credit and mortgage insurance; 3) being financially vulnerable under the low interest rate environment and volatile equity market; and 4) providing insurance that is vital to the economy but lacks substitutes, such as property, liability, marine, transport and aviation insurance. In the U.S., the federal Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act) was enacted in 2010 to improve stability and enhance consumer protection in the financial industry. Under the Dodd-Frank Act, the FSOC was established to address the systemic risk generated by financial institutions, including, inter alia, insurers. Given the specific channels through which insurers generate systemic risk, the Dodd-Frank Act also created the Federal Insurance Office (FIO), which is responsible for monitoring all aspects of the insurance sector and identifying potential regulation gaps and issues that contribute to systemic risk in the insurance industry.

Despite the numerous studies and policy development discussed above, whether the methodology proposed by the IAIS is effective in identifying systemically important insurers remains an unanswered question. Against this backdrop, we examine the issue of how insurers' CDS data, which is forward-looking and market-consistent, can help regulators improve their G-SII identification methodology, which is mainly based on historical accounting data.

The use of CDS spread data to measure systemic risk has been well documented in literature. Acharya *et al.* (2017) use CDS data to construct a systemic risk measure called marginal expected shortfall (MES), which is defined as the expected loss of an insurer when the overall market return is below its 95% value-at-risk. They find empirical evidence supporting the ability of MES constructed from CDS data to forecast future loss of firm value during financial crisis. Puliga *et al.* (2014) measure the systemic risk of financial institutions by the networks constructed from CDS data. These networks are taken as a proxy of interdependencies among financial institutions. They find that when supplemented with macroeconomic indicators, the network measures based on CDS data can detect systemic instabilities in the financial system. Kritzman *et al.* (2011) propose to measure systemic risk by the absorption ratio, which is the total variance of a set of asset returns that can be explained by their first principal component. A high absorption ratio indicates that the assets are tightly coupled and hence, they are more fragile in the sense that negative shocks transmit more quickly and broadly. As the type of asset class is not restricted, CDS spread returns can also be used to construct the absorption ratio as a measure of systemic risk.

Using CDS data over accounting data to measure systemic risk has several advantages. First, CDS data is forward-looking, which reflects the market's perception of future risks, while accounting data captures historical risks (Kanagaretnam *et al.*, 2016). In addition, after insurers' financial year-end dates, the regulators usually have to wait several months before getting the audited financial statements. CDS data, by contrast, does not suffer from the time-lag problem. As regulators are concerned with the risk of G-SIIs' financial distress in the future, the CDS-based systemic risk measures can supplement the IAIS' proposed identification methodology. Second, CDS spread provides a pure signal on the likelihood of a firm's default, which avoids the complications from inferring the default risk from accounting data (Kaplan, 2011). As CDS can be considered as a put option on a firm's debt, an increase in the CDS spread reflects the market expectation of the increased likelihood of the firm's financial distress or the increased volatility of the firm's assets. Third, the CDS-based systemic risk measures—such as the MES, absorption ratio, and networks aforementioned—take into account the interdependencies among insurers. On the contrary, it is difficult to quantify the co-movement of insurers' default risk with accounting data. As negative shocks transmit more quickly and broadly when insurers' assets are tightly coupled, co-movement of insurers' default risk is an important dimension in the measure of systemic risk and can be better captured by CDS data. Fourth, due to the existence of different accounting treatments and interpretations of insurance business terms in various jurisdictions, the identification methodology based on accounting data may produce inconsistent results. This is a major challenge the IAIS admitted during one of its presentations (Maroney, 2013). On the other hand, CDS spread data is market-consistent and provides a more coherent signal for insurers in different jurisdictions.

When compared to other systemic risk measures documented in literature, CDS-based systemic risk measures also have several advantages in the context of G-SII identification. For example, Kreis and Leisen (2017) construct a structural model based on Merton (1974) in a balance sheet framework and calculate the systemic risk of banks using a measure of default called conditional expected default frequency. Such a structural model involves the calculation of asset correlation. However, as previously mentioned, the regulators usually have to wait for several months before getting the audited financial statements to calculate the asset correlation and hence, the structural model based on balance sheet framework suffers from the time-lag problem. There are also other market-consistent systemic risk measures documented in literature that are free of the time-lag problem, such as Acharya *et al.* (2017)'s MES and Adrian and Brunnermeier (2016)'s ΔCoVAR, which are based on co-movement of stock returns. However, regulators and policyholders are more concerned with insurers' ability to fulfill their obligations instead of their stock performance. As CDS can be viewed as put options on insurers' debts and CDS spreads, when compared to stock returns, they can better capture insurers' ability to fulfill their obligations. We consider that CDS-based systemic risk measures are better than other market-consistent systemic risk measures in the context of G-SII identification.

Despite the advantages of using CDS data to measure systemic risk of insurers, the IAIS' proposed G-SII identification methodology only focuses on insurers' accounting data. This motivates us to supplement the G-SII identification methodology with the CDS-based systemic risk measures. Specifically, we follow Kritzman *et al.* (2011), Puliga *et al.* (2014) and Acharya *et al.* (2017) to construct CDS-based systemic risk measures, which are the absorption ratio, networks of CDS spreads and MES^{CDS}, respectively.

Our sample consists of 42 life insurers, non-life insurers and reinsurers from 11 countries. The sample period is from the beginning of 2011 to the year-end of 2015, as the FSB's first designation event in July 2013 was based on the assessment results of 2011 data. The systemic risk of insurers in our sample are then compared with the FSB's G-SII designation results. By graphical representation, one-tailed paired t-test, and multivariate regression that controls for macroeconomic variables, country-specific factors, and time-varying variables, we find that the systemic risk of G-SIIs identified by the FSB is, on average, higher than that of other insurers.

The difference is statistically and economically significant, suggesting that the regulators' G-SII identification framework is, in general, sound and effective. However, further analysis based on the rankings of CDS-based systemic risk measures reveals that such identification framework still has room for improvement. The CDS-based systemic risk measures suggest that Hannover Rück SE, Münchener Rückversicherungs-Gesellschaft Aktiengesellschaft and Swiss Reinsurance Company Ltd., which have been excluded from the IAIS' identification methodology due to their focus on reinsurance business, have systemic risk higher than that of some insurers designated by the FSB as G-SIIs.[1] This finding raises the alarm for the IAIS to speed up the G-SII identification methodology for reinsurers.

The regulators also face substantial litigation risk from those insurers previously designated as G-SIIs but have less systemic risk than the three reinsurers aforementioned. The recent court case of MetLife is a good example.

1. A chart comparing the approaches used by the FSB and the FSOC can be found in the appendix.

Based on the CDS-based measures, we find that the systemic risk of MetLife was below the median of our sample of insurers in 2015, which is a striking finding that cannot be neglected in regulators' G-SII assessment exercise. We believe that the regulators can better substantiate their G-SII assessments in courts if the CDS-based systemic risk measures are incorporated into the identification methodology. We also examine whether the FSB's change of G-SII list in November 2015 was consistent with the results suggested by the CDS-based systemic risk measures. We find that the removal of Assicurazioni Generali SpA from the G-SII list is against our observation that this insurer has the highest systemic risk among our sample of insurers in 2015. Our analysis indicates the need for the FSB to increase transparency regarding its designation decisions so that any discrepancies on the designations can be openly discussed.

We complement the literature on systemic risk and insurance regulation by examining the FSB's G-SII designations with the CDS-based systemic risk measures. To the best of our knowledge, we are the first to identify inconsistencies between the G-SII designations and the CDS-based systemic risk measures, and to recommend several areas for improvement of the G-SII identification framework based on these inconsistencies. To be specific, our analysis raises the need for the regulators to speed up the development of G-SII identification methodology for reinsurers and increase transparency for the G-SII designations. In response to the litigation risk faced by the regulators, we recommend the regulators to supplement their identification methodologies with the CDS-based systemic risk measures. Our study sheds light on the discussion of how the G-SII identification framework can be improved by analyzing insurers' CDS data.

We organize the remainder of this paper as follows. Section 2 provides an overview of the G-SII identification methodology that the IAIS proposed. Section 3 presents the data and discusses the construction of CDS-based systemic risk measures. Section 4 discusses how the CDS-based systemic risk measures supplement the IAIS' G-SII identification methodology. Section 5 discusses the limitation of using CDS data to identify G-SIIs. Section 6 states the concluding remarks.

2. Overview of the G-SII Identification Methodology that the IAIS Proposed

In July 2013, the IAIS published the initial identification methodology for G-SIIs (IAIS, 2013), which was further updated in June 2016 (IAIS, 2016). The identification methodology is built upon the IAIS' earlier study (IAIS, 2011), which concludes that insurers engaging in nontraditional and non-insurance (NTNI) activities are more vulnerable to market fluctuations and generate more systemic risk than insurers engaging in traditional insurance business. The updated identification methodology is based on five phases.

Phase I – Annual Data Collection Phase

The IAIS collects information from insurers around the globe satisfying either one of the following conditions: 1) total assets are more than $60 billion, and the ratio of overseas premium exceeds 5%; or 2) total assets are more than $200 billion, and the ratio of overseas premium is greater than 0%. In general, around 50 insurers need to submit information for the IAIS' assessment each year.

Phase II A – Quality Control and Scoring Phase

The IAIS assesses the systemic importance of each insurer based on the data collected in Phase I. The systemic importance score is calculated with reference to 17 indicators, which are constructed from accounting data. The indicators together with their applicable weights are summarized in Table 1.

Table 1:
IAIS' Proposed Indicators for G-SII Identification

Category	Subcategory	Indicator	Weight
Size		Total assets	2.5%
		Total revenues	2.5%
Global activity		Revenues derived outside of home country	2.5%
		Number of countries	2.5%
Interconnectedness	Counterparty exposure	Intra-financial assets	6.7%
		Intra-financial liabilities	6.7%
		Reinsurance	6.7%
		Derivatives	6.7%
	Macroeconomic exposure	Derivatives trading (credit default swap [CDS] or similar derivatives instrument protection sold)	7.5%
		Financial guarantees	7.5%
		Minimum guarantees on variable products	7.5%
Asset liquidation		Non-policyholder liabilities and non-insurance revenues	7.5%
		Short-term funding	7.5%
		Level 3 assets	6.7%
		Turnover	6.7%
		Liability liquidity	7.5%
Substitutability		Premiums for specific business lines	5%

Source: IAIS, 2016

Phase II B – Determination of Quantitative Threshold

Insurers with systemic importance scores above a quantitative threshold, which is established by the IAIS following statistical and analytical approaches, are subject to further evaluation in Phases III, IV and V. Insurers with systemic importance scores below the quantitative threshold are not considered as prospective G-SIIs, unless the IAIS has analytically supported grounds to include the relevant insurers for further analysis.

Phase III – Discovery Phase

The IAIS and the relevant authorities request additional quantitative and qualitative information from the prospective G-SIIs for further analyses. Information collected by the IAIS in this phase includes data on large exposures, intra-group commitments, derivatives trading, interconnections with other financial counterparties, trading securities, debt and debt-like liabilities with provisions that can accelerate payment, minimum guarantee on variable products, liquidity of asset and liability portfolios, and reinsurance arrangements. Phase III is designed to complement Phase II, and insurers are advanced to Phase IV if the IAIS determines that their failure would cause substantial disruption to the economic activity and financial system.

Phase IV – Exchange with Prospective G-SIIs

The IAIS informs the prospective G-SIIs of the IAIS' assessment results in Phases I, Phase II and Phase III. Such information is only disclosed to the relevant prospective G-SIIs, and the IAIS does not share insurer-specific information with the public. The prospective G-SIIs have an opportunity to present information relevant to their assessment to the regulators before the final designation.

Phase V – IAIS Recommendation to the FSB

After completing Phase I through Phase IV, the IAIS recommends a list of designated G-SIIs to the FSB. Subsequently, the FSB has discretion to accept the IAIS' recommendation and to disclose the list of G-SIIs to the public.

3. Data and Systemic Risk Measures

To construct the sample of our study, we select all the insurers that are constituents of the World Datastream Insurance Index, which is developed by Thomson Reuters and consists of 250 insurers around the globe. Next, all insurers with CDS spread data unavailable for download from the S&P Capital IQ or Bloomberg database during the sample period of 2011–2015 are omitted. We choose the beginning of our sample period to be 2011 because the first designation the FSB made was based on the IAIS' assessment of 2011 data.

Table 2a:
List of Insurers in the Sample

Insurer Name	Country	Sector
Aegon NV*	Netherlands	Life and Health Insurance
Ageas SA	Belgium	Multi-line Insurance
Allianz SE	Germany	Multi-line Insurance
Allstate Corp.	United States	Property/Casualty (P/C) Insurance
American International Group Inc.	United States	Multi-line Insurance
AON Corp.	United States	Insurance Brokers
Assicurazioni Generali SpA*	Italy	Multi-line Insurance
Assured Guaranty Corp.	United States	P/C Insurance
Aviva PLC	United Kingdom	Multi-line Insurance
Axa SA	France	Multi-line Insurance
AXIS Capital Holdings Ltd.	United States	P/C Insurance
Banca Mediolanum SpA	Italy	Other Diversified Financial Services
Berkshire Hathaway Inc.	United States	Multi-Sector Holdings
Chubb Ltd	United States	P/C Insurance
CNA Financial Corp.	United States	P/C Insurance
Everest Reinsurance Holdings Inc.	United States	Reinsurance
Fairfax Financial Holdings Ltd.	Canada	Multi-line Insurance
Genworth Holdings Inc.	United States	Multi-line Insurance
Hannover Rück SE	Germany	Reinsurance
Hartford Financial Services Group Inc.	United States	Multi-line Insurance
Legal & General Group PLC	United Kingdom	Life and Health Insurance
Lincoln National Corp.	United States	Life and Health Insurance
Loews Corp.	United States	Multi-line Insurance
Marsh & McLennan Companies Inc.	United States	Insurance Brokers
MBIA Inc.	United States	P/C Insurance
MetLife Inc.	United States	Life and Health Insurance
Mitsui Sumitomo Insurance Co., Ltd.	Japan	P/C Insurance
Münchener Rückversicherungs-Gesellschaft Aktiengesellschaft	Germany	Reinsurance
Odyssey Re Holdings Corp.	United States	Reinsurance
Old Mutual PLC	United Kingdom	Life and Health Insurance

To construct the sample of our study, we select all the insurers that are constituents of the World Datastream Insurance Index, which is developed by Thomson Reuters and consists of 250 insurers around the globe. Next, all insurers with credit default swap (CDS) spread data unavailable for download from the S&P Capital IQ or Bloomberg database are omitted. We are then left with 42 insurers from 11 countries as listed in Tables 2a and 2b. The names of the insurers and their countries are extracted from the S&P Capital IQ database and the Worldscope database, respectively. The sector of each insurer is based on the categorization of the S&P Capital IQ database. Insurers designated by the Financial Stability Board (FSB) as global systemically important insurers (G-SIIs) are highlighted.

* Based on the financial data as of year-end 2014, the Financial Stability Board (FSB) updated the G-SII list and replaced Assicurazioni Generali SpA with Aegon NV.

Table 2b:
List of Insurers in the Sample

Insurer Name	Country	Sector
Prudential Financial Inc.	United States	Life and Health Insurance
Prudential PLC	United Kingdom	Life and Health Insurance
QBE Insurance Group Ltd.	Australia	P/C Insurance
RSA Insurance Group PLC	United Kingdom	P/C Insurance
SCOR SE	France	Reinsurance
Sompo Japan Nipponkoa Insurance Inc.	Japan	P/C Insurance
Swiss Reinsurance Company Ltd.	Switzerland	Reinsurance
Tokio Marine & Nichido Fire Insurance Co., Ltd.	Japan	P/C Insurance
The Travelers Companies Inc.	United States	P/C Insurance
Unipol Gruppo SpA	Italy	Multi-line Insurance
XLIT Ltd.	United States	P/C Insurance
Zurich Insurance Company Ltd.	Switzerland	P/C Insurance

We are then left with 42 life insurers, non-life insurers and reinsurers from 11 countries after the above procedures. Among these insurers, Allianz SE, American International Group (AIG), Assicurazioni Generali SpA, Aviva plc, AXA SA, MetLife, Prudential Financial Inc. and Prudential plc were designated as G-SIIs by the FSB in July 2013.[2] Subsequent to the IAIS' review exercise based on the financial data as of year-end 2014, Assicurazioni Generali SpA. was removed from the list of G-SIIs in November 2015. Aegon N.V. was designated as G-SII on the same day. The names of insurers in our sample can be found in Tables 2a and 2b, and the corresponding descriptive statistics are reported in Tables 3a and 3b.

3.1 MES^{CDS} Calculated from CDS Spreads

We follow Acharya et al. (2017) to construct the MES using CDS spread data, which can be interpreted as the expected increase of an insurer's CDS spread in the tail of the whole portfolio's CDS spread distribution. Mathematically, MES^{CDS} can be expressed as:

$$MES^{CDS}_i = E\ [\ R_i \mid R_p > VaR_\alpha] \tag{1}$$

where MES^{CDS}_i is the MES calculated by CDS spreads of insurer i, R_i is the log-return of insurer i's CDS spreads, R_p is the average log-return of the whole sample's CDS spreads, and VaR_α is the value-at-risk of the log-return of the whole sample's CDS spreads with confidence level 1-α%.

2. Ping An Insurance (Group) Company of China Ltd was designated by the FSB as a G-SII. However, the CDS data for this insurer is not available for download from *Bloomberg* and *S&P Capital IQ* database. This is because China did not open up its CDS market until September 2016 (Mak, 2016). Hence, we do not include Ping An Insurance (Group) Company of China Ltd in our sample.

Table 3a:
Summary Statistics

Variable	Moments				Percentiles					N
	Mean	Std. dev	Skewness	Kurtosis	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	
Panel A: Systemic risk measures (%)										
MES^{CDS}	4.06	2.77	1.19	3.96	0.98	2.17	3.71	5.55	7.60	840
- G-SII	5.02	2.46	0.54	-0.09	1.93	3.26	4.77	6.62	8.62	164
- Non-G-SII	3.84	2.78	1.40	5.19	0.82	1.99	3.37	5.28	7.25	676
Networks of CDS spreads	45.49	6.96	0.06	-0.74	35.97	40.22	45.24	50.7	54.72	840
- G-SII	50.28	5.20	-0.04	-0.29	43.84	46.76	50.59	54.11	56.57	164
- Non-G-SII	44.36	6.83	0.22	-0.67	35.52	38.88	43.80	49.59	53.97	676
Absorption ratio	0.94	0.80	4.51	36.39	0.23	0.46	0.83	1.25	1.71	840
- G-SII	1.19	0.58	0.35	-0.30	0.54	0.73	1.12	1.59	1.92	164
- Non-G-SII	0.88	0.83	5.04	39.77	0.21	0.40	0.75	1.16	1.58	676
Panel B: Abnormal systemic risk measures (%)										
Abnormal MES^{CDS}	0.00	2.26	0.81	4.43	-2.56	-1.41	-0.03	1.18	2.55	820
- G-SII	0.90	1.66	0.57	0.45	-1.24	-0.16	0.80	1.77	3.03	164
- Non-G-SII	-0.22	2.33	1.00	5.09	-2.80	-1.63	-0.31	0.96	2.36	656
Abnormal networks of CDS spreads	0.00	5.7	-0.44	-0.44	-7.78	-4.22	0.43	4.59	6.92	820
- G-SII	4.75	3.28	-0.82	0.66	1.16	3.08	5.10	7.05	8.54	164
- Non-G-SII	-1.19	5.56	-0.28	-0.45	-8.41	-5.18	-1.00	3.28	6.15	656
Abnormal absorption ratio	0.00	0.70	3.68	31.21	-0.72	-0.33	-0.02	0.29	0.58	820
- G-SII	0.21	0.45	0.29	0.44	-0.39	-0.06	0.19	0.44	0.85	164
- Non-G-SII	-0.05	0.74	4.00	32.04	-0.77	-0.37	-0.10	0.23	0.54	656

Tables 3a and 3b present the summary statistics for the variables used in our analysis. The sample is constructed by first selecting all the insurers that are constituents of the World Datastream Insurance Index. Next, all insurers with credit default swap (CDS) spread data unavailable for download from the S&P Capital IQ or Bloomberg database are omitted. The final dataset consists of 42 insurers from 11 countries. All the variables are defined in Table 7.

In our study, we calculate the MES^{CDS} on a quarterly basis for each insurer with α to be 95. A higher value of MES^{CDS} represents more systemic risk. After calculating the MES^{CDS} for the 42 insurers from 2011 to 2015, we plot the time evolution of MES^{CDS} for G-SIIs and non-G-SIIs in Figure 1. As Aegon N.V. replaced Assicurazioni Generali SpA as G-SII based on the IAIS' assessment of its financial data as of year-end 2014, Aegon N.V. is only considered as G-SII for the year of 2015, and Assicurazioni Generali SpA is considered as G-SII for the whole sample period except for the year 2015.

3.2 Insurers' Networks Calculated from CDS Spreads

Following Puliga *et al.* (2014), the second systemic risk measure used in this study is based on the networks constructed by CDS spreads. These networks are taken as a proxy of interdependencies among insurers. Each insurer is considered as a "node," and all nodes are connected with each other.

Table 3b:
Summary Statistics

Variable	Moments				Percentiles					N
	Mean	Std. dev	Skewness	Kurtosis	10^{th}	25^{th}	50^{th}	75^{h}	90^{th}	
Panel C: Country-specific macroeconomic variables (%)										
GDP growth	1.58	1.08	-1.56	3.54	0.22	1.18	1.71	2.43	2.43	840
- G-SII	1.51	1.21	-1.53	3.16	0.26	1.16	1.69	2.33	2.43	164
- Non-G-SII	1.60	1.05	-1.54	3.57	0.18	1.36	1.74	2.43	2.43	676
Inflation	1.54	1.18	0.13	-0.52	0.05	0.34	1.57	2.34	3.16	840
- G-SII	1.66	1.18	0.40	-0.33	0.12	0.60	1.62	2.55	3.16	164
- Non-G-SII	1.51	1.18	0.07	-0.60	0.04	0.24	1.52	2.12	3.16	676
Interest rate	0.35	0.55	4.17	23.79	0.05	0.13	0.13	0.50	1.00	840
- G-SII	0.37	0.34	1.28	1.25	0.05	0.13	0.20	0.50	1.00	164
- Non-G-SII	0.35	0.59	4.15	22.17	0.05	0.13	0.13	0.50	1.00	676
Δ Exchange rate	1.08	5.79	-0.09	1.79	-4.90	-2.67	1.13	3.05	9.81	840
- G-SII	1.44	4.80	0.74	0.33	-4.90	-1.70	1.13	3.05	7.56	164
- Non-G-SII	0.99	6.00	-0.17	1.79	-4.90	-3.05	1.13	3.05	10.66	676
Credit-to-GDP gap	-9.12	9.12	0.62	-0.16	-15.9	-14.70	-12.15	-2.00	5.60	840
- G-SII	-10.77	9.08	0.46	0.09	-22.1	-15.00	-12.35	-7.35	4.20	164
- Non-G-SII	-8.72	9.09	0.67	-0.25	-15.80	-14.70	-12.10	-0.60	6.20	676
Credit spreads	56.69	69.73	3.85	17.31	16.54	19.56	37.64	52.19	107.55	820
- G-SII	66.30	85.05	3.16	10.95	16.81	19.97	37.66	66.05	139.24	164
- Non-G-SII	54.29	65.20	4.09	19.98	16.54	19.31	37.64	52.19	99.84	656
Market volatility	16.14	6.74	1.33	1.29	9.48	11.25	14.14	18.98	26.77	840
- G-SII	16.91	6.90	1.24	1.21	9.66	11.98	14.87	19.75	27.32	164
- Non-G-SII	15.95	6.69	1.36	1.34	9.41	10.93	14.09	18.66	26.77	676

To measure the weight of the link between node i and j (such weight is denoted as w_{ij}) and the impact of node i on other nodes, we perform the following steps:

(a) Measure the Pearson correlation ρ_{ij} between nodes i and j

$$\rho_{ij} = \frac{E[(X_i(t)-\bar{X}_i)(X_j(t)-\bar{X}_j)]}{\sigma_i\sigma_j} \tag{2}$$

where $X_i(t)$ is the log-return of insurer i's CDS spread at time t.

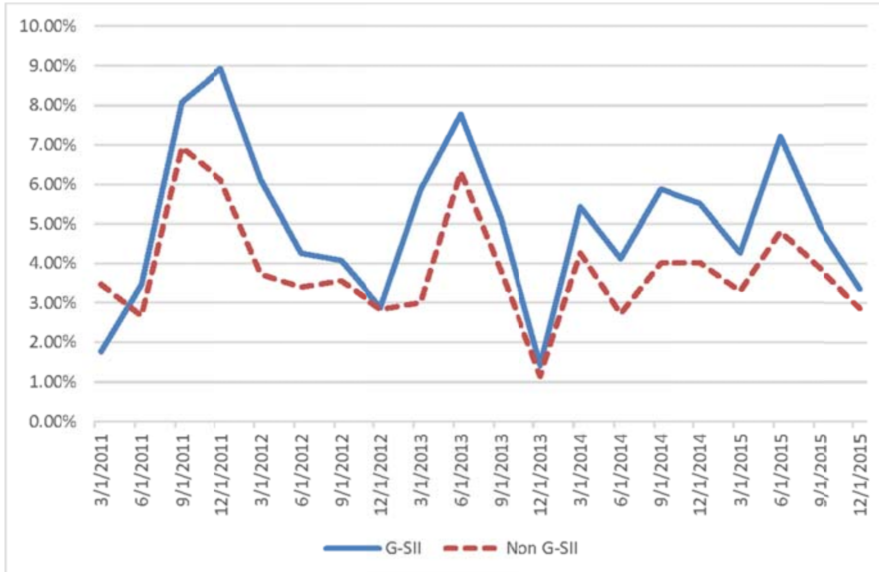
(b) As the value of ρ_{ij} in equation (2) ranges in the interval (-1, 1), we remap it into the interval (0,1) and measure the weight of the link w_{ij} as follows:

$$w_{ij} = 1 - \frac{\sqrt{2(1-\rho_{ij})}}{2} \tag{3}$$

(c) The impact of node i on other nodes is measured by the equation below:

$$Impact\ of\ node\ i = \sum_{j=1}^{42} w_{ij}v_j \tag{4}$$

Figure 1:
Time Evolution of Systemic Risk Calculated by MES^{CDS}



where v_j is a measure of the economic size of node j. Following Puliga *et al.* (2014), we take v_j as a constant 1 instead of the market capitalization of insurer j because market capitalization varies a lot, and changes in market capitalization can be affected by many factors not related to systemic risk.

(d) Finally, the systemic risk of node i is measured by the impact of node i standardized by the economic size of insurers, as described by the equation below:

$$Systemic\ risk\ of\ node\ i = \frac{\sum_{j=1}^{42} w_{ij} v_j}{\sum_{j=1}^{42} v_j} \quad (5)$$

We calculate the systemic risk measure of each insurer on a quarterly basis according to the method described above. A higher value of risk measure represents more systemic risk. The time evolution of the systemic risk measure for G-SIIs and non-G-SIIs from 2011 to 2015 can be found in Figure 2.

3.3 Absorption Ratio Calculated from CDS Spreads

For the third systemic risk measure, we follow Kritzman *et al.* (2011) to construct the absorption ratio, which is the percentage of total variance of the 42 insurers' CDS spread returns that can be explained by the first principal component, as a measure for systemic risk of the whole portfolio. The absorption ratio captures the extent to which the CDS spreads of the 42 insurers are coupled. When the 42 insurers' CDS spreads are tightly coupled (i.e., the absorption ratio is high), they are more fragile in the sense that negative shocks propagate more quickly and broadly than when they are loosely linked (i.e., the absorption ratio is low). Mathematically, absorption ratio can be expressed as:

$$Absorption\ Ratio = \frac{{\sigma_p}^2}{\sum_{i=1}^{42} {\sigma_i}^2} \tag{6}$$

${\sigma_p}^2$ = the variance of the first principal component constructed from the 42 insurers' CDS spread returns

${\sigma_i}^2$ = the variance of insurer i's CDS spread returns

Figure 2:
Time Evolution of Systemic Risk Calculated by Networks of Pearson Correlation

After calculating the absorption ratio for the portfolio of 42 insurers, the absorption ratio is then decomposed based on the systemic risk contribution of each insurer, which is represented by the eigenvector of the first principal component. The systemic risk of each insurer equals the absorption ratio multiplied by the adjusted eigenvalue of the relevant insurer in the first principal component.

Mathematically, the systemic risk of insurer i can be expressed as:

$$\textit{Systemic risk of insurer } i = \textit{absorption ratio} * a_i^{adjusted} \tag{7}$$

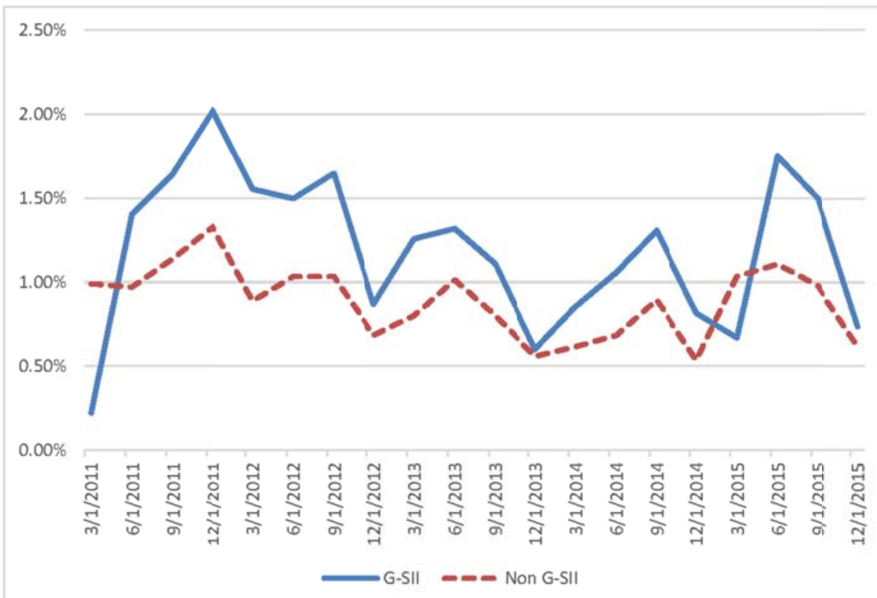
$$a_i^{adjusted} = \frac{a_i}{\sum_{j=1}^{42} a_j} \tag{8}$$

$a_i^{adjusted}$ = adjusted eigenvalue of insurer i in the first principal component

a_i = eigenvalue of insurer i in the first principal component

We calculate the systemic risk measure of each insurer on a quarterly basis according to the method described above. A higher value of systemic risk measure represents more systemic risk. We plot the time evolution of the systemic risk measure for G-SIIs and non-G-SIIs from 2011 to 2015 in Figure 3.

Figure 3:
Time Evolution of Systemic Risk Calculated by Absorption Ratio



4. Discussion on G-SII Designation and CDS-Based Systemic Risk Measures

In this section, we discuss how insurers' CDS data supplement the IAIS' G-SII identification methodology, which is mainly based on accounting data.

Specifically, we aim to identify any discrepancies for the list of G-SIIs disclosed by the FSB and the list of G-SIIs identified by CDS-based systemic risk measures.

4.1 Is the Systemic Risk of G-SIIs Identified by the FSB on Average Higher Than That of Non-G-SIIs?

To assess whether the IAIS proposed methodology accurately identifies systemically important insurers, we first examine whether the systemic risk of insurers designated by the FSB as G-SIIs is on average higher than that of other insurers. In fact, Figure 1, Figure 2 and Figure 3 offer an insight into the issue. No matter if we measure systemic risk by MES^{CDS}, networks of CDS spreads or absorption ratio, all the figures indicate that the risk measures for G-SIIs and non-G-SIIs co-moves together, suggesting that the systemic risk of these insurers is affected by some time-varying factors. More importantly, the systemic risk of G-SIIs is higher than that of non-G-SIIs for most of the time. This observation motivates us to further examine if the difference in systemic risk of G-SIIs and non-G-SIIs is statistically significant.

We conduct the one-tailed paired t-test to investigate whether the systemic risk of G-SIIs is on average higher than that of non-G-SIIs. The results are documented in Panel A of Table 4a. The t-test results indicate that when systemic risk is measured by MES^{CDS}, networks of CDS spreads and absorption ratio, the systemic risk of G-SIIs is higher than that of non-G-SIIs by 31%, 13% and 35%, respectively. Their corresponding t-statistics are 5.36, 23.91 and 4.17, respectively, which are highly statistically significant.

To control for the possibility that the one-tailed paired t test results are biased by other omitted or unobservable factors, we collect macroeconomic variables from the relevant national authorities—World Development Indicators (WDI) of World DataBank, the BIS database and the S&P Capital IQ database—and conduct the following multivariate regression to study whether the systemic risk of designated G-SIIs is higher than that of non-G-SIIs. The empirical model is described below.

$$
\begin{aligned}
&\textit{Systemic risk}_{it} = \beta_0 + \beta_1\, \textit{GSII}_{it} + \beta_2\, \textit{GDP Growth}_{ct} + \beta_3\, \textit{Inflation}_{ct} + \\
&\beta_4\, \textit{Interest Rate}_{ct} + \beta_5\, \Delta \textit{Exchange Rate}_{ct} + \beta_6\, \textit{Credit-to-GDP Gap}_{ct} + \\
&\beta_7\, \textit{Credit Spreads}_{ct} + \beta_8\, \textit{Market Volatility}_{ct} + f_c + s_t + e_{it} \qquad (9)
\end{aligned}
$$

where *i* denotes an insurer; *c* denotes the country insurer *i* is based in; *t* denotes a quarter; $\textit{Systemic risk}_{it}$ is the systemic risk measured by MES^{CDS}, networks of CDS spreads or absorption ratio; $\textit{GSII}_i$ is a dummy variable that equals 1 if insurer *i* is designated by the FSB as G-SII; and e_{it} is the error term. We use $\textit{GDP Growth}_{ct}$ and $\textit{Inflation}_{ct}$ as control variables because a previous study indicates that high inflation rates and falling GDP increase the risk of financial institutions (Baselga-Pascual *et al.*, 2015). Following Mendonca and Silva (2017), we add $\textit{Interest Rate}_{ct}$ and $\Delta\textit{Exchange Rate}_{ct}$ as control variables as the empirical results in their study suggest that higher monetary policy interest rate and currency devaluation increase systemic risk. *Interest Rate*$_{ct}$ is measured by the local monetary policy interest rate, while *ΔExchange Rate*$_{ct}$ is measured by the changes of real effective exchange rate. We use *Credit-to-GDP Gap*$_{ct}$ and *Credit Spreads*$_{ct}$ as control variables because Drehmann *et al.* (2011) find that these two variables are associated with vulnerabilities of the financial system. *Credit-to-GDP Gap*$_{ct}$ is measured by the difference between the credit-to-GDP ratio and its long-term trend, while *Credit Spreads*$_{ct}$ is measured by the CDS spread of local government bond. As Chuang (2015) finds that realized volatility of the stock market is positively associated with the financial network density, which can be a probe to systemic risk, we include *Market Volatility*$_{ct}$ as one of the control variables. To control for unobserved country-specific variables and time-specific variables, we also add the country-fixed effect f_c and time-fixed effect s_t. Standard errors are clustered at the firm level to control for heteroscedasticity. As the G-SII designation is highly correlated with firm-specific variables, we deliberately do not include any firm-specific control variables to avoid the multicollinearity problem. If the systemic risk of insurers designated by the FSB as G-SIIs is higher than that of non-G-SIIs, we expect the estimated coefficient β_1 to be positive and statistically significant. The regression results are documented in Panel B of Table 4b.

Table 4a:
One-Tailed Paired T-Test and Multivariate Regression Results

Panel A: One-tailed paired t-test results

	MES^{CDS} (%) (1)	Networks of CDS Spreads (%) (2)	Absorption Ratio (%) (3)
Average systemic risk of designated G-SIIs	5.02	50.28	1.19
Average systemic risk of non-G-SIIs	3.84	44.36	0.88
Difference	1.18***	5.92***	0.31***
	(5.36)	(23.91)	(4.17)

Panel A of the table above reports the results of running the one-tailed paired t-test on the whole sample from 2011 to 2015. The computation of MES^{CDS}, networks of credit default swap (CDS) spreads and absorption ratio is described in Section 3. T-statistics are reported in parentheses; *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively. All the variables are defined in Table 7.

Column 1, Column 2 and Column 3 of Tables 4a and 4b report the regression results with fixed effects but without macroeconomic control variables; Column 4, Column 5 and Column 6 of Tables 4a and 4b report the regression results with macroeconomic control variables but without fixed effects; and Column 7, Column 8 and Column 9 of Tables 4a and 4b report the regression results with both macroeconomic control variables and fixed effects. Based on the regression results, we note that the estimated coefficients for the *GSII*$_{it}$ dummy are positive and highly statistically significant, suggesting that insurers designated by the FSB as G-SIIs have higher systemic risk than non-G-SIIs. The magnitude of the estimated coefficients for the $GSII_{it}$ dummy is comparable to the difference between systemic risk of G-SIIs and non-G-SIIs reported in Panel A of Table 4a, suggesting that the results of one-tailed paired t-test are consistent with that of the multivariate regression.

Table 4b:
One-Tailed Paired T-Test and Multivariate Regression Results

Panel B: Multivariate regression results

	Dependent variable								
	MES^{CDS} (%)	Networks of CDS Spreads (%)	Absorption Ratio (%)	MES^{CDS} (%)	Networks of CDS Spreads (%)	Absorption Ratio (%)	MES^{CDS} (%)	Networks of CDS Spreads (%)	Absorption Ratio (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	3.135***	37.599***	0.839**	1.506***	39.539***	0.543***	-0.315	38.576***	-0.374
	(4.45)	(48.99)	(2.66)	(2.87)	(19.90)	(3.76)	(-0.24)	(28.00)	(-0.68)
G-SII	1.041***	5.063***	0.249***	1.055***	5.667***	0.275***	1.047***	5.049***	0.253***
	(4.66)	(5.18)	(4.57)	(3.98)	(5.89)	(4.35)	(4.67)	(5.11)	(4.70)
GDP growth (%)				-0.166	-0.403	-0.135**	-0.381*	-0.630***	-0.218***
				(-0.78)	(-0.72)	(-2.40)	(-1.84)	(-3.24)	(-2.91)
Inflation (%)				-0.033	1.731***	-0.015	-0.158	1.674***	-0.139***
				(-0.32)	(4.91)	(-0.58)	(-1.25)	(2.85)	(-2.92)
Interest rate (%)				-0.133	-0.830	-0.009	-0.868**	-0.219	-0.143
				(-0.84)	(-0.76)	(-0.15)	(-2.04)	(-0.29)	(-1.01)
Δ Exchange rate (%)				0.052	0.082	0.016*	0.083	-0.127***	0.029
				(1.28)	(0.83)	(1.76)	(1.55)	(-3.35)	(1.57)
Credit-to-GDP gap (%)				-0.012	0.076	-0.002	-0.086**	-0.176**	-0.015
				(-0.46)	(0.64)	(-0.24)	(-2.60)	(-2.65)	(-1.26)
Credit spreads (%)				-0.006**	-0.017*	-0.002**	-0.002	-0.012***	-0.001
				(-2.46)	(-1.78)	(-2.57)	(-1.30)	(-2.79)	(-1.65)
Market volatility (%)				0.179***	0.295***	0.041***	0.186***	-0.139***	0.099***
				(9.12)	(5.11)	(5.28)	(2.79)	(-2.78)	(3.26)
Country-fixed effect	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Time-fixed effect	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Observations	840	840	840	820	820	820	820	820	820
R^2	0.373	0.622	0.185	0.171	0.241	0.125	0.413	0.664	0.297

Panel B of the table above reports the results of running the multivariate regression on the whole sample from 2011 to 2015. The computation of MES^{CDS}, networks of CDS spreads and absorption ratio is described in Section 3. Standard errors are clustered at the firm level, and t-statistics are reported in parentheses; *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively. All the variables are defined in Table 7.

Figures 1 to 3, the one-tailed paired t-test results and the multivariate regression results indicate that the systemic risk measures constructed by insurers' CDS data are, in general, consistent with the IAIS' identification methodology. The insurers designated by the FSB as G-SIIs are likely to have more systemic risk than other insurers. This is not surprising as the development of identification methodology involves experts from the industry, as well as references to scholastic work (e.g., see IAIS, 2011; Klein, 2011; The Geneva Association, 2010).

The IAIS also engaged various stakeholders for more than 140 hours in 2015 for the update of the assessment methodology (IAIS, 2016). Nevertheless, is the FSB's list of G-SIIs comprehensive? Are there any systemically important insurers excluded from the FSB's list of G-SIIs? We examine this issue in the next sub-section.

Table 5a:
Rank of Insurers by the Average of Systemic Risk Measures
(In Descending Order)

Insurer Name	2011	2012	2013	2014	2015
Aegon NV	18	17	8	5	5
Ageas SA	41	39	34	38	35
Allianz SE	3	4	1	1	6
Allstate Corp.	9	15	22	20	12
American International Group Inc.	8	8	11	10	22
AON Corp.	26	22	32	41	32
Assicurazioni Generali SpA	12	11	9	2	2
Assured Guaranty Corp.	30	29	27	26	29
Aviva PLC	6	9	5	3	4
Axa SA	16	11	4	4	1
AXIS Capital Holdings Ltd	32	34	31	29	37
Banca Mediolanum SpA	19	24	35	31	13
Berkshire Hathaway Inc.	15	20	26	21	11
Chubb Ltd.	7	13	17	25	14
CNA Financial Corp.	31	25	38	40	31
Everest Reinsurance Holdings Inc.	34	42	33	27	25
Fairfax Financial Holdings Ltd.	42	40	40	35	39
Genworth Holdings Inc.	25	26	13	18	38
Hannover Rück SE	11	5	7	6	7
Hartford Financial Services Group Inc.	2	6	10	12	15
Legal & General Group PLC	28	27	20	15	10
Lincoln National Corp.	4	7	17	13	33
Loews Corp.	23	18	28	24	23

In Tables 5a and 5b, we rank the insurers in our sample in descending order of their systemic risk measures constructed with their credit default swap (CDS) data on a quarterly basis. To reduce the volatility of systemic risk measures, the ranks of each insurer are averaged within each year, resulting in one averaged rank for each insurer for each systemic risk measure. As there are subtle differences among the systemic risk measured by MES^{CDS}, networks of CDS spreads and absorption ratio, we further take average of the ranks indicated by these measures, and report the rank of these averaged values in this table. As our sample consists of eight insurers designated by the Financial Stability Board (FSB) as global systemically important insurers (G-SIIs), we highlight the top eight insurers with the most systemic risk for comparison with the FSB's G-SII designation.

4.2 Is the FSB's List of G-SIIs Comprehensive?

To investigate whether the FSB's list of G-SIIs is comprehensive, we rank the insurers in descending order of their CDS-based systemic risk measures on a quarterly basis. To reduce the volatility of systemic risk measures, the ranks of each insurer are averaged within each year, resulting in one averaged rank for each insurer for each systemic risk measure. As there are subtle differences among the systemic risk measured by MES^{CDS}, networks of CDS spreads and absorption ratio, we further take average of the ranks indicated by these three measures and report the rank of these averaged values in Tables 5a and 5b.

Table 5b:
Rank of Insurers by the Average of Systemic Risk Measures
(In Descending Order)

Insurer Name	2011	2012	2013	2014	2015
Marsh & McLennan Companies Inc.	28	23	30	39	26
MBIA Inc.	22	28	29	34	27
MetLife Inc.	1	10	14	11	21
Mitsui Sumitomo Insurance Co., Ltd.	38	36	41	22	28
Münchener Rückversicherungs-Gesellschaft Aktiengesellschaft	5	2	6	8	8
Odyssey Re Holdings Corp.	40	38	39	37	42
Old Mutual PLC	37	30	24	28	24
Prudential Financial Inc.	10	16	16	16	17
Prudential PLC	21	21	19	17	16
QBE Insurance Group Ltd.	34	35	36	42	35
RSA Insurance Group PLC	24	30	21	36	20
SCOR SE	27	32	24	14	18
Sompo Japan Nipponkoa Insurance Inc.	36	41	37	23	19
Swiss Reinsurance Company Ltd.	20	3	3	9	3
Tokio Marine & Nichido Fire Insurance Co., Ltd.	39	37	42	33	41
The Travelers Companies Inc.	17	19	23	32	40
Unipol Gruppo SpA	33	33	15	30	34
XLIT Ltd.	13	14	12	19	30
Zurich Insurance Company Ltd.	14	1	2	7	9

One may be concerned that the systemic risk of G-SIIs is affected by country-specific and time-varying macroeconomic variables, which are beyond insurers' control. Hence, ranking insurers according to their systemic risk measures without controlling for these macroeconomic variables may cause bias in G-SII assessment. To address this concern, we calculate the residuals e_{it} in equation (10) for each insurer i on a quarterly basis and define these residuals e_{it} as abnormal systemic risk measures.

$$Systemic\ risk_{it} = \gamma_0 + \gamma_1\ GDP\ Growth_{ct} + \gamma_2\ Inflation_{ct} + \gamma_3\ Interest\ Rate_{ct} + \gamma_4\ \Delta Exchange\ Rate_{ct} + \gamma_5\ Credit\text{-}to\text{-}GDP\ Gap_{ct} + \gamma_6\ Credit\ Spreads_{ct} + \gamma_7\ Market\ Volatility_{ct} + s_t + e_{it} \quad (10)$$

Table 6a:
Rank of Insurers by the Average of Abnormal Systemic Risk Measures
(In Descending Order)

Insurer Name	2011	2012	2013	2014	2015
Aegon NV	17	25	11	5	3
Ageas SA	31	31	39	35	23
Allianz SE	6	10	4	4	6
Allstate Corporation	10	15	23	17	12
American International Group Inc.	11	5	12	6	25
AON Corp.	27	21	33	40	36
Assicurazioni Generali SpA	3	7	8	14	1
Assured Guaranty Corp.	28	29	27	23	30
Aviva PLC	5	9	1	2	4
Axa SA	15	10	5	6	2
AXIS Capital Holdings Ltd.	34	35	32	26	38
Banca Mediolanum SpA	9	22	36	41	10
Berkshire Hathaway Inc.	14	19	26	18	11
Chubb Ltd.	7	13	17	24	16
CNA Financial Corp.	33	25	35	37	33
Everest Reinsurance Holdings Inc.	37	41	34	25	27
Fairfax Financial Holdings Ltd.*	NA	NA	NA	NA	NA
Genworth Holdings Inc.	26	24	13	14	39
Hannover Rück SE	16	12	9	9	5
Hartford Financial Services Group Inc.	2	4	6	11	17
Legal & General Group PLC	24	30	14	18	9
Lincoln National Corp.	4	3	18	12	35
Loews Corp.	23	16	28	22	25

In Tables 6a and 6b, we rank the insurers in our sample in descending order of their abnormal systemic risk measures constructed with their credit default swamp (CDS) data on a quarterly basis. To reduce the volatility of abnormal systemic risk measures, the ranks of each insurer are averaged within each year, resulting in one averaged rank for each insurer for each abnormal systemic risk measure. As there are subtle differences among the abnormal systemic risk measured by MES^{CDS}, networks of CDS spreads and absorption ratio, we further take average of the ranks indicated by these measures and report the rank of these averaged values in this table. As our sample consists of eight insurers designated by the Financial Stability Board (FSB) as global systemically important insurers (G-SIIs), we highlight the top eight insurers with the most systemic risk for comparison with the FSB's G-SII designation.

* The abnormal systemic risk measures for Fairfax Financial Holdings Ltd. are not available because one of the macroeconomic variables, credit spreads, for Canadian government bonds is missing from our dataset.

By construction, abnormal systemic risk measures e_{it} probe the systemic risk of insurers after controlling for macroeconomic variables and unobserved time-varying variables. We deliberately do not include country-fixed effect in equation (10) as firm characteristics are likely to be clustered within a country, and it is our intention for the abnormal systemic risk measures to capture firm-specific characteristics. After calculating the residuals e_{it} in equation (10), we repeat the above ranking procedure with the abnormal CDS-based systemic risk measures and report the results in Tables 6a and 6b.

Table 6b:
Rank of Insurers by the Average of Abnormal Systemic Risk Measures (In Descending Order)

Insurer Name	2011	2012	2013	2014	2015
Marsh & McLennan Companies Inc.	29	23	31	36	31
MBIA Inc.	21	28	30	31	31
MetLife Inc.	1	6	18	8	24
Mitsui Sumitomo Insurance Co., Ltd.	39	39	40	28	21
Münchener Rückversicherungs-Gesellschaft Aktiengesellschaft	12	8	7	10	8
Odyssey Re Holdings Corp.	41	37	37	33	41
Old Mutual PLC	36	34	21	32	28
Prudential Financial Inc.	7	18	9	20	20
Prudential PLC	19	20	21	13	18
QBE Insurance Group Ltd.	38	27	24	29	15
RSA Insurance Group PLC	20	33	15	34	22
SCOR SE	32	36	29	21	19
Sompo Japan Nipponkoa Insurance Inc.	35	40	37	27	12
Swiss Reinsurance Company Ltd.	25	2	3	3	7
Tokio Marine & Nichido Fire Insurance Co., Ltd.	40	38	41	39	37
The Travelers Companies Inc.	18	17	25	29	40
Unipol Gruppo SpA.	30	32	20	38	34
XLIT Ltd.	13	14	16	16	29
Zurich Insurance Company Ltd.	22	1	1	1	14

As our sample consists of eight insurers designated by the FSB as G-SIIs, we highlight the top eight insurers with the most systemic risk in Tables 5a and 5b and Tables 6a and 6b and examine whether they are equal to those eight insurers designated by the FSB.[3] We find that Aegon N.V., Allianz SE, American International Group, Assicurazioni Generali SpA, Aviva plc, Axa SA and MetLife are occasionally ranked as the top eight insurers with the most systemic risk in the sample period. This is consistent with the FSB's assessment result, as these seven insurers have been designated by the FSB as G-SIIs. However, it is obvious that Hannover Rück SE, Swiss Reinsurance Company Ltd. And Münchener Rückversicherungs-Gesellschaft Aktiengesellschaft have more systemic risk than

3. While it can be argued that the appropriate number of designated G-SIIs could be larger or smaller than eight, this "threshold" issue is outside the scope of our study. The appropriate number of designated G-SIIs can vary from time to time, and it is possible that none of the insurers around the globe will be designated as G-SIIs in the future if the whole insurance industry changes its characteristics to reduce systemic risk. We recommend that the "threshold" issue should be more openly discussed among insurance and finance academics, industry professionals, and regulators.

some of the designated G-SIIs, such as Prudential Financial Inc. and Prudential plc. Ironically, the former three reinsurers are excluded from the FSB's list of G-SIIs, while the latter two insurers are included in the list. Because of the different nature of insurance business between direct insurers and reinsurers, the FSB decided to postpone the decision to identify reinsurers as G-SIIs, pending further development of identification methodology specifically designed for reinsurers (FSB, 2015).

Our results indicate that reinsurers do have significant amount of systemic risk that is even higher than some G-SIIs designated by the FSB. The IAIS should speed up the development of identification methodology for reinsurers to prevent reinsurers from falling out of the G-SII supervision and becoming the source of the next financial crisis. This argument is consistent with Acharya *et al.* (2009) in the sense that the reinsurance market increases the interconnectedness of insurers and amplifies the systemic risk in the overall system, and Hufeld *et al.* (2016) in the sense that the largest global reinsurers can create systemic risk by engaging in NTNI activities.

Without disclosure of detailed explanation for including Prudential Financial Inc. and Prudential plc in the G-SII list, the regulators also face the litigation risk from these insurers as the systemic risk measures constructed by CDS data indicate that, for most of the time in the sample period, they are not among the top eight insurers generating the most systemic risk. The court ruling in March 2016 overturning the FSOC's systemic importance designation of MetLife Inc. may encourage other G-SIIs to challenge their G-SII designations in court. The exclusion of Hartford Financial Services Group Inc. and Zurich Insurance Company Ltd., which generate significant amount of systemic risk during most of the time in the sample period, from the G-SII list also puts the regulator in a difficult position to justify their G-SII designation in court. The IAIS' identification strategy may be subject to challenge due to its heavy reliance on accounting data and limited usage of market data. Given the advantages of using CDS data over accounting data to measure systemic risk,[4] we advise the IAIS to incorporate the CDS-based systemic risk measures into its identification methodology so that it can substantiate the G-SII designation in court.

4.3 Was the FSB's Change of G-SII List in November 2015 Appropriate?

Since its first designation in July 2013, the FSB has not changed its G-SII list for several rounds of annual review except for the designation in November 2015, which was based on the financial data as of year-end 2014. For that designation, Assicurazioni Generali SpA was replaced by Aegon N.V. as one of the G-SIIs. This was subsequent to Assicurazioni Generali SpA's sale of its private banking

4. A detailed discussion about the advantages of using CDS data over accounting data to measure systemic risk can be found in Section 1.

unit BSI, and the FSB opined that the removal of Assicurazioni Generali SpA from and the addition of Aegon N.V. to the G-SII list reflected the changes in the level and type of activities undertaken by these two insurers (Riemsdijk, 2015).

However, we observe from Tables 5a and 5b and Tables 6a and 6b that the systemic risk of Assicurazioni Generali SpA remains huge throughout the sample period. As the FSB removed Assicurazioni Generali SpA from the G-SII list in November 2015, we would have expected that the systemic risk of this insurer decreased substantially and remained at a low level in 2015. Surprisingly, as noted from Tables 5a and 5b and Tables 6a and 6b, Assicurazioni Generali SpA ranks the second and first, respectively, among our whole sample of insurers in 2015. Although the structural transformation taken by Assicurazioni Generali SpA seems to successfully convince the FSB to remove it from the G-SII list, the market suggests otherwise. Based on the systemic risk measures constructed from CDS data, we do not find any evidence supporting the FSB's decision.

The addition of Aegon N.V. to the G-SII list is consistent with the systemic risk measures reported in Tables 5a and 5b and Tables 6a and 6b, as we observe that there is an increasing trend for the systemic risk of Aegon N.V. in recent years. The ranking of Aegon N.V. increases from 18 in 2011 to 5 in 2015 (Tables 5a and 5b), and from 17 in 2011 to 3 in 2015 (Tables 6a and 6b). We find that the FSB made a timely decision to add Aegon N.V. to the G-SII list.

As the FSB did not disclose the concrete reasons for removing Assicurazioni Generali SpA from the G-SII list, we have no basis to examine whether the FSB's rationales are valid. Nevertheless, given the inconsistency between the FSB's removal decision and the systemic risk measures constructed by the CDS data, we urge the FSB to increase transparency regarding its designation decisions so that any inconsistencies on the designations can be openly discussed.

4.4 Should MetLife be Designated as a G-SII?

Although the recent court case overturned the FSOC's decision to designate MetLife as systemically important, the judge only opined that the regulator departed from its guidance during the G-SII assessment process and refused to consider the cost borne by MetLife for being designated as systemically important (MetLife, 2016), leaving open the controversial question of whether MetLife is systemically important. We offer some insight into the question in this sub-section.

While we acknowledge that the regulators need to consider various factors for designating insurers as G-SIIs, the CDS-based systemic risk measure can be a good reference to begin with. As noted from Tables 5a and 5b and Tables 6a and 6b, MetLife had the highest systemic risk among all insurers in our sample in 2011, no matter whether we control for macroeconomic factors and time-varying variables. This is consistent with the FSB's assessment, and it is not surprising to find MetLife on the G-SII list when the FSB first announced the designation result. However, as time goes by, the systemic risk of MetLife decreased gradually. By the end of 2015, the systemic risk of MetLife ranked 21st (before controlling for macroeconomic factors and time-varying variables) and 24th (after controlling for macroeconomic factors and time-varying variables) among all insurers in our sample in 2015. In other words, more than half of the insurers in our sample generated more systemic risk than MetLife did in 2015.

The findings naturally trigger an avoidable question of whether the regulator should continue to keep MetLife on the G-SII list. As the FSB did not disclose the concrete reasons for keeping MetLife on the G-SII list in the latest assessment, we cannot comment on whether the FSB's decision is appropriate and up-to-date. However, we urge the FSB and IAIS to take into consideration the declining trend of MetLife's CDS-based systemic risk measures in the upcoming assessment, as the regulators are unlikely to justify themselves for neglecting the fact that the value of MetLife's CDS-based systemic risk measures was below the median of our whole sample in 2015.

5. Limitations of the CDS-Based Systemic Risk Measures

Although the CDS data has several advantages over accounting data regarding the measurement of systemic risk, the availability of CDS data is limited to large insurers only. For the 250 constituents of the World Datastream Insurance Index, only 42 have CDS spread data available for download from the S&P Capital IQ and Bloomberg database. It is possible that some of the insurers without CDS spread data are systemically important. In addition, the limited availability of CDS data poses practical difficulties to extend the G-SII assessment to small and medium-sized insurers. As it is an over-generalization that small and medium-sized insurers would not be systemically important, it is currently not feasible to solely rely on the CDS-based systemic risk measures to identify all systemically important insurers. Nevertheless, the G-SIIs identified by the FSB are giant financial conglomerates. Eight out of nine of them, with the exception of Ping An Insurance (Group) Company of China Ltd., have CDS data available for analysis. In other words, CDS data for the majority of potential G-SIIs are available for assessment. As the CDS market continues to develop, we believe that CDS data for more insurers will be available for examination when the market matures in the near future.

Another potential criticism of CDS-based systemic risk measures is that they reflect insurers' systemic risk perceived by market participants, who only possess public information. As some private information, which can be accessed by regulators only, is also relevant in analyzing insurers' systemic importance, we do not recommend the IAIS replace its identification methodology with CDS-based systemic risk measures. Instead, we propose that CDS-based systemic risk measures can serve as timely indicators of systemic risk and be used to supplement the IAIS' identification framework.

Table 7:
Definitions of Variables

Variables	Definitions
Δ Exchange rate	Δ Exchange rate is measured by the change of real effective exchange rate.
Abnormal absorption ratio	Abnormal absorption ratio captures the extent to which the credit default swap (CDS) spreads are coupled by principal component analysis, after controlling for macroeconomic factors and time-varying variables. Refer to Section 4.2 for detailed methodology and calculation.
Abnormal MES^{CDS}	Abnormal MES^{CDS} is the expected increase of an insurer's CDS spread in the tail of the whole portfolio's CDS spread distribution, after controlling for macroeconomic factors and time-varying variables. Refer to Section 4.2 for detailed methodology and calculation.
Abnormal networks of CDS spreads	Abnormal networks of CDS spreads measures the interdependencies among insurers by networks of Pearson correlations, after controlling for macroeconomic factors and time-varying variables. Refer to Section 4.2 for detailed methodology and calculation.
Absorption ratio	Absorption ratio captures the extent to which the CDS spreads are coupled by principal component analysis. Refer to Section 3.3 for detailed methodology and calculation.
Credit spreads	Credit spreads are measured by the CDS spreads of local government bond.
Credit-to-GDP gap	Credit-to-GDP gap is measured by the difference between the credit-to-GDP ratio and its long-term trend.
GDP growth	GDP growth is measured by the annual percentage growth of gross domestic product.
GSII (1/0)	The G-SII dummy, which equals to 1 if the insurer has been designated by the Financial Stability Board (FSB) as global systemically important, and 0 otherwise.
Inflation	Inflation is measured by the change in consumer price index.
Interest rate	Interest rate is measured by the local monetary policy interest rate.
Market volatility	Market volatility is measured by the realized volatility of the local stock market
MES^{CDS}	MES^{CDS} is the expected increase of an insurer's CDS spread in the tail of the whole portfolio's CDS spread distribution. Refer to Section 3.1 for detailed methodology and calculation.
Networks of CDS spreads	Networks of CDS spreads measures the interdependencies among insurers by networks of Pearson correlations. Refer to Section 3.2 for detailed methodology and calculation.

6. Conclusion

The recent court case overturning the FSOC's systemic importance designation of MetLife raises the public awareness of whether the designation methodology proposed by the regulators can accurately identify systemically important insurers. From the academic perspective, the identification methodology proposed by the IAIS lacks empirical support (see Weiβ and Mühlnickel, 2014;

Bierth *et al.*, 2015). The heavy reliance on historical accounting data also poses difficulties for the regulators to identify G-SIIs based on their potential systemic risk (see Kanagaretnam *et al.*, 2016). From the industry practitioners' perspective, there is no consensus as to which insurers should be designated as G-SIIs. The ruling of the MetLife court case opens the door for other G-SIIs to challenge their G-SII designations. The announcement made by the U.S. President Donald Trump stressing the need to improve the designation process (Chiglinsky and Harris, 2017) further undermines the credibility of the designation methodology proposed by the regulators. Against this backdrop, we examine how the systemic risk measures constructed from insurers' CDS data can improve the G-SII identification methodology proposed by the IAIS.

Using insurers' CDS data to construct three different systemic risk measures, we find that G-SIIs designated by the FSB, on average, have higher systemic risk than other insurers, suggesting that the G-SII identification methodology is, in general, sound and effective. However, a closer investigation reveals that there is room for improvement in the identification methodology. The IAIS should speed up the development of methodologies to identify and regulate systemically important reinsurers, as three reinsurers in our sample have systemic risk higher than some G-SIIs designated by the FSB. The systemic risk measures indicate that the IAIS should not remove Assicurazioni Generali SpA, which generated the most systemic risk in 2015, from the G-SII list. Keeping MetLife Inc. on the G-SII list is not supported by CDS-based systemic risk measures as well. The IAIS should increase transparency in the designation process so that any discrepancies between the designation results and various kinds of systemic risk measures can be openly discussed.

We shed light on the literature on systemic risk and insurance regulation by demonstrating how insurers' CDS data can supplement the IAIS' G-SII identification methodology. From a public policy standpoint, our findings have important implications for the identification of G-SIIs. Our results show that the identification methodology that the IAIS proposed is, in general, sound and effective, but can be further supplemented by the CDS-based systemic risk measures. While facing substantial litigation risk from the designated G-SIIs after the MetLife court case, the regulators can better substantiate their designation decisions in court by incorporating the CDS-based systemic risk measures into their G-SII identification framework.

Our study can lead to further studies and discussions about the applicability of CDS data on the G-SII identification methodology. Future studies can focus on studying how the CDS-based systemic risk measures introduced in this paper and other systemic risk measures documented in literature can be validated in the context of G-SII identification. Simulation models can be developed to study how G-SIIs identified by different systemic risk measures experience simulated financial distress, and the ripple effects of their distress can be assessed as they extend to other insurers and financial institutions. In addition, given the limited availability of insurers' CDS spread data, future empirical studies can analyze the factors and conditions that affect CDS spreads. These factors and conditions can be used as proxies for CDS spreads, and, hopefully, the analysis using CDS-based systemic risk measures can be extended to insurers without CDS spread data. Finally, given the broad array of tools used by regulators to assess the risks of insurers, future studies can focus on how CDS-based systemic risk measures can be used in conjunction with other tools to optimize the G-SII identification framework.[5]

5. We would like to thank the anonymous reviewer for suggesting these topics for further researches.

Appendix

Financial Stability Board (FSB)	**Financial Stability Oversight Council (FSOC)**
The aim of approach described below is to identify global systemically important insurers (G-SIIs). The approach consists of five phases.	The aim of the approach described below is to identify systemically important nonbank financial companies, which include insurers, brokerage firms and other companies that provide financial services. The approach consists of three stages.
Phase I	**Stage 1**
Collects annual information from insurers that satisfy either one of the following conditions: (a) Total assets are more than US$60 billion, and ratio of overseas premium exceeds 5%. (b) Total assets are more than US$200 billion, and the ratio of overseas premium is greater than 0%.	Collects quarterly information from nonbank financial companies that satisfy either two of the following conditions: (a) Total credit default swaps for which the nonbank financial company is the reference entity are more than US$30 billion. (b) Total derivative liabilities are more than US$3.5 billion. (c) Total debt outstanding is more than US$20 billion. (d) Leverage ratio is higher than 15. (e) Short-term debt-to-asset ratio is higher than 10%.
Phase II	**Stage 2**
The systemic importance score for each insurer is calculated with reference to 17 indicators constructed from accounting data. Insurers with systemic importance scores above a quantitative threshold are considered as prospective G-SIIs and are advanced to Phase III for detailed analysis.	Each nonbank financial company is assessed based on existing public information, regulatory information and information available from the company's primary financial regulatory agency or home country supervisor. However, unlike the FSB, the FSOC does not publicly disclose the exact type of information it considers for assessment. Based on the initial evaluation in Phase II, the FSOC may vote to advance the nonbank financial company for detailed analysis in Phase III.
Phase III	**Stage 3**
Additional quantitative and qualitative information is requested from the prospective G-SIIs for further analysis.	Additional quantitative and qualitative information is requested from the nonbank financial companies for further analysis.
Phase IV	
The prospective G-SIIs have opportunities to present information relevant to their assessment to the regulators before the final designation.	The prospective nonbank financial companies have opportunities to present information relevant to their assessment to the regulators before the final designation The FSOC votes to make a formal designation and subsequently discloses the designation to the public.
Phase V	
The FSB formally designates G-SIIs and subsequently discloses the designation to the public.	

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