Crisis Sentiment in the U.S. Insurance Sector*

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23rd February 2016

Forthcoming in the Journal of Risk and Insurance

Abstract

We use internet search volume data to measure idiosyncratic and market-wide crisis sentiment to explain insurer stock return volatility. We find that market-level crisis sentiment was a significant predictor of stock return volatility of U.S. insurers between 2006 and 2010. Higher levels of crisis sentiment are associated with higher levels of price uncertainty. This effect is strongest for insurers with less exposure to the adverse effects of the financial crisis. Further, crisis sentiment also affects the cross-section of movements in insurer stock prices. Our results imply that investors exited insurer stocks mainly due to crisis sentiment rather than a rational assessment of the insurers' actual exposure to the crisis.

Keywords: Financial crises, insurance, investor sentiment.

JEL Classification: G01, G22, D03.

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*Former title: Crisis Sentiment and Insurer Performance. We received very useful comments from Keith Crocker (the editor), an anonymous co-editor, two anonymous referees, David Cummins, Ty Leverty, Ludger Linnemann, David Pankoke, Marc Ragin, André Uhde, Jaqueline Volkman-Wise, Mary Weiss, and participants of the 2014 Western Risk and Insurance Association Meeting (Napa Valley) and the ARIA 2014 Annual Meeting (Seattle). Support by the Collaborative Research Centers "Statistical Modeling of Nonlinear Dynamic Processes" (SFB 823, project A7) and "Economic Risk" (SFB 649) of the German Research Foundation (DFG) and the Mercator Research Center Ruhr (grant no. Pr-2013-0037) is gratefully acknowledged.

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1 Introduction

Looking back at the recent financial crisis, it appears that not only shareholders of banks but also investors of insurer stocks were hit hard by the turmoil in international stock markets. In fact, insurer stocks suffered even higher losses than stocks of banks. The question remains what exactly caused stocks of insurers to experience such massive declines. In this paper, we analyze whether the abnormal movements in insurer stock prices can be explained by investor sentiment that intensified during the financial crisis. More precisely, we argue that investors were measuring both banks and insurance companies by the same yardstick during the crisis and exited stock investments of financial institutions indiscriminately and regardless of the institutions' actual exposure to the crisis. If this were the case, investors would have been punishing insurers beyond the degree to which they were actually exposed to the adverse effects of a crisis that originated from the banking sector.

Intuitively, we would expect insurers to be less affected than banks by the financial crisis for several reasons: First, insurers are neither vulnerable to bank runs by depositors (see Diamond and Dybvig, 1983) and creditors (see Duffie, 2010; Gorton and Metrick, 2012) nor to liquidity shortages arising from the interbank market as seen during the financial crisis. On the contrary, insurer stocks should experience a flight to quality during an episode of turmoil in the financial sector as investors exit their investments in volatile bank stocks. However, the near-collapse of *American International Group* led to a reassessment of the insurance sector's potential to cause systemic risk and thus potentially causing investor sentiment to increase during the financial crisis. At the same time, the question why investors punished insurer stocks to such a high extent, especially non-life insurers that were economically less affected by the crisis, still remains unanswered. Insurance providers guarantee protection against future losses and thus, allow firms to take on their desired level of risks. However, insurance companies are not as interconnected and systemically important in functioning economy as banks (see Chen et al., 2014). Therefore, our study helps in understanding the effects of the financial crisis on insurers by studying if noise trading and sentiment were the driving forces for the stock downturn in this relatively uninvolved

Electronic copy available at: http://ssrn.com/abstract=2364365

sector.

We first test whether the time-varying presence of uninformed traders in the market caused insurer stocks to be more volatile, as it is predicted by theory (see De Long et al., 1990). Using a direct measure of retail investor attention on individual stocks based on internet search volume data from Google's search engine, we show that a higher level of investor attention is indeed associated with more stock price volatility. Further, we confirm the findings in Da et al. (2011) that abnormal retail investor attention increases prices in the next week, followed by a price reversal the weeks afterwards. Finally, we investigate the effect of market-wide sentiment on the cross-section of insurer stocks by running separate analyses for different types of insurers accounting for individual arbitrage opportunities.

In this paper, we argue that insurer stock returns and volatility during the financial crisis were significantly driven by irrational components such as general negative investor sentiment. To proxy for an individual insurer's susceptibility to the adverse effects of the crisis as perceived by market investors, we employ new measures of "crisis sentiment" based on internet search volume data. First, we use the first principal component of several Google search volumes for crisis-related queries (e.g., "financial crisis", "subprime crisis") to measure the level of market-wide crisis sentiment as proposed in Irresberger et al. (2015). Additionally, we employ the FEARS-index introduced in Da et al. (2015) as a variable that represents household-level sentiment. To measure the extent of idiosyncratic crisis sentiment, we employ the abnormal search volume on a firm's ticker symbol as a proxy of retail investor attention (see Da et al., 2011) and the correlation of such idiosyncratic search volume with market-level crisis sentiment. Thus, we also capture the degree to which investors are negatively influenced by the financial crisis in their perception of the insurance market. We estimate our proposed measure of crisis sentiment for a sample of U.S. insurance companies and carry out regressions of weekly stock returns and volatility on the new measures of crisis sentiment. To account for the different levels of exposure to the crisis, we run separate regressions for the different types of insurance companies.

Our results show that our measure of market-level (or general) crisis sentiment is significantly negatively correlated with insurers' stock returns and positively related to volatility. Further, crisis sentiment also affects the cross-section of insurers' stock return volatility, e.g., larger insurers are less affected by market-wide sentiment. The impact of crisis sentiment is strongest on non-life insurers which were only weakly exposed to the negative effects of the crisis. Higher values of abnormal investor attention on an individual insurer induces higher stock price volatility in the next week followed by a reversal in the weeks after, but not vice versa. The relation of individual investor attention and market-wide sentiment to stock returns and volatility, however, is weak. Consequently, (retail) investors did indeed act on the sentiment of a general economic downturn rather than a differential and rational assessment of the idiosyncratic exposure of insurers to the crisis.

Our paper is related to few but influential previous studies on the usefulness of internet search data.[1] Ginsberg et al. (2009) were among the first to use search engine queries to detect health trends and predict influenza epidemics. In an economic context, the usefulness of Google search volume data for portfolio diversification and investment strategies has recently been investigated by Kristoufek (2013) and Preis et al. (2013). Methodically, our empirical approach differs from theirs in that we make use of the search volume index (SVI) provided by Google Trends while Ginsberg et al. (2009) compute a time series of weekly counts for the most common search queries themselves. The usefulness of quantifying internet search behaviour has also been studied in the finance literature, most notably through the work of Da et al. (2011) and Da et al. (2015). In the latter, the authors also study investor sentiment measured through internet search behaviour but focus on the pricing of financial assets. Their approach resembles ours with respect to the construction of a new index of investor sentiment. Their so called FEARS index is based on the SVI of sentiment revealing search terms such as "recession" or "bankruptcy", which they find to increase in the years around the financial crisis. However, Da et al. (2015) focus on the effect investor sentiment has on asset prices, volatility, and fund flow from equity mutual funds to bond funds. Our paper differs significantly from previous studies, however, as we measure the correlation between two sets of

[1] As noted by Choi and Varian (2009), search data from Google may have the potential to describe interest in a variety of economic variables.

search terms and provide the first use of big data from Google in the empirical insurance literature. In addition, our work also complements the findings on the relation between investor mood and asset prices (see, e.g., Shu, 2010). But instead of using mood proxies, such as biorhythms or wheather, we employ a direct measure of the bearish sentiment of investors. Finally, our paper is also related to the recent study by Wisniewski and Lambe (2013) which examines the impact of negative media speculation on the performance of bank sector indices. In contrast to their paper, we refine the notion of negative sentiment by analyzing crisis sentiment and concentrate on the consequences for individual insurers rather than the whole financial sector.

The rest of our paper is structured as follows. We provide an overview of the most relevant literature that we use to build our hypotheses in Section 2. In Section 3, we briefly describe the construction of our data sample, followed by an outline of the measures we employ to proxy for investor attention and sentiment and other variables used in this study. Section 4 presents the results of our empirical analysis into the question whether insurer stock prices and volatility during the crisis was driven by crisis sentiment and retail investor attention. Afterwards, we discuss several robustness tests in Section 5 and conclude in Section 6.

2 Literature overview and hypothesis building

The literature on the interplay of heterogeneous investor attention, sentiment, and asset pricing is vast and still growing (see, e.g., Merton, 1987; Gervais et al., 2001; Sims, 2003; Hirshleifer and Teoh, 2003; Seasholes and Wu, 2007; Tetlock, 2007; Barber and Odean, 2008; Hou et al., 2009). Since the introduction of the *noise trading hypothesis* by Black (1986) that explains why expected actual stock prices may differ from their expected funndamental value, several studies have empirically analyzed the impact of positive or negative sentiment and noise trading on the valuation of stocks. The presence of uninformed noise traders in financial markets may lead to unexpected movements in prices and make the valuation of assets even more difficult.[2]

[2] Further, in the presence of short-sale contrainsts, overconfident noise traders could drive informed or institutional traders out of the market completely, as shown by the model of Baker and Stein (2004).

In our study, we measure time-varying retail investor attention as proposed by Da et al. (2011) and investigate its impact on the predictability of insurer stock prices. The model of De Long et al. (1990) suggests that the presence of uninformed trading leads to an increase in asset price volatility. Consequently, the first hypothesis that we test in our study reads as follows:

Hypothesis 1: Higher *retail investor attention* leads to *higher levels of volatility* in the short term.

Stocks of financial firms are special in the way that investors often incorporate the relatively high importance of these institutions for large parts of the economy (e.g., banks' lending activities) into asset prices. Due to their vital function for the economy, financial institutions have benefitted from being "too-big-to-fail" and receiving (implicit) bailout guarantees from governments, which could also be reflected in the pricing of their stocks (see, e.g., Gandhi and Lustig, 2015; Schweikhard and Tsesmelidakis, 2014). While there is some evidence that insurance companies were victims of the crisis rather than perpetrators (see Chen et al., 2014), there is still no consensus about the mechanisms that caused insurer stock prices to drop to such an extent as they did during the crisis. In this study, we provide evidence that market-wide and individual crisis sentiment affected insurer stock prices negatively and made their valuation more difficult during the crisis. The impact of market-level crisis sentiment but also the individual association of banks with the financial crisis on the prices of bank stocks have been analyzed by Irresberger et al. (2015). We extend their study by investigating the importance of co-movement of retail investor attention on insurers' equities and crisis sentiment for the predictability of insurer stock prices. We suspect the following statement to be true:

Hypothesis 2: The *association of individual insurers with the crisis* is *positively related to volatility* and *negatively related to stock returns*.

In line with the arguments in Baker and Wurgler (2006), we expect market-wide sentiment to increase the overall level of aggregate uncertainty about prices. Further, due to differences in their business models and involvement with the crisis, sentiment is supposed to not only affect the overall level of price volatility, but also to affect the cross-section of insurer stocks. We test the following hypotheses:

Hypothesis 3a: Sentiment waves have a differential effect on the cross-section of insurance firms and possess an idiosyncratic component.

First, we account for differences in arbitrage opportunities for the different insurer stocks and test how crisis sentiment affects the individual stocks. Second, we split our sample of U.S. insurers into different sub-samples and thus, indirectly control for the actual exposure to the elements of the crisis. Specifically, we test the following hypothesis:

Hypothesis 3b: Insurers that were more exposed to the adverse effects of the crisis are less affected by crisis sentiment.

In the next section, we describe the construction of our sample of U.S. insurers and introduce our main variables of interest that we use to test the stated hypotheses.

3 Data and variables

This section describes the construction of our sample of insurance firms which is retrieved from the *Center for Research in Security Prices* (CRSP) and *Compustat* databases. Afterwards, we discuss the data taken from *Google Trends* that we use to construct our measures of investor attention and sentiment.

3.1 Sample construction

We build our initial sample from insurer stocks available in the CRSP database. Specifically, we restrain our sample to those insurers with available stock price data in the time period from the beginning of 2006 to the end of 2010. By doing so, we ensure that our sample includes enough observations for the periods before, during, and after the crisis (i.e., we employ the crisis as a natural experiment).

We employ all companies with SIC codes 6311, 6321, 6331 or 6411 from the dead and active lists in *CRSP*.Afterwards, we screen our resulting list of names of insurance companies for words suggesting a non-insurance nature of the companies' business. For our purposes, it is necessary to have sufficient data on weekly quotes and thus, we restrict our sample by requiring a firm to have at least 100 weeks of data starting from the first week in 2006 to the end of 2010 to remain in our sample.[3] Applying these filters leaves us with a final sample of 105 publicly listed U.S. insurance companies. For each firm, we retrieve its unique ticker symbol from *CRSP* but also do individual research on the ticker of a firm when it is not shown in *CRSP*.

The identification of life and non-life insurers and financial holding companies via SIC codes is not unique. We thus compare SIC codes with respective NAICS codes and manually screen the company names and look up information on the firm's website in order to categorize our sample firms. Whenever the SIC code classification matches the NAICS code (e.g., SIC code 6311 matches the NAICS code 524113 for life insurers), we identify the firm according to the SIC code. When the NAICS code does not match the SIC code, we do additional research on the insurance firm to ensure a better classification. Eventually, we manually distinguish between life insurers (16 firms), non-life insurers (41 firms), reinsurers (7 firms), and financial groups (41 firms).[4]

The names, ticker symbols, and the chosen classification of all insurance companies in our sample are listed in Appendix II.

3.2 Dependent variables

Our two dependent variables of interest are an insurer's weekly *stock return* and *volatility*. Stock returns are defined as percental changes in stock prices. To model stock return volatility, we employ a GJR-GARCH model based on weekly returns (see Glosten et al., 1993).[5] Estimation is based on

[3] It is important to have a sufficient number of data points for regression estimates and also to efficiently estimate volatility using *GJR-GARCH* models and related specifications. Further, approximately two years of data gives a reasonable insight on the dynamics of insurers stocks and investor sentiment.

[4] For example, sometimes the NAICS codes 524298 (all other insurance) and 524210 (brokers agents) are assigned to financial groups.

[5] As noted Glosten et al. (1993), the GJR-GARCH approach is particularly well suited for stock market data as it allows for asymmetric effects of up- and downward stock movements on volatility.

all available stock return data and is performed firm by firm. In Figure 1, we plot the time evolution of the 20%- and 80%-quantiles and mean values of stock returns and volatility from 2006 to the end of 2010.

Insert Figure 1 about here.

The upper panel provides evidence of non-stationarity in our time-series as ranges of stock returns differ substantially over time. The minimum of the 20%-quantile is about -4% and the maximum of the 80%-quantile is about +5% in the time from 2006 to mid-2007. This range of weekly stock returns is extended up until mid-2008, after which it is widened to a window of -15% to +15% in the middle of the crisis period. Mean values of returns range from -10% to +10% but are mainly within the window of -5% to 5% over the full sample period.

The lower panel shows that volatility was relatively flat from 2006 to the end of 2007. Occasional peaks can be found in the beginning of 2008. Large spikes are present in the fourth quarter of 2008, the peak of the crisis, where even the 20%-quantiles are higher than the 80%-quantiles of volatility of the years before. A second peak can be observed in the first quarter of 2009. Mean values in our sample are generally close to the 80%-quantiles, which hints at the presence of few outliers among the insurance firms that have extremely volatile asset prices.

3.3 Google Trends

In this study, we measure investor attention and sentiment by employing internet search volume data obtained from *Google Trends*, a service provided by Google Inc. for its users.[6] When typing single words or phrases into *Google Trends*, its user is given a graph that indicates the number of searches that occured in a specified time period, relative to the total amount of all searches.[7] Google users are then able to export the so called *Search Volume Index* (SVI) at a weekly frequency, in case the search volume is sufficiently high over the given time period in a given geographic area

[6] Access to this tool is given at `www.google.com/trends`.
[7] The values of the relative search volumes are then scaled to a range of 0 to 100.

(in our case the United States). As Google's search engine is the most frequently used in the U.S., the SVI gives a proper estimate of the time-varying interest of U.S. households on specific topics.[8]

In our study, we restrict all queries on *Google Trends* to the United States in the time period from January 2005 to December 2010, if not stated otherwise.[9] We now describe the construction of several attention and sentiment indicators from the literature that are used to test our hypotheses.

3.4 Household sentiment - FEARS

As our first measure build from Google Trends data, we calculate the *Financial and Economic Attitudes Revealed by Search* (FEARS) index proposed by Da et al. (2015). The authors combine the search volume from *Google Trends* on thirty economics-related phrases taken from the Harvard dictionary that reveal to have a strong negative relation to market returns. Most of the words are not necessarily related to financial crises or investing but rather reflect households' current emotional status or expectations of the economy. For our purposes, the FEARS-index is a way of measuring negative (household) sentiment that proxies the general perceivement of the economy by a large part of the population. To calculate the FEARS-index, we first take the log changes of the search volume levels.[10] The time-series of log-changes is then winsorized at the 5% level and adjusted for seasonality by regressing on month dummies. Afterwards, we divide each of the thirty time-series by its standard deviation to account for heteroskedasticity. Eventually, we combine the thirty time-series by averaging.

The phrases used to construct the index were chosen to be negatively related to market returns. Thus, we predict that higher values of FEARS, a higher level of negative sentiment among households, is associated with a decrease in insurers' stock prices in our sample as well. The cor-

8 Other advantages of using internet search volume data are that it reflects active information retrieval, is anonymous, and easy accessability of information on public interests (see Da et al., 2011; Irresberger et al., 2015; Irresberger and Weiß, 2015). In this respect, using internet search volume data to measure investor attention and sentiment beats other approaches such as implicit market sentiment measures derived, e.g., from textual analysis (see, e.g., Tetlock, 2007; Tetlock et al., 2008) or surveying.

9 We start our time period in 2005 in order to use data from the first year to calculate correlations of SVIs on the basis of a rolling window of 52 weeks of data later on.

10 We add one to each of the time-series values so that the natural logarithm is well defined for every point in time.

relation of insurers' stock return volatility and FEARS, however, is not obvious. On the one hand, a higher level of negative sentiment could indicate that irrationality is driving the decision making of households and possibly investors and thus, prices may fluctuate from fundamental values and make market prices less predictable. On the other hand, negative sentiment could reflect the actual economic environment and does not necessarily make prices less predictable, as there simply might be a downward trend in markets. We therefore have no expectation regarding the sign of the coefficients of FEARS in our analyses.

3.5 Retail investor attention

Next, we construct a measure that proxies for the attention of retail investors on an individual company by employing abnormal search volume on a firm's ticker symbol. We follow Da et al. (2011) and employ the abnormal search volume on an insurer's ticker symbol in Google Trends, which is given by

$$\mathrm{ASVI}_{i,t} = \log\left[\mathrm{SVI}_{i,t}\right] - \log\left[\mathrm{median}\left(\mathrm{SVI}_{i,t-1}, \ldots, \mathrm{SVI}_{i,t-8}\right)\right],$$

where $\mathrm{SVI}_{i,t}$ is the search volume retrieved from *Google Trends* of ticker i in week t.[11] In their study, Da et al. (2011) show that abnormal attention on a single stock predicts higher stock prices in the subsequent two weeks and price reversals after a certain time period. Also, in their paper they argue that *ASVI* captures the attention of retail investors and thus, higher values of *ASVI* represent an increased activity of this subset of market participants.[12] As in Da et al. (2011), we expect a positive effect of abnormal retail investor attention and stock returns in the short run, with price reversals afterwards. Further, we test whether a higher activity of retail investors, a potential source of noise trading, leads to increases in asset volatility as proposed in theory (see

[11] Again, we add one to each value of SVI in order to ensure that the logarithm is well-defined.

[12] Da et al. (2011) argue that their measure is very likely to represent the attention of retail investor attention (they also provide empirical evidence for this) and thus, we view this measure as a valid proxy for the presence of such a sub-group of investors. Available data on ownership structures in 2010 from *Compustat* suggest that on average 75% of insurers' shares are owned by institutional investors, leaving a large portion to non-institutional traders that are more likely to engage in noise trading.

De Long et al., 1990).

Although this rather new approach comes with a lot of flexibility and a possibility to directly measure attention on single firms, it also comes with some disadvantages. Some of the insurers' ticker symbols are very generic expressions such as “ALL” or have a double meaning, e.g. “CIA”. Also, for ticker symbols like “Y”, the time evolution of its SVI in Google Trends is very unusual for interest on a firm's stock. Another shortcoming is that for some ticker symbols there simply is not sufficient search volume to retrieve enough or any data at all. Therefore, we manually screen the list of ticker symbols to identify those with ambiguous meaning in the spirit of Da et al. (2011). For increased transparency, we indicate which companies were removed from the sample when we include variables that use the search volume on a firm's ticker symbol due to lack of data availability or due to ambiguity. In total, we only have data on the search volume of ticker symbols for a total of 54 insurers.

3.6 Crisis Sentiment Index

While the former two variables proxy for individual retail investor attention and general household sentiment, we also want to account for investor attention and sentiment that is specifically geared towards the U.S. financial crisis and test its impact on returns and volatility of insurer stocks. Having a specific crisis sentiment as explanatory variable is particularly interesting due to the uniqueness of the financial crisis. Because of this, investors were left with high uncertainty about the economic outcome of the crisis, especially for relatively uninvoled sectors such as parts of the insurance sector. For this reason, it is very likely that aggregate uncertainty about this special time of turmoil may have increased volatility in asset prices.

In this study, we employ the *General Crisis Sentiment Index* (General CSI), which is build from the search volume of four variations of the term “financial crisis”. We follow Irresberger et al. (2015) and download the weekly SVI for the phrases “financial crisis”, “credit crisis”, “bank crisis", and "subprime crisis", which account for the evolution of the naming of the crisis over time.[13] The calculation then proceeds as follows: We first employ the 52 weekly GSVI values of the four crisis-related search terms in the year 2005 and estimate the first principal component of the four time series (see Baker and Wurgler, 2006; Irresberger et al., 2015). The resulting values of the first principal component are then used to proxy for the search volume of crisis-related search terms during the year 2005. To estimate the values of SVI of crisis-related terms in each remaining week in our sample, we use rolling windows that are enlarged by one week after each estimation (i.e., the principal component analysis used to compute the first principal component in week t is performed on data for weeks one through week t).[14] Then, let Z_t be the resulting value of the first principal component of the SVI of the four search terms at time t, scaled to the range of 0 to 100.[15] We then consider the estimate of Z_t to be our primary proxy for the general crisis sentiment. We follow Irresberger et al. (2015) and define Z_t as the *General CSI*.[16]

Whereas our proxy for the general crisis sentiment as constructed above is supposed to capture the overall angst of investors towards the financial crisis, we additionally introduce a measure of the relation between individual insurers and the financial crisis as perceived by investors. We estimate time-varying correlations ϱ_t^i between the general crisis sentiment Z_t and the search volume index $SVI_{i,t}$ of insurer i. To avoid a possible look-ahead bias in the estimation of the correlations, we estimate ϱ_t^i using rolling windows of length 52 weeks using data up to week t (the rolling windows are skipped ahead one week for each estimation). Finally, we construct the *Crisis Sentiment*

[13] Additional variations of the search terms, e.g. "the banking crisis", are highly correlated to at least one of the existing four phrases and are therefore dropped from consideration.

[14] Obviously, the principal component analysis could have also been performed on our complete data set. The estimation procedure described above, however, guarantees that the time series of the first principal component of crisis-related search terms does not suffer from a look-ahead bias.

[15] The scaling is done as in the Google Trends tool through dividing by the maximum value of the series and then multiplying by 100.

[16] We decide to employ the levels of search volumes rather than changes. Taking changes (e.g., when constructing the FEARS index) is reasonable when the search volumes are not comparable in size as it is the case, e.g., for "gold" and "gold prices" and one wants to consolidate several time-series. For example, taking the average of the search volumes of the two phrases just mentioned does not yield a reasonable estimate of the combined search volume ("50" can mean totally different magnitudes of the search volume for "gold" than for "gold prices") when the series are retrieved separately. By taking log-changes, the volumes become comparable but we lose the easy interpretation. However, for the phrases related to "financial crisis", the search volumes are comparable in their size (which can be seen when they are typed into Google Trends simultaneously).

Index (CSI) by combining the dynamic correlation between the first principal component Z_t and a firm's $\mathrm{SVI}_{i,t}$, multiplying the estimated correlation with the sum $(\mathrm{SVI}_{i,t} + Z_t)$ and then dividing the resulting term by 200 (see Irresberger et al., 2015):

$$\mathrm{CSI}_{i,t} := \left(\frac{\mathrm{SVI}_{i,t} + Z_t}{200}\right) \cdot \varrho_t^i. \tag{1}$$

This specific construction of the CSI accounts for several issues. First, by employing the time-varying correlations of the first principal component and the normalized search volume index of the firms, we capture the time variation in the crisis-related attention retail investors (together with the general public) paid to the insurance firms in our sample. This correlation, however, does not provide us with any information on the actual level of the search volumes in a given week. As such, it could be that both the insurer's SVI and the crisis-related search terms are highly correlated simply because both their search volume indices were zero. We correct this issue in equation (1) by multiplying the dynamic correlation with the sum of the indices and the scaling factor of $\frac{1}{200}$ (each of the two SVIs has a range of 0 to 100). When market-wide crisis sentiment is high at a given time and a single insurer is associated with such sentiment, we expect the respective stock price to decrease. Volatility of stock prices is assumed to increase with aggregate uncertainty on an individual level as well and thus, CSI is expected to enter regressions employing volatility as a dependent variable with a positive sign of the coefficient.

In Figure 2, we show plots of the time-evolution of mean values of *CSI* and *ASVI* as well as quantiles for the full sample. Also, we compare the SVI for the four crisis-related search terms with its combined values.

Insert Figure 2 about here.

The upper panel reveals that the average values of *CSI* have peaks at the end of 2007 and at the end of 2008, but generally remain flat around a mean value of zero. Even extreme values such as the 20%-quantile do not fall below a value of -20% and the highest value is only at around 22% for the 80%-quantile. Interestingly, the mean *CSI* is negative in mid-2009, where the peak of the crisis had already passed by and insurer stocks did not suffer from crisis sentiment to a large extent anymore.

The second panel shows that the mean values of the abnormal search volume measure *ASVI* often exceed the 20%- and 80%-quantiles indicating extreme differences in the dynamics of the attention measure across our sample. The results suggest that some of the insurance firms experienced more rapid changes in retail investor attention than others. However, we also observe that most of the values range from -0.2 to 0.2. An interesting insight from this figure is that individual attention on a stock is strongly time-varying and times of higher attention are often followed by periods with lower abnormal attention.

Not surprisingly, the market-wide crisis sentiment shown in the lower panel increased in summer 2007 and rose steeply around the collapse of Lehman Brothers in 2008. Nevertheless, search volume indices also varied significantly before and after the collapse of Lehman. Second, differences between the SVI of the individual search terms can be quite high as evidenced, e.g., by the high search volumes for “subprime crisis” in late 2007 and early 2008 thus underlining the need to consolidate the search volume data via principal component analysis.

3.7 Other explanatory variables

In addition to our proxies for market-wide and individual sentiment or attention, we include commonly used firm-specific variables for which we control for in our regression analyses. First, we employ an insurer stock’s (absolute) *bid-ask-spread*, which is the difference of end-of-week ask-quotes and bid-quotes. When the spread is high, an equity is considered to be less liquid. Second, we proxy for an insurer’s size by using the market capitalization calculated by multiplying share price and number of shares outstanding. Next, we build two variables by combining equity market data with book values of assets and book values of equity taken from the *Compustat* database.[17] We define the (quasi-market) *leverage* as one plus the ratio of book value of assets mi-

[17] Due to data unavailability in *Compustat*, however, the number of observations for these variables is significantly lower than for market data.

nus book value of equity over the weekly market value of equity (see Acharya et al., 2010). Also, we employ an insurer's *market-to-book ratio* defined as the market value of equity divided by book value of common equity.

4 Empirical results

4.1 Descriptive statistics

We now present descriptive statistics for the dependent and independent variables used in our empirical study. Table I shows summary statistics for the full sample of U.S. insurers as well as summary statistics for the sub-samples of life insurers, non-life insurers, groups and reinsurers.

Insert Table I about here.

Not surprisingly, financial groups' stocks have the highest average prices. However, although the group sub-sample contains the firm with the maximum market capitalization of around $186,800 million, the 75%-quantiles are higher for reinsurers ($6,151 million) and especially for life insurers ($9,970 million). Also, the spread between the smallest and the largest quartile of market capitalization is highest for the sample of life insurers, which seems to include a more heterogenous set of firms. On average, life insurers had a much higher market-to-book ratio of around 19, compared to the other samples which are in the range of 5 to 9.[18] Looking at the average weekly volatility, we do not observe stark differences across our different sub-samples.

The average of weekly stock returns is around zero for the full sample period. In general, life insurance firms have much higher leverage ratios than, e.g., P&C insurers (see also Cummins and Weiss, 2014). Comparing the average quasi-market leverage of life insurers with the other sub-samples confirms this notion, but mean values of leverage for non-life insurers are equally high. However, this is most likely due to a few outliers driving this number, since looking at the median values or the 75%-quantile reveals much lower leverage ratios than for life insurers.

[18] Note that the number of observations for market-to-book ratios and leverage ratios are significantly lower than for other variables that are purely based on equity market data due to lack of availability in the *Compustat* database.

Instead of focusing on the summary statistics for the *CSI* of each sub-sample, we plot the evolution of the 20%- and 80%-quantiles across firms as well as mean values over time to get a better picture of its dynamics across different insurer business lines. Figure 3 provides an overview of the *CSI* values from 2006 to end-2010 for the four sub-samples.

Insert Figure 3 about here.

The time evolution of the *CSI* for financial groups is very similar to the values for the full-sample with peaks around the same time periods during the crisis. However, mean values before the crisis are significantly higher than for the full sample and are slightly positive instead of being close to zero. The *CSI* for reinsurers appears to be opposite of the CSI of the other groups, as it is significantly lower and negative in the time before the crisis years. It is highest in the end of 2007 and has a downward trend until the end of 2009, where it is, again, negative and thus, individual reinsurance firms were associated with low crisis sentiment levels, rather than following along.[19]

Looking at the *CSI* for life insurance firms, we observe that the overall range of values is consistently wider than for groups and reinsurers, with values from almost -20% to 20%. Association with crisis sentiment is very low in the end of 2009, while it was extremely high during the peak of the crisis. Compared to the mean of the full sample *CSI*, it is more volatile over the whole time period. The average *CSI* for the non-life insurers is relatively flat before the crisis years, but is highly negative in the aftermath of the crisis. Overall, the *CSI* for the non-life sample has the widest range of its smaller and larger quantile indicating heterogeneity across the firms in this sub-sample regarding crisis sentiment.

4.2 Panel regressions

We now perform several multivariate regressions to analyze the effect of (market-wide) crisis sentiment on insurer stocks. We test whether insurer stocks in the U.S. suffered from retail investors' association of the insurance sector with the banking crisis and whether crisis sentiment

[19] Note that this sub-sample only includes seven reinsurance firms and thus, mean values and respective quantiles are very close together.

affected some business lines more than others. In doing so, we account for the actual exposure of insurers to distressed parts of the financial sector due to the crisis. The sample period ranges from 2006 to end-2010 leaving us with up to 261 weekly observations for each insurance company.

As a first step, we run panel regressions of weekly stock returns and volatility on contemporaneous values of our measures of retail investors' attention and crisis sentiment constructed from internet search volume data on relevant phrases. We estimate OLS panel regressions with firm-fixed effects of the following form:

$$\text{VOLATILITY}_{i,t} \text{ or } \text{RETURNS}_{i,t} = \mu_i + \beta \times \text{GOOGLE}_{i,t} + \varepsilon_{i,t}, \tag{2}$$

where μ_i are firm-fixed effects and $\text{GOOGLE}_{i,t}$ is one of the four variables based on search volume data, namely *CSI*, *General CSI*, *ASVI* or *FEARS*. Standard errors are corrected for clustering on the firm level. The specification above is meant to capture most basic cross-sectional and time-serial correlations of our dependent variables and the main independent variables of interest. Results for the full sample and for the sub-samples *Groups*, *Life*, and *Non-life* are presented in Table II.

Insert Table II about here.

First of all, we notice that the *CSI*, the association of individual insurer stock with crisis sentiment is insignificant in almost all of the regressions. We find no clear pattern in the correlation of *CSI* and a stock' volatility. Similar to these results, we find little evidence that retail investor attention is correlated with insurer stock volatility. Only for the non-life insurer do we find that including only *ASVI* in column (1) as explanatory variable yields a negative correlation that is significant at the 5% level. This is contrary to predictions from the theoretical work on the impact of retail investors on the predictability of prices (se De Long et al., 1990). In this scenario, a higher abnormal search volume and thus, retail investor attention (see Da et al., 2011), reduces volatility and makes prices more predictable. However, two observations are noteworthy. First, we have a signifantly lower number of observations for the search volume on ticker symbols, which leaves us with only about half of the insurers from our full sample. Second, the model fit is extremely poor, since we have an adjusted R^2 of about zero.

The regressions of weekly insurer stock returns on *CSI* and *ASVI* lead to a similar conclusion: the two indicators of attention and sentiment are only a weak indicator of movements in stock prices in this specification. Although a higher association of individual stocks with the crisis is negatively related with returns, this holds only at the 10% significance level for the full sample. *CSI* is insignificant in the regressions using the sub-samples of life insurers and groups, but the 10% significance level can be found for the non-life insurer sample. Looking at this correlation, we suspect that non-life insurers are more affected by crisis-related sentiment from 2006 to 2010 than life insurers or financial groups.

Turning to the two market-wide sentiment measures, *General CSI* and *FEARS*, we observe that the former is strongly positively related to stock return volatility in all sub-samples. However, the magnitude of the effect varies across the samples. For all but the life insurer sample, a one standard deviation increase of the *General CSI* (+12.36) is associated with an increase in volatility of 0.3708 % (12.36×0.0003) in one week. This increase is only 0.2472 % ((12.36×0.0002) for the life insurer sample and thus, market-wide sentiment has a 1.5 times larger effect on the stock volatility of the non-life sample. A very similar situation can be found in the regression of stock returns on the *General CSI*, where life insurers are less affected by the negative influence of the market-wide crisis sentiment than other insurers. These correlations support the notion that our measures of sentiment may have influenced equity prices of those insurers that were actually less exposed to the adverse effects of the banking crisis but still suffered losses on their stocks (e.g., non-life insurers).

Similar to the *General CSI*, we find that *FEARS* as a proxy of household-level negative sentiment (not necessarily tied to this specific crisis) is strongly negatively correlated to weekly stock returns, which is in line with previous findings (see Da et al., 2015; Irresberger et al., 2015). Interestingly, *FEARS* is negatively correlated with insurers' stock return volatility. Only for the life insurer sample, we are left with a statistically insignificant coefficient estimate. It thus seems as if higher negative household sentiment could reflect actual economic downturns instead of time periods of uncertainty leading to gradual downturns and low volatility in asset prices.

Our first correlation analysis reveals that higher levels of market-wide sentiment have a stronger influence on movements in insurer stock prices than idiosyncratic measures of attention and crisis sentiment. In slight contrast, Da et al. (2011) find that a higher level of individual attention and thus, a higher proportion of active retail investors, increases stock prices in the short-term and revert to their original level in the longer term. In further analyses, we investigate the predictive power of our measures by employing lags of their values as independent variables. Since we find that the magnitude of the effects of sentiment on stock prices and volatility differs across sub-groups of insurance companies with different exposure to the financial crisis, we perform most of our analyses for each of the sub-samples separately.

4.3 Vector autoregressive analyses

We extend our analysis by using volatility and retail investor attention to test the hypothesis that noise traders make stock prices less predictable. Further, we investigate whether attention and sentiment for individual insurer stocks are self-fulfilling (e.g., highly volatile stocks may also attract more attention of investors). To capture the lead-lag dynamics of insurers' stock return volatility and the idiosyncratic attention measures *ASVI* and *CSI*, we perform vector autoregressions (VARs). We follow Hilscher et al. (2015) and estimate pooled VARs using OLS regressions with firm-fixed effects and up to four lags of volatility and *ASVI*. The regressions are of the following type:

$$\begin{aligned}
\text{VOLATILITY}_{i,t} &= \alpha_1 + \sum_{k=1}^{4} \beta_k \times \text{GOOGLE}_{i,t-k} + \sum_{k=1}^{4} \gamma_k \times \text{VOLATILITY}_{i,t-k} + \varepsilon_{i,t} \qquad (3)\\
\text{GOOGLE}_{i,t} &= \alpha_2 + \sum_{k=1}^{4} \delta_k \times \text{GOOGLE}_{i,t-k} + \sum_{k=1}^{4} \eta_k \times \text{VOLATILITY}_{i,t-k} + \epsilon_{i,t}, \qquad (4)
\end{aligned}$$

where $\text{GOOGLE}_{i,t}$ is either $\text{ASVI}_{i,t}$ or $\text{CSI}_{i,t}$. Table III shows the results for the VAR analysis for volatility and *ASVI* (Panel A) and volatility and *CSI* (Panel B) for the full sample and for the sub-samples of different insurer types.

Insert Table III about here.

From Panel A we see that lagged values of *ASVI* are statistically highly significant determinants of volatility for the full sample. The one-week-lag is strongly positively related to stock return volatility. The second lag of *ASVI*, however, is strongly negatively correlated with volatility of the current week with coefficients of the same magnitude as for the first lag. From this we find that an increase in uncertainty in the next week, due to an increase in retail investor attention, is reversed in the week after that. In turn, when we take *ASVI* as the dependent variable in equation (4), we find no significant influence of the lags of volatility on retail investor attention. Building on these results, we conclude that the presence of abnormal retail investor attention on single insurer stocks increases uncertainty about stock price movements for the full sample of 105 insurers, while there is no reversed effect of volatility on individual attention. The same holds true for the sub-sample of financial groups, with even larger coefficients.

Before, we saw that there might be different magnitudes of the effect of sentiment and attention on volatility and returns across different sub-samples of insurance firms. For life insurers, non-life insurers, and reinsurers, we find no statistically significant relation between *ASVI* and volatility in either direction, confirming the insignificant correlations from Table II.

From Panel B, where we replace the attention measure with the *CSI*, we infere similar conclusions. For financial groups, we observe that a higher individual association of the equity with the crisis leads to higher volatility in the next week and reverts in week two. However, different from the VARs with *ASVI*, we cannot infere a causal relation since higher volatility in one week leads to less attention in the next week and reverts in week two. Thus, we can only assume a strong correlation of individual crisis sentiment and an insurer's stock return volatility for insurer group companies. We conclude that the idiosyncratic measures of retail investor attention and association with crisis sentiment of insurer stocks are strongly related to stock return volatility for insurer groups, which are, e.g., larger in size than single-line insurers, but less so for the other sub-samples of insurance companies.

4.4 Does market-wide sentiment influence the cross-section of stock return volatility?

To compare the predictive power of our market-level sentiment measures on stock returns and volatility for the different insurer sub-samples, we perform additional regressions including lags of up to three weeks. Table IV shows results from OLS panel regression with firm-fixed effects of volatility (Panel A) and weekly stock returns (Panel B) on lags of the *General CSI* and *FEARS*.

Insert Table IV about here.

Overall, we find higher crisis sentiment from the previous weeks to significantly increase volatility levels, regardless of the insurer type. However, the sample of non-life insurers stands out with highly significant coefficient estimates in all lags. Further, the size of the coefficients for the two-week and three-week lag is the largest among all groups. This underlines the differential effect of crisis sentiment on non-life insurance companies' stocks, which suffered from rather irrational sentiment, although their exposure was significantly lower compared to, e.g., financial groups or life insurers.

Next, we include *FEARS* and three of its lags as explanatory variables. Values of *FEARS* in the same week are negatively correlated with volatility. The values in the previous three weeks, however, are only relevant in explaining stock return volatility of the non-life sample. Higher negative sentiment predicts lower volatility in the next few weeks, as there is a general downward trend in prices, indicated by its clear negative correlation with (future) stock returns.

For stock returns as dependent variable, we find an intuitive negative relation with *General CSI* at first, which is reversed after two to three weeks, similar to the impact of investor attention on stock prices. However, this is not the case for all sub-samples. *FEARS*, on the other hand, is a clear predictor of negative returns in the future weeks.

Again, we see that the influence of crisis sentiment is of different magnitude and significance for different insurer types. Non-life insurers, who are supposed to have only little exposure to the critical parts of the financial crisis, e.g., mortgage markets or derivative trading, experience the largest effects of sentiment on asset prices. This supports the hypothesis that the sentiment measures are only a weak determinant of stock price movements of other insurers, since the negative information is already priced in due to declining fundamental values, opposed to investors simply exiting the stocks out of irrational speculation.

Our findings suggest that crisis sentiment increases uncertainty about insurers' stock prices and predicts downward movements in the short-term. We also observe that this effect is different across certain types of insurers with differing fundamental values of their business operations. To further address this issue, we run panel regressions in the spirit of Baker and Wurgler (2006), who test whether waves of market-wide sentiment affect the cross-section of stock returns. We extend this analysis to the insurance sector and test whether crisis sentiment had an influence on the cross-section of insurers' stock price movements. In order to test this, we interact the *General CSI* with idiosyncratic variables and run regressions of the following type:

$$\begin{aligned} \text{VOLATILITY}_{i,t} &= \mu_i + \beta \cdot \text{CRISIS SENTIMENT}_{i,t} + \gamma \cdot \text{X}_{i,t} \\ &\quad + \delta \cdot (\text{CRISIS SENTIMENT}_{i,t} \times \text{X}_{i,t}) + \varepsilon_{i,t}, \end{aligned}$$

where $\text{X}_{i,t}$ includes firm-specific characteristics such as bid-ask-spreads, size, leverage and market-to-book ratio. The rationale behind this is that stocks with higher limits to arbitrage are also more difficult to price and thus, sentiment may have a differential effect on the cross-section of insurer stocks (see Baker and Wurgler, 2006). The coefficient δ is of special interest to us since its estimate indicates whether sentiment has cross-sectional effects (when it is statistically significantly different from zero) or simply raises the overall level of volatility. As before, we estimate the regressions for the full sample but also for three different sub-samples of insurance companies. Results are shown in Table V.

Insert Table V about here.

The main effects of *General CSI* are strongly positively correlated with insurers' stock return volatility. It is significant at the 1% level for the full sample and the sub-sample of financial groups. However, there is a different magnitude of this influence for the sample of life insurers versus non-life insurers. The coefficients for non-life insurers are the largest of all, again, suggesting a higher impact of crisis sentiment on insurers with only little exposure to the overall crisis. Not only are the estimated coefficients of *General CSI* smaller than for other sub-samples, they also are less statistically significant, a circumstance we observed before.

Except for the life sample, we find that prices of illiquid stocks in the absence of crisis sentiment are less predictable, since the coefficient of the insurers' bid-ask-spreads is positive and highly significant. The interaction term of the crisis sentiment and illiquidity variables is statistically significant and enters the regressions with a negative sign of the coefficient. When crisis sentiment is high, the most illiquid insurer stocks seem to be less volatile. Larger stocks tend to be less volatile. This correlation is intensified in the presence of high levels of crisis sentiment. However, this relation is only significant for the full sample.

An insurer's leverage ratio is mostly positively correlated with volatility. Although the coefficient of the leverage interaction term is not significant in the full sample setting, we find a significant negative coefficient for all sub-sample regressions. In times of crisis sentiment, where uncertainty about prices is on a high level, highly levered insurers stock prices are more predictable. Including an insurer's market-to-book ratio as explanatory variables yields mixed results. Neither the main effect nor the interaction is significant in regressions using the full sample. For financial groups, however, we find that the coefficient of the interaction term of market-to-book ratio and crisis sentiment is negative and statistically significant at the 10% level. Stocks of financial groups that have higher market valuations are less likely to be volatile in times of higher crisis sentiment. On the other side, we find the exact opposite results for life insurers, although this effect is about four times less strong than for the group companies.

5 Robustness

We now briefly report on several robustness tests that we perform to ensure the validity of our conclusions. First of all, we re-run our panel regressions with time dummies that indicate the respective month to account for unobserved heterogeneity over time (such as seasonality effects). Second, we repeat the regressions on lags of general crisis sentiment (Table IV) and the interaction terms (Table V) with a weekly time trend.[20] Also, we run regressions with bootstrapped standard errors to mitigate an otherwise potential bias that may arise from heteroskedasticity in our generated sentiment variables. However, our overall results are quantitatively and qualitatively very similar. As an additional robustness check, we treat zeros in the search volume data as missing when constructing the Google variables (as a zero indicates that there is close to zero search volume and thus, there might be no data points) and repeat the main regressions without substantial changes to our main results.

Next, we want to compare the effect of crisis sentiment on insurer stock volatility with bank stocks and stocks of industrial firms. Irresberger et al. (2015) find that banks are less affected by the *General CSI* than non-financial firms as they are more likely to receive implicit bailout guarantees and are generally considered "safe" by investors. To see in how far our results for insurers match these results, we run additional (pooled) vector autoregressions of volatility, *ASVI*, and *CSI* (as in Table III) and panel regressions of volatility on lags of the *General CSI* (as in Table IV) for samples of banks and firms from the industrial sector.[21] The vector autoregressive analysis shows that neither retail investor attention nor volatility are significant when explaining the other one in the bank sample. For stocks of industrial firms we find an increase in volatility followed by a reversal the week after when retail investor attention increases, but not the other way around. For both samples, we observe that higher association with the crisis results in higher volatility the next

[20] In another robustness test, we also include the *VIX* as a proxy for time-varying risk-aversion in our main regressions along with the (general) CSI. The two indices are positively correlated but the inclusion of the VIX does not alter our main conclusions regarding the impact of sentiment on insurer volatility

[21] The samples consist of the 100 largest firms in the respective sector measured by average market capitalization over our sample period (SIC codes 6000-6300 without 6211 and 6282 for banks and 2000-3999 for manufacturing/industrials). We require firms to have at least 100 data points in 2006-2010.

week, an effect that reverts in the second week. Results from the other set of regressions using the industrial sample are similar to those for insurers, although coefficients for both *General CSI* and *FEARS* are much smaller and thus, we observe a weaker effect. The effect of crisis sentiment is largest for the insurance sector, which obviously did not receive implicit guarantees like banks, but still suffered from being associated with the banking crisis as they are part of the financial sector.

As an additional analysis, we look at the sensitivity of individual insurer stock returns to the stock market's returns, a CDS index (we employ the *Datastream* NA Bank 5YR CDS index), and a mortgage-backed-securities index (Barclays MBS 1000). Comparing the betas from regressions of stock returns on these indexes with average volatility does not reveal an obvious pattern (e.g., scatter plots). We also run panel regressions of volatility where we divide the full sample into quartiles of the beta coefficients on lags of general crisis sentiment as in Table IV. We find some evidence that, e.g., stocks that have negative co-movements with the MBS market index are slightly more affected by crisis sentiment than insurers in the other quartiles. [22]

Similar to banks, some insurers required financial support via the TARP program which might have distorted stock price movements of these insurers. To check whether this influences our results, we exclude these insurers from our sample and re-estimate our main regressions.[23] Our conclusions, however, remain valid.

6 Conclusion

In this paper we analyze the impact of measures of idiosyncratic and market-wide investor attention and sentiment based on internet search volume data from Google on the volatility of U.S. insurer stocks between 2006 and 2010. As our first finding, we show that higher levels of crisis sentiment explain higher levels of volatility. Perhaps more importantly, we find investor sentiment to have a differential effect on the cross-section of insurer. The influence of crisis sentiment on volatility is strongest for those insurers that were only marginally exposed to the downward mov-

[22] Regressions in quartiles of the other betas, however, does not yield a clear pattern.
[23] The three companies we exclude are AIG, Hartford Financial Services, and Lincoln National Corporation.

ing markets during the financial crisis. Aggregate sentiment lead to unusually high, unjustifiable uncertainty about insurer stock prices which implies that investors did not necessarily base their decision on rational assessments of insurers' actual exposure to the crisis. Also, comparing the insurance and banking sector reveals that the effects of crisis sentiment were dominant in the former part of the financial sector, although the crisis originated in the latter.

Appendix I: Variable definitions and data sources.

The appendix presents definitions as well as data sources for all dependent and independent variables that are used in the empirical study.

Variable name	*Definition*	*Data source*
Dependent variable and main explanatory variables of interest		
Volatility	End-of-week equity volatility based on GJR-GARCH(1,1)-model estimation of weekly stock returns.	CRSP.
Returns	End-of-week buy-and-hold returns	CRSP.
General crisis sentiment	First principal component of the four GSVIs of the search terms “financial crisis”, “credit crisis”, “subprime crisis” and “bank crisis”, calculated using a rolling window enlarged by one week after each estimation, starting with a window of 52 weeks for the first year. For each quarter, the Crisis-GSVI is the average of the weekly first principal components in that quarter.	Google Trends, own calc.
CSI	The Crisis Sentiment Index is computed using data from *Google Trends* via $CSI_t^i := \left(\frac{GSVI_t^i + Z_t}{200}\right) \cdot \rho_t^i$. where Z_t is the first principal component of the Google Search Volume Indices (GSVI) for several crisis-related search query terms, $GSVI_t^i$ is the GSVI for insurer ith ticker symbol and ρ_t^i is the (dynamic) correlation between Z_t and $GSVI_t^i$.	CRSP, Google Trends, Irresberger et al. (2015).
Control variables		
ASVI	$\log[\mathrm{GSVI}_t] - \log[\mathrm{median}(\mathrm{GSVI}_{t-1}, \ldots, \mathrm{GSVI}_{t-8})]$. $GSVI_t^i$ is the GSVI for insurer ith ticker symbol.	Google Trends, Da et al. (2011).
FEARS	The FEARS index is defined as $FEARS_t = \frac{1}{30}\sum_{j=1}^{30} \Delta AGSVI_t^j$, where $\Delta AGSVI_t^j$ is the adjusted weekly change in search term j. The thirty economic-related search terms are introduced in Da et al. (2015).	Google Trends, Da et al. (2015)
Bid-Ask-Spread	An equity’s bid-ask-spread calculated by the difference of end-of-week ask-quotes and bid-quotes.	CRSP, own calc.
Size	Total market capitalization calculated by multiplying share price and number of shares outstanding.	CRSP, own calc.
Leverage	Quasi-market leverage as defined in Acharya et al. (2010) as one plus the ratio of book value of debt over market value of equity.	CRSP, Compustat.
Market-to-book-ratio	Market value of common equity divided by book value of common equity.	CRSP, Compustat.
Google	Dummy variable that is one if an insurer is included in our sample and zero when it is excluded due to ambiguous meaning (unusual search volume) or has no search volume for the time period 2006 to 2010.	Google Trends.

Appendix II: Insurance companies

The appendix presents names, ticker symbols, business type classification for insurance companies used in this study as well as an indicator for availability of the respective data on a ticker symbol's search volume in *Google Trends*.

NAME	TICKER	CLASSIFICATION	GOOGLE DATA	NAME	TICKER	CLASSIFICATION	GOOGLE DATA
ACE LTD NEW	ACE	GROUP	YES	METLIFE INC	MET	LIFE	YES
AFFIRMATIVE INSURANCE HOLDINGS INC	AFFM	GROUP	NO	MONTPELIER RE HOLDINGS LTD	MRH	GROUP	NO
ALFA CORP	ALFA	LIFE	YES	N Y M A G I C INC	NYM	NON-LIFE	NO
ALLEGHANY CORP DE	Y	NON-LIFE	YES	NATIONAL ATLANTIC HOLDINGS CORP	NAHC	GROUP	NO
ALLIED WORLD ASSURANCE CO HOLDINGS AG	AWH	GROUP	NO	NATIONAL INTERSTATE CORP	NATL	NON-LIFE	YES
ALLSTATE CORP	ALL	NON-LIFE	YES	EMPLOYERS HOLDINGS INC	EIG	GROUP	NO
ALTERRA CAPITAL HOLDINGS LTD	MXRE	GROUP	NO	FLAGSTONE REINSURANCE HOLDINGS SA	FSR	REINSURER	YES
AMCOMP INC NEW	AMCP	NON-LIFE	NO	GREENLIGHT CAPITAL RE LTD	GLRE	REINSURER	NO
AMERICAN EQUITY INVESTMENT LIFE HOLDING CO	AEL	GROUP	NO	MAIDEN HOLDINGS LTD	MHLD	REINSURER	NO
AMERICAN FINANCIAL GROUP INC NEW	AFG	GROUP	YES	NATIONAL SECURITY GROUP INC	NSEC	GROUP	NO
AMERICAN INDEPENDENCE CORP	AMIC	GROUP	NO	NATIONAL WESTERN LIFE INS CO	NWLI	LIFE	NO
AMERICAN INTERNATIONAL GROUP INC	AIG	GROUP	YES	OLD REPUBLIC INTERNATIONAL CORP	ORI	NON-LIFE	YES
AMERICAN NATIONAL INS CO	ANAT	LIFE	NO	ONEBEACON INSURANCE GROUP LTD	OB	GROUP	YES
AMERICAN PHYSICIANS CAPITAL INC	ACAP	NON-LIFE	NO	PARTNERRE LTD	PRE	REINSURER	YES
AMERISAFE INC	AMSF	NON-LIFE	NO	PLATINUM UNDERWRITERS HOLDINGS LTD	PTP	GROUP	YES
ARCH CAPITAL GROUP LTD NEW	ACGL	GROUP	NO	PRIMERICA INC	PRI	LIFE	YES
ASPEN INSURANCE HOLDINGS LTD	AHL	GROUP	YES	PRINCIPAL FINANCIAL GROUP INC	PFG	GROUP	YES
ASSURANT INC	AIZ	GROUP	NO	PROASSURANCE CORP	PRA	NON-LIFE	YES
ASSURED GUARANTY LTD	AGO	GROUP	YES	PROGRESSIVE CORP OH	PGR	NON-LIFE	YES
AXIS CAPITAL HOLDINGS LTD	AXS	GROUP	NO	PROTECTIVE LIFE CORP	PL	LIFE	YES
BERKLEY W R CORP	BER	NON-LIFE	YES	REINSURANCE GROUP OF AMERICA INC	RGA	REINSURER	YES
BERKSHIRE HATHAWAY INC	BRK	GROUP	YES	RENAISSANCE RE HOLDINGS LTD	RNR	GROUP	YES
CITIZENS INC	CIA	LIFE	YES	SEABRIGHT HOLDINGS INC	SBX	GROUP	NO
COMMERCE GROUP INC MASS	CGI	NON-LIFE	YES	STANCORP FINANCIAL GROUP INC	SFG	GROUP	NO
DARWIN PROFESSIONAL UNDERWRITERS	DR	NON-LIFE	YES	SYMETRA FINANCIAL CORP	SYA	LIFE	NO
DELPHI FINANCIAL GROUP INC	DFG	LIFE	YES	TORCHMARK CORP	TMK	LIFE	NO
DIRECT GENERAL CORP	DRCT	NON-LIFE	NO	TOWER GROUP INTERNATIONAL LTD	TWGP	NON-LIFE	NO
EASTERN INSURANCE HOLDINGS INC	EIHI	GROUP	NO	TRANSATLANTIC HOLDINGS INC	TRH	GROUP	NO
ENDURANCE SPECIALTY HOLDINGS LTD	ENH	GROUP	YES	TRAVELERS COMPANIES INC	TRV	NON-LIFE	YES
ENSTAR GROUP INC GA	ESGR	GROUP	NO	TRIPLE S MANAGEMENT CORP	GTS	NON-LIFE	YES
EVEREST RE GROUP LTD	RE	GROUP	YES	UNICO AMERICAN CORP	UNAM	GROUP	YES
FIRST ACCEPTANCE CORP	FAC	NON-LIFE	YES	UNITED FIRE GROUP INC	UFCS	NON-LIFE	NO
FIRST MERCURY FINANCIAL CORP	FMR	NON-LIFE	YES	UNIVERSAL INSURANCE HOLDINGS INC	UVE	GROUP	NO
GAINSCO INC	GAN	NON-LIFE	YES	UNUM GROUP	UNM	LIFE	YES
GENWORTH FINANCIAL INC	GNW	LIFE	YES	VALIDUS HOLDINGS LTD	VR	GROUP	YES
GLOBAL INDEMNITY PLC	INDM	NON-LIFE	NO	WHITE MOUNTAINS INS GROUP LTD	WTM	GROUP	NO
GREAT AMERICAN FINANCIAL RES INC	GFR	LIFE	YES	CASTLEPOINT HOLDINGS LTD	CPHL	GROUP	NO
HALLMARK FINANCIAL SERVICES INC	HALL	GROUP	YES	IMPERIAL HOLDINGS INC	IFT	GROUP	YES
HANOVER INSURANCE GROUP INC	THG	NON-LIFE	NO	NATIONWIDE FINANCIAL SERVICES IN	NFS	LIFE	YES
HARTFORD FINANCIAL SERVICES GROUP INC	HIG	NON-LIFE	YES	NORTH POINTE HOLDINGS CORP	NPTE	GROUP	NO
HORACE MANN EDUCATORS CORP NEW	HMN	NON-LIFE	NO	ODYSSEY RE HOLDINGS CORP	ORH	GROUP	NO
INDEPENDENCE HOLDING CO NEW	IHC	GROUP	YES	PAULA FINANCIAL	PFCO	NON-LIFE	NO
INFINITY PROPERTY & CASUALTY CORP	IPCC	NON-LIFE	YES	PENN AMERICA GROUP INC	PNG	NON-LIFE	YES
JAMES RIVER GROUP INC	JRVR	NON-LIFE	NO	PENN TREATY AMERICAN CORP	PTYA	NON-LIFE	NO
KANSAS CITY LIFE INS CO	KCLI	LIFE	NO	PROCENTURY CORP	PROS	NON-LIFE	YES
KINGSWAY FINANCIAL SERVICES INC	KFS	NON-LIFE	NO	QUANTA CAPITAL HOLDINGS LTD	QNTA	GROUP	NO
LINCOLN NATIONAL CORP	LNC	LIFE	NO	REPUBLIC COMPANIES GROUP INC	RUTX	NON-LIFE	NO
LOEWS CORP	LTR	NON-LIFE	YES	SAFECO CORP	SAF	NON-LIFE	YES
MAJESTIC CAPITAL LTD	CRMH	GROUP	NO	SCOTTISH RE GROUP LTD	SCT	REINSURER	YES
MEADOWBROOK INSURANCE GROUP INC	MIG	NON-LIFE	YES	SPECIALTY UNDERWRITERS ALLIANCE INC	SUAI	REINSURER	NO
MERCER INSURANCE GROUP INC	MIGP	NON-LIFE	NO	VESTA INSURANCE GROUP INC	VTA	NON-LIFE	YES
MERCHANTS GROUP INC	MGP	NON-LIFE	YES	ZENITH NATIONAL INSURANCE CORP	ZNT	NON-LIFE	NO
MERCURY GENERAL CORP NEW	MCY	NON-LIFE	NO				

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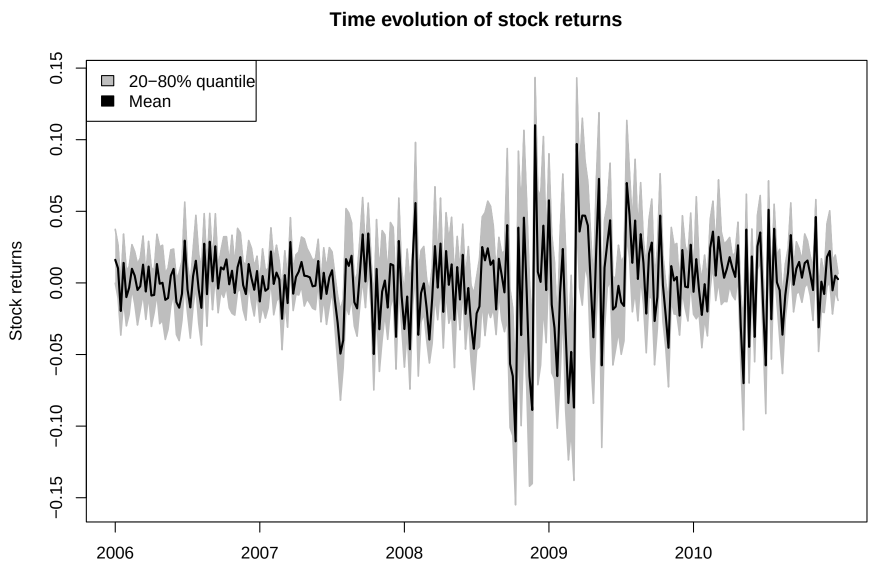
Figures and Tables

Figure 1: Insurer stock returns and volatility (2006-2010).

The figure shows a plot of the evolution of stock returns and volatility for a sample of 105 U.S. insurers from 2006 to end-2010. Returns are the weekly percental changes in end-of-week stock prices. Volatility is obtained from estimating a GJR-GARCH model for an insurer's weekly stock returns for the full sample period. The solid line shows the mean values across the sample. The area shaded in grey shows the range between the empirical 20%- and 80% quantiles, which are computed separately for each point of time.



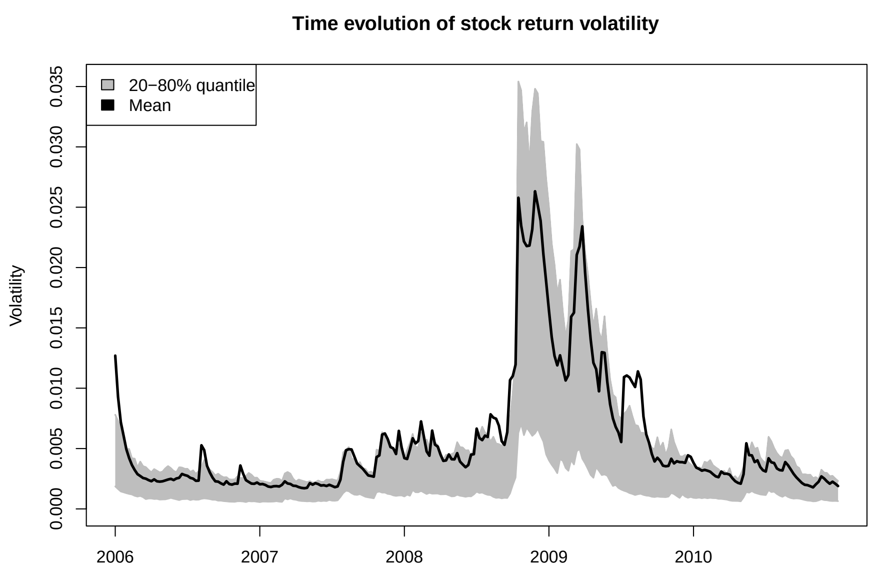


Figure 2: Crisis Sentiment Index, Abnormal Search Volume, and General Crisis Sentiment.

The figure shows a plot of the evolution of the *Crisis Sentiment Index* (CSI) in the upper panel and *abnormal search volume* (ASVI) second panel across the sample of 105 U.S. insurers for the sample period from 2006 to end-2010. The *CSI* for firm i at week t is defined as $\text{CSI}_{i,t} := (\text{SVI}_{i,t} + Z_t)/200 \cdot \varrho_t^i$, where $\text{SVI}_{i,t}$ is the Search Volume Index (SVI) for the i-th firm's ticker symbol, Z_t is the first principle component of the SVI for four crisis-related search terms, and ϱ_t^i is the correlation between Z_t and $\text{SVI}_{i,t}$. *ASVI* is the abnormal SVI introduced in Da et al. (2011) and is calculated as the log-changes of SVI in week t and the median value of SVI in the previous eight weeks. The solid line shows the mean values across the sample. The area shaded in grey shows the range between the empirical 20%- and 80% quantiles, which are computed separately for each point of time. The lower panel shows the SVI for the four crisis-related search terms (grey lines) and its principal component Z_t (black line).

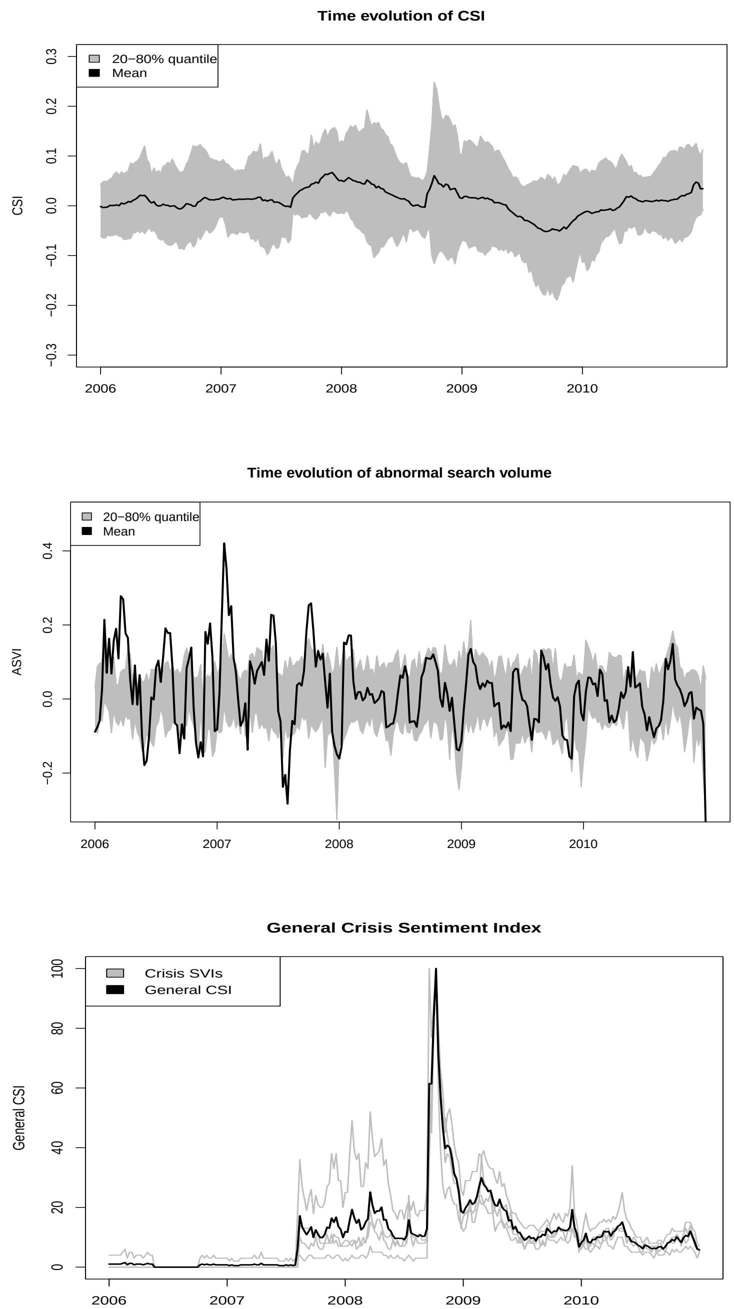


Figure 3: Time evolution of the Crisis Sentiment Index by insurer type.

The figure shows a plot of the evolution of the *Crisis Sentiment Index* (CSI) for sub-samples of 105 U.S. insurers for the sample period from 2006 to end-2010. The *CSI* for firm i at week t is defined as $\mathrm{CSI}_{i,t} := (\mathrm{SVI}_{i,t} + \mathrm{Z}_t)/200 \cdot \varrho_t^i$, where $\mathrm{SVI}_{i,t}$ is the Search Volume Index (SVI) for the i-th firm's ticker symbol, Z_t is the first principle component of the SVI for four crisis-related search terms, and ϱ_t^i is the correlation between Z_t and $\mathrm{SVI}_{i,t}$. The solid line shows the mean values across the sub-sample. The area shaded in grey shows the range between the empirical 20%- and 80% quantiles, which are computed separately for each point of time. The sub-samples are life insurers (16 firms), non-life insurers (41 firms), financial groups (41 firms) and reinsurers (7 firms).

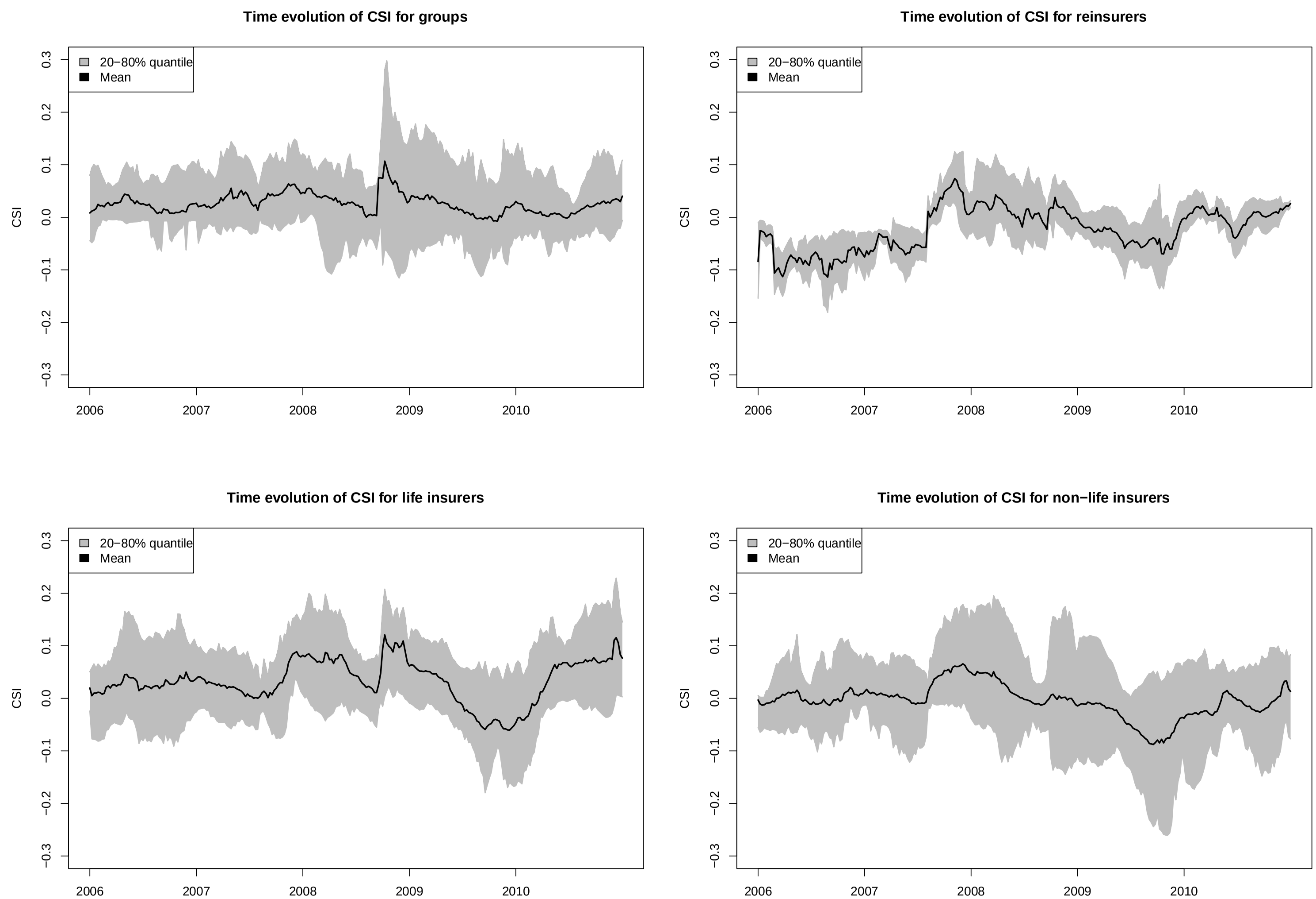


Table I: Summary statistics

The table presents descriptive statistics of the 105 U.S. insurers and sub-samples for the period from 2006 to end-2010. Additionally, descriptive statistics for the *General CSI* and *FEARS-index* from Da et al. (2015) shown. We report the number of observations, minimum and maximum values, 1st and 3rd quartile, mean and median values. Variables based on stock price data are winsorized at the 5% level to mitigate a potential bias from outliers. All variables and data sources are defined in Appendix I.

	Min	**1st quartile**	**Median**	**Mean**	**3rd quartile**	**Max**	**N**
FEARS	-1.7866	-0.1935	0.0049	0.0040	0.2253	2.2352	261
General CSI	0.0000	1.0150	9.9550	11.0690	13.3750	100.0000	261
All (105 firms)	**Min**	**1st quartile**	**Median**	**Mean**	**3rd quartile**	**Max**	**N**
Price (in US dollars)	0.1900	13.1200	25.3300	73.1400	48.5200	4,950.0000	24,544
Market capitalization (in million US $)	15.5500	378.1000	1,798.0000	6,030.0000	4,075.0000	186,800.0000	18,098
Returns	-0.3994	-0.0236	0.0002	0.0006	0.0244	0.5214	24,529
BAS	0.0000	0.0100	0.0300	0.2687	0.0800	122.4000	24,528
Volatility	0.0000	0.0011	0.0021	0.0056	0.0046	0.5071	24,529
CSI	-0.4560	-0.0490	0.0050	0.0110	0.0760	0.7140	13,604
Market-to-book ratio	0.0040	0.3830	0.9430	9.3200	1.6750	616.6810	11,167
Leverage	1.0050	2.4730	4.5580	33.1300	15.6750	834.2930	11,167
ASVI	-4.5050	-0.0670	0.0000	0.0210	0.0730	4.6150	14,194
Life (16 firms)	**Min**	**1st quartile**	**Median**	**Mean**	**3rd quartile**	**Max**	**N**
Price (in US dollars)	0.2500	11.3200	20.8600	33.0600	48.2100	158.6500	3,305
Market capitalization (in million US $)	17.6900	436.9000	1,785.0000	5,493.0000	9,970.0000	23,360.0000	2,215
Returns	-0.3994	-0.0215	0.0000	-0.0005	0.0222	0.5214	3,302
BAS	0.0000	0.0100	0.0300	0.0976	0.0700	2.4300	3,299
Volatility	0.0000	0.0011	0.0020	0.0051	0.0036	0.2658	3,302
CSI	-0.3913	-0.0302	0.0356	0.0325	0.1046	0.5995	2,467
Market-to-book ratio	0.0185	0.1262	0.9481	19.0565	4.3033	169.3384	1,616
Leverage	1.0250	1.9470	8.9240	42.7810	53.6480	549.6730	1,616
ASVI	-3.8177	-0.0579	0.0000	0.0134	0.0658	3.9512	2,610
Groups (41 firms)	**Min**	**1st quartile**	**Median**	**Mean**	**3rd quartile**	**Max**	**N**
Price (in US dollars)	0.3300	15.3600	27.9000	115.1500	48.8200	4,950.0000	9,814
Market capitalization (in million US $)	15.5500	431.4000	1,981.0000	7,544.0000	4,066.0000	186,800.0000	8,617
Returns	-0.3155	-0.0225	0.0008	0.0009	0.0239	0.3723	9,810
BAS	0.0000	0.0200	0.0300	0.3902	0.0800	122.4000	9,808
Volatility	0.0002	0.0011	0.0019	0.0053	0.0042	0.5071	9,810
CSI	-0.3280	-0.0300	0.0110	0.0270	0.0900	0.7140	4,168
Market-to-book ratio	0.0110	0.4320	0.8350	8.9730	1.2320	616.6810	6,296
Leverage	1.0210	3.0990	4.5090	23.6680	9.9370	823.3900	6,296
ASVI	-4.5050	-0.0690	0.0000	0.0270	0.0670	4.6150	4,437
Reinsurers (7 firms)	**Min**	**1st quartile**	**Median**	**Mean**	**3rd quartile**	**Max**	**N**
Price (in US dollars)	1.5000	17.9600	26.2600	55.8100	54.1200	275.0000	1,628
Market capitalization (in million US $)	50.2100	635.2000	1,831.0000	4,971.0000	6,151.0000	46,860.0000	1,016
Returns	-0.1571	-0.0232	0.0004	0.0004	0.0231	0.1353	1,627
BAS	0.0100	0.0100	0.0200	0.4428	0.0575	9.6250	1,626
Volatility	0.0005	0.0010	0.0018	0.0040	0.0038	0.0461	1,627
CSI	-0.2454	-0.0632	-0.0092	-0.0198	0.0273	0.1512	978
Market-to-book ratio	0.0134	0.0620	0.0898	6.3221	0.2022	160.7071	422
Leverage	1.0050	16.1220	28.6460	58.0970	92.7590	551.6410	422
ASVI	-3.9512	-0.0790	0.0000	0.0165	0.0690	4.3438	1,044
Non-life (41 firms)	**Min**	**1st quartile**	**Median**	**Mean**	**3rd quartile**	**Max**	**N**
Price (in US dollars)	0.1900	11.8900	23.7400	47.4700	47.3200	606.0200	9,797
Market capitalization (in million US $)	40.1400	331.6000	1,285.0000	4,306.0000	3,527.0000	40,130.0000	6,250
Returns	-0.3781	-0.0256	0.0000	0.0007	0.0258	0.4118	9,790
BAS	0.0000	0.0100	0.0300	0.1758	0.0800	10.9600	9,795
Volatility	0.0001	0.0012	0.0025	0.0064	0.0053	0.1466	9,790
CSI	-0.4560	-0.0680	-0.0010	-0.0040	0.0610	0.6310	5,991
Market-to-book ratio	0.0040	0.8710	1.4050	4.9810	2.9900	149.2310	2,833
Leverage	1.0170	1.9070	3.2150	44.9310	5.9970	834.2930	2,833
ASVI	-4.3170	-0.0660	0.0000	0.0210	0.0790	4.6150	6,003

Table II: OLS panel regressions of stock returns and volatility on attention and sentiment indicators

The table shows the results of OLS panel regressions for (sub-)samples of U.S. insurance companies' weekly stock returns and volatility on measures of investor attention and sentiment. All regressions are performed with firm-fixed effects and are of the following form:

$$\text{VOLATILITY}_{i,t} \text{ or } \text{RETURNS}_{i,t} = \mu_i + \beta \times \text{GOOGLE}_{i,t} + \varepsilon_{i,t},$$

where μ_i are firm-fixed effects and $\text{GOOGLE}_{i,t}$ is one of the four variables based on search volume data, namely *CSI*, *General CSI*, *ASVI* or *FEARS*. Standard errors are corrected for clustering at the firm level. Panel A shows results using the full sample, while the other panels present estimates from the sub-samples of *Groups* (Panel B), *Life* (Panel C), and *Non-life* (Panel D). Variables based on stock price data are winsorized at the 5% level to mitigate a potential bias from outliers. All variable definitions and data sources are given in AppendixI. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

Panel A: All	(1) Volatility	(2) Volatility	(3) Volatility	(4) Volatility	(5) Returns	(6) Returns	(7) Returns	(8) Returns
ASVI	0.0004				-0.0002			
	(0.432)				(0.511)			
CSI		0.0052				**-0.0111***		
		(0.597)				(0.082)		
General CSI			**0.0003*****				**-0.0004*****	
			(0.000)				(0.000)	
FEARS				**-0.0007*****				**-0.0037*****
				(0.000)				(0.000)
N	12,484	12,019	24,529	24,529	12,484	12,019	24,529	24,529
Adj. R^2	0.000	0.001	0.058	0.001	-0.000	0.000	0.008	0.001
Panel B: Groups	(1) Volatility	(2) Volatility	(3) Volatility	(4) Volatility	(5) Returns	(6) Returns	(7) Returns	(8) Returns
ASVI	0.0008				-0.0001			
	(0.392)				(0.795)			
CSI		0.0369				-0.0133		
		(0.207)				(0.406)		
General CSI			**0.0003*****				**-0.0004*****	
			(0.000)				(0.000)	
FEARS				**-0.0006*****				**-0.0039*****
				(0.000)				(0.003)
N	4,098	3,854	9,810	9,810	4,098	3,854	9,810	9,810
Adj. R^2	0.000	0.012	0.037	0.000	-0.000	0.000	0.009	0.001
Panel C: Life	(1) Volatility	(2) Volatility	(3) Volatility	(4) Volatility	(5) Returns	(6) Returns	(7) Returns	(8) Returns
ASVI	0.0003				**-0.0037***			
	(0.705)				(0.068)			
CSI		0.0033				-0.0002		
		(0.318)				(0.988)		
General CSI			**0.0002****				**-0.0003****	
			(0.040)				(0.010)	
FEARS				-0.0006				**-0.0055****
				(0.152)				(0.027)
N	1,990	1,847	3,302	3,302	1,990	1,847	3,302	3,302
Adj. R^2	-0.000	-0.000	0.038	0.000	-0.000	-0.001	0.006	0.002
Panel D: Non-life	(1) Volatility	(2) Volatility	(3) Volatility	(4) Volatility	(5) Returns	(6) Returns	(7) Returns	(8) Returns
ASVI	**-0.0004****				0.0001			
	(0.047)				(0.889)			
CSI		-0.0086				**-0.0137***		
		(0.427)				(0.096)		
General CSI			**0.0003*****				**-0.0004*****	
			(0.000)				(0.000)	
FEARS				**-0.0010*****				**-0.0037*****
				(0.000)				(0.003)
N	5,470	5,458	9,790	9,790	5,470	5,458	9,790	9,790
Adj. R^2	0.000	0.009	0.108	0.001	-0.000	0.000	0.007	0.001

Table III: Vector autoregressions of stock return volatility and abnormal search volume

This table shows the results from pooled vector autoregressions as inHilscher et al. (2015) using OLS regressions with firm-fixed effects and up to four lags of volatility and *ASVI* or *CSI* for the full sample of 105 U.S. insurers and sub-samples. The regressions are of the following type:

$$\begin{aligned}\mathrm{VOLATILITY}_{i,t} &= \alpha_1 + \sum_{k=1}^{4}\beta_k \times \mathrm{GOOGLE}_{i,t-k} + \sum_{k=1}^{4}\gamma_k \times \mathrm{VOLATILITY}_{i,t-k} + \varepsilon_{i,t}\\ \mathrm{GOOGLE}_{i,t} &= \alpha_2 + \sum_{k=1}^{4}\delta_k \times \mathrm{GOOGLE}_{i,t-k} + \sum_{k=1}^{4}\eta_k \times \mathrm{VOLATILITY}_{i,t-k} + \epsilon_{i,t},\end{aligned}$$

where $\mathrm{GOOGLE}_{i,t}$ is either $\mathrm{ASVI}_{i,t}$ (Panel A) or $\mathrm{CSI}_{i,t}$ (Panel B). Volatility is winsorized at the 5% level. Variable definitions and data sources are given in AppendixI. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

Panel A: ASVI	All		Group		Life		Non-life		Reinsurers	
	Volatility	ASVI	Volatility	ASVI	Volatility	ASVI	Volatility	ASVI	Volatility	ASVI
$\mathrm{Volatility}_{t-1}$	**0.8640*****	-0.2200	**0.9170*****	-0.3350	**0.6470*****	0.4000	**0.9300*****	0.4350	**0.9900*****	2.0130
	(0.000)	(0.620)	(0.000)	(0.628)	(0.000)	(0.475)	(0.000)	(0.738)	(0.000)	(0.809)
$\mathrm{Volatility}_{t-2}$	**-0.0462*****	-0.0426	**-0.1350*****	0.0209	0.1680***	-0.2060	**-0.0347***	-2.1150	0.0110	-13.5400
	(0.000)	(0.942)	(0.000)	(0.982)	(0.000)	(0.758)	(0.063)	(0.233)	(0.815)	(0.248)
$\mathrm{Volatility}_{t-3}$	**0.0611*****	0.5640	**0.1290*****	0.9520	**-0.0650****	-0.7260	0.0087	1.6840	-0.0589	4.6980
	(0.000)	(0.335)	(0.000)	(0.307)	(0.017)	(0.278)	(0.642)	(0.342)	(0.211)	(0.688)
$\mathrm{Volatility}_{t-4}$	**-0.0361*****	-0.355	**-0.0805*****	-0.5640	**0.0995*****	0.3850	0.0108	-0.5500	0.0088	8.8120
	(0.000)	(0.403)	(0.000)	(0.387)	(0.000)	(0.496)	(0.431)	(0.673)	(0.798)	(0.304)
ASVI_{t-1}	**0.0008*****	**0.7410*****	**0.0014*****	**0.7470*****	0.0000	**0.7930*****	0.0000	**0.6960*****	0.0001	**0.7750*****
	(0.000)	(0.000)	(0.000)	(0.000)	(0.988)	(0.000)	(0.892)	(0.000)	(0.685)	(0.000)
ASVI_{t-1}	**-0.0009*****	-0.0001	**-0.0016*****	-0.0153	0.0005	**-0.1130*****	0.0000	**0.0426*****	0.0000	0.0183
	(0.000)	(0.996)	(0.000)	(0.428)	(0.641)	(0.000)	(0.917)	(0.009)	(0.990)	(0.657)
ASVI_{t-1}	0.0001	**0.0195***	0.0004	**0.0539*****	-0.0004	-0.0017	-0.0001	-0.0188	-0.0001	-0.0412
	(0.632)	(0.077)	(0.360)	(0.005)	(0.747)	(0.953)	(0.742)	(0.250)	(0.705)	(0.292)
ASVI_{t-1}	0.0001	**-0.2760*****	0.0002	**-0.3290*****	0.0002	-0.0283	0.0000	**-0.2120*****	0.0000	**-0.2550*****
	(0.391)	(0.000)	(0.632)	(0.000)	(0.800)	(0.214)	(0.810)	(0.000)	(0.877)	(0.000)
Constant	**0.0009*****	**0.0125*****	**0.0011*****	0.0144	**0.0009*****	0.0034	**0.0005*****	**0.0158*****	**0.0003*****	0.0059
	(0.000)	(0.004)	(0.000)	(0.141)	(0.000)	(0.567)	(0.000)	(0.008)	(0.003)	(0.785)
N	12,268	12,279	4,030	4,033	1,950	1,954	5,378	5,381	910	911
Adj. R^2	0.715	0.572	0.717	0.595	0.637	0.502	0.826	0.516	0.879	0.636

Panel B: CSI	All		Group		Life		Non-life		Reinsurers	
	Volatility	CSI	Volatility	CSI	Volatility	CSI	Volatility	CSI	Volatility	CSI
$\mathrm{Volatility}_{t-1}$	**0.8690*****	**-0.0760*****	**0.9380*****	**-0.1290*****	**0.6480*****	**0.1310*****	**0.9290*****	0.0604	**0.9880*****	-0.4840
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.419)	(0.000)	(0.160)
$\mathrm{Volatility}_{t-2}$	**-0.0419*****	**0.1020*****	**-0.1230*****	**0.1310*****	**0.1690*****	-0.0146	**-0.0343***	-0.0162	0.0116	0.2910
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.780)	(0.066)	(0.874)	(0.812)	(0.548)
$\mathrm{Volatility}_{t-3}$	**0.0486*****	-0.0334	**0.0857*****	-0.0065	**-0.0665****	**-0.0998***	0.0087	-0.0038	-0.0622	0.0976
	(0.000)	(0.241)	(0.000)	(0.869)	(0.019)	(0.056)	(0.635)	(0.971)	(0.202)	(0.840)
$\mathrm{Volatility}_{t-4}$	**-0.0302*****	-0.0326	**-0.0632*****	-0.0306	**0.0977*****	-0.0130	0.0098	**-0.1270***	0.0161	-0.1740
	(0.001)	(0.114)	(0.000)	(0.255)	(0.000)	(0.770)	(0.475)	(0.090)	(0.653)	(0.624)
CSI_{t-1}	**0.0641*****	**1.0120*****	**0.1600*****	**0.9380*****	**-0.0212***	**1.0770*****	-0.0008	**1.0750*****	0.0032	**0.8780*****
	(0.000)	(0.000)	(0.000)	(0.000)	(0.097)	(0.000)	(0.756)	(0.000)	(0.359)	(0.000)
CSI_{t-2}	**-0.0840*****	**0.0564*****	**-0.2070*****	**0.1170*****	0.0298	-0.0246	-0.0024	0.0166	0.0002	**0.1040****
	(0.000)	(0.000)	(0.000)	(0.000)	(0.113)	(0.481)	(0.509)	(0.408)	(0.963)	(0.025)
CSI_{t-3}	0.0041	-0.0120	0.0194	0.0091	-0.0060	-0.0530	0.0010	**-0.0345***	-0.0010	0.0441
	(0.462)	(0.364)	(0.132)	(0.701)	(0.743)	(0.119)	(0.786)	(0.086)	(0.831)	(0.326)
CSI_{t-4}	**0.0168*****	**-0.0917*****	**0.0350*****	**-0.1160*****	-0.0044	-0.0257	0.0015	**-0.0868*****	-0.0009	**-0.0749****
	(0.000)	(0.000)	(0.000)	(0.000)	(0.722)	(0.266)	(0.545)	(0.000)	(0.793)	(0.022)
Constant	**0.0009*****	**0.0008*****	**0.0010*****	**0.0018*****	**0.0010*****	**0.0013****	**0.0005*****	0.0005	**0.0003*****	0.0003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.014)	(0.000)	(0.175)	(0.003)	(0.757)
N	11,803	11,814	3,786	3,789	1,807	1,811	5,366	5,369	844	845
Adj. R^2	0.721	0.946	0.741	0.915	0.636	0.960	0.826	0.960	0.881	0.907

Table IV: OLS panel regressions of stock returns and volatility on crisis sentiment

This table shows results from OLS panel regression with firm-fixed effects of volatility (Panel A) and weekly stock returns (Panel B) on (lags of) market-wide crisis sentiment and household sentiment measures. *General CSI* is the principal component of four crisis-related search volume indices from Google Trends (see Irresberger et al., 2015). *FEARS* is a household sentiment measure based on the search volume of thirty economics-related search terms in the United States (see Da et al., 2015). Variables based on stock price data are winsorized at the 5% level to mitigate a potential bias from outliers. All variable definitions and data sources are given in Appendix I. Standard errors are corrected for clustering at the firm level. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

Panel A: Volatility	All	Groups	Life	Non-Life	Reinsurer	All	Groups	Life	Non-Life	Reinsurer
General CSI	-0.0103	0.0137	0.0280	**-0.0471***	0.0041					
	(0.658)	(0.790)	(0.271)	(0.057)	(0.950)					
General CSI$_{t-1}$	**0.0853****	0.1300	0.0393	**0.0640*****	0.0474					
	(0.016)	(0.139)	(0.245)	(0.002)	(0.111)					
General CSI$_{t-2}$	0.0396	0.0004	0.0451	**0.0780****	0.0163					
	(0.147)	(0.995)	(0.134)	(0.034)	(0.804)					
General CSI$_{t-3}$	**0.2310*****	**0.1820*****	**0.1330****	**0.3150*****	**0.1920****					
	(0.000)	(0.001)	(0.015)	(0.000)	(0.018)					
FEARS						**-0.9440*****	**-0.7060*****	**-0.4150****	**-1.3800*****	-0.7750
						(0.000)	(0.005)	(0.047)	(0.000)	(0.219)
FEARS$_{t-1}$						**-0.0005*****	-0.2720	0.1630	**-1.0200*****	-0.5400
						(0.007)	(0.470)	(0.702)	(0.000)	(0.315)
FEARS$_{t-2}$						**-0.0003****	-0.2400	0.3690	**-0.6490*****	-0.4490
						(0.028)	(0.366)	(0.534)	(0.002)	(0.269)
FEARS$_{t-3}$						-0.0002	-0.0667	0.4430	**-0.4810*****	-0.3780
						(0.173)	(0.754)	(0.485)	(0.007)	(0.273)
Constant	**1.7400*****	**1.5500****	**2.6300****	**1.7200***	1.1300	**5.5800*****	**5.1800*****	**5.1500*****	**6.3800*****	**4.0600*****
	(0.001)	(0.037)	(0.027)	(0.091)	(0.230)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	24,259	9,699	3,263	9,688	1,609	24,259	9,699	3,263	9,688	1,609
Adj. R^2	0.091	0.054	0.049	0.181	0.294	0.001	0.000	-0.001	0.002	0.002
Panel B: Returns	All	Groups	Life	Non-Life	Reinsurer	All	Groups	Life	Non-Life	Reinsurer
General CSI	**-0.0007*****	**-0.0007*****	**-0.0006***	**-0.0008*****	-0.0004					
	(0.000)	(0.000)	(0.098)	(0.000)	(0.235)					
General CSI$_{t-1}$	-0.0002	**-0.0004***	-0.0002	0.0000	**-0.0009****					
	(0.123)	(0.090)	(0.647)	(0.897)	(0.041)					
General CSI$_{t-2}$	**0.0004*****	**0.0006*****	0.0002	0.0002	**0.0011***					
	(0.006)	(0.006)	(0.699)	(0.398)	(0.077)					
General CSI$_{t-3}$	**0.0002****	0.0002	0.0003	**0.0003***	-0.0001					
	(0.030)	(0.325)	(0.352)	(0.056)	(0.898)					
FEARS						**-0.0095*****	**-0.0098*****	**-0.0097*****	**-0.0099*****	**-0.0049*****
						(0.000)	(0.000)	(0.002)	(0.000)	(0.007)
FEARS$_{t-1}$						**-0.0104*****	**-0.0106*****	**-0.0103****	**-0.0103*****	**-0.0104*****
						(0.000)	(0.000)	(0.026)	(0.000)	(0.005)
FEARS$_{t-2}$						**-0.0116*****	**-0.0110*****	**-0.0093*****	**-0.0133*****	**-0.0087****
						(0.000)	(0.000)	(0.000)	(0.000)	(0.024)
FEARS$_{t-3}$						**-0.00746*****	**-0.00845*****	-0.00236	**-0.00828*****	**-0.00640*****
						(0.000)	(0.000)	(0.256)	(0.000)	(0.003)
Constant	**0.0038*****	**0.0042*****	**0.0023***	**0.0039*****	**0.0035*****	**0.0009*****	**0.0012*****	**-0.0002*****	**0.0010*****	**0.0007*****
	(0.000)	(0.000)	(0.076)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	24,259	9,699	3,263	9,688	1,609	24,259	9,699	3,263	9,688	1,609
Adj. R^2	0.012	0.014	0.008	0.011	0.018	0.012	0.014	0.010	0.012	0.011

Table V: OLS panel regressions of stock return volatility on crisis sentiment interaction terms

The table shows results from OLS Panel regressions of stock return volatility on market-wide crisis sentiment and interaction terms.

$$\text{VOLATILITY}_{i,t} = \mu_i + \beta \cdot \text{CRISIS SENTIMENT}_{i,t} + \gamma \cdot \text{X}_{i,t} + \delta \cdot (\text{CRISIS SENTIMENT}_{i,t} \times \text{X}_{i,t}) + \varepsilon_{i,t},$$

where $\text{X}_{i,t}$ includes firm-specific characteristics such as bid-ask-spreads, size, leverage and market-to-book ratio. CRISIS $\text{SENTIMENT}_{i,t}$ is the *General CSI* (see Irresberger et al., 2015) and CRISIS $\text{SENTIMENT}_{i,t} \times \text{X}_{i,t}$ is the interaction term. μ_i are firm-fixed effects. Standard errors are corrected for clustering at the firm level. Panel A shows results using the full sample, while the other panels present estimates from the sub-samples of *Groups* (Panel B), *Life* (Panel C), and *Non-life* (Panel D). Variables based on stock price data are winsorized at the 5% level to mitigate a potential bias from outliers. All variable definitions and data sources are given in AppendixI. All coefficients are multiplied by 1000 for readability. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

Panel A: All	(1)	(2)	(3)	(4)	(5)
General CSI	**0.3000*****	**0.3000*****	**0.2000*****	**0.3000*****	**0.2000*****
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BAS	**0.1000****				**75.7000***
	(0.043)				(0.066)
BAS × General CSI	**-0.0010****				**-0.0051***
	(0.037)				(0.057)
Size ($\times 10^{-9}$)		**-0.4000*****			**-0.2000*****
		(0.000)			(0.001)
Size × General CSI ($\times 10^{-9}$)		**-0.0047***			**-0.0026***
		(0.057)			(0.092)
Leverage			**0.2000****		**0.1000***
			(0.040)		(0.060)
Leverage × General CSI			-0.0002		-0.0002
			(0.739)		(0.622)
Market-to-book ratio				-0.0020	-0.0004
				(0.818)	(0.959)
Market-to-book ratio × General CSI				-1.8000	-0.8000
				(0.196)	(0.424)
Constant	**2.5000*****	**4.7000*****	-3.4000	**2.4000*****	-0.3000
	(0.000)	(0.000)	(0.278)	(0.001)	(0.909)
N	24,513	18,086	11,161	11,161	11,149
Adj. R^2	0.058	0.103	0.117	0.036	0.138

Panel B: Groups	(1)	(2)	(3)	(4)	(5)
General CSI	**0.2730*****	**0.2690*****	**0.2660*****	**0.3090*****	**0.2780*****
	(0.000)	(0.000)	(0.000)	(0.005)	(0.001)
BAS	**0.0890****				**0.0628****
	(0.036)				(0.032)
BAS × General CSI	**-0.0067****				**-0.0045****
	(0.032)				(0.034)
Size ($\times 10^{-9}$)		**-0.3590*****			-0.1070
		(0.000)			(0.188)
Size × General CSI ($\times 10^{-9}$)		-0.0037			-0.0016
		(0.180)			(0.120)
Leverage			**0.3140*****		**0.2680*****
			(0.000)		(0.005)
Leverage × General CSI			**-0.0023*****		**-0.0020*****
			(0.000)		(0.003)
Market-to-book ratio				-0.0009	0.0014
				(0.824)	(0.447)
Market-to-book ratio × General CSI				**-0.0064***	**-0.0046****
				(0.095)	(0.028)
Constant	**2.2600*****	**5.0500*****	**-4.2400****	**2.2500****	-2.3100
	(0.002)	(0.000)	(0.038)	(0.023)	(0.440)
N	9,804	8,614	6,293	6,293	6,289
Adj. R^2	0.037	0.113	0.158	0.029	0.163

Table V: OLS panel regressions of stock return volatility on crisis sentiment interaction terms (continued)

Panel C: Life	(1)	(2)	(3)	(4)	(5)
General CSI	**0.2100***	0.2590	**0.1270*****	**0.0786****	0.1120
	(0.052)	(0.220)	(0.005)	(0.038)	(0.112)
BAS	**-1.5700***				**-1.6600*****
	(0.055)				(0.000)
BAS × General CSI	-0.0394				0.0312
	(0.518)				(0.277)
Size ($\times 10^{-9}$)		-0.1650			-0.0301
		(0.355)			(0.241)
Size × General CSI ($\times 10^{-9}$)		-0.0095			-0.0056
		(0.544)			(0.278)
Leverage			-0.0093		-0.0097
			(0.183)		(0.136)
Leverage × General CSI			**-0.0013****		-0.0010
			(0.031)		(0.185)
Market-to-book ratio				0.0023	**0.0045*****
				(0.138)	(0.002)
Market-to-book ratio × General CSI				**0.0011*****	**0.0017*****
				(0.008)	(0.000)
Constant	**3.1600*****	**4.0700*****	**1.8400*****	**1.3800*****	**2.2600*****
	(0.006)	(0.002)	(0.001)	(0.000)	(0.001)
N	3,296	2,213	1,616	1,616	1,612
Adj. R^2	0.039	0.032	0.324	0.335	0.390

Panel D: Non-life	(1)	(2)	(3)	(4)	(5)
General CSI	**0.3290*****	**0.2480*****	**0.3330***	**0.2590***	**0.3550***
	(0.000)	(0.006)	(0.074)	(0.067)	(0.071)
BAS	**0.3850****				0.4060
	(0.035)				(0.219)
BAS × General CSI	**-0.0425****				-0.0259
	(0.036)				(0.330)
Size ($\times 10^{-9}$)		-0.3460			-0.1220
		(0.144)			(0.280)
Size × General CSI ($\times 10^{-9}$)		-0.0098			-0.0095
		(0.105)			(0.220)
Leverage			0.0151		0.0121
			(0.323)		(0.293)
Leverage × General CSI			**-0.0008***		**-0.0008***
			(0.072)		(0.069)
Market-to-book ratio				**-1.9500****	**-1.8100****
				(0.015)	(0.016)
Market-to-book ratio × General CSI				-0.0372	-0.0563
				(0.530)	(0.400)
Constant	**2.6900*****	**4.2500*****	2.1900	**13.6000*****	**12.9000*****
	(0.002)	(0.000)	(0.239)	(0.001)	(0.000)
N	9,788	6,244	2,830	2,830	2,828
Adj. R^2	0.110	0.112	0.113	0.271	0.288