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What's the value of a TBTF guaranty? Evidence from the G-SII designation for insurance companies

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Abstract

We document average abnormal stock returns of 14% for international insurance firms designated as Global Systemically Important Insurers (G-SII). These gains are associated with a fall in average default probability of 15.6%, and statistically weak and economically marginal increases in expected asset risk. Over the same event window, identical measures for other large insurance firms show no significant changes in equity returns or implied asset risk, but an increase in default probability of 27%. These results suggest that G-SII investors still perceive a net gain from TBTF protection, despite new compliance requirements and costs. Our evidence also suggests that these gains are driven primarily from reductions in default probability, as results are consistent with investor expectations that the new regulatory regime will limit moral hazard effects from the guaranty.

Key words: Too big to fail (TBTF), Global systemically important financial institutions (G-SIFI); Global Systemically Important Insurers (G-SII), Insurance, Financial regulation
JEL: G22: Insurance Companies, G23: Non-bank Financial Institutions, G28: Government Policy and Regulation

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1. Introduction

In July 2013 the Financial Stability Board (FSB) designated nine global insurance firms in six countries as global systemically important insurers (G-SII), a subset of global systemically important financial institutions (G-SIFI). We examine whether this government protection, in the form of a "Too Big to Fail" (TBTF) guaranty, conveys a net gain or loss to the equity holders of these firms. To provide some insight into the offsetting costs and benefits of financial regulation, we also investigate three possible channels for regulatory policies to contribute to the observed effects on equity: the probability of default, implied asset risk, and debt markets.

We begin our event study period with the first event that raised the issue of protection for large, systemically important insurance firms -- the AIG bailout in 2008.[1] We extend our announcement period through the 2013 announcement when the FSB named the nine insurance firms it identified as G-SII. We aggregate stock market abnormal returns for eight announcements over the period that cover initial discussions of the method for selecting the G-SII, details on their new compliance requirements, and the final selection of the G-SII. The average abnormal cumulative increase in equity across all announcements for the G-SII is 14%. Over the same set of eight announcements, the average G-SII probability of default falls 15.6% and the average G-SII implied asset risk rises by less than 1%, while results for G-SII debt markets are mixed.

[1] While Egginton, Hilliar, Leibenberg and Liebenberg (2010), Joines (2010), and Safia, Hassan, Maroney (2013) assess the AIG bailout, to our knowledge ours is the first paper to conduct an analysis of the entire sequence of G-SIFI announcements in the insurance industry leading up to the official G-SII designation. See Bongini, Nieri, Piccini (2014) for an assessment of the effects on equity of a subset of announcements that we consider. See Zanghieri (forthcoming) for an analysis of equity effects for the G-SII beginning in 2011.

We apply the same analysis to a group of other large insurance firms (OLIF) located in the same countries as the G-SII group. On average, across all announcements, the OLIF have no significant responses in equity prices, asset risk, or bond prices, and an average 26.8% increase in default probability.

We find that the riskiest G-SII firms have the biggest equity price gains at the time of the AIG bailout, consistent with findings by O'Hara and Shaw (1990). For later announcements, however, the riskiest G-SII have the biggest equity losses, as well as the biggest drop in implied asset risk.

We also explore country-level differences in the abnormal responses to the G-SII process and find that the premium accrued to equity from TBTF policies is larger in countries with weaker institutions, consistent with Kane (2000).

Taken together, our results suggest that investors expect a net equity gain for the insurance firms that are ultimately included under the TBTF umbrella, despite the substantial new compliance requirements in G-SIFI policies set by the FSB. Reductions in default probability appear to be the primary driver of the gains, as results are consistent with investor expectations that the new regulatory regime will limit moral hazard effects. In the sections that follow, we present our motivation; data; methodology and empirical framework; results, related robustness checks, and companion analyses; a supplemental cross-country analysis; and conclusions.

2. Motivation

To motivate our research question, we discuss the potential effects that can arise from TBTF policies, describe the specific response to the financial crisis in 2008 that led to the current regulatory actions of the FSB and related agencies, and lay the foundation for our empirical analysis.

2.1. Effects of "Too Big to Fail" Policies

Interest in TBTF policies first arose in the U.S. in 1984 when the U.S. Comptroller of the Currency testified before Congress that 11 U.S. banks were "too big to fail," and that the government would provide total deposit insurance to them. O'Hara and Shaw (1990) note that the protected banks potentially face both direct and indirect costs and benefits. The direct costs arise from meeting regulatory requirements, and direct benefits stem from a lower probability of default, which should lower borrowing costs and result in higher profits. The indirect benefits accrue from moral hazard: the implied government guaranty allows the bank to engage in riskier activities, which should lead to higher risk-adjusted expected returns, given regulatory protection. O'Hara and Shaw find that on the day of the Comptroller of the Currency's announcement, the stock prices of the 11 banks rose by an average of 1.3% (statistically significant), while the prices of their competitor banks fell by -0.16% (not statistically significant). The observed effects are positively correlated with both bank size and solvency. Their results suggest that the stock market viewed the selection as TBTF as being positive for the designated banks. Since this initial analysis, economists have extensively studied the impact of TBTF policies on banks.[2]

These potential effects of regulatory protection have not changed substantially since the initial TBTF discussion in 1984. At the macro level, the regulations necessarily

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[2] Recent banking studies include Abreu and Gulamhussen (2015), Bongini, Nieri, and Pelagatti (2015), and Kleinow, Nell, Rogler and Horsch (2014). Papers that extensively review the TBTF literature include Strahan (2013) and White (2014). The bulk of the TBTF studies focus on the effects of the guarantee on borrowing costs after protection was put in place. We could find no papers that attempted to measure the magnitude of the TBTF guarantee on asset risk or the probability of default.

shift risk from the protected firm to the governmental/regulatory body that is providing protection in case of default. The expectation is that this protection will create a benefit in the form of financial stability. This stability will add value to the economy by lowering borrowing costs for all economic agents and preventing disruptive, extreme market moves. This same protection creates a potential cost because incentives for investment by protected firms are likely to change: once protected, firms may have a higher risk threshold for investment choices, i.e. moral hazard is created. This can raise the cost of protection to the larger financial system, as a bailout is more likely at the margin if protected firms do engage in riskier activities.

At the firm level, this same moral hazard is a potential benefit to investors: higher risk is associated with higher expected returns. Additionally, the firms will likely benefit from lower borrowing costs, both because the default protection provided by the regulatory umbrella lowers borrowing costs for the firm, and because more economic stability is likely to decrease interest rate levels, generally. Importantly, these benefits come at the cost of complying with the regulatory requirements that run in tandem with protection.

In this paper, we focus on the expected firm level *net* effects of these TBTF costs and benefits on firm equity value. We also investigate the possible sources of any observed equity changes by examining default probability, asset risk, and bond and CDS values for the affected firms.

2.2. The FSB's G-SIFI regime

Events surrounding the 2008 crisis in international financial markets raised the issue of TBTF at both domestic and international levels. Countries responded individually (e.g., the U.S. with the Dodd-Frank Act in 2010) and collectively (through the FSB), and implemented policies to provide more formal and continuing support for the financial sector.

The FSB mandate includes coordinating the work of individual national financial authorities and international standard setting bodies in order to develop and promote the implementation of effective regulatory, supervisory and other financial sector policies at the international level.[3] The FSB's initial efforts focused on global banks. The FSB next broadened the list of systemically important financial institutions to include firms in the insurance industry, a decision made in recognition of both the economic importance of the industry and the role key insurance firms play in the global financial system.[4] In the case of protecting systemically important insurance firms, the FSB worked closely with the International Association of Insurance Supervisors (IAIS) to identify systemically important firms to be included under the G-SIFI regime. (IAIS, May 31, 2012, pg. 6):

> *The focus of IAIS analysis is in relation to potential global systemically important insurers (G-SIIs). To this end, the IAIS has developed an assessment methodology to identify any insurers whose distress or disorderly failure, because of their size, complexity and interconnectedness, would cause significant disruption to the global financial system and economic activity. Any such insurers should be regarded as systemically important on a global basis.*

The FSB's aim is to design a regulatory system which "allow[s] authorities to resolve financial institutions in an orderly manner without taxpayer exposure to loss from solvency support, while maintaining continuity of their vital economic functions." The objective is to "make it feasible to resolve an insurer without severe systemic disruption

[3] For details see: http://www.fsb.org/about/

[4] The U.S. Bureau of Economic Analysis data show that insurance firms contribute the same amount to U.S. GDP as does the banking sector. For an analysis of the legal and regulatory framework and sources of concern for TBTF in the insurance industry, see Schwartz and Schwartz (2014).

or exposing taxpayers to losses…For insurers, the resolution regime should have as a specific objective the protection of policyholders, beneficiaries and claimants.” As part of the system, resolution authorities should have “privately-financed policyholder protection schemes or resolution funds that can assist in securing continuity of insurance coverage…and compensating policyholders for their losses in the event of a wind-up or liquidation.” (FSB, October 15, 2014, p. 1, 75-6, and 79-80, respectively)

The FSB document announcing the G-SII firms in July 2013 includes a description of the types of policy measures that would apply to the firms ultimately designated as G-SII (FSB, 2013): (1) recovery and resolution planning requirements, (2) enhanced group-wide supervision, and (3) higher loss absorbency requirements. The recovery and resolution requirements include the establishment of a Crisis Management Group (responsible for assessing the effectiveness of a firm to resolve a potential future crisis), the development of institution-specific cross-border cooperation agreements among the relevant resolution authorities, and firm-level requirements to develop individual recovery and resolution plans, i.e. a "living will."

While the FSB left the details of many of these requirements for future work, (many of which are still on-going through 2017, see the timeline in FSB, 2013), it is clear from the announcement, and earlier discussions in IAIS and FSB releases, that protected firms would incur additional and potentially substantial costs to meet the FSB standards.[5]

[5] MetLife and Prudential Financial, two of the three U.S. firms on the final G-SII list, formally protested the designation based, in part, on an argument that the costs of protection would outweigh the benefits. MetLife eventually filed a formal court action in U.S. District court to avoid regulation; that decision is under appeal by the U.S. Dept. of Justice, and still pending as of early December, 2017. Final designation is further complicated by the U.S. presidential executive order issued April 21, 2017, to review all G-SIFI policies in the U.S. See, Katz and Tracer (2014), Wall Street Journal (2015, 2017), and The Financial Times (2016). See Internet Appendix Section 2.2 Robustness Discussion for an event study analysis of the US Financial Stability Oversight Council (FSOC) announcements related to US G-SII designation for MetLife and Prudential.

This discussion at the international level highlights the components of TBTF policies that we will examine in the remainder of the paper: protection from default, the incentive to increase asset risk, and the cost of compliance with regulatory/governmental bodies who provide the protection.

3. Event dates, data, and summary statistics

We begin our analysis with the announcement of the AIG bailout in September 2008. Table 1 reports subsequent announcements that we consider. These FSB-related announcements contain information that could change investors' perceptions as to the probability that the FSB would extend the G-SIFI system to insurance firms, the types of information the IAIS and FSB would then consider when selecting the G-SII firms, the expected benefits and costs of the G-SII regulatory regime, and end with the final announcement of the designated firms in November 2013.[6]

We take our sample from the FSB's 2013 list of nine G-SII in six countries.[7, 8] We focus our analysis on the G-SIIs other than AIG because the bailout of AIG removed

[6] It is common for regulatory event studies to examine reactions to multiple announcements. The earliest finance-related example we could find is a 1988 study of New York's 1985 changes in takeover statutes (Schumann 1985). More recently Bongini, et al. (2015) conduct an event study of three FSB announcements related to designating systemically important banks. Most of these studies find significant reactions to only a subset of the announcements. The earlier studies, like Schumann, tend to have samples that only include the firms ultimately affected by the proposed regulations, while later studies, like Bongini et al, (2015) tend to look at both the affected firms as well as a set of non-affected firms.

[7] The FSB actions taken in 2013 included planned annual updates to the designated firms. Scheduled updates for 2014 were postponed to November, 2015, at which time Aegon was added and Assicurazioni Generali Spa was dropped from the formal G-SII list, effective in 2016. As of December 11, 2017, no other updates have occurred. Since our event window ends in 2013, these changes do not affect our sample. See: Financial Stability Board, (2014, 2015).

[8] We note that on September 29, 2017, the FSOC rescinded the designation of AIG as G-SII. This is well outside our sample period, and likely reflects the political environment after the 2016 presidential election in the U.S. (Bradford, Oct. 2, 2017). The case of MetLife was still pending (Heltman, Oct. 2, 2017); see also FN 5.

any uncertainty about government support for AIG.[9] We then identify a set of other insurance firms, similar to the G-SII, for comparison. Since the nine firms designated G-SII are all categorized as life and/or full insurance firms, we limit our list of candidate firms to those classified as life or full insurance.[10] We also restrict the sample to firms from the same countries as the G-SII to control for country factors (e.g., regulatory or macroeconomic) that might affect performance even in the absence of a G-SII effect, based on evidence that country-level factors affect insurance company performance (Nissim, 2010).

We use FTSE's Industrial Classification Benchmark and Bureau van Dijk's ORBIS dataset to classify insurance firms by category. We then identify the companies in our initial sample with 2007 - 2014 financial statements in the ORBIS data set, and with systemic risk data at NYU Stern's Volatility Laboratory (V-Lab). These screens leave us with 22 other life insurance firms (OLIF) for comparison, listed in Appendix A. Table 2 provides a ranking of the 30 largest insurance firms in the world as of 2012 with the G-SII in bold type and the OLIF in italics. The G-SII and OLIF are dispersed across this set.[11]

[9] We provide results with the full G-SII sample in Internet Appendix, Table 5A. The results are substantively the same when AIG is included.

[10] The IAIS document (May 2012) indicates that a substantive analysis was done to choose the G-SII firms (consideration of five categories of information with a total of 30 different variables). The IAIS and FSB did not make the data they used in their assessments publically available. The G-SII final list was limited to full and life insurance firms, based on evidence that their activities create more systemic risk than other types of insurance activities, in part because of their reliance on asset value for solvency and the associated risk of interest rate risk exposure. See Dungey, Luciani, and Veredas (2014), Harrington (2011), Kaserer and Klein (2016), and Wymeersch (2017) for detailed discussions of the systemic risk of insurers and Banulescu and Dumitrescu (2015) for methodology as applied to G-SIFIs in 2007 and 2009. For a discussion of the IAIS analysis of systemic risk in these categories see the consultative document from the International Actuarial Association (May, 2013) and IAIS (2012). See Chapter 3 in IMF (April, 2016), for a discussion of systemic risk for insures and its relationship to interest rate risk and asset price swings.

[11] The systemic risk values for our sample firms confirm the same interspersed pattern for G-SII and OLIF firms as with total assets; see Internet Appendix Table 2A.

Table 3 lists and defines our measures of size, returns, and risk. Additional detail on the definition and identification codes for these data, and all data used in this study, are available in Internet Appendix, Table 3A. We have three measures of size (total assets, gross premiums, and market capitalization); three measures of returns (investment yield, ROE, and ROA); and four measures of risk (solvency ratio from the balance sheet, leverage calculated from both balance sheet and market data, the market Beta, and V-Lab's Systemic Risk (SRISK) measure). Higher values of the solvency measure indicate less risk, while higher values of the remaining risk measures indicate more risk.

Table 4 provides summary statistics for the 2012 values of these variables and tests of differences for the G-SII versus OLIF.[12] Here, and in all subsequent tables, we report values significant at the 1% 5% or 10% levels with ***, **, and *, respectively. The tests show that, with means or medians, prior to G-SII designation, the G-SII as a group are larger than the OLIF (measured with assets, gross premiums, or market capitalization), have higher levels of market or systemic risk (measured with the market beta or SRISK), and have lower balance sheet solvency (with means and, weakly, with medians). There are no significant differences at the five percent or better level between the G-SII and OLIF with respect to returns.

We also collect ORBIS data on government ownership for use as a control variable. Government shareholdings do not significantly differ across the G-SII versus OLIF, though we note the high government ownership for Chinese firms in both groups.

[12] The May 2012 IAIS methodology document says that the regulators would rely on 2010 financial statements to make their designation decisions. We present the 2012 data because those are the most recent data available to investors at the time of the 2013 designation announcement. If we conduct the same tests of differences in Table 4 on 2010 data, we find the same significant differences as with 2012 data. The two exceptions are that the solvency ratio is significantly higher for OLIF than G-SII, at the 10% level, in 2010, but not significantly different in 2012, and that OLIF CDS spreads are significantly higher in 2010, but not significantly different in 2012. See Table 4A in the Internet Appendix.

The information in Table 4 confirms that, prior to G-SII designation, the OLIF and G-SII are not "otherwise identical." Moreover, the anticipation and implementation of the new G-SII international regulatory regime could affect the OLIF performance during our sample period. To the extent that the new regulations affect the overall financial system, the OLIF could also encounter indirect benefits or costs. Benefits could include lower borrowing costs and default probabilities from having a generally safer financial system. Or, as we have seen in the U.S. with the implementation of the Dodd Frank banking regulations, local regulators could extend the more rigorous international rules to a broader set of local firms, raising compliance costs for all (see, e.g., American Bankers Association, 2012). For these reasons, the OLIF sub-set does not constitute a "randomized control group" of firms identical to the G-SII except for the "treatment," i.e., G-SII designation. On the one hand, the OLIF are the closest, most obvious "matching" firms available – the largest insurance firms in the same line of business from the same countries. On the other hand, they are not perfectly matched and policies affecting the G-SII can indirectly affect the comparison group. As a result of these issues, we provide the OLIF numbers as a benchmark for comparison, but are careful not to interpret the results as a formal "difference-in-differences" analysis.

Table 4 also provides summary data for our key event study variables: equity returns, probability of default, asset risk, bonds and CDS spreads. We estimate equity returns using Datastream's Return Index (RI) series. The monthly mean and median values for G-SII equity returns are 0.0094 and 0.0117, respectively, and do not differ significantly from the OLIF.

Our measure for the probability of default comes from the Credit Research Initiative (CRI) at National University of Singapore. Following Duan, Sun and Wang (2016), Shin and Kim (2015), Duan and Miao (2015), and Kanno (2014), we use the probability measure as developed in Duan, Sun and Wang (2012), and documented in Duan (2012).[13] The measure that we use, referred to as CRI:PD, provides the probability of default over a five-year horizon, for a given month, and uses a mix of firm specific and market-wide data.[14, 15] Table 4 indicates that the means for the G-SII and OLIF probability of default are equal, while the G-SII median is higher than for the OLIF.

While data used as inputs for the CRI:PD are updated on a daily basis, the majority of the firm specific data is available, at most, in quarterly financial statements, with the exception of daily equity price data (levels and volatility). We note that the lags in updates for data and the potential for a mis-match of data release and the monthly PD calculation affect the ability of the measure to quickly capture changes in the probability of default.[16] Additionally, the PD measure does not directly account for default protection policies; the only mechanism for recognition of protection comes through indirect

[13] The model structure is quite complex. In the interest of brevity, we refer the reader to RMI Staff Technical Reports (2012, 2015, 2017a, b) for details. We note that this is a forward intensity model, similar in spirit to Duffie, Saifa, and Wang (2007).

[14] For a detailed list of data inputs into the model see, RMI Staff, 2017b, page 4. The macroeconomic factors are calibrated by economic groupings based on stages of economic development and geographic location of their listed exchanges. For our firm sample the relevant groupings are: North American, Europe, and China (RMI Staff, 2017b, page 7).

[15] CRI provides an additional measure of default: Actuarial Spread (CRI:AS). This measure shares the same contract structure as a conventional CDS contract, but without the upfront fee in the contract, thus providing a potentially cleaner estimate for the credit component in the contract over time. (See RMI Staff (2017a, 2017b). For both measures, CRI provides estimates of default probability at multiple horizons, ranging from one month to five years. The CRI:PD and CRI:AS series are highly correlated with each other and across horizons: Corr(PD5yr,PD1yr)=0.994 and Corr(CRI:AS5yr, PD5yr)=0.911. Thus, it is not surprising that inferences from our analysis in this paper are the same across these alternative measures.

[16] The best candidate to capture changes in the probability of default is the daily equity channel. We thank the referee for bringing these points to our attention.

adjustments in related equity prices as the market absorbs information about regulatory policy.[17]

We calculate implied asset risk for eight G-SII and 14 OLIF with the firm's implied equity volatility, from daily option price data in Datastream, multiplied by the ratio (Equity/(Debt + Equity)), from V-Lab's leverage time series.[18] Each month's implied asset risk value equals the average of daily values. Table 4 indicates that mean implied asset risk is slightly lower for the G-SII than the OLIF, and the median for the OLIF is higher.

We use the Return Index (RI) series, from Datastream, for "plain vanilla" bonds outstanding as of the initial AIG bailout in our event window, that were issued on the firm's home country exchange and in the home currency with price series covering at least 2008-2013.[19] This allows us to focus on changes in value for bonds whose payout stream was set prior to our event window. Thus, we compare the changes in value that we measure during our event window to a baseline that was set prior to any expectation of regulatory intervention. The value of these bonds is also unaffected by the impact of G-SII policies on special bond provisions in newly issued bonds, such as call features. We can find one bond that fits these criteria for seven G-SII and 13 OLIF. Table 4 provides weak evidence, for medians only, that G-SII bond returns are lower than for the OLIF.

[17] We thank Jin Duan for useful discussions on this point.

[18] See Correia, Kang, and Richardson (2013) for a description of this method and a comparison of it with other methods to calculate asset volatility. Datastream provides calculated implied volatilities from American equity options with the Cox-Rubenstein binomial model. See "Datastream: Options User Companion" February 2008. We use their continuous call series, which are calculated using one year options. We combine these data with V-Lab's leverage data to calculate implied volatility.

[19] Datastream codes: Bond Type = Straight, Coupon Type = Fixed, Data Type = Return Index. Note that "Data Type = Clean Price (returns)" is highly positively correlated with the Return Index measure. We use only one bond per firm. In the rare instances where a firm has more than one bond that meets our criteria, the correlation in bond prices is over 0.98.

We take our CDS spread data from Datastream. The data is for five year spread horizons and is available for seven G-SII and 10 OLIB. Table 4 documents that the CDS data mean and median are higher for the OLIF than for the G-SII.

4. Methodology and empirical framework

Our main focus is on changes in equity value during our event window, but we also investigate the various channels through which regulatory effects may travel to produce any observed equity effects.

Since the CRI:PD measure is only available on a calendar month basis, we calculate abnormal monthly returns across the calendar month of each announcement. We discuss any meaningful differences between these monthly and the more standard daily data for all the other variables we study. These comparisons are in Robustness Section 4.4 and in the Internet Appendix, Tables 5D, 7A, and 8B.[20]

While data availability is the main reason for our decision to focus on the monthly analyses, our decision is also consistent with the pattern of news releases that we observe both before and after an FSB related announcement.[21] As illustrative evidence of the potential importance of information released in a longer, monthly window, Figure 1 provides an article count for G-SIFI related articles in the month of November 2010, to correspond with announcement #3 on November 12, 2010. This figure shows a typical

[20] The accuracy of monthly estimates is addressed in Bessembinder et al (2008) who find, with event studies of monthly bond returns, that standard t-statistics have excessive Type I errors, while nonparametric statistics are better specified and more powerful with events that affect all of the sample firms. Nevertheless, they conclude (pages 4222-23) that it is best to examine both parametric and nonparametric tests. In the results reported in the paper, we rely on the standard t-statistics because they address the important issue of event date clustering, while nonparametric tests do not. In Internet Appendix Table 5C, we report the p-values for non-parametric tests for the monthly SURs reported in Tables 5, 6, 7, and 8.

[21] It is surprisingly difficult to find references for finance event studies that explore results for daily versus monthly data. Three studies that link the differences in abnormal returns in short versus longer windows to the nature of the information revealed in the announcements are: Rucker, Thurman, and Yoder (2005), Stotz, Wanzenreid, and Donhert (2010), and Gupta and Reid (2013).

pattern where the specific announcement came within a stream of broader, but potentially related, articles both before and after the announcement day. It seems reasonable to expect that investors may continue to process the additional information that could extend beyond the three-day window commonly used in event studies; the regulatory regime under consideration is new and quite complicated. As such, both the financial press and investors may need additional time to fully comprehend new information.[22]

For each performance measure discussed above, we conduct an event study in three steps. First, we estimate an OLS regression for each firm that allows the intercept and coefficients on the control variables to vary across time. Since the announcements that we are tracking span 6 years, from January 2008 to July 2013, we must allow for variations across time in the relation between the performance measure and the explanatory variables. We estimate the following regression:

$$\sum$$

$$\sum \qquad \sum$$

Eq. (1)

where *PerformanceMeasure* equals, in turn, equity return, the change in default probability, the change in implied asset risk, bond returns, and the change in CDS spreads. Our measures of changes in default probability and CDS spreads are first

[22] We acknowledge that this interpretation essentially assumes that the business press and knowledgeable investors are slower in this instance to interpret information than strong form market efficiency would suggest. We note that in this instance the "bottom line" summary abnormal returns we report are substantially the same based on both sets of daily and monthly data.

differences; our change in implied asset risk is calculated as a "return" (PD_1-PD_0/PD_0) to facilitate interpretation in percentage terms. *D* represents six dummy variables, each set equal to 1 across a different year from 2008-2013. *Market* is a broad, country-level measure of returns in the same, or similar, asset class. *Liquidity* is a broad, country-level measure of liquidity in the same, or similar, asset class.

We use market returns and market liquidity as control variables to capture the state of financial markets during this unusual post-crisis period. If we are to capture the effects of the regulatory process we explore, we must account for other economic factors that could affect results. Specifically, we include the relevant market index for each asset in the regressions to capture economy wide effects that may occur in our event window. While large financial firms, like those we study here, have moved to global status, it is possible that local effects still matter and may matter more during the period of financial turbulence following 2008 (see, e.g., Bekaert, Ehrmann, Fratzscher, and Mehl, 2014). To capture possible global effects, we also include a local currency return for the Datastream world market index when considering equity returns.

We include a liquidity measure in our analysis in response to evidence in Dick-Nielsen, Feldhutter, and Lando (2012) and Chordia, Sarkar, and Subrahmanyam (2015). The former paper documents a severe contraction in bond liquidity, particularly for the bonds of financial firms, around the Bear Stearns and Lehman defaults. (The Lehman default occurred the day before the AIG bailout.).[23] The latter paper documents strong cross correlation in liquidity between bond and equity markets. In recognition of the

[23] For additional evidence on the importance of liquidity during this period, see Goyenko, Subrahmanyam, and Ukhov (2011) and Friewald, Jankowitsch, and Subrahmanyam (2012).

strong ties between asset risk, the probability of default, and bond and equity valuation, we include a liquidity variable in all our specifications.

Internet Appendix, Table 3A provides details on the proxies we use for *Market* and *Liquidity*. If we reject equality of the year dummies when estimating Eq. 1, then we keep the separate year-based coefficient estimates. If we do not reject, then we eliminate the year dummies and estimate only one coefficient for that control variable.[24]

In the second step of our event study, we add event dummies to each adjusted regression and then stack the individual firm regressions into a seemingly unrelated regression (SUR) format. This specification allows us to test whether, on average, the G-SII or the OLIF firms have significant abnormal responses to the event announcements. The SUR format, which takes into account the cross correlations of returns when determining significance, is important in this setting because we have event date clustering, i.e., the same event days for all firms.[25] To simplify the presentation, the SUR equations presented below collapse each of the explanatory variable coefficients into one, as if we failed to reject equality across the year-based estimates in step one above.

$$\sum$$

$$\vdots$$

$$\sum$$

$$\sum$$

$$\vdots$$

$$\sum$$

[24] Internet Appendix Table 5B provides diagnostics on both the frequency for rejecting equality of the time-based coefficient estimates, and how often the control variables are significant.

[25] See Karpoff and Malatesta (1995) and Malatesta (1986) for a discussion of the econometric issues with clustering.

Eq. (2)

Notice, the SUR allows the alpha, beta and gamma coefficient estimates to differ for each firm, but constrains the event dummy variables to be the same across the G-SII firms and the same across the OLIF. The SUR has eight event dummies, one for each of the announcement months.

This setting allows us to measure the impact of changes in market expectation from the initial event (AIG announcement) all the way through to the final announcement of the protected firms. We also have cleanly verifiable announcement dates allowing us to carefully measure the effects of changing expectations over our entire timeframe, and to test whether, on average, each set of firms has a significant reaction to each announcement, and whether those reactions differ between the two sets of firms.[26]

In the third event study step, we break apart the SUR to separately estimate individual firm OLS equations. This allows us to measure firm-specific abnormal returns to each of the announcements. We use the firm-specific abnormal returns in cross sectional analyses, testing whether the abnormal responses are related to firm-specific risk measures.

5. Hypotheses, empirical results, and robustness checks

In this section, we discuss our main hypothesis and present the related empirical results regarding equity returns. We then turn to our analysis of the potential transmission channels discussed above and companion analyses. The section concludes

[26] Bongini et al. (2015) use a similar method to estimate abnormal responses to the FSB announcements for banks. They show that results with this method closely parallel results with several non-parametric measures of abnormal returns.

with related robustness checks. We couch our presentation in the context of the prior discussion of the benefits and costs related to the G-SII designation.

5.1 Changes in equity returns

As discussed above, protected firms should experience a drop in default probability, which should lead to lower borrowing costs. Protected firms may also have higher expected income from taking on riskier investments, the moral hazard effects commonly observed in regulatory settings. When taken together, any potential benefits of protection will be offset to some degree, if not completely, by the compliance costs of regulation, and by the stated efforts of regulators to control the anticipated additional risk-taking behavior through ****regulatory requirements. These effects lead us to two alternative hypotheses for the net effects on equity value:

Hypothesis A: Investors perceive that G-SII designation conveys net benefits to the protected firms, resulting in a gain to equity holders.

Hypothesis B: Investors perceive that the costs of G-SII designation outweigh the benefits, resulting in negative returns to the equity holders of G-SII designated firms.

Table 5, Panel A provides the SUR results: monthly ARs for each announcement, with p-values reported below. The SUR results document a positive and significant 14% (at 1%), overall effect for the G-SII and zero abnormal returns for the OLIF; the difference is statistically significant. Figure 2 illustrates the accumulation of ARs over the eight announcements. In response to the AIG bailout, *both* sets of firms have a boost to equity. Subsequently, the G-SII abnormal returns fall slightly, while the OLIF returns drop to a value near zero, a pattern consistent with investors identifying which firms are likely to be included in the final G-SII group before the final announcement.

To further investigate the relation between firm level ARs and risk, in Table 5, Panel B, we report Spearman rank correlations for the firm-specific ARs with two of the firm risk measures we list in Table 3, leverage and SRISK.[27] We match the firm risk measures as of the year-end prior to each announcement. When we consider SRISK as our measure of firm risk, the G-SII have a weakly significant positive correlation between equity ARs and risk for the first announcement. We also find a significant (at 5%) negative correlation for the third announcement, the announcement about the intention to include insurance firms in the regulatory scheme. The OLIF show no significant correlations with SRISK, but are weakly significant with a negative correlation with AR for the 7th announcement, the announcement releasing information about specifics of G-SII policies. OLIF firms with more leverage are more likely to see a drop in equity.

The first announcement pattern showing higher equity returns for the riskiest, protected firms, is consistent with findings in O'Hara and Shaw (1990). The negative correlation at announcement #3 is consistent with investors anticipating that the promised future regulatory policies will have the greatest impact on the riskiest, and more likely to be protected, firms.

In sum, we accept hypothesis A and reject hypothesis B, finding that investors perceive a net gain to equity holders of firms designated as G-SII, absolutely and relative to the OLIF.

5.2 Transmission channels and companion results

The equity results strongly support a conclusion that the market views the G-SII designation as adding value for equity holders. We now investigate the extent to which

[27] Firm-specific summary CARs for equity returns, default probability, implied asset risk, bond returns and CDS spreads are reported in the Internet Appendix Table 5E.

expected changes in default probability and asset risk can explain the equity change. We then consider a companion set of bond and CDS results for the firms.

5.2.1. Changes in probability of default

Figure 3 illustrates the cumulative abnormal changes in default probability over our event window, showing, in contrast to the equity results, a divergence in effects for the two groups of firms beginning with the very first announcement. Table 6, Panel A presents the SURs for the CRI:PD measure of default probability, with several significant announcements for the G-SII (events #1 and #6; summary) and OLIF (events #1 and #2; summary), as well as several announcements with significantly different reactions between the two groups (#1, #2, #6 , and summary). Across all announcements, the G-SII summary abnormal monthly change in CRI:PD is -0.007 (significant at 5%) which, when divided by the average PD level for the G-SII (0.045, from Table 4), is consistent with a drop in G-SII PD of -15.6%. The OLIF experience a positive summary abnormal change in PD of 0.011 (significant at 1%), indicating a change of 26.8% in OLIF PD when divided by the average PD level for the OLIF (0.041, from Table 4). The results are consistent with initial investor expectations at the time of the AIG bailout that the G-SII would be protected, while OLIF would not, and this pattern is borne out in the summary abnormal returns.

We also note that, across the announcements, the firm-specific CRI:PD and equity abnormal returns (discussed above in Table 5) are highly negatively correlated for both G-SII and OLIF. Firms with the biggest drops in default probability have the biggest increases in equity, consistent with the expectation that the TBTF guaranty will lower default probability and, thus, help equity holders (see Internet Appendix, Table 5B).

Given the significant increase in OLIF default probability, it is surprising that the OLIF summary abnormal equity returns are not negative. While there may have been a general perception that the new regulatory regime would result in a safer system, thus providing benefits to all firms whether G-SII or not, we think it is unlikely that this effect could totally offset the 26.8% increase in default probability the OLIF experience. This finding deserves further study.

Table 6, Panel B, indicates weakly significant negative correlations for the ARs of the G-SII firm CRI:PD data with firm risk measures, consistent with investors' ability to anticipate which firms would fall under, the TBTF umbrella. However, correlations for the OLIF are mixed: positive and large for Announcement #2, and negative and large for Announcement #6.

The results indicate G-SII designation is associated with a drop in default probability for the designated firms, absolutely and relative to the OLIF.

5.2.2 Changes in asset risk

Table 7, Panel A reports the results of the SUR regressions with implied asset risk. The reported results show only one significant summary abnormal change in implied asset risk for the G-SII, for event #1 (at 5%) and none for the OLIF. The point estimates for that first announcement indicate implied asset risk rises 9.4% for the G-SII and 6.2% for the OLIF. The insignificant summary G-SII CAR of 0.0024 is consistent with a 0.24% rise is asset risk, essentially zero. Figure 4 again shows common movement with the AIG announcement – both sets of firms have a small increase in implied asset risk. Over time, both series fall to zero.

We see three possible reasons for the zero summary CARs. One possible driver of the results relates to data. Our estimates of implied volatilities are based on market prices, which reflect risk-premiums. These risk premiums will be particularly volatile at times of crisis, or during periods of great regulatory change, making it hard to cleanly pull out the effects we want to measure. In addition, firms will take time to respond to large regulatory changes, so our relative short event windows, one month, may only capture initial, incomplete responses. In the case of this study, the longer timeframe (five years) during which we consider the development of the regulatory framework may partially mitigate those concerns as corrections are captured over time. We also control for liquidity and market effects that tie into volatility.

A second possible driver of our results is related to the fact that firms can chose to adjust asset risk through increasing leverage as opposed to increasing asset risk. Thus, the responses of option prices to the announcements we report may represent incomplete pictures of the firms' responses to the moral hazard effects of the TBTF policies. We do not study leverage as a main point in this paper, as leverage changes typically take some time to occur, and would likely fall outside our TBTF event window.[28]

A third, alternative interpretation is that these results reflect investor expectations regarding the ability of the new regulatory regime to limit asset risk. This interpretation is consistent with the correlation results for the cross section of individual firm abnormal returns associated with asset risk and our measures for SRISK and Leverage, reported in Panel B of Table 7. We find five significant correlations, all negative, indicating that

[28] Earlier in the development of this paper, we reviewed basic firm data in ORBIS, including leverage. We found no meaningful pattern in changes in leverage (+,0,-) across firms in our sample during or immediately after our event window (results not reported here).

firms with the highest risk levels have the biggest drop in implied asset risk.[29] In addition, virtually all G-SII correlations after the AIG event are negative with the strongest pattern of statistical significance occurring near and on the event date when the identification methodology for the G-SII firms was released. These results are consistent with investors believing the new regulatory regime will curtail the moral hazard effects of the guaranty, in particular for the riskiest firms.

5.2.3 Companion results: debt markets and CDS analyses

As discussed above in our data section, we limit our bond sample to fixed coupon bonds issued before the AIG event to avoid any ambiguity in interpretation of outcome. This means the bonds under consideration have fixed payments, but face the possibility of changes in yield as both interest rates in the general economy and their individual firm risk profile change over time.

The effects of regulatory protection on bonds are easily illustrated in an expression for the present value of a zero coupon bond:

$$PV = \frac{PD*R + (1-PD)}{(1 + R_f + R_p)}$$

Eq. (3)

where, PD is the probability of default, R is the recovery rate in the case of default, (1-PD) represents the value with no default, R_f is the risk free rate, and R_p includes all risk premia associated with the bond. If the recovery amount provides full coverage, expected payments for the bond are unaffected by the possibility of default.

[29] To our knowledge, the extensive TBTF literature (primarily banking research) has not provided comparable analyses that provide measures of expected changes in asset risk.

Additionally, the default protection lowers R_p from its pre-protection level, all things being equal.

To set the stage for interpreting our results, we investigate possible outcomes with simulations of the bond pricing model in Eq. (3), reported in Internet Appendix, Table 8A. With base case values taken from the literature and from our SUR results above, we cannot generate a negative bond return: the probability of default is so low with protection that the negative effects of decreases in recovery rates are overwhelmed by the positive effects of a fall in default probability and risk premium from the TBTF guaranty. We can generate a change in bond return that is virtually zero, but only at extreme values for the recovery rate.

Taken together, these factors lead us to conclude that bond value should move with equity: we still must balance any compliance costs against these expected gains, so either both equity and debt will rise (benefits outweigh costs) or both will fall (costs outweigh benefits). Since our equity results above show a clear gain for equity, we expect to see gains for bonds in our sample, as well.

Table 8, Panel A reports the results of the bond SURs, using the same format as above in Tables 5-7.[30] The results provide significant evidence that G-SII bond returns fall 6.6% over the period, with no significant change for the OLIF, but a significant

[30] As is common in international research, data constraints force us to compromise in our specific choices for control variables. We could not find country-level measures for bond liquidity – either volume or spreads – across all countries. In lieu of country level measures, we construct a firm-specific zero return measure for daily bond data. Substituting a US-based measure of bond liquidity or a proxy for liquidity in the equity markets does not alter inferences. For the monthly bond series, we must use the same liquidity measure as in the equity equations, because no firms have "zero returns" across a month. Following Kamara (1988), in our daily analysis we also proxy for liquidity with the first difference of yields for AAA US agency instruments (AAA US Agency debt 1-3 Yr) minus the US T-bill 1Yr, a measure preferable to corporate spreads which would contain default premia. Neither of these alternative liquidity measures changes inferences.

difference in the two groups.[31] Figure 6 shows the OLIF bond returns fairly level over all announcements, while the G-SII bond returns fall in response to the early announcements and then begin to rise with announcement #5.

Table 8, Panel B provides Spearman Rank correlations, for both bonds and CDS spreads, showing only four significant correlations out of the possible 32 measures provided, with only one result significant at the 5% or better level, consistent with our conclusion below that these results are inconclusive.[32]

The SUR results reject any similarities in effects on bonds with those we find on equity. Even in the face of weak statistical significance, we find the magnitude of the abnormal bond return in the monthly SUR results puzzling, particularly given the evidence above that the probability of default fell for these firms and the equity investors experienced a substantial gain of 14%.[33]

Midway through our event window, discussions began regarding possible "bail-in" requirements that would give bondholders a "haircut" in the event of a bailout. While we acknowledge that the negative effects of possible bail-in procedures are impossible to measure directly, our prior is that they are relatively small, and thus will only affect bond returns at the margin.[34] Thus, we believe it highly unlikely that bail-in provisions could totally swamp the expected gains, leading to a loss in bond value relative to equity.

[31] With individual firm ARs, three of eight G-SII (includes AIG), and seven of 13 OLIF with both bond and equity data have equity and bond returns moving in the same direction**.**

[32] The weakly significantly 0.714 G-SII correlation for announcement #2 is consistent with Penas and Unal (2004) who find bondholders gain in bank mergers among medium sized banks where the combined assets push the bank above the TBTF threshold.

[33] To improve sample size, we relax our criteria for five firms and include bonds not classified as "fixed/floating." Our results (not reported in full here) are unchanged: the G-SII summary CAR is insignificant at -0.065 (0.146).

[34] The G-SII resolution under discussion at that time would entail, first, wiping out equity holders, and then writing down and transforming debt into equity (FSB, 2011; FDIC and Bank of England, 2012). Additional details bail-in policies are provided in Internet Appendix, Section 5.3, Discussion.

Following earlier work, and given the weak bond results we find, we also consider changes in risk as captured in CDS spreads. We note that in a recent paper Hilscher and Wilson (2016) make the case that, while CDS measures are often used to capture changes in risk, the spreads are not necessarily appropriate to capture default probability. Additionally, Hilscher, Pollet, and Wilson (2015) document that causality seems to run from equity to CDS contracts, rather than having changes in default expectations affect both equity and CDS contracts simultaneously. Longstaff, Mithal, and Neis (2005) and Tang and Yan, (2010) also provide evidence on this point. Still, we believe it is meaningful to investigate effects captured in the CDS data, as changes in CDS spreads do inform us about expectations in future risk.

The CDS results provide almost no significant abnormal returns. The insignificant summary abnormal change point estimate of -12.69 for G-SII in the first column corresponds to 6.4% of the average CDS spread for the G-SII (equal to 197.6, reported in Table 4). This drop in risk supports an expectation that bond prices should rise, flying in the face of our bond results.

We note that an important factor in our results may be that available bond data for our sample is relatively small, covering about 2/3 of our firms in an already small sample. Internet Appendix, Table 9A provides results of SUR estimates for the equity, CRI:PD and implied asset risk samples using only firms for which we have bond data. The results are markedly different from the full sample results, suggesting the bond sub-sample may not be representative of the full sample of firms. Given our data constraints, and our conflicting results when compared to results with both equity and CDS data, we draw no conclusions and leave further investigation into this puzzle to future research.

5.3 Robustness checks

We now move to our robustness tests. We consider: (1) potential effects of confounding announcements around our events on our equity results, (2) results based on analyses with daily data (standard window: -1, 0, +1) for equity returns, bond returns and asset risk, the variables for which we have daily data, and (3) results based on an alternative measure for the probability of default. We group these results by the dependent variable of interest: equity, asset risk, debt and probability of default.

5.3.1 Equity – robustness

To ensure that the equity results are not driven by confounding announcements within the event windows, we searched in ProQuest for both *Wall Street Journal* and *Financial Times* articles on the G-SII and OLIF for announcements on senior management turnover, takeovers or mergers, and earnings/dividend announcements. We find 20 announcements for the G-SII and 15 for the OLIF within the eight monthly announcement windows. Excluding these events does not alter our results in any meaningful way. If we exclude firms with government ownership (4 G-SII and 3 OLIF), we find the summary G-SII equity CAR drops from 14% to 4%, while the other results do not change. For brevity, we report results for these analyses in the Internet Appendix, see Tables 5F and 5G.

Results for a SUR with daily equity returns are reported in Internet Appendix Table 5D. These daily results show a significant (insignificant) summary CAR for the G-SII (OLIF) of 11.4% (-0.1%), with a significant difference between the two, in line with monthly results.

5.3.2. Asset risk - robustness

This SUR analysis is one instance where the daily and monthly data provide different inferences for the summary effects. The daily data, reported in Internet Appendix, Table 7A, provide weak evidence (p-value of 0.085) that summary abnormal changes in implied asset risk for the G-SII rise 10% over the announcements, in contrast to the monthly analysis which shows an insignificant 1% increase.

5.3.3 Debt markets - robustness

Results with daily data, reported in Internet Appendix Table 8B, show essentially no average change in G-SII or OLIF bonds (at statistically insignificant -0.02 (0.217) and -0.018 (0.281), respectively), providing more evidence of inconsistent bond return results. In addition, as noted above, if we re-estimate the prior equity, default, and implied asset risk SURs on the subset of firms for which we have bond data, some results differ, suggesting that this smaller bond subsample may not be representative of the full sample. See Internet Appendix Table 9A.

5.3.4. Alternative measure of default

We repeat our analysis for the probability of default using an alternative default measure, the Actuarial Spread from the Credit Research Initiative (CRI:AS), as developed in Duan (2014) and RMI Staff (2015). [35] While based on many of the same components as the CRI:PD measure, the CRI:AS measure was designed as an alternative to CDS spreads. The CRI:AS measure shares the same contract structure as a conventional market CDS contract, but without the upfront fee in the contract: thus, it potentially provides a more direct estimate for the credit component in the contract over time. (See RMI Staff (2017a, 2017b), for details of its implementation). Despite this

[35] The CRI:AS measure follows the CRI:PD measure in relying on a mix of firm specific and market data, and thus has the same potential mis-match in timing (noted above) of the availability of data and the monthly calculation point for the measure.

adjustment, the results reported in Internet Appendix, Table 6Awith the CRI:AS measure closely track those with the CRI:PD measure.

6. Cross country comparisons

The value of the TBTF guaranty may systematically vary across countries. Discussing banking regulation, Kane (2000, p. 40) argues that local systems for "transparency, deterrence and accountability" affect "private and government regulator's capacity for valuing banking institutions, for disciplining risk-taking and resolving insolvencies promptly and (above all) for being held accountable for how well they perform these tasks." The impact of strong or weak institutions could easily apply to insurance firms. Kane's argument suggests that the incremental benefit of FSB designation as G-SII may be smaller in strong institution countries since rigorous and effective regulatory oversight should reduce the probability of failure and, thus, the value of a TBTF guaranty. An alternative interpretation with similar predictions is that the relative value of the TBTF promise could be greater in the weak institution countries because the new regulatory regime adds transparency to a currently opaque system.

To examine these possibilities, we calculate a country-level TBTF "premium" as the difference between the (average if more than one) G-SII and OLIF CARs. These country-level equity CAR premiums equal: Italy (145.0%), France (31.1%), Germany (15.6%), China (13.4%), U.K. (1.9%), and U.S. (-8.7%). We compare these premiums to the quality of the country's insurance regulations, measured with the IMF's assessment of how many of the IAIS' insurance core principles the country is observing or largely observing. The compliance values equal: China (68%), France (81%), Italy (81%), U.S.

(89%), U.K. (93%), and Germany (100%).[36] The correlation between the TBTF premiums and the regulatory quality measures is -0.25. If we regress the TBTF country premiums against the quality measure of the individual country regulations, we get a slope coefficient of -0.0125. Consider France or Italy as an example: this slope coefficient of -0.0125 suggests that a movement from France or Italy's level of compliance (81%) to the UK level (93%) would be associated with a drop in the TBTF premium of 15%. This drop is six times larger than the average firm specific summary CAR (and has a value of 0.34 of the CAR standard deviation). A lower incremental TBTF value in relatively strong institution countries is consistent with Kane's argument that strong institutions contribute to more effective regulatory oversight.

The results are similar if we use alternative, more common measures of institutional quality (the Rule of Law, Regulatory Quality, and Control of Corruption indices from the World Bank Worldwide Governance Indices, and the index of Economic Freedom from the Heritage Foundation). This result is not surprising since the average correlation between these indices and the IAIS compliance measure is 0.88. Moreover, the patterns are the same if we use the G-SII – OLIF premium calculated with the abnormal changes in default probability and implied asset risk. These results are available in the Internet Appendix, Addendum Figure 5. All of these results suggest that country-level differences in the value of the TBTF guaranty exist, and that these differences vary systematically with the rigor of country-level institutions.

7. Conclusions

[36] We take these values from country reports conducted under the IMF's Financial Sector Assessment Program (FSAP), available on the IMF website. Compliance with each IAIS Insurance Core Principle is ranked as: Observed, Largely Observed, Partly Observed, and Not Observed. The six country reports that we use are dated: Italy and France (2013), China (2012), Germany and the U.K. (2011), and U.S. (2010).

The 2008 bailout of AIG was the first time a federal government bailed out a major global insurance company. Five years later, in 2013, the Financial Stability Board extended its G-SIFI regulatory umbrella to cover nine insurance firms located in six countries, a group collectively known as Global Systemically Important Insurers, or G-SII. These two events, plus related interim announcements, provide a well-defined window that yields a relatively clean estimate of the net value of a TBTF guaranty.

We provide evidence that investors expect G-SII regulation to reduce the probability of default by an average 15.6%, thus providing additional safeguards for the financial system. These same firms experience a statistically weak and economically marginal increase in implied asset risk, a result consistent with expectations that regulatory policies may mitigate the moral hazard effects of the TBTF policy. On balance, equity investors in the protected firms expect that the potential benefits from the lower default probability outweigh potential compliance costs for the designated firms, with stock prices rising an average 14% across the eight announcements.

Our analysis shows that other large non-designated insurance firms (OLIF) do not, on average, enjoy any net benefits or costs from the new regulatory regime. However, there is evidence that default probabilities rise for the OLIF an average 26.8%, consistent with their exclusion from the regulatory umbrella.

Our results also provide evidence that investors identified the likely candidates for G-SII designation very early in the process, with most of the net benefit embedded in stock prices as much as a year before the final announcement of specific firm names. This pattern may explain why our estimate of a summary equity CAR of 14%, cumulating returns across eight announcements, is so much larger than the 1.3% estimate found by

O'Hara and Shaw (1990), who had only a single announcement to work with when individual TBTF banks were identified in 1984. This pattern across the two studies also suggests that any attempt to measure the value of a TBTF guaranty must account for relevant ex ante expectations.

Finally, we provide two additional analyses. The first provides limited, and puzzling, results on the effects of G-SII protection on bondholders. The second provides evidence that larger TBTF gains occur in countries with lower regulatory standards, consistent with Kane (2000).

Both the contradictory pattern we find for the relationship between OLIF default probability and equity returns, and our puzzling results for bonds merit further investigation. Additional questions for future research that are related to post-designation performance include determining whether or not regulators can successfully mitigate moral hazard incentives for regulated firms, whether we can we better document compliance costs for the regulated entities, and whether and how the new regulatory regime affects non-designated insurance firms.

References

Abreu, J.F. and M. A. Gulamhussen, 2015, "The Stock Market Reaction to the Public Announcement of a Supranational List of Too-Big-to-Fail Banks during the Financial Crisis." *Journal of International Financial Markets, Institutions and Money*, July 2013, 25:49-72.

Acharya, Viral V., Thomas F. Cooley, Matthew P. Richardson, Ingo Walter, and Myron Scholes, 2010, Regulating Wall Street: The Dodd-Frank Act and the new global architecture of finance, John Wiley & Sons, Inc.: New York.

American Banker's Association, 2012, "Dodd Frank and Community Banks," http://www.aba.com/aba/documents/dfa/dfguide.pdf

Banulescu, Georgiana-Denisa, and Elena-Ivona Dumitrescu, 2015, "Which are the SIFIs? A component expected shortfall approach to systemic risk," *Journal of Banking and Finance* 50: 575-588.

Bekaert, Geert, Michael Ehrmann, Marcel Fratzscher, and Arnaud Mehl, 2014, "The Global Crisis and Equity market Contagion," Journal of Finance, 69(6): 2597-2649

Bessembinder, Hendrik, Kathleen M. Kahle, William F. Maxwell, and Danielle Xu, 2008, "Measuring abnormal bond performance," *The Reviews of Financial Studies*, 22(10): 4219-4258.

Bongini, Paoloa, Laura Nieri and Matteo Pelagatti, 2015, "The importance of being systemically important financial institutions," *Journal of Banking and Finance*, (50): 562-574.

Bongini, Paola, Laura Nieri and Andrea Piccini, 2014, "Curbing the moral hazard of a SIFI: mission impossible?" SSRN Working Paper: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2572660

Bradford, Hazel, 2017, "FSOC rescinds systemically important financial institution designation for AIG," Pensions & Investments, October 2, (12:39 p.m.) http://www.pionline.com/article/20171002/ONLINE/171009967/fsoc-rescinds-systemically-important-financial-institution-designation-for-aig

Chordia, Tarun, Asani Sarkar, and Avanidhar Subrahmanyam, 2005, "An empirical analysis of stock and bond market liquidity," *Review of Financial Studies*, 18(1): 85-129.

Correia, Maria, Johnny Kang, and Scott Richardson, 2013, "Asset Volatility," SSRN working paper, http://ssrn.com/abstract=2361686

Dick-Nielsen., Jens, Peter Feldhutter, and David Lando, 2012,"Corporate Bond Liquidity Before and After the Onset of the Subprime Crisis, *Journal of Financial Economics*, 103: 471-492.

Duan, Jin-Chuan, 2014, "Actuarial Par Spread and Empirical Pricing of CDS by Decomposition," *Global Credit Review*, 4: 51-65.

______________. and A. Fulop, 2013, "Multiperiod corporate default prediction with the partially-conditioned forward intensity," National University of Singapore working paper.

______________. and Weiman Miao, 2015, "Default Correlations and Large-Portfolio Credit Analysis," *Journal of Business and Economic Statistics*, 34(4): 536-546.

______________., J. Sun and T. Wang, 2012, "Multiperiod corporate default prediction – A forward intensity approach," *Journal of Econometrics*, 170: 191-209.

______________., and E. Van Laere, 2012, "A public good approach to credit ratings from concept to reality, *Journal of Banking & Finance*, 36, 3239-3247.

Duffie, Darrel, Leandro Saita, and Ke Wang, 2007, "Multi-Period Corporate Default Prediction with Stochastic Covariats," Journal of Financial Economics, 83(3): 635-665.

Dungey, Mardi, Matteo Luciani, and David Veredas, 2014, "Emergence of systemically important insurers," Research Report of the Centre for International Finance and Regulations, Working Paper No. WP038/2014.

Egginton, Jared F., and James I Hilliard, Andre P. Liebenberg, and Ivonne A. Liebenberg, 2010, "What effect did AIG's bailout, and the preceding events, have on its competitors?," *Risk Management and Insurance Review*, 13(2): 225-249.

Federal Deposit Insurance Corporation and the Bank of England, 2012, "Resolving Globally Active, Systemically Important, Financial Institutions," White Paper (December 10).

Financial Stability Board, 2011, "Policy measures to address systemically important financial institutions," November. http://www.fsb.org/wp-content/uploads/r_111104bb.pdf?page_moved=1

_____________., 2013, "FSB identifies G-SIIs and the Policy Measures that will Apply to Them," July 18: http://www.fsb.org/2013/07/r_130718/

_____________., 2014, "2014 Update of List of Global Systemically Important Insurers (G-SII)," November 6: http://www.fsb.org/2014/11/2014-update-of-list-of-global-systemically-important-insurers-g-siis/

_____________., 2015, "FSB published the 2015 update of the G-SII list," November 3: http://www.fsb.org/2015/11/fsb-publishes-the-2015-update-of-the-g-sii-list/
Financial Times, 2016, "U.S. government puts itself on the line in MetLife challenge," June 20: https://www.ft.com/content/5d312de6-fd14-11e5-b3f6-11d5706b613b
Friewald, Nils, Rainer Jankowitsch, and Marti G. Subrahmanyam, 2012, "Illiquidity or credit deterioration: A study of liquidity in the US corporate bond market during financial crisis," *Journal of Financial Economics*, 105(1): 18-36.
Goyenko, Ruslan, Avanidhar Subrahmanyam, and Andrey Ukhov, 2011, "The term structure of bond market liquidity and its implications for expected bond returns," *Journal of Financial and Quantitative Analysis*, 46(1): 111-139.
Gupta, Rangan, Monique Reid, 2013, "Macroeconomic surprises and stock returns in South Africa," *Studies in Economics and Finance*, 30(3): 266-82.
Harrington, Scott E., 2011, "Insurance regulation and the Dodd-Frank Act," Policy Brief, Networks Financial Institute at Indiana State University, 2011-PB-01.
Heltman, John, 2017, "MetLife may e next to lose 'too big to fail' label," American Banker, Oct. 2, 5:23 p.m.: https://www.americanbanker.com/news/metlife-may-be-next-to-lose-too-big-to-fail-label
Hilscher, Jens and Mungo Wilson, 2016, "Credit ratings and credit risk: Is one measure enough?" *Management Science*, http://pubsonline.informs.org/doi/abs/10.1287/mnsc.2016.2514
_____________., Joshua N. Pollet, and Mungo Wilson, 2015, "Are credit default swaps a sideshow? Evidence that information flows from equity to CDS markets," *Journal of Financial and Quantitative Analysis*, 50(3): 543-567.
International Actuarial Association, 2013 (May), "Actuarial Viewpoints on and Roles in Systemic Risk Regulation in Insurance Markets," http://www.actuaries.org/CTTEES_INSREG/Documents/ IAASystemicRiskRegulationPaper_Final_May2013.pdf .
International Association of Insurance Supervisors, 2012 (May 31), "Global Systemically Important Insurers: Proposed Assessment Methodology," http://www.iaisweb.org/Supervisory-Material/Financial-Stability-Macroprudential-Policy-Surveillance-988
Joines, Adam, 2010, "Signals to the market: Too big to fail banks and the recent crisis," Working Paper, University of Notre Dame.
Kamara,, Avi, 1988. "Market Trading Structure and Asset Pricing: Evidence from the Treasury Bills Market," *Review of Financial Studies*, 1:357-375.
Kane, Edward J. 2000. "Designing financial safety nets to fit country circumstances." World Bank Policy Research Working Paper No. 2453,
Kanno, M., 2014, "An assessment of systemic risk in the Japanese banking sector," *Global Credit Review*, 4(1):1-15.
Karaca-Mandic, Pinar, Jean M. Abraham, and Charles Phelps, 2011, "How do health insurance loading fees vary by group size?: Implications for Healthcare reform," *International Journal of Health Care Finance and Economics*, 11(3): 181-207.
Karpoff J.M., and P.H. Malatesta, 1995, "State takeover legislation and share values: the wealth effects of Pennsylvania's Act 36," *Journal of Corporate Finance* ,1(3-4): 367-382.
Kaserer, Christoph and Christian Klein, 2016, "Systemic Risk in Financial Markets: How Systemically Important are Insurers?" SSRN: http://papers.ssrn.com/sol3/papers. cfm?abstract_id=2786947
Katz, Ian and Zachary Tracer, 2014, "MetLife Unwavering in Battle Over Systemic Risk Rules," *Insurance Journal*, June 3, http://www.insurancejournal.com/news/national/ 2014/06/03/ 330722. htm

Kleinow, Jacob, Tobias Nell, Silvia Rogler, and Andreas Horsch, 2014, "The Value of Being Systemically Important: Event Study on Regulatory Events for Banks," *Applied Financial Economics*, 24(24): 1585-1604.

Kroner, Kenneth F., and Douglas S. West, 1995, "The relationship between firm size and screening in an automobile insurance market," *Journal of Risk and Insurance*, 62(1), 12-29.

Longstaff, Francis A., Sanjay Mithal, and Eric Neis, 2005, "Corporate yield spreads: default risk or liquidity? New evidence form the credit default swap market," *Journal of Finance*, 60(5): 2213-2253.

Malatesta P., 1986, "Measuring abnormal performance: The event parameter approach using joint generalized least squares," *Journal of Financial and Quantitative Analysis*, 21(1): 27-38.

Nissim, Doron, 2010, "Analysis and valuation of insurance companies," Working Paper, CE/ASA Center for Excellence in Accounting and Security Analysis, Columbia Business School.

O'Hara, Maureen and Wayne Shaw, 1990, "Deposit insurance and wealth effects: The value of being 'Too big to fail'," *The Journal of Finance*, 45(5):1587-1600.

Penas, Maria F., and Haluk Unal, 2004, "Gains in bank mergers: Evidence from the bond markets," *Journal of Financial Economics* 74(1): 149-179.

RMI Staff, 2017a, "NUS-RMI Credit Research Initiative Technical Report Version: 2017 update 1," http://d.rmicri.org/static/pdf/2017update1.pdf

______________, 2017b, "Probability of Default," NUS-RMI Credit Research Initiative White Paper (August 14), https://www.rmicri.org/en/white_paper/.

______________, 2015, "NUS-RMI Credit Initiative Technical Report Version: 2015 Update 1," *Global Credit Review* 5: 1-91.

______________, 2012, "NUS-RMI Credit Research Initiative Technical Report Version: 2012 update 2," *Global Credit Review* 2: 109-167.

Rucker, Randal R., Walter Thurman, and Jonathan K. Yoder, 2005, "Estimating the structure of market reaction to news: Information events and lumber futures prices," *American Journal of Agricultural Economics*, 87(2): 482-500.

Safia, M. Faisal, Hassan, M. Kabir, and Neal C. Maroney, 2013, "AIGs announcements, Fed's innovation, contagion and systemic risk in the financial industries," *Applied Financial Economics*, 23(16): 1337-1348.

Schumann, Laurence, 1985, "State regulation of takeovers and shareholder wealth: the case of New York's 1985 takeover statutes" *Rand Journal of Economics*, 19(4): 557-567.

Schwartz, Daniel and Stephen L. Schwartz, 2014, "Regulating Systemic Risk in Insurance." *The University of Chicago Law Review*, 81(4): 1569-1640.

Shin D. and B. Kim, 2015, "Liquidity and credit risk before and after the global financial crisis: Evidence from the Korean corporate bond market," *Pacific Basin Finance Journal*, 33: 38-61.

Stotz, Olaf, Gabrielle Wanzenried, and Karsten Dohnert, 2010, "Open-market purchases of public equity by private equity investors: Size and home bias effects," *Journal of Economics and Business*, 62(6): 562-76.

Strahan, Philip E., 2013, "Too Big to Fail: Causes, Consequences, and Policy Responses," *Annual Review of Financial Economics*, 5: 42-61.

Tang, Dragon Yongjun and Yong Yan, 2010, "Market conditions, default risk, and credit spreads, *Journal of Banking and Finance*, 34(4): 743-753.

Wall Street Journal, 2015, "MetLife's systemically important case," April 29, Eastern Ed., Section A, Page 12.

_________________., 2015, "MetLife Suit Sets Up Battle over Regulation," January 14, 12:16 a.m., https://www.wsj.com/articles/federal-judge-rescinds-federal-government-determination-that-metlife-is-systemically-important-1459349828

White, Lawrence J, 2016, "The Basics of 'Too Big to Fail'," NYU Working Paper No. 2451/33564, April 25. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2769232

Wymeersch, Eddy, 2017, "Shadow banking and systemic risk," European Banking Institute Working Paper Series, No. 1. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2912161

Zanghieri, Paolo, *forthcoming*, "The Value and Price of a "too-big-to-fail" guarantee: evidence from the insurance industry," Journal of Financial Perspectives: Insurance (Ernst &Young).

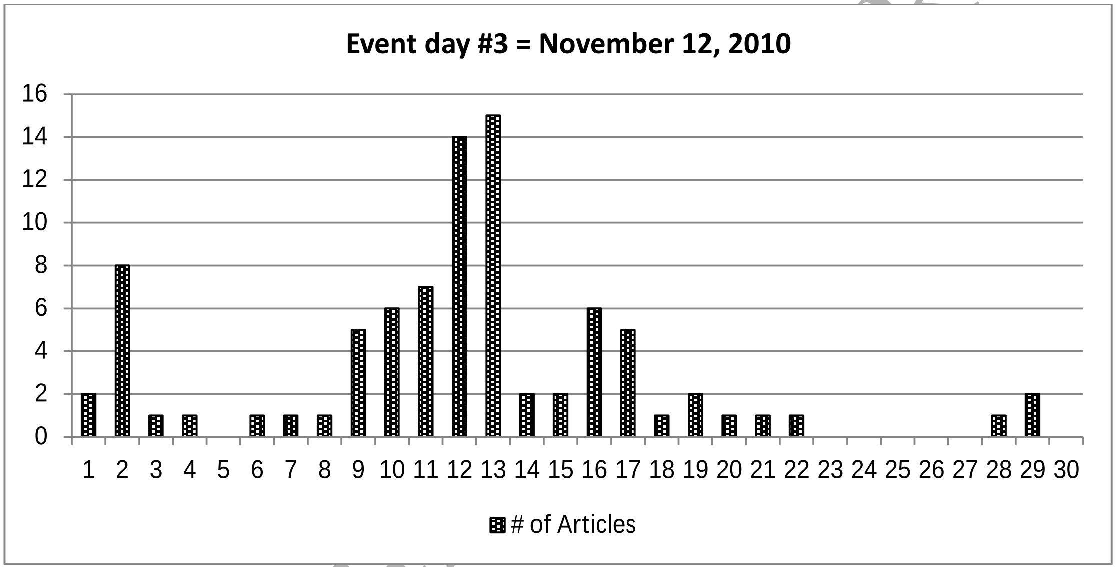

Figure 1. G-SIFI related announcements over November 2010
We report the number of articles found with search terms: "global systemically important," "financial stability board," or "G-SIFI" in ProQuest, all domestic and foreign newspapers, over the month of November 2010. We exclude articles that are clearly re-prints from the count.

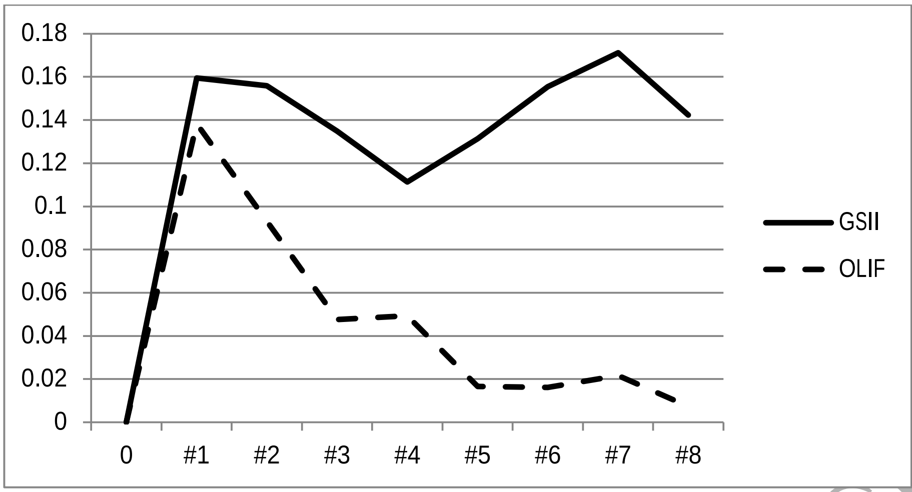

Figure 2. Cumulated abnormal equity returns (Monthly data)
We present the event study average cumulated abnormal equity returns reported in Table 5 (monthly data). The announcement dates are in Table 1. The sample includes 8 firms from 6 countries designated G-SII by the FSB in July 2013, plus 22 full or life insurance companies from the same 6 countries that have available data on ORBIS and V-Lab, collectively referred to as Other Large Insurance Firms (OLIF).

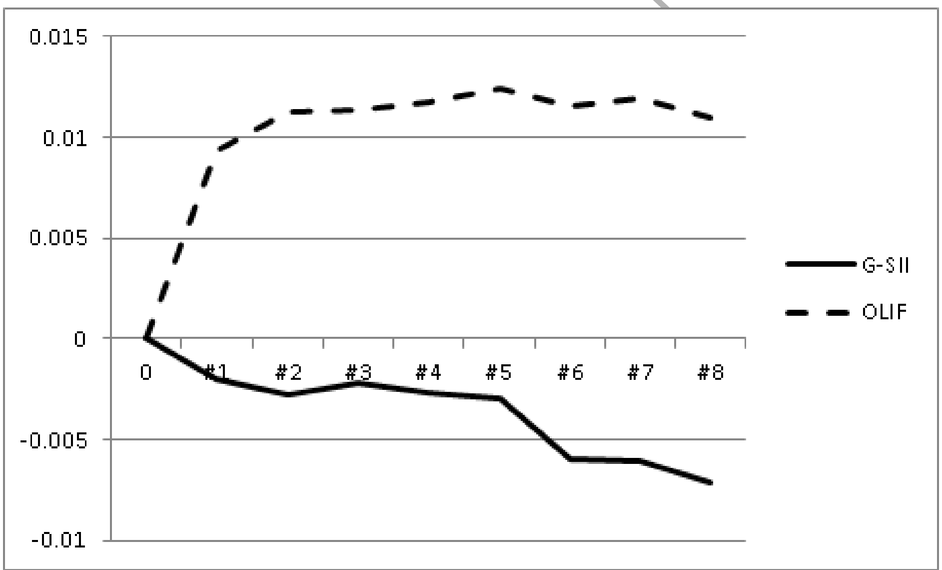

Figure 3. Cumulated abnormal changes in default probability (Monthly data)
We present the event study average cumulated abnormal change in default probability (monthly data) reported in Table 6. The announcement dates are in Table 1. The sample includes 8 firms from 6 countries designated G-SII by the FSB in July 2013, plus 22 full or life insurance companies from the same 6 countries that have available data on ORBIS and V-Lab, collectively referred to as Other Large Insurance Firms (OLIF).

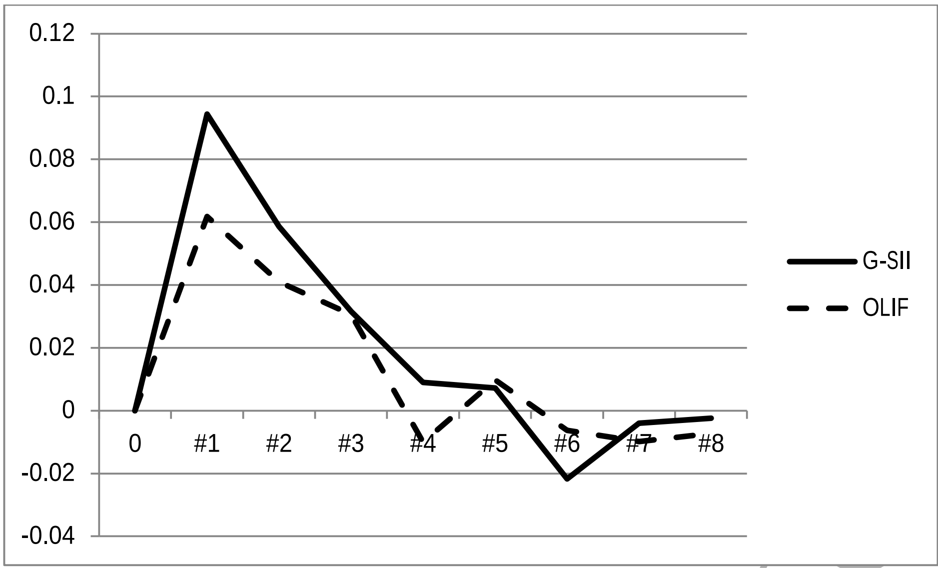

Figure 4. Cumulated abnormal percentage changes implied asset risk (Monthly data)

We present the event study average cumulated abnormal percentage changes in implied asset risk reported in Table 7 (monthly data). The announcement dates are in Table 1. The sample includes 8 firms from 6 countries designated G-SII by the FSB in July 2013, plus 13 full or life insurance companies from the same 6 countries that have available data on ORBIS and V-Lab, collectively referred to as Other Large Insurance Firms (OLIF).

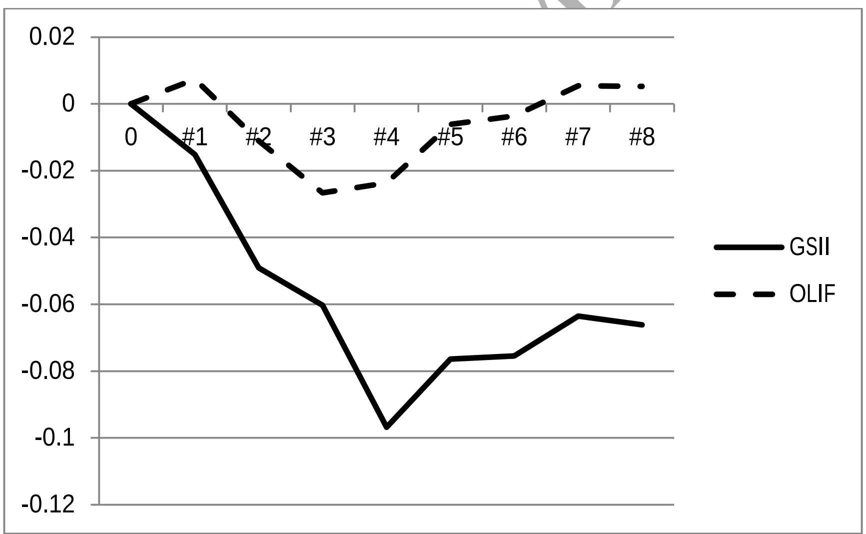

Figure 5. Cumulated abnormal bond returns (Monthly data)

We present the event study average cumulated abnormal bond returns reported in Table 8 (monthly data). The announcement dates are in Table 1. The sample includes 7 firms from 6 countries designated G-SII by the FSB in July 2013, plus 13 full or life insurance companies from the same 6 countries that have available data on ORBIS and V-Lab, collectively referred to as Other Large Insurance Firms (OLIF).

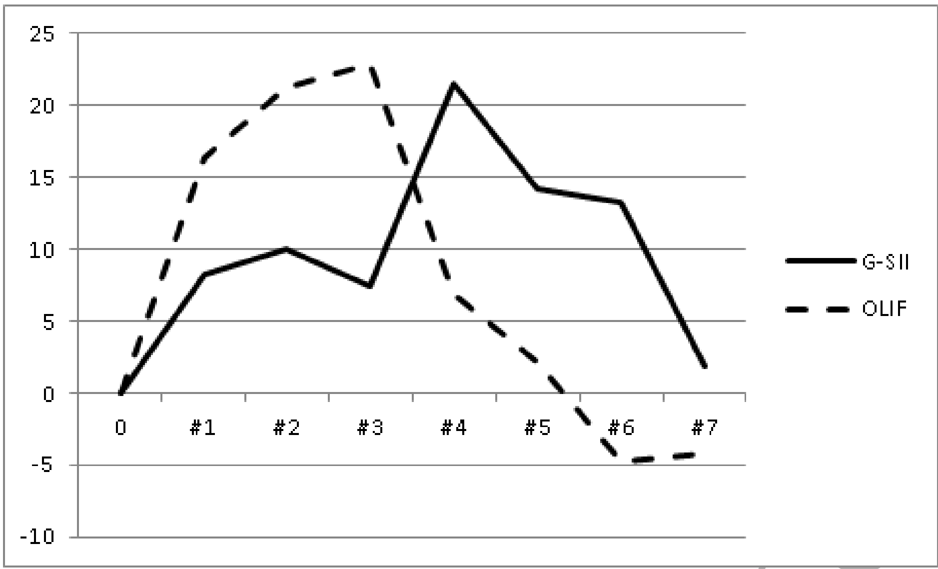

Figure 6. Cumulated abnormal changes in CDS Spreads (Monthly data)
We present the event study average cumulated abnormal changes in CDS spreads reported in Table 8 (monthly data). The announcement dates are in Table 1. The sample includes 7 firms from 6 countries designated G-SII by the FSB in July 2013, plus 10 full or life insurance companies from the same 6 countries that have available data on ORBIS and V-Lab, collectively referred to as Other Large Insurance Firms (OLIF).

Table 1. FSB-related G-SII announcements.
This table provides relevant G-SII-related announcements from a Factiva search of the *Wall Street Journal* and *The Financial Times* from September 2008 through 2013 with search words: Financial Stability Board (FSB), International Association of Insurance Supervisors (IAIS), Global Systemically Important Financial Institutions (G-SIFI), and insurance. The June 4, 2012, announcement date for identification methodology is noted as May 31, 2012, in Bongini, Nieri, and Piccini (2014). We were not able to find a reference for an announcement on May 31, but as a robustness check we duplicated our event study with that date; our results were essentially unaffected. We also note that while June 4 was a Bank Holiday in Great Britain, followed by the Queen's Jubilee on June 5, other markets around the globe were in full operation.

Event day 0	Content of announcement
1: September 17, 2008	U.S. government announces AIG bailout (announced at 10:00 pm on the 16th).
2: November 30, 2009	*Financial Times* reports 6 insurance firms are on an FSB list of 30 financial institutions "for cross border supervision exercise." Firms are AXA, Allianz, and Aviva which make the final 2013 list, and Aegon, Zurich Financial Services, and Swiss Reinsurance which do not.
3: November 12, 2010	FSB says it will look at extending the regulatory framework to non-banking companies, including insurance firms.
4: November 4, 2011	FSB announces the initial list of 29 G-SIBs, saying it will begin work to define how to extend to other G-SIFIs. The FSB expects the IAIS to complete its work on a

	methodology for insurers by June 2012.
5: January 10, 2012	FSB says it will extend the “safety frameworks” to insurance firms.
6: June 4, 2012	IAIS releases a report on the identification methodology for G-SII (announced on Sunday June 3).
7: December 3, 2012	IAIS releases a paper on policies with respect to G-SII (announced on Sunday December 2).
8: July 18, 2013	The FSB announces the list of 9 G-SII, including AIG, while IAIS publishes revised policy measures.

Table 2.
Ranking of global life insurance companies by 2012 total assets in ORBIS.
(**G-SII** in bold type, *OLIF* in italics)

Size ranking	Company name	Country	Total assets 2012
1	**AXA**	France	991,270,462
2	JAPAN POST INSURANCE CO LTD	Japan	960,832,369
3	**ALLIANZ SE**	Germany	898,766,012
4	NIPPON LIFE INSURANCE COMPANY	Japan	585,933,225
5	**GENERALI ASSICURAZIONI SPA**	Italy	575,768,987
6	ZENKYOREN & PREFECTURAL INSURANCE FEDERATIONS	Japan	544,339,320
7	*LEGAL & GENERAL GROUP PLC*	U.K.	542,519,539
8	**AMERICAN INTERNATIONAL GROUP INC**	U.S.	529,424,000
9	MANUFACTURERS LIFE INSURANCE CO. (THE)	Canada	495,388,823
10	STICHTING PENSIOENFONDS ABP	Netherlands	494,931,991
11	**AVIVA PLC**	U.K.	484,288,184
12	**PRUDENTIAL PLC**	U.K.	474,646,605
13	MANULIFE FINANCIAL CORP	Canada	468,566,144
14	AEGON NV	Netherlands	465,641,312
15	*CNP ASSURANCES*	France	454,255,022
16	**PING AN INSURANCE (GROUP) COMPANY OF CHINA LIMITED**	China	450,732,148
17	BERKSHIRE HATHAWAY INC	U.S.	424,527,000
18	ZURICH VERSICHERUNGS GESELLSCHAFT AG	Switzerland	388,632,000
19	DAI-ICHI LIFE INSURANCE COMPANY LIMITED (THE)	Japan	379,122,808
20	**METROPOLITAN LIFE INSURANCE COMPANY**	U.S.	360,500,954
21	CREDIT AGRICOLE ASSURANCES	France	359,479,753
22	MEIJI YASUDA LIFE INSURANCE COMPANY	Japan	351,360,863

23	MUNCHENER RUCKVERSICHERUNGS-GESELLSCHAFT AKTIENGESELLSCHAFT	Germany	333,393,896
24	PREDICA	France	306,462,823
25	*CHINA LIFE INSURANCE COMPANY LIMITED*	China	301,768,467
26	*HARTFORD FINANCIAL SERVICES GROUP INC*	U.S.	298,513,000
27	**PRUDENTIAL INSURANCE COMPANY OF AMERICA**	U.S.	285,087,049
28	LIFE INSURANCE CORPORATION OF INDIA	India	284,538,720
29	SUMITOMO LIFE INSURANCE COMPANY	Japan	282,173,351
30	POWER CORPORATION OF CANADA	Canada	270,868,182

This table provides a ranking of insurance firms by 2012 Total Assets as reported in ORBIS, to reflect data available for 2013 G-SII announcement. Subsidiaries of Sumitomo and General and Legal Group PLC are large enough to be included, but are omitted to avoid double counting.

Table 3.
Data definitions and sources.

This table defines the variables and provides data sources. Accounting and ownership data are from Bureau van Dijk's ORBIS data set and company annual reports. Financial risk data are from NYU Stern's Volatility Laboratory (V-Lab), except CDS spreads, collected from Datastream. Default probability data are from the Credit Research Initiative at National University of Singapore. See also Internet Appendix, Table 3A. All data are collected from 2007 through 2013.

Measures	Definition	Source
Size		
Assets	Total assets in U.S.$ millions	ORBIS
Gross premiums	Gross premiums in U.S.$ millions	ORBIS
Market cap	Market capitalization in U.S.$ millions	V-Lab
Returns		
Investment yield	100*Net investment income/ (2-yr average of: liquid assets + other Investments)	ORBIS
ROE	100*Pre-tax profit/Surplus	ORBIS
ROA	100* Pre-tax profit/Total Assets	
Risk		
Solvency ratio	100*Surplus/Total assets	ORBIS
Leverage	Quasi market value of assets / market value of equity. Quasi market value of assets = (book value of assets – book value of equity + market value of equity)	V-Lab
Beta	Beta of the firm with respect to the MSCI World Index, using Rob Engle's Dynamic Conditional Beta model	V-Lab
SRISK	Firm's estimated loss of equity value for a full financial crisis of a 40% decline in a broad market index, using a 5.5% capital requirement for Europe and an 8% capital requirement everywhere else (U.S.$ millions)	V-Lab
Event study variables		
Equity	Daily and monthly returns from firm equity return indices	Datastream

returns	(RI)	
Prob.Default	Monthly CRI:PD probability of default measure, five year horizon	CRI at NUS
Implied asset risk	Monthly average of daily option price implied volatility*(Equity/(Debt+Equity)), 8G-SII and 14 OLIF	Datastream, V-Lab
Bond returns	Daily and monthly bond returns from total return series (fixed coupon, home exchange and home currency), 7 G-SII and 13 OLIF	Datastream
CDS	Daily and monthly credit default swap spreads	Datastream

Table 4.
Summary statistics, 2012 U.S.$ millions.

This table reports summary statistics with data for insurance firms designated Global Systemically Important Insurers (G-SII) and other large insurance firms (OLIF). Sample includes 8 of 9 firms designated G-SII by the FSB in July 2013 (AIG is omitted), plus 22 full or life insurance companies from the same countries that have available data on ORBIS and V-Lab. See Table 3 for a definition of and source for all variables. Data cover the period 2012 for the accounting variables and 2008-13 for the event study variables. Mean test of difference is a t-test. Median test of difference is a Mann-Whitney test. Significant differences at the 5 and 1% levels are in bold type; significance at the 10% level is denoted with an "*".

	G-SII N=8			**OLIF N=22**			**Test of difference G-SII - OLIF**	
	Mean	**Median**	**St Dev**	**Mean**	**Median**	**St Dev**	**Mean**	**Median**
Size								
Assets	678,431	642,358	211,055	137,707	90,105	148,501	540,724***	552,253***
Gross premiums	64,169	56,882	28,462	12,311	7,023	12,698	51,858***	49,859***
Market cap	34,177	32,984	13,915	9,816	4,491	17,169	24,361***	28,493***
Returns								
Investment yield	3.7	3.93	0.87	4.07	4.01	1.33	-0.37	-0.08
ROE	7.8	9.1	16.9	11.81	12.7	7.3	-4.01	-3.6
ROA	0.5	0.54	0.7	1.26	0.83	1.14	-0.76*	-0.29
Risk								
Solvency ratio	5.63	5.58	1.85	11.76	11.79	7.77	-6.13**	-6.21*
Leverage	20.35	23.31	9.09	21.96	19.71	17.21	-1.61	3.6
Beta	1.53	1.45	0.34	1.14	1.13	0.46	0.39**	0.32**
SRISK	21.1	20	16.2	2.6	0.9	10.3	18.5***	19.1***
Event study variables								

Equity returns	0.0094	0.0117	0.1280	0.0126	0.0117	0.1600	-0.0032	0.0000
CRI: prob. of default	0.0450	0.0380	0.0260	0.0410	0.0330	0.0290	0.0040	0.0050
Implied asset risk	0.0300	0.0183	0.0380	0.0384	0.0190	0.0450	**-0.0084**	0.0007
Bond returns	0.0070	0.0060	0.0770	0.0124	0.0082	0.0770	-0.0054	-0.0022*
CDS spreads	197.6	190.9	68.5	260.4	233	141	-62.8	-42.1

Table 5. Empirical results for equity returns.

Panel A of this table reports results of an event study of announcements, reported in Table 1, related to the establishment and naming of Global Systemically Important Insurers (G-SII). The sample includes 8 of 9 firms (excludes AIG) from 6 countries designated G-SII by the FSB in July 2013, plus 22 full or life insurance companies from the same 6 countries that have available data on ORBIS and V-Lab, collectively referred to as Other Large Insurance Firms (OLIF). We report SUR specifications with monthly equity return data from 1-2008 through 7-2013. The SUR specification includes one equation for each firm. Each firm's equation includes an intercept, its home country total market return, from Datastream Total Market Indices, Datastream's World Market index return (local currency), a control for liquidity (volume for a country-level stock index from Bloomberg), and one event dummy for each announcement month. We list the control variables and specific identification codes in Internet Appendix Table 3A. Each regression breaks apart the intercept and control variable coefficients into 5 separate year-based (2008 – 2013) estimates if Wald tests reject equality of the 5 year-based estimates. The event dummies are restricted to be equal across the G-SII firms and across the OLIF firms. The table provides the abnormal returns (AR) for each of the 8 announcements, plus the summary CAR across all announcements, as well as a Chi-square test of equality of the G-SII vs. OLIF ARs. P-values are in parentheses in Panel A. Panel B reports Spearman rank correlations (at the firm level) for the risk variables defined in Table 3 with the cumulative abnormal returns (CARs) from firm-specific OLS regressions on equity returns. CARs are paired with the performance measure for the year end prior to the announcement, e.g., 2007 for announcement #1, 2012 for #8. Abnormal returns, G-SII versus OLIF differences, and correlations significant at the 10, 5 or 1% levels are marked with a "*, **, or ***," respectively.

Panel A: SUR estimates of abnormal returns

	G-SII N = 8	**OLIF N = 22**	**G-SII-OLIF**
#1	0.160***	0.138***	0.021
	(.000)	(.000)	(.338)
#2	-0.004	-0.045***	0.042***
	(.812)	(.001)	(.002)
#3	-0.021	-0.046***	0.025
	(.192)	(.001)	(.103)
#4	-0.024	0.002	-0.025*
	(.113)	(.891)	(.054)
#5	0.020	-0.033**	0.053***

	(.224)	(.030)	(.001)
#6	0.024	0.000	0.025*
	(.138)	(.974)	(.097)
#7	0.016	0.005	0.011
	(.301)	(.691)	(.466)
#8	-0.029	-0.014	-0.015
	(.135)	(.390)	(.421)
Sum	0.142***	0.007	0.135***
	(.007)	(.870)	(.005)

Panel B: Spearman rank correlation (Firm equity abnormal returns; Firm risk measure)

	#1	#2	#3	#4	#5	#6	#7	#8
G-SII								
Leverage	0.214	-0.500	-0.738**	0.143	0.143	0.286	-0.119	0.095
SRISK	0.690*	-0.310	-0.833**	-0.238	0.048	0.167	-0.429	0.238
OLIF								
Leverage	0.105	-0.361	0.210	-0.240	-0.056	-0.333	-0.398*	-0.059
SRISK	0.053	-0.320	0.069	-0.181	0.032	-0.178	-0.242	0.002

Table 6.
Empirical results for changes in default probability.

Panel A of this table reports results of an event study of announcements, reported in Table 1, related to the establishment and naming of Global Systemically Important Insurers (G-SII). The sample includes 8 of 9 firms (excludes AIG) from 6 countries designated G-SII by the FSB in July 2013, plus 22 full or life insurance companies from the same 6 countries that have available data on ORBIS and V-Lab, collectively referred to as Other Large Insurance Firms (OLIF). We report results for National University of Singapore Credit Research Institute's (CRI) default probability measure, CRI:PD, 5 year horizon, monthly data. The SUR specifications include one equation for each firm. Each equation includes an intercept, the CRI's corresponding country-level CRI:PD measure, 5-year horizon measure, and a control for liquidity (spreads from a regional or country (US and UK) bank CDS index, from Datastream). All equations include one dummy for each announcement month. We list the control variables and their specific identification codes in Internet Appendix Table 3A. Each regression breaks apart the intercept and control variable coefficients into 5 separate year-based (2008 – 2013) estimates if Wald tests reject equality of the 5 year-based estimates. The event dummies are restricted to be equal across the G-SII firms and across the OLIF firms. The table provides the abnormal returns (AR) for each of the 8 announcements, plus the summary CAR across all announcements, as well as a Chi-square test of equality of the G-SII vs. OLIF ARs. P-values are in parentheses. Panel B reports Spearman rank correlations (at the firm level) for the risk variables defined Table 3 with the CARs from firm-specific OLS regressions on default probability. CARs are paired with the performance measure for the year-end prior to the announcement, e.g., 2007 for announcement #1, 2012 for #8, Abnormal returns, G-SII versus OLIF differences, and correlations significant at the 10, 5 or 1% levels are marked with a "*, **, or ***," respectively.

Panel A: SUR estimates of abnormal changes

	CRI: PD, 5YR horizon		
	G-SII	**OLIF**	**G-SII-OLIF**
#1	-0.0020*	0.0093***	-0.0112***

	(.082)	(.000)	(.000)
#2	-0.0008	0.0020**	-0.0027**
	(.473)	(.042)	(.018)
#3	0.0006	0.0001	0.0005
	(.576)	(.950)	(.630)
#4	-0.0005	0.0003	-0.0009
	(.616)	(.718)	(.443)
#5	-0.0003	0.0007	-0.0010
	(.757)	(.449)	(.367)
#6	-0.0030***	-0.0009	-0.0021*
	(.006)	(.351)	(.064)
#7	-0.0001	0.0004	-0.0005
	(.961)	(.652)	(.679)
#8	-0.0010	-0.0009	0.0000
	(.709)	(.319)	(.970)
Sum	-0.0070**	0.0110***	-0.0180***
	(.030)	(.000)	(.000)

Panel B: Spearman rank correlations (Firm PD abnormal returns; Firm risk measure)

	#1	**#2**	**#3**	**#4**	**#5**	**#6**	**#7**	**#8**
G-SII								
Leverage	-0.357	-0.286	0.214	-0.667*	0.405	-0.452	0.000	-0.619*
SRISK	-0.190	0.143	0.357	-0.119	-0.190	-0.619*	0.429	0.095
OLIF								
Leverage	0.095	0.508**	-0.010	0.107	-0.062	-0.416*	0.266	-0.197
SRISK	0.061	0.358	0.245	0.070	-0.142	-0.469**	0.223	0.032

Table 7. Empirical results for changes in implied asset risk.

Panel A of this table reports results of an event study of announcements related to the establishment and naming of Global Systemically Important Insurers (G-SII). The announcement dates are in Table 1. The sample includes 8 of 9 firms (excludes AIG) from 6 countries designated G-SII by the FSB in July 2013, plus 13 of 22 full or life insurance companies from the same 6 countries that have available data on ORBIS and V-Lab, collectively referred to as Other Large Insurance Firms (OLIF). Panel A reports results from a SUR specification with monthly percentage changes in implied asset risk from 1-2008 through 7-2013. Implied asset risk equals the firm's implied equity volatility, from option price data in Datastream, multiplied by the ratio (Equity/Debt + Equity) from V-Lab's leverage time series. The value for any monthly equals the average across daily values for that month. The SUR specification includes one equation for each firm. Each firm's equation includes an intercept, a control for home market volatility (implied volatility on an option on the local market index from Datastream), a control for liquidity (volume on an option on the local market index from Datastream), and event window dummies, one dummy for each announcement month. We list the control variables with specific identification codes in Internet Appendix Table 3A. Each regression breaks apart the intercept and control variable coefficients into 5 separate year-based (2008 – 2013) estimates if Wald tests reject equality of the 5 year-based estimates. The event dummies are restricted to be equal across the G-SII firms and across the OLIF firms. The table provides the abnormal returns (AR) for each of the 8 announcements, plus the summary CAR across all announcements, as well as a Chi-square test of equality of the G-SII vs. OLIF ARs. P-values are in parentheses. Panel B reports Spearman rank correlations (at the firm level) for the risk variables defined Table 3 with the CARs from firm-specific OLS regressions on default probability. CARs are paired with the performance measure for the year-end prior to the announcement, e.g., 2007 for announcement #1, 2012 for #8. Abnormal returns,, G-SII versus OLIF differences, and correlations significant at the 10, 5 or 1% levels are marked with a "*, **, or ***," respectively.

Panel A: SUR estimates for abnormal returns

	G-SII	**OLIF**	**G-SII - OLIF**
	N = 8	**N = 13**	
#1	0.0944**	0.0618	0.0327
	(.018)	(.114)	(.365)
#2	-0.0358	-0.0207	-0.0151
	(.323)	(.504)	(.624)
#3	-0.0270	-0.0105	-0.0165
	(.430)	(.722)	(.572)
#4	-0.0227	-0.0406	0.0179
	(.508)	(.168)	(.535)
#5	-0.0017	0.0198	-0.0216
	(.966)	(.587)	(.556)
#6	-0.0290	-0.0160	-0.0129
	(.430)	(.612)	(.680)
#7	0.0177	-0.0036	0.0213
	(.610)	(.904)	(.470)
#8	0.0016	0.0026	-0.0010
	(.969)	(.942)	(.978)
SUM	-0.0024	-0.0073	0.0048
	(.982)	(.938)	(.958)

Panel B: Spearman rank correlations (Firm asset risk abnormal returns; Firm risk measure)

	#1	**#2**	**#3**	**#4**	**#5**	**#6**	**#7**	**#8**
G-SII								
Leverage	0.107	-0.381	-0.071	-0.881***	-0.619*	-0.643*	-0.262	-0.262
SRISK	0.357	-0.214	0.190	-0.381	0.071	-0.619*	-0.119	-0.476
OLIF								
Leverage	-0.378	0.225	-0.236	-0.022	-0.209	-0.527*	-0.258	-0.082
SRISK	-0.308	0.060	-0.132	-0.060	-0.192	-0.313	-0.099	0.126

Table 8. Empirical results for changes in bond returns and CDS spreads.

Panel A of this table reports results of an event study of announcements, provided in Table 1, related to the establishment and naming of Global Systemically Important Insurers (G-SII). The sample includes 7 of 9 firms (excludes AIG) from 6 countries designated G-SII by the FSB in July 2013, plus 13 of 22 full or life insurance companies from the same 6 countries that have available data on ORBIS and V-Lab, collectively referred to as Other Large Insurance Firms (OLIF). Panel A reports results from a SUR specification with monthly bond returns from 1-2008 through 7-2013. The SUR specification includes one equation for each firm. Each firm's equation includes an intercept, the local government long term bond return from Datastream, and a control for home market liquidity (volume for the local market stock index from Datastream), and event window dummies, one for each announcement month in the monthly data SUR). We list the control variables with specific identification codes in Internet Appendix Table 3A. Each regression breaks apart the intercept and control variable coefficients into 5 separate year-based (2008 – 2013) estimates if Wald tests reject equality of the 5 year-based estimates. The event dummies are restricted to be equal across the G-SII firms and across the OLIF firms. The table provides the abnormal returns (AR) for each of the 8 announcements, plus the summary CAR across all announcements, as well as a Chi-square test of equality of the G-SII vs. OLIF ARs. P-values are in parentheses. Panel B reports Spearman rank correlations (at the firm level) for the risk variables defined Table 3 with the CARs from firm-specific OLS regressions on bond returns and changes in CDS spreads. CARs are paired with the performance measure for the year end prior to the announcement, e.g., 2007 for announcement #1, 2012 for #8. Abnormal returns, G-SII versus OLIF differences, and correlations significant at the 10, 5 or 1% levels are marked with a "*, **, or ***," respectively.

Panel A: SUR estimates of abnormal returns

	Bond returns			**CDS spreads**		
	G-SII	**OLIF**	**G-SII-OLIF**	**G-SII**	**OLIF**	**G-SII-OLIF**
	N = 7	**N = 13**		**N = 7**	**N = 10**	
#1	-0.015	0.007	-0.023	8.31	16.37	-8.07
	(.440)	(.732)	(.182)	(.316)	(.255)	(.558)
#2	-0.034***	-0.018	-0.015	1.75	4.92	-3.16
	(.004)	(.168)	(.177)	(.805)	(.633)	(.746)
#3	-0.011	-0.016	0.004	-2.6	1.63	-4.22
	(.251)	(.213)	(.694)	(.704)	(.868)	(.653)
#4	-0.036***	0.003	-0.039***	14.02**	-16.08	30.10***
	(.000)	(.813)	(.000)	(.044)	(.116)	(.002)
#5	0.020**	0.018	0.003	-7.21	-4.72	-2.49
	(.049)	(.168)	(.794)	(.321)	(.648)	(.803)
#6	0.001	0.003	-0.002	-1.000	-6.89	5.88
	(.939)	(.848)	(.885)	(.886)	(.486)	(.536)
#7	0.012	0.009	0.003	-11.37	0.5	-11.87
	(.222)	(.470)	(.791)	(.104)	(.961)	(.229)
#8	-0.003	0	-0.002	-14.60*	-1.84	-12.75
	(.807)	(.989)	(.841)	(.053)	(.877)	(.237)
Sum	-0.066*	0.005	-0.089**	-12.69	-6.11	-6.58

(.064)	(.898)	(.044)		(.556)	(.849)	(.829)

Panel B: Spearman rank correlations (Firm bond abnormal returns; Firm risk measure)

	#1	#2	#3	#4	#5	#6	#7	#8
G-SII								
Leverage	-0.257	0.571	0.107	0.643	-0.429	0.036	0.536	0.071
SRISK	-0.371	0.714*	0.571	0.643	-0.464	0.286	0.143	-0.036
OLIF								
Leverage	0.109	-0.313	-0.291	-0.346	0.407	0.297	-0.027	0.093
SRISK	-0.245	-0.341	-0.346	-0.137	0.626**	0.291	-0.346	0.115

Spearman rank correlations (Firm CDS spread abnormal returns; Firm risk measure)

	#1	#2	#3	#4	#5	#6	#7	#8
G-SII								
Leverage	0.107	-0.500	0.357	-0.071	0.679*	-0.286	0.750*	0.390
SRISK	0.143	-0.143	0.607	0.214	-0.107	-0.179	0.429	0.643
OLIF								
Leverage	0.190	0.033	-0.200	0.433	-0.500	-0.100	0.533	0.067
SRISK	0.071	-0.267	-0.350	0.333	-0.433	-0.067	0.367	0.167

Appendix: G-SII and OLIF samples

The G-SII sample includes nine insurance firms designated Global Systemically Important Insurers (G-SII) by the Financial Stability Board in 2013. The Other Large Insurance Firm (OLIF) sample includes 22 full and life insurance firms in the same 6 countries as the G-SII firms who have financial statements in ORBIS, stock price information on Datastream, and systemic risk information from V-LAB. We use FTSE's Industrial Classification Benchmark to ensure that we consider only firms classified as either life or full insurance companies. Following the IAIS selection process, we then use ORBIS industry codes to verify that firms in the FTSE classification list do not engage in substantial activities unrelated to systemic risk (no conflicts arose across the two datasets). We also require firms to have data in V-Lab. The V-Lab data cover large firms as they tend to have the most systemic risk, which is consistent with the IAIS selection process.

G-SII	Country
Ping An Insurance	China
Axa SA	France
Allianz SE	Germany
Assicurazioni Generali Spa	Italy
Aviva Plc	U.K.
Prudential Plc	U.K.
American International Group	U.S.
MetLife	U.S.
Prudential Financial	U.S.
OLIF	**Country**
China Life Insurance Co	China
China Pacific Insurance	China
CNP Assurances	France
Generali Deutschland Holding	Germany
Nuernberger Beteiligungs	Germany
Societa Cattolica Di Assicurazioni	Italy
Unipol Gruppo Finanziario Spa	Italy
Legal & General Group Plc	U.K.
Standard Life Plc	U.K.
Aflac	U.S.
American National Insurance Co	U.S.

Assurant Inc	U.S.
CNA Financial Corp	U.S.
CNO Financial Group, Inc	U.S.
Genworth Financial	U.S.
Hartford Financial Services	U.S.
Kemper Corp	U.S.
Lincoln National Corp	U.S.
Primerica, Inc	U.S.
Protective Life Corp	U.S.
Torchmark Corp	U.S.
Unum Group	U.S.