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Spillover Duration of Stock Returns and Systemic Risk*

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Abstract

Common systemic risk measures focus on the instantaneous occurrence of triggering and systemic events. However, in this article we show that the distress of a systemically important institution may impact a market also after several days. This time-lagged dependence motivates our measure of systemic risk, the Conditional Shortfall Probability (CoSP), which is related to other common systemic risk measures, but is substantially more reliable. While other systemic risk measures are largely driven by systematic risk, we strengthen the directionality of systemic risk by considering an institution as systemically risk only if its distress has a significant as well as persistent negative effect on the market. Our empirical results suggest, that the financial market is exposed to the systemic risk of systemically important banks on an average of 28 days, while systemically important brokers have a significantly longer and systemically important insurers a significantly shorter impact. Moreover, we show that brokers trigger the largest systemic risk but are exposed to the smallest, while insurers are exposed to the largest systemic risk.

Keywords: Systemic Risk Measures, Spillover Duration, Financial Stability, Tail Dependence

JEL Classification: C58, E32, G01, G14, G21, G22, G23, G24, G32

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1 Introduction

How do financial crises evolve? Usually, they start with the financial distress or failure of certain institutions. Subsequently, other institutions are infected, until the whole financial sector is impaired and the real economy suffers losses. We observe this pattern particularly clearly during the 2007-2008 financial crisis, but also in other crises like the 1997-1998 Asia crisis, or 1980s savings and loans crisis. Intuitively, financial crises do not happen instantaneously and disappear after a few days. In contrast, the reaction of customers, investors, managers, and regulators on distress events and new information naturally takes time and affects each other.

For example, prior to the 2007-2008 financial crisis subprime mortgage defaults already increased considerably in February 2007 (see Brunnermeier (2009)). These led to the shut-down of UBS' internal hedge fund Dillon Read after suffering substantial subprime-related losses in May 2007. However, it took approximately one year until the full risk of subprime-related products was acknowledged and the ultimate consequences for financial institutions were realized: In March 2008 Bear Stearns collapsed, followed in September 2008 by the Fannie Mae/Freddie Mac conservatorship, Lehman bankruptcy, and AIG bailout. The first major policy reaction in the U.S. was the passing of the TARP financial stabilization package in October 2008. Figure 1 shows the build up and decrease of distress in the global financial market over time with regard to stock returns. This observation leads to our conclusion, that particularly during crises the distress events may have an enduring effect on a market.

This timing dimension of financial crises, which may result in systemic events, is usually not actively acknowledged, but also not denied. For example, the Committee on Capital Markets Regulation defines systemic risk as "the risk of collapse of an entire system or entire market, exacerbated by links and interdependencies" (see Committee on Capital Markets Regulation (2009, p. ES-3)), while an institution is considered as systemically important for a particular market "if its failure or malfunction causes widespread distress, either as a direct impact or as a trigger for broader contagion" (see Financial Stability Board (2009)). However, it seems clear from the observations made above, that widespread distress does not necessarily completely materialize instantaneously following the malfunction of an institution.

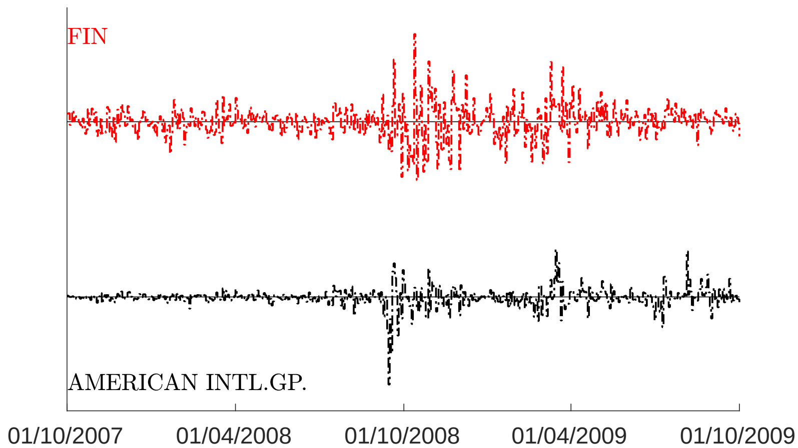


Figure 1: Daily stock returns of the global financial index (as described in Section 4.1) and AIG from October 2007 to October 2009.

Although there is often no obvious direct trigger of a crisis (see Marshall (1998)), institutions may contribute to a crisis via the negative externalities they create. Thus, when measuring systemic risk, it is usually not possible to construct a causal relationship between different events. In contrast, common systemic risk measures, as the MES (Marginal Expected Shortfall) or SES (Systemic Expected Shortfall) by Acharya et al. (2016), SRISK by Acharya et al. (2012), or ΔCoVaR by Adrian and Brunnermeier (2016), are based on statistical tail-dependence of (daily) stock returns. In their line of reasoning, a very strong dependence between an institution's and a market's distress is an indicator for this institution contributing to a market's systemic risk. Regardless of the missing causal relationship, these measures establish directionality by conditioning on either the market or the institution being in distress.

These commonly used cross-sectional systemic risk measures are based on the assumption that the impact of the financial distress of one institution materializes instantaneously on the market. In other words, they assume that systemic market events are independent from previous institutions' distress. Following this line of reasoning, all market participants should have realized their total exposure to the risk of subprime-related products already after subprime mortgage defaults increased in February 2007. In this case, the 2007-2008 financial crisis would have happened during one day. However, the complexity of products and institutions as well as the interconnectedness of markets in particular prevented institutions from immediately capturing the total impact of increasing subprime mortgage defaults. Therefore, it is not clear whether commonly used cross-sectional systemic risk measures fully capture the timing dimension of crises. Furthermore, these measures are largely driven by the correlation between the institution and the market: When solely focusing on simultaneous events of distress, it is intuitively difficult to identify the direction of spillovers. Consequently, these measures exhibit a very large correlation with systematic risk. Moreover, these measures often exhibit a very large estimation error, which makes it difficult to assess the significance of systemic risk. In response to these shortcomings, several studies question the ability of common systemic risk measures to distinguish systemic from systematic risk, and reliably identify systemically important institutions.

In this article we tackle the three shortcomings of traditional systemic risk measures described above: Firstly, we propose a new systemic risk measure, the Conditional Shortfall Probability (CoSP), which is similar to the dependence-consistent $\Delta\text{CoVaR}^{\leq}$ proposed by Ergün and Girardi (2013) and Mainik and Schaanning (2014) but exhibits a substantially smaller estimation error. Secondly, we introduce a time-lag between institutions' and markets' distress, which strengthens the directionality of the measure. In our empirical analysis CoSP displays a significantly positive dependence between certain institution's and market's returns, also for time-lags up to 50 days. This result is robust when controlling for intra-market spillovers and liquidity. Thirdly, by aggregating CoSP over time, we propose measures for the average excess probability of a systemic event, i.e. the Average Excess CoSP, and for the average time-lag between systemic and triggering events, i.e. the Spillover Duration. The correlation of these time-aggregate CoSP-based measures with systematic risk is substantially smaller than that of MES or $\Delta\text{CoVaR}^{\leq}$.

Our results indicate that brokers trigger the largest and most persistent systemic risk. In contrast, insurance and non-financial companies are exposed to the largest and most persistent systemic risk but trigger the smallest systemic risk. We contribute to the understanding and measurement of systemic risks in two ways: Firstly, we find that institutions may expose a significant systemic risk on markets even after several days. Secondly, we propose a systemic risk measure, CoSP, which including this time-lag. Thus, CoSP combines the ideas behind Granger causality, the ΔCoVaR, and default probabilities. Thereby, we achieve a notion of econometric directionality similar to Granger-causality (see Granger (1969)): If the distress of an institution at time t and a market's distress at time $t + \tau$ are positively dependent, the market's distress cannot have had an impact on the institution's distress.[1]

The remainder of the article is organized as follows. In Section 2 we relate our article to other studies of systemic risk and time-lagged dependence of stock returns. Thereupon, in Section 3 we introduce the Conditional Shortfall Probability and review its properties. In the empirical analysis in Section 4 we examine the Conditional Shortfall Probability and related aggregated measures over time and cross-sectionally. Section 5 concludes and provides an outlook to future research directions.

2 Literature Review

This article is related to three strains of literature. The first is the literature on systemic risk in general, the second is aiming to develop measures for the contribution or exposure of single institutions to systemic risk, while the third provides evidence for the auto- and cross-serial dependence of financial market movements with regard to stock returns.

2.1 Background on Systemic Risk

Systemic events are fundamentally linked to negative externalities: While a single institution mainly focuses on managing its own business, its risk management may also have severe consequences for other institutions and its market and/or other markets in general (see Financial Stability Board (2009)). As described by Benoit et al. (2016) three main mechanisms contribute to a systemic crisis: systemic risk-taking (i.e., non-welfare-maximizing risk-taking of institutions), contagion (i.e., a positive exposure of one institution to another institution's shocks), and amplifi-

[1] This argument may not be true for institutions and markets that are not liquidly traded. However, in Section 4.4 we show that our results are robust with regard to liquidity.

cation (i.e., large losses resulting from small shocks). In total and over time, systemic loops, that consist of these three mechanisms, lead to systemic events.

As Marshall (1998) observes, many systemic crises lack a clear triggering event. In contrast, they crucially depend on the market structure: A market may become vulnerable for systemic risk through direct linkages between firms, e.g. contractual links or counterparty risk, or through indirect linkages due to the exposure to common risk factors, e.g. excessive piling-on of debt (for example, see Kindlebeger (1978), Minsky (1982), Feldstein (1991)). Then, if investors loose confidence in specific assets, a cascade of distress events is fueled by the vulnerability and interconnectedness of institutions in a market. Finally, the financial system may be impaired - with possible severe consequences for the real industry.

Several studies of systemic risk focus on specific direct linkages, as for example CDS exposure (see Peltonen et al. (2013)), or interbank loans (see Allen and Gale (2000), Chan-Lau et al. (2009), Gai and Kapadia (2010), Georg (2013), Acemoglu et al. (2015)). Indirect transmission channels include the spillover of volatility (see Hamao et al. (1990), Diebold and Yilmaz (2014), Diebold and Yilmaz (2012)) or information (see Acharya and Yorulmazer (2002), Wongswan (2006), Ahnert and Bertsch (2015)). Indirect linkages may also manifest themselves through several factors, as for example correlated investments (see Acharya and Yorulmazer (2008a), Acharya and Yorulmazer (2008b), Farhi and Tirole (2012)), liquidity risk (see Bhattacharya and Gale (1987), Shleifer and Vishny (1992), Allen and Gale (2004), Brunnermeier and Pedersen (2009), Brunnermeier and Oehmke (2013)) or leverage cycles (see Danielsson et al. (2004), Brunnermeier and Sannikov (2014)).

2.2 Measuring Systemic Risk

Due to spillover effects in general, institutions' asset and liability values are affected such that these may fall below or rise above levels purely justified by fundamental values. Therefore, unusually large negative changes in an institution's equity value can serve as an proxy for financial distress of an institution. For listed institutions this change is reflected by stock price returns, and, thus, is easily observable. Following this line of reasoning, several cross-sectional systemic risk measures assess systemic risk by studying tail return (spillovers) of institutions and markets.

For example, Acharya et al. (2016) develop the marginal expected shortfall (MES) and systemic expected shortfall (SES), that quantify the level to which institutions are exposed to a financial crisis. Their measures indicate which institutions suffer particularly large losses during crises, but not which institutions contribute to crises.[2] The SRISK measure, proposed by Acharya et al. (2012) and Brownlees and Engle (2016), connects the MES with an institution's market capitalization and leverage.

In contrast, the ΔCoVaR proposed by Adrian and Brunnermeier (2016) aims at measuring the contribution of institutions to systemic crises. By conditioning on an institution's distress event, at first sight, it seems that ΔCoVaR is based on a causal relationship between institution and market. However, in common frameworks, ΔCoVaR is the result of the co-movement of (tail-)returns: This can directly be verified in case of bivariate normally distributed returns, for which Adrian and Brunnermeier (2016) show that

$$\Delta\text{CoVaR} = \sigma^M(-\Phi^{-1}(q))\rho^{I,M}, \tag{1}$$

where σ^M is the standard deviation of market returns, Φ^{-1} is the inverse of the cumulative density function of the standard normal distribution, and $\rho^{I,M}$ is the correlation coefficient between market and institution returns.[3] Thus, ΔCoVaR is mainly driven by the institution's correlation with the market.

Moreover, several studies indicate that the estimation error of ΔCoVaR makes it a very unreliable systemic risk measure (see Castro and Ferrari (2012), Guntay and Kupiec (2014), or Danielsson et al. (2016)). Extensions of ΔCoVaR include the dependence-consistent $\Delta\text{CoVaR}^{\leq}$ proposed by Ergün and Girardi (2013) and Mainik and Schaanning (2014), and the state-dependent sensitivity value-at-risk approach proposed by Adams et al. (2014). However, to the best of our knowledge, no extension of ΔCoVaR addresses the large estimation error or dependence on the correlation with

[2] This implies up to 100% correlation between an institution's MES and beta (see Benoit et al. (2013)). In our empirical analysis, we find a correlation of 95.5% between MES and beta.

[3] More generally, Benoit et al. (2013) find that ΔCoVaR is proportional to the institution's firm-specific risk if the dependence between financial asset returns is linear. In this case, the proportionality coefficient depends on the market's volatility and the correlation between market's and institution's returns.

the market.

Other cross-sectional risk measures are proposed by Hartmann et al. (2005), who focus on extreme systematic risk of bank systems, and Huang et al. (2009), who base their measure on the price of insurance against systemic financial distress as implied by credit default swap (CDS) prices.

To the best of our knowledge, none of the proposed cross-sectional systemic risk measures includes a time-lag between different distress events, while other studies of systemic risk and stock returns explicitly account for it. Diebold and Yilmaz (2014) study the spillover of volatility at different time-lags. Similarly, Corsi and Ren (2012) find very persistent leverage and volatility effects for the S&P 500. Billio et al. (2012) propose Granger-causality tests to measure the time-lagged propagation of return spillovers in general. While our approach is closely related to the dependence-consistent $\Delta\text{CoVaR}^{\leq}$, our rationale is very similar to Granger-causality tests. However, there are two very important differences between our approach and Billio et al. (2012): Firstly, we only focus on tail returns (i.e., distress events), while Billio et al. (2012) study return distributions in general. Thus, our results are solely driven by the dependence of distress events. Secondly, Billio et al. (2012) propose to quantify dependence by the number of significant lags. However, in addition to the significance, we aim to measure the magnitude of dependence between an institution's and market's distress for specific time-lags.

2.3 Auto- and Cross-Serial Dependence of Stock Returns

The correlation between time-lagged returns is an extensively studied phenomenon. In particular, short-horizon portfolio returns are found to be significantly autocorrelated and highly cross-serially correlated (among others, see Fama (1965), Gibbons and Ferson (1985), Conrad and Kaul (1988), Lo and MacKinlay (1990), Boudoukh et al. (1994)). Possible explanations include time-varying risk premiums (see Keim and Stambaugh (1984), Conrad and Kaul (1989), Conrad et al. (1991a), Conrad et al. (1991b), Füss et al. (2016)) and market overreactions (see Lehmann (1990), Lo and MacKinlay (1990), Jegadeesh and Titman (1995)).

Furthermore, various studies argue that auto- and cross-correlations are due to market frictions such as measurement errors. Measurement errors may materialize, for example, due to non-synchronous trading (see Fisher (1966), Cohen et al. (1983), Conrad and Kaul (1988), Lo and MacKinlay (1990), Boudoukh et al. (1994)). Non-synchronous trading periods naturally arise since reported stock prices only reflect the last trade on one specific day. This reported price may deviate from the "true" price and is followed by a non-trading period, which induces a correlation with the next day's price. However, market frictions like information, decision, or transaction costs also account for a substantial part of the dependence between returns (see Atchinson et al. (1987), Hou and Moskowitz (2005)).

Finally, the high complexity and opaqueness of interconnected markets and institutions, particularly in the financial services sector (see Arora et al. (2009), Moghadam and Viñals (2010), Adrian et al. (2014), Battiston et al. (2015)), but also complex products like hybrid debt, reinsurance, specific forms of parent-subsidiary relationships, captives and other forms of capital transfer mechanisms make it difficult to immediately assess the entire impact of events and information. Time-lags with regard to the information processing of investors are studied by AitSahlia and Yoon (2016), who provide evidence for time-lagged price adjustments prior and after events that contain information about a specific stock. Similarly, Boguth et al. (2016) document significant correlation between average returns at different horizons, and show that slow reaction to market information is an important cause for this finding.

3 The Conditional Shortfall Probability

3.1 Methodology

Consistent with the dependence-consistent $\Delta\text{CoVaR}^{\leq}$ proposed by Ergün and Girardi (2013) and Mainik and Schaanning (2014), we interpret the occurrence of one of the $q^I \cdot 100\%$ smallest institution's daily returns, r^I, as a signal for financial distress of this institution, ID. Similar to Acharya et al. (2012), we interpret one of the $q^M \cdot 100\%$ smallest market's daily returns, r^M, as a proxy for systemic market distress, MD.[4] To assess the impact of an institution's distress event on the market after τ days, the Conditional Shortfall Probability (CoSP) is defined by

$$\psi_\tau(q^M, q^I) = \mathbb{P}\left(MD_\tau \mid ID_0\right) = \mathbb{P}\left(r_\tau^M \leq VaR^M(q^M) \mid r_0^I \leq VaR^I(q^I)\right). \tag{2}$$

Thus, CoSP measures the systemic risk related to a spillover of lower tail returns from an institution to a market. The identification of the VaR-levels q^M and q^I is both necessary and challenging: For one exemplary market solely the 5% smallest market returns may relate to a systemic event, while the 10% smallest market returns may be systemic for a different market, for example due to a larger market capitalization. For other markets that exhibit no systemic risk, q^M would equal zero. Thus, q^M and q^I depend on the respective markets' and institutions' properties.

Clearly, the choice of q^M and q^I also depends on the definition of financial and systemic distress. However, presently there is no common agreement on the definition and level of market-specific systemic risk and institution-specific distress probabilities. For this reason, in the empirical analysis we set (analogously to ΔCoVaR) $q^M = q^I = q$, and denote $\psi_\tau(q) = \psi_\tau(q, q)$.

The reference level q^M of CoSP allows to differentiate between independence and positive or negative dependence between an institution's and market's distress, since ID_0 and MD_τ are independent if, and only if,[5]

$$\psi_\tau(q^M, q^I) = q^M. \tag{3}$$

Thus, if $\psi_\tau(q^M, q^I) > q^M$, the institution's distress event ID_0 increases the likelihood of a systemic market event after τ days, MD_τ. This is an indicator for systemic risk. Larger values for $\psi_\tau(q^M, q^I)$ indicate a larger systemic risk. For very large lags τ one would intuitively presume that the influence of the institution's return r^I on the market return r_τ^M diminishes, and, consequently, that ID_0 and MD_τ become independent. Hence, we conjecture (and find this confirmed in the empirical analysis

[4] Note that the definition of CoSP also allows for other proxies of triggering and systemic events.

[5] In Appendix A.3 we derive this property and give an example with independent student-distributed returns.

in Section 4) that

$$\lim_{\tau \to \infty} \psi_\tau(q^M, q^I) = q^M. \tag{4}$$

If $\psi_\tau(q^M, q^I)$ declines slowly, more systemic events occur at large lags and, thus, the influence of the institution's distress events lasts longer.

The estimation of CoSP is described in Appendix B.1. We propose to estimate CoSP in a Generalized Linear Model (GLM)-setting based on the observed properties of CoSP discussed above.

3.2 Properties of CoSP

In this section we discuss several properties of CoSP.[6] The methodology of CoSP is related to several other studies of systemic risk. For example, the condition of CoSP is reversed to the tail-β introduced by Hartmann et al. (2005), which quantifies the vulnerability of single institutions to an extreme negative systematic shock. The idea behind CoSP is also very similar to the idea of the distress spillover measure by Chan-Lau et al. (2012), which assesses extreme changes in banks' distance to default (DD). CoSP is also similar to the non-linear Granger-causality test as proposed in Billio et al. (2012). In contrast to Billio et al. (2012), in our approach we particularly focus on a specific state of the returns, namely being in the lower tail. Moreover, while Granger-causality determines if or if not there is dependence, we also examine the magnitude of this dependence.

Our definition of a distress event is based on CoVaR$^{\leq}$ introduced by Ergün and Girardi (2013) and Mainik and Schaanning (2014). In fact, one might also define a time-lagged CoVaR$_E^\tau$ by

$$\mathbb{P}\left(r_\tau^M \leq \mathrm{CoVaR}_E^\tau(q^M) \mid E\right) = q^M. \tag{5}$$

Then, $\mathrm{CoVaR}^\tau_{r^I \leq VaR^I(q^I)}$ and ψ_τ are properties of the same conditional distribution, namely the q-quantile and the tail probability. When considering the same market, CoSP and $\mathrm{CoVaR}^\tau_{r^I \leq VaR^I(q^I)}$ also generate the same ranking of institutions according to systemic risk if the conditional market

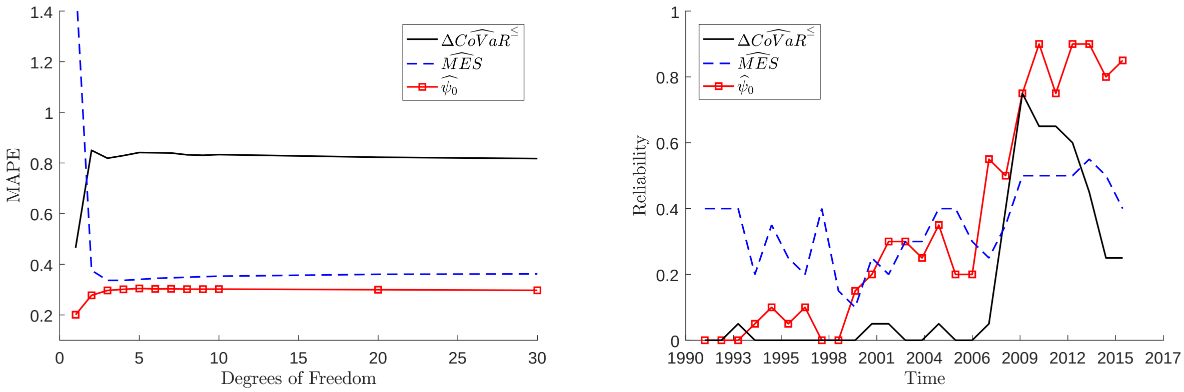
[6] Appendix A provides an overview of all properties of CoSP.

returns stochastically dominate each other (see Appendix A.4). However, the interpretation for the two measures is different: CoSP captures the likelihood of a systemic market event (i.e. the likelihood of being in the lower tail of the conditional distribution). In contrast, ΔCoVaR reflects additional tail risk of the market (i.e. the change in quantiles) and, thus, also depends on market volatility.[7]

Nonetheless, systemic events like market distress or failure have important implications beyond additional tail risk of market returns. A small return loss on a largely capitalized market may be more adverse than a large return loss on a less capitalized market. In addition, the distress of one market may also impact other markets and industries, but also affect political and socioeconomic dimensions. Therefore, Chan-Lau (2010) suggests to regulate too-connected-to-fail institutions based on societal losses. Boyd and Heitz (2016) study the cost to the macro-economy due to increased systemic risk triggered by too-big-to-fail banks. Consequently, in contrast to ΔCoVaR, we suggest to employ a predetermined definition of a systemic market event. In this article, we set a maximum level of systemic market returns that corresponds to a systemic event, i.e. adjust q^M to the level of a market's systemic risk probability. However, CoSP may also be based on other definitions for a systemic market event, that may not depend on returns.

CoSP exhibits several advantages from a statistical point of view: For example, asymptotic confidence bounds for CoSP are available in closed form, which permits assessing the statistical significance of CoSP in a straightforward manner (see Appendix B.2). This is not possible for most other systemic risk measures. Moreover, the estimation error of CoSP is substantially smaller than the estimation error of $\Delta\text{CoVaR}^{\leq}$ and it is also smaller than the estimation error of MES (see Figure 2 (a) and Appendix C.1). Thus, less data are needed to estimate CoSP. Consequently, CoSP exhibits a larger reliability than $\Delta\text{CoVaR}^{\leq}$ in the sense of Danielsson et al. (2016), as we show in Appendix C.2 and in Figure 2 (b). Moreover, in most years subsequent to 1998 CoSP is also more reliable than MES.

[7] For the Gaussian case the impact of spillover effects measured by ΔCoVaR are solely driven by market volatility, as Equation (1) shows.



(a) Mean Absolute Percentage Error (MAPE) for student-distributed returns.

(b) Reliability. The dates correspond to the last year in the respective time period that the estimates are based on.

Figure 2: Estimation Error and Reliability of $\hat{\psi}_0$, $\hat{MES}$, and $\Delta\widehat{\text{CoVaR}}^{\leq}$ for a sample size of 1500 observations (a description of the error and reliability measure can be found in Appendix C.2).

Systemic risk measures naturally are not able to establish a causal relationship between different events, which is also true for CoSP. In contrast, it quantifies the level of dependence between an institution and market. Hence, when considering an institution's distress event $ID_0^{I_1}$ at time 0 and a subsequent market distress event MD_τ at time τ, also the distress of another institution $ID_t^{I_2}$ may occur in between, $t > 0$. Still, if institutions I_1 and I_2 (or at least their distress) is independent, the CoSP of I_1 is not affected by I_2.[8] Clearly, this may change, if the distress of I_1 is channeled through institution I_2. Then, the CoSP of I_1 might increase. In the case where $ID_0^{I_1}$ and $ID_t^{I_2}$ occur simultaneously, i.e. $t = 0$, it is not possible to identify the direction of spillovers between I_1 and I_2. To account for this case, we check the robustness of our results when controlling for intra-market spillovers in Section 4.5.

3.3 Aggregate Systemic Risk and the Spillover Duration

Since both the magnitude and speed of decline of CoSP reflect the persistence of an institution's triggering event, we propose two measures of systemic risk that capture these dimensions: the

[8] We show this property in Proposition 1 in Appendix A.2.

Average Excess CoSP and the Spillover Duration. The Average Excess CoSP is given as

$$\bar{\psi} = \frac{1}{\tau^{\max}} \int_0^{\tau^{\max}} \psi_\tau(q^M, q^I) - q^M \, d\tau. \tag{6}$$

By definition, the Average Excess CoSP reflects the average extent to which a triggering event of an institution increases the likelihood of a systemic event. A second measure is the Spillover Duration, which is

$$\bar{\tau} = \frac{1}{\bar{\psi}\tau^{\max}} \int_0^{\tau^{\max}} \tau \, \left(\psi_\tau(q^M, q^I) - q^M\right) \, d\tau. \tag{7}$$

The Spillover Duration explicitly focuses on the timing dimension of systemic events. In particular, it is an average of all time-lags, which are weighted with their contribution to the Average Excess CoSP. Therefore, it reflects the average time horizon, at which a market is affected by the distress of an institution. A major advantage of $\bar{\tau}$ is, that it is measured in time units (e.g. days).

4 Empirical Analysis

4.1 Data and Descriptive Statistics

Our data sample consists of historical daily total return indices from January 1, 1981, to January 1, 2016, as provided by Datastream for the following institutions:

1) Publicly traded financial institutions that are classified as bank (i.e. commercial bank and depository institution; BAN), broker (i.e. non-depository credit institution, investment bank, security and commodity broker; BRO), insurer (i.e., insurance carrier; INS), or real estate firm (RE) according to their first 4-digit SIC classification.[9]

2) Dead or suspended financial institutions in the five largest global markets,[10] that were publicly traded between January 1981 and January 2016. These institutions are classified as described above.

[9] We classify an institution as bank if its SIC is 6021, 6022, 6029, 6035, 6036, 6061, 6062, 6081, or 6082 (i.e., we exclude central reserve institutions and functions related to depository banking), as broker if its SIC is between 6100 and 6280, as insurer (i.e., insurance carrier) if its SIC is between 6300 and 6400, and as real estate firm if its SIC is between 6500 and 6600.

[10] These are the United States, Germany, United Kingdom, China, and Japan. We choose this restriction to narrow down the resulting amount of data.

3) The 100 largest publicly traded non-financial companies (NoFIN) according to their market capitalization in March 2015, as reported by Dullforce (2015).

The names of the 10 largest institutions in each subsector included in the sample are reported in Appendix D.2 in Table 4. In Appendix D.2 we report descriptive statistics for the returns of all institutions included in the data sample.

We consider 6 different kinds of markets: 5 of these markets are global financial markets, namely the banking (BAN), brokerage (BRO), insurance (INS), real estate (RE) and overall financial (FIN) market. The respective value-weighted indices are composed of all corresponding institutions in our sample but exclude the currently considered institution as described in Appendix D.1. In Appendix D.2 in Figure 16 (a) we show the resulting indices for banks (BAN), brokers (BRO), insurers (INS), real estate (RE) and the overall financial market (FIN) if no institution is excluded from the index.

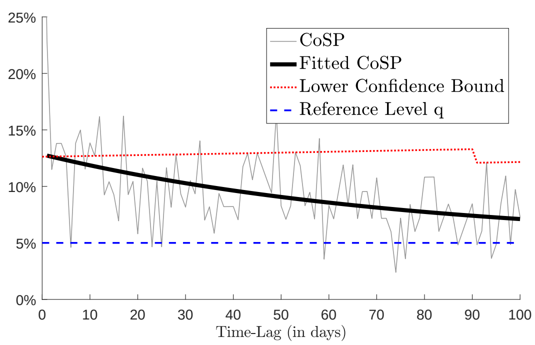
Since many authors highlight the implications of systemic events for the real industry (e.g., see The Group of Ten (2001) for an exemplary definition, or Smaga (2014) for an overview of different definitions of systemic risk), we also study an exemplary non-financial market via the Datastream non-financial index for the continent Americas (AMC). The non-financial index is shown in Appendix D.2 in Figure 16 (b).

4.2 Time-Conditional Analysis

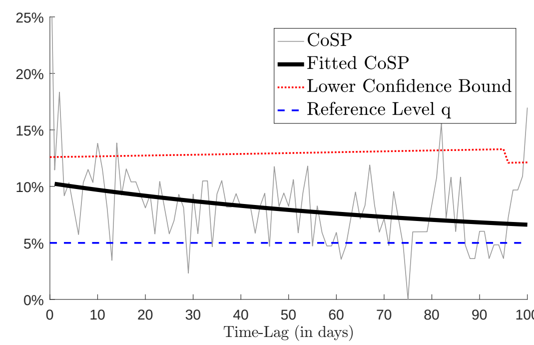
As described in Section 3, we set $q^M = q^I = q = 5\%$ for markets' systemic risk and institutions' distress probability. To compute the lower bound of significance we use the significance level $\alpha = 1\%$, and the maximum considered time-lag is $\tau^{\max} = 100$ days.

Since the systemic risk of a specific institution with respect to a specific market is likely to change over time, we compute the systemic risk measures for rolling windows with a size of 7 years. Thus, for example $\overline{\psi}_t$ corresponds to the Average Excess CoSP based on years $t-6, t-5, ..., t$. In other words, at the end of year t it was possible to observe the reported value $\overline{\psi}_t$. An institution is excluded from the sample for a particular time period, if it does not include at least 1500 observations of the total return index during the respective time period.

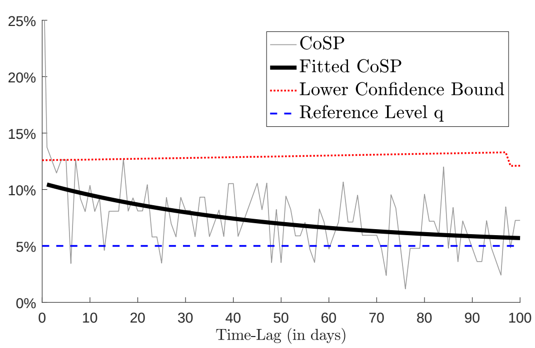
In Figure 3 we show the CoSP with respect to the global financial index for several exemplary institutions that exhibit a typical pattern. The time period covers the years 2000 - 2006 and, thus, reflects the CoSP one would have observed in the end of the year 2006 directly before the 2007-2008 financial crisis. As presumed in Section 3.1, CoSP is declining and converges to the reference level q for $\tau \to \infty$. In general, CoSP is quite small and fast declining for all institutions, which implies a small Average Excess CoSP and a small Spillover Duration, respectively. For all four considered institutions the fitted CoSP ψ_τ^{GLM} (computed as described in Appendix B.1) is below the lower confidence bound for a 1% level.



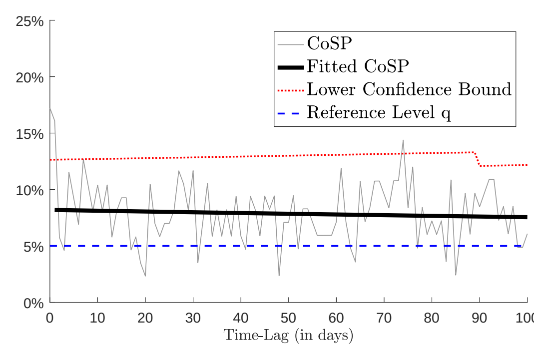
(a) JP Morgan Chase (BAN)



(b) Goldman Sachs (BRO)



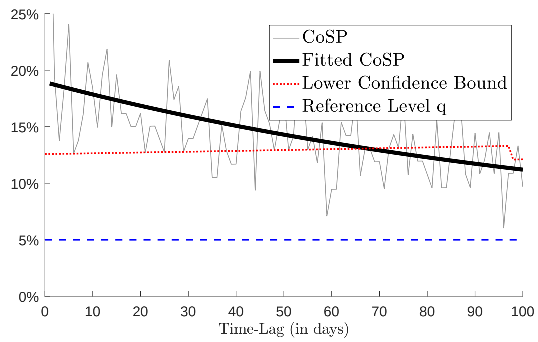
(c) AIG (INS)



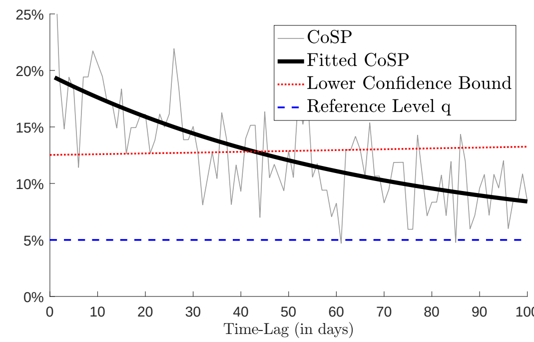
(d) Amazon.com (NoFIN)

Figure 3: CoSP during 2000-2006 triggered by exemplary institutions w.r.t. the FIN index.

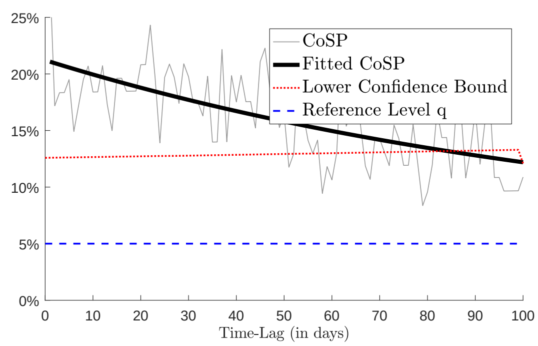
This situation changes substantially when considering the time period from 2002-2008 in Figure 4, which reflects the view directly after the first two years of the 2007-2008 financial crisis.[11] In comparison to the time period from 2000-2006, the magnitude of CoSP sharply increases at almost all lags, which in turn implies a larger Average Excess CoSP. Thus, during the 2007-2008 financial crisis, institutions' distress had a substantially larger impact on the financial sector. Moreover, CoSP is larger than the lower confidence bound for all four institutions. Thus, there is statistically significant dependence between the institutions' distress events and the financial market's distress events for several time-lags. We classify such an institution as significantly systemically important (s.s.i.) for a specific market.[12]



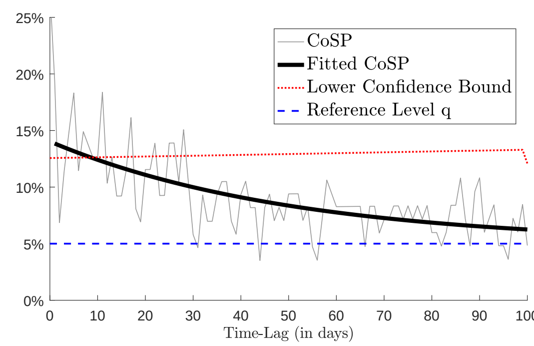
(a) JP Morgan Chase (BAN)



(b) Goldman Sachs (BRO)



(c) AIG (INS)



(d) Amazon.com (NoFIN)

Figure 4: CoSP during 2002-2008 triggered by exemplary institutions w.r.t. the FIN index.

[11] More examples are shown in Appendix E.1.

[12] More specifically, an institution is classified as s.s.i. if the fitted CoSP (computed as described in Appendix B.1) fulfills $\psi_\tau^{\text{GLM}} \geq k_\tau^*$ for at least one time-lag $\tau > 0$. We use the fitted CoSP instead of the Maximum-Likelihood estimate of CoSP to determine the significance since this contributes to the robustness of our results.

When comparing the level of CoSP for a fixed time-lag among the institutions, we find substantial differences. For example, at all time-lags AIG exhibits a larger CoSP than the other exemplary institutions. This indicates, that in this time period the magnitude of systemic risk is larger when triggered by AIG than by JP Morgan Chase, Goldman Sachs, or Amazon.com. The magnitude of systemic risk for single time-lags is integrated into one measure by the Average Excess CoSP $\overline{\psi}$. Comparing the Average Excess CoSP of the exemplary institutions in Table 1 shows, that AIG clearly triggers the largest Average Excess CoSP, followed by JP Morgan Chase, Goldman Sachs, and, lastly, Amazon.com. Also the speed of decline is different for the institutions. For example, CoSP declines faster for Amazon.com than for AIG. Thus, we expect the Spillover Duration to be smaller for Amazon.com than for AIG, and find this confirmed in Table 1. Consequently, among the four exemplary institutions the financial distress of AIG poses the largest and most persistent impact on the financial market, while distress of Amazon.com poses the smallest and least persistent.

	JP Morgan Chase	Goldman Sachs	AIG	Amazon.com
$\overline{\psi}$	9.4%	7.9%	11.2%	4%
$\overline{\tau}$	42.1	36.5	42.4	33.7

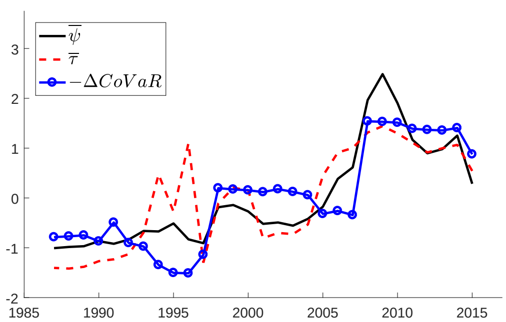
Table 1: Average Excess CoSP, $\overline{\psi}_{2008}$, and Spillover Duration, $\overline{\tau}_{2008}$, during 2002-2008 triggered by exemplary institutions w.r.t. the FIN index.

Figure 5 compares the evolution of the Average Excess CoSP and the Spillover Duration with the dependence-consistent $\Delta\text{CoVaR}^{\leq}$ over time. For each institution all measures are standardized across the full time period. Thus, the measures are not comparable between different institutions but only for each institution over time.[13]

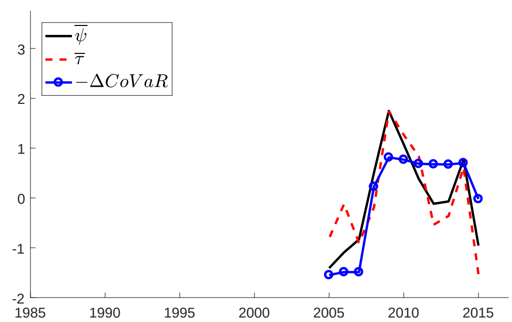
All measures in Figure 5 show peaks for the 2007-2008 financial crisis and around 2000. The peak around 2000 includes the 1997 Asian Financial Crisis, 1998 Russian financial crisis, 1999-2002 Argentine economic crisis, 2001 Turkish economic crisis, and 2001 dot-com bubble. Moreover, the Spillover Duration peaks around 1995 for JP Morgan Chase and AIG, while the Average Excess CoSP slightly increases and $\Delta\text{CoVaR}^{\leq}$ decreases in this period. The value in 1995 is based on the

[13] More examples may be found in Appendix E.1.

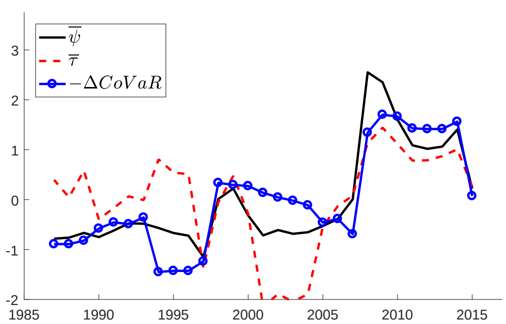
years 1989 until 1995, including the 1989-91 United States Savings & Loan crisis, 1990 Japanese asset price bubble, 1990 Scandinavian banking crisis, 1992-1993 Black Wednesday, and 1994 economic crisis in Mexico. Thus, $\Delta\text{CoVaR}^{\leq}$ indicates that, in contrast to these crises, systemic risk decreased around 1995, while the Spillover Duration reflects an increased persistence of distress and the Average Excess CoSP suggests that the systemic risk did not decrease but slightly increased for JP Morgan Chase.



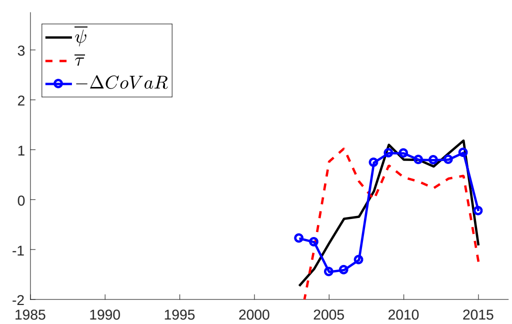
(a) JP Morgan Chase (BAN)



(b) Goldman Sachs (BRO)



(c) AIG (INS)



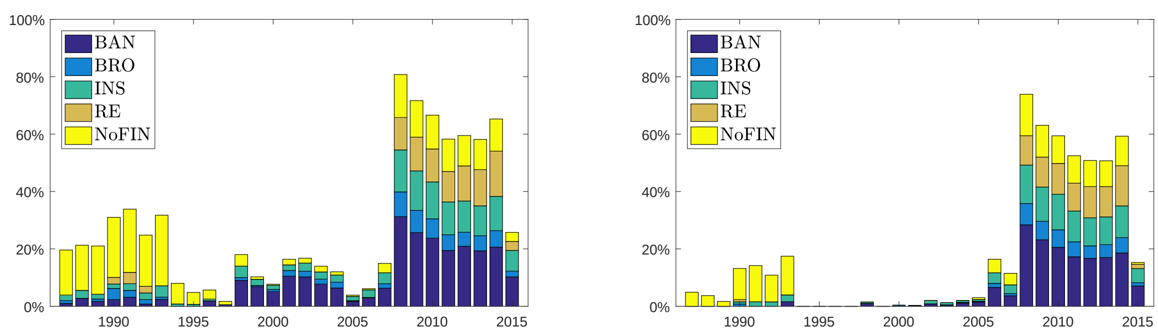
(d) Amazon.com (NoFIN)

Figure 5: Standardized Average Excess CoSP, Spillover Duration, and $-\Delta\text{CoVaR}^{\leq}$ triggered by exemplary institutions w.r.t. the FIN index.

Also subsequently to the peak around 1995, the measures do not completely move in the same direction. For example, the Spillover Duration of JP Morgan Chase and AIG rises already in 2005. This indicates, that prior to the 2007-2008 financial crisis the persistence of financial distress of these institutions increased, which would have served as an early warning for systemic risk. Also, the Average Excess CoSP increases in 2006 already. Thus, both CoSP-based measures seem to detect an increased dependence between distress of institutions' and the financial market earlier than $\Delta\text{CoVaR}^{\leq}$. In Section 4.6 we examine how strong the relationship between the different measures is over time and cross-sectionally.

4.3 Cross-Sectional Analysis

In this section we compare the systemic risk triggered by different institutions. To this end, we focus on the global financial market and the American non-financial market.[14] Figure 6 depicts the fraction of companies in the sample for a respective time-period that are identified by CoSP as significantly systemically important (s.s.i.) for the global financial and American non-financial market, respectively. Clearly, during the 2007-2008 financial crisis the number of s.s.i. institutions is the largest throughout the whole sample. During this time, between 50% and 80% of all institutions are s.s.i. w.r.t. to the financial market and American non-financial market. Before the 2007-2008 financial crisis, substantially more institutions were s.s.i. w.r.t. the financial market than w.r.t. the American non-financial market. Thus, the ratio of s.s.i. institutions w.r.t. the American non-financial market relative to those w.r.t. the financial market increased during the 2007-2008 financial crisis. This shows that the (American) real industry was more affected by this crisis than by previous crisis. This finding is in line with the 2007-2008 financial crisis commonly being perceived as the worst recession since the 1930s (for example, see Reinhart and Rogoff (2011)).



(a) w.r.t. the FIN index

(b) w.r.t. the AMC index

Figure 6: Fraction of significantly systemically important institutions on the 1% level relative to the total number of institutions in the sample w.r.t. the FIN and AMC market.

[14]The results are similar w.r.t. other markets, which can be found in Appendix E.2.

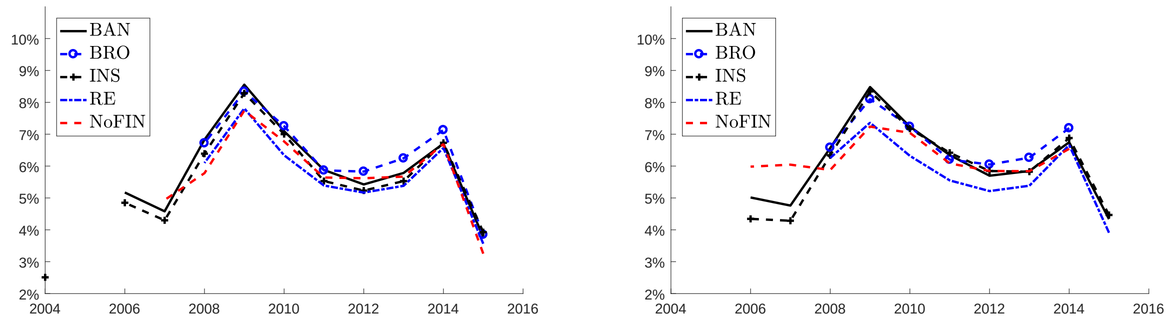
Moreover, there is a substantial shift in the type of s.s.i. institutions over time: While in the 1990s mainly non-financial companies were s.s.i. for all considered markets, from 2000 on banks are the major type of s.s.i. institutions. Moreover, in the 2007-2008 financial crisis the fraction of s.s.i. real estate firms substantially increases, which is intuitive due to the links of the crisis to housing prices. During the 2007-2008 financial crisis, the number of s.s.i. non-financial institutions and s.s.i. insurers is approximately equal, while there are less s.s.i. brokers.

In general, Regression 1 in Appendix D.3 shows that insurers and real estate firms are most likely to be s.s.i. (i.e., a large fraction of these companies is s.s.i.), while it is least likely for non-financial companies. Interestingly, the market capitalization of an institution is a significant and important driver for the significant systemic importance of an institution. The linear model implies that an increase of 100% in market capitalization (i.e., when the market capitalization doubles) is related to an increase of the likelihood of this institution being s.s.i. by 3.9 percentage points. Since market capitalization partly reflects the size of an institution, our finding partly confirms the reasoning of the SIFI identification by the Basel Committee on Banking Supervision (2013) and International Association of Insurance Supervisors (2016), that take size as an important indicator for systemic relevance.

In the following, we compare the Average Excess CoSP and Spillover Duration of s.s.i. institutions. Thereby, we aim to identify differences between the different types of institutions. Hence, we focus on the impact of different business models on the systemic risk of a significantly systemically important institution. Figure 7 depicts the evolution of the median Average Excess CoSP of each subsector over time.[15] For both the American non-financial and overall financial market, the median Average Excess CoSP tends to be the largest for brokers, slightly smaller for banks and insurers, and the smallest for real estate firms, and non-financial companies.

To confirm the significance of this result and also control for the market capitalization of each institution, we perform several panel regressions in Regression 2 in Appendix D.3. The results

[15] We only include years with at least 10 s.s.i. institutions in the respective subsectors. The results are similar w.r.t. other markets, which can be found in Appendix E.2.



(a) w.r.t. the FIN index

(b) w.r.t. the AMC index

Figure 7: Median Average Excess CoSP triggered by systemically important institutions in the subsectors BAN, BRO, INS, RE, and NoFIN w.r.t. the FIN and AMC market.

show significant differences between banks and other institutions that exhibit a similar market capitalization. S.s.i. brokers trigger the largest Average Excess CoSP. However, in contrast to the previous observation, real estate firms also trigger a significantly larger Average Excess CoSP than banks. This results from controlling for the market capitalization in the regression. The Average Excess CoSP triggered by non-financial companies is significantly smaller than that of banks, while insurers are not found to trigger a significantly different Average Excess CoSP than banks.

When comparing the exposure of different markets in Regression 2, we also find significant differences: Generally, the insurance market is exposed to the largest Average Excess CoSP. This finding is similar to the qualitative assessment of Cummins and Weiss (2014) and the empirical results of Chen et al. (2013) who also find that the exposure of insurers to systemic risk is particularly large in comparison to their contribution relative to other sectors. The exposure of the American non-financial market to the Average Excess CoSP is similar to the exposure of the banking market. This finding suggests that the vulnerability of the real economy towards systemic risk is mostly driven by the vulnerability of banks towards systemic risk, and highlights the importance of the banking sector for the real economy. The brokerage, real estate, and overall financial markets are exposed to a smaller Average Excess CoSP than the banking market. Thus, the role of brokers is opposite to the role of insurers: While brokers trigger the largest systemic risk, they are exposed to the smallest.

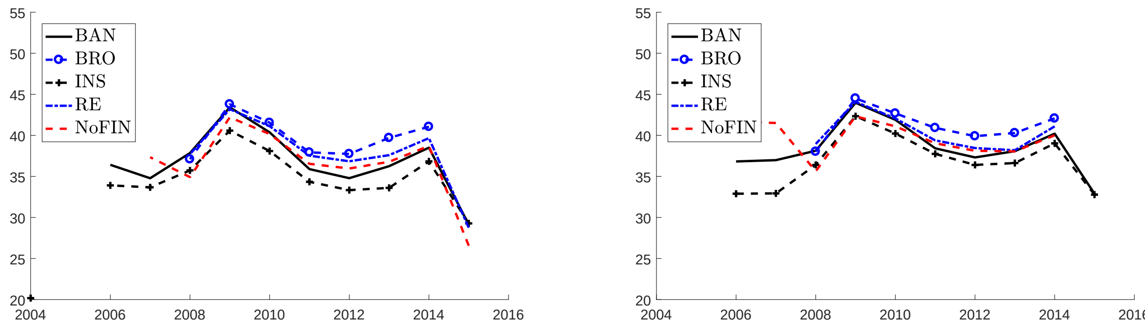
Regression 2 also sheds light on the role of the market capitalization of the institutions: The larger the market capitalization of a company is, the larger is the median Average Excess CoSP. This effect is significant on the 1% level. Since market capitalization partly reflects the size of an institution, this result confirms the common reasoning that larger institutions pose a larger systemic risk (for example, see Weiß and Mühlnickel (2014), Basel Committee on Banking Supervision (2013), and International Association of Insurance Supervisors (2016)). In particular, the linear regression model implies that an increase in market capitalization by 100% (i.e., if market capitalization doubles) is related to an increase of the Average Excess CoSP by 0.14 percentage points. This result is in line with the lead-lag effect described by Lo and MacKinlay (1990), who find that the returns of large stocks lead the returns of small stocks.

For the Spillover Duration in Figure 8 and Regression 2 in Appendix D.3 the results are similar to the Average Excess CoSP.[16] The average Spillover Duration for banks triggering systemic risk on the banking market is 28. While brokers trigger the largest Spillover Duration (approximately 0.8 days larger than that triggered by banks), followed by real estate firms (approximately 0.5 days larger than that triggered by banks). Insurers trigger the smallest Spillover Duration (approximately 0.7 days smaller than that triggered by banks). Thus, while the contribution in terms of the magnitude of systemic risk is not significantly different between the banking and insurance sector, the persistence of systemic events is significantly larger if triggered by bans than by insurers. The Spillover Duration triggered by non-financial companies is slightly larger than triggered by insurers (approximately 0.3 days smaller than that triggered by banks). All differences to banks are significant on the 1% level.

Interestingly, the insurance market is also exposed to the largest spillover duration. Thus, institutions' distress generally has the most persistent effect on insurers. The average Spillover Duration is approximately 3.8 days longer on the insurance market than on the banking market, which is followed by 1.6 days on the American non-financial market. Thus, while the vulnerability in terms of the magnitude of systemic risk is similar between the banking and American non-financial market, the vulnerability with regard to the persistence of systemic events is significantly larger on the American non-financial market than on the banking market. The Spillover Duration is the smallest

[16] The results are similar w.r.t. other markets, which can be found in Appendix E.2.

on the brokerage market with approximately 4.4 days less than on the banking market. Again, Regression 2 confirms that these differences to the banking market are significant on a 1% level.



(a) w.r.t. the FIN index

(b) w.r.t. the AMC index

Figure 8: Median Spillover Duration triggered by systemically important institutions in the subsectors BAN, BRO, INS, RE, and NoFIN w.r.t. the FIN and AMC market.

We find that market capitalization is also significantly positively related to the Spillover Duration. In particular, an increase in market capitalization by 100% (i.e., when market capitalization doubles) is related to an increase of the Spillover Duration by 0.08 days. While this effect is statistically significant on the 1% level, it seems not to be economically significant. Thus, from an economic perspective, a larger market capitalization is mainly related to a substantially larger systemic risk but not to a substantially longer-lasting impact on a market.

In conclusion, we find that brokers trigger the largest Average Excess CoSP and Spillover Duration, while the brokerage market is exposed to the smallest Average Excess CoSP and Spillover Duration. In contrast, insurers trigger a similar Average Excess CoSP as bans but a significantly smaller Spillover Duration. In contrast, they are exposed to the largest Average Excess CoSP and Spillover Duration.

4.4 The Impact of Liquidity

The literature on auto- and cross-correlation of stock return identifies illiquidity as an important driver of large time-lagged dependence (see Section 2.3). In this line of reasoning, when a stock is not traded frequently, the response to new information may be time-lagged. Thus, it seems possible that illiquidity is an important driver for the Spillover Duration and Average Excess CoSP. To examine this relationship, we employ the turnover by value and by volume as a proxy for the liquidity of a stock. To account for the liquidity of a market, we compute a value-weighted turnover index for respective markets.

In Regression 3 in Appendix D.3 we firstly examine the influence of a market's and institution's liquidity on the Average Excess CoSP and Spillover Duration when controlling for market, institution, and time fixed effects. In other words, we focus on changes of a market's or institution's liquidity over time. As expected, we find a significantly negative relationship between an institution's liquidity and Average Excess CoSP. Thus, for illiquid stocks, this measure is larger. The Spillover Duration is significantly related to the turnover by value but not the turnover by volume of single institutions. This suggests, that particularly small prices but not trading volume affect the Spillover Duration. The relationship between the measures and a market's turnover by volume is significantly negative. Thus, the Average Excess CoSP and Spillover Duration are larger for a smaller trading volume. There are two potential explanations for this effect: On the one hand, the stocks of institutions may be traded less if these institutions are more systemically risky. On the other hand, if stocks are traded less frequently, the systemic risk as measured by the Average Excess CoSP and Spillover Duration increases. It seems reasonable that both directions contribute to the overall effect.

These results are not in contrast to our previous results. In particular, the exposure of different markets in Regression 3 is still similar to the results in Section 4.3 and significant on the 1% level. Hence, the different vulnerability of markets does not only arise from different liquidities but also other market-specific factors. Moreover, in Regression 4 in Appendix D.3 we perform panel regressions of the Average Excess CoSP and Spillover Duration for different types of institutions and markets while controlling for liquidity and market capitalization. The ranking of subsectors and markets is very robust in comparison to the results from Section 4.3. Interestingly, the results show that the trading volume of single institutions within a certain subsector does not significantly change their systemic risk contribution.

In general, our results show that the illiquidity of institutions and markets is a important driver for systemic risk. However, the impact of illiquidity is not economically significant: A decrease in a market's turnover volume by 200 000 units (the largest observed differences between markets' turnover by volume is 174 720) would only be related to an increase by 0.98 percentage points and 3.5 days of the Average Excess CoSP and Spillover Duration, respectively. Thus, CoSP-based measures are not driven by illiquidity to a great extent.

4.5 Robustness towards Intra-Market Spillovers

In Section 3.2 we showed that CoSP is not affected by independent events that occur between institutions' and markets' distress. However, simultaneous market and institution distress at time 0 may have an effect on the market at time τ. In this section we examine, if our results are robust with respect to such intra-market spillovers. For this purpose, we employ the following Binomial Generalized Linear Model for a fixed market, institution, and time-lag:

$$f\left(\mathbb{P}(MD_{t+\tau})\right) = \beta_0 + \beta_1 ID_t + \beta_2 MD_t. \tag{8}$$

Since our previous results indicate an exponential shape of CoSP, we use a logit link-function. In the following we address the question, whether a single distress event of an institution still has a significant time-lagged impact on the financial market when controlling for the current state of the market. We assess the impact of the current market state on the significance of the institution's distress in the following way: Let $n_{1,i}$ and $n_{2,i}$ be the fraction of considered time-lags τ, at which β_1 and β_2 of institution i are significant differently from zero at the 10% level, respectively. Then,

$$L(\delta) = \frac{1}{n_{ssi}} \sum_{i=1}^{n_{ssi}} 1\{n_{2,i} - n_{1,i} < \delta\} \tag{9}$$

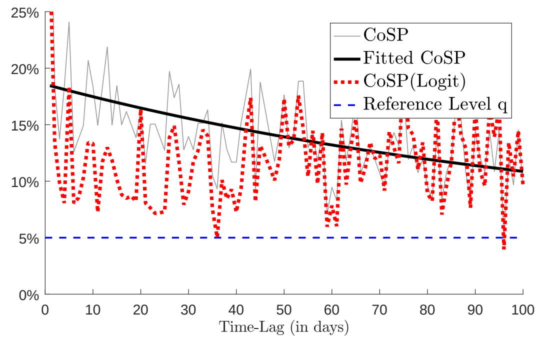
is the fraction of s.s.i. institutions, for which the difference between the fraction of time-lags that are significant for the institutions' distress and those that are significant for the market's current distress is less than δ. In other words, for $L(\delta) \cdot 100\%$ s.s.i. institutions there are at least $n_{2,i} - \delta$ time-lags, at which their distress if significant for the market. Thus, with a tolerance level of $\delta \cdot 100\%$ time-lags spillovers from these institutions are at least as intra-market spillovers. In Figure 9 we show $L(\delta)$ over time for $\delta = 20\%$ and $\delta = 10\%$ w.r.t. the financial market. Clearly, $L(0.2)$ is larger than 50% in most time periods. Therefore, for the major part of s.s.i. institutions, the time-lagged dependence between the institutions' and the financial market's distress is not purely caused by intra-market spillovers.

Figure 9: Fraction of s.s.i. institutions, for which there are at least $n_{2,i} - \delta$ time-lags, at which their distress is significant for the market.

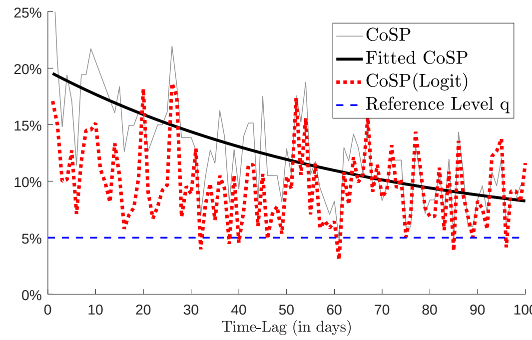
Moreover, as the examples in Figure 10 show, when controlling for the market's current state, the robust CoSP implied by the Generalized Linear Model in (8) does not substantially differ in its magnitude from the previous estimation. Interestingly, the robust CoSP is smaller than the original CoSP solely for time-lags smaller than 50 days, but almost identical for larger time-lags. Thus, the dependence between an institution's and market's distress at large time-lags seems to be solely driven by the institution, while for smaller time-lags also intra-market spillovers contributes to a positive dependence. A possible explanation may be that a market may generally be able to incorporate new information associated with general market distress faster than information associated with an institution's distress.

Finally, the level of intra-market dependence, i.e. between a market's distress at times t and $t+\tau$, i.e. MD_t and $MD_{t+\tau}$, is generally independent from the distress of a single institution.[17] Thus, intra-market dependence is a property associated with the market, i.e. is captured by market fixed effects. Thus, it does not affect our previous time-conditional and cross-sectional results.

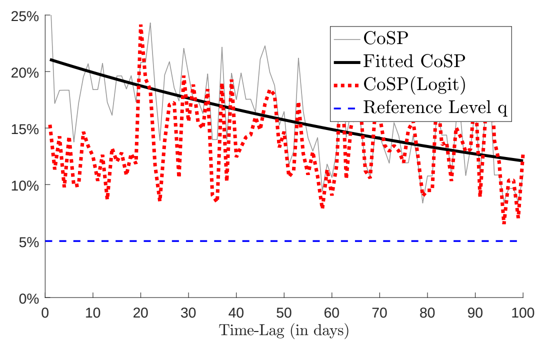
[17]Several panel regressions for β_2 with market, time, and institution fixed effects confirm this result.



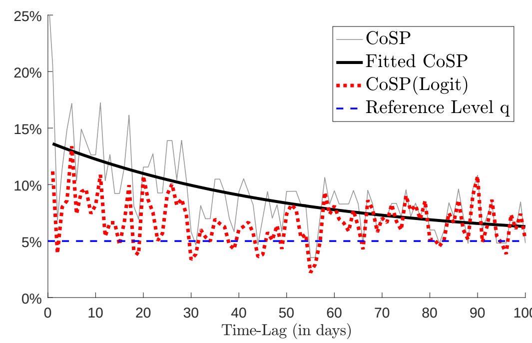
(a) JP Morgan Chase (BAN)



(b) Goldman Sachs (BRO)



(c) AIG (INS)



(d) Amazon.com (NoFIN)

Figure 10: CoSP and robust CoSP during 2002-2008 triggered by exemplary institutions w.r.t. the FIN index.

4.6 CoSP, CoVaR, MES, and Systematic Risk

In this section we assess the relationship between different measures of systemic and systematic risk. All systemic risk measures and Value-at-Risks are computed on a 5%-level. Firstly, in Regression 5 in Appendix D.3 we assess the differences in the level of $\Delta\text{CoVaR}^{\leq}$ with respect to different types of institutions, markets, and market capitalization. In contrast to the ranking of subsectors implied by the Average Excess CoSP, insurers are found to trigger the largest systemic risk. Also, according to $\Delta\text{CoVaR}^{\leq}$ non-financial companies trigger a significantly larger systemic risk than banks and real estate firms. This result is similar to Guntay and Kupiec (2014), who find that ΔCoVaR detects more non-financial than financial firms to be systemically relevant. However, the ranking of institutions implied by $\Delta\text{CoVaR}^{\leq}$ is very different to that implied by the Average Excess CoSP, which implies that non-financial companies trigger the smallest systemic risk (see Regression 2). In general, the latter seems to coincide more with economic intuition, since most large crises were associated with the distress of financial institutions, while the distress of non-financial companies was the result of the financial crises.

Table 2 reports the correlation between the Average Excess CoSP, Spillover Duration, $\Delta\text{CoVaR}^{\leq}$, Marginal Expected Shortfall, Value-at-Risk, and the β-factor based on all observations of s.s.i. institutions in all considered markets (BAN, BRO, INS, RE, FIN, AMC) and time periods.[18] In line with Benoit et al. (2013), we find that MES exhibits a correlation of almost 100% with systematic risk, as measured by β. Also, the correlation between $\Delta\text{CoVaR}^{\leq}$ and β is large (51%), which may result from the ΔCoVaR being dependent on a market's volatility (see Section 2.2). In contrast, both the Average Excess CoSP and Spillover Duration have a substantially smaller correlation with systematic risk, namely 26% and -4%, respectively. This result shows that - in contrast to $\Delta\text{CoVaR}^{\leq}$ and MES - CoSP-based measures are less driven by systematic risk, and may, therefore, be more suitable to distinguish between systematic and systemic risk.

	$\overline{\psi}$	$\overline{\tau}$	$-\Delta\text{CoVaR}^{\leq}$	$-MES$	$-VaR^M$	$-VaR^I$	β
$\overline{\psi}$	100%	75.6%	39.6%	33.7%	4.5%	19.9%	25.9%
$\overline{\tau}$		100%	12.7%	3.7%	17.7%	15.5%	-4%
$-\Delta\text{CoVaR}^{\leq}$			100%	55%	25.3%	-0.2%	50.8%
$-MES$				100%	11.9%	55%	95.5%
$-VaR^M$					100%	18.2%	-2.7%
$-VaR^I$						100%	44.2%
β							100%

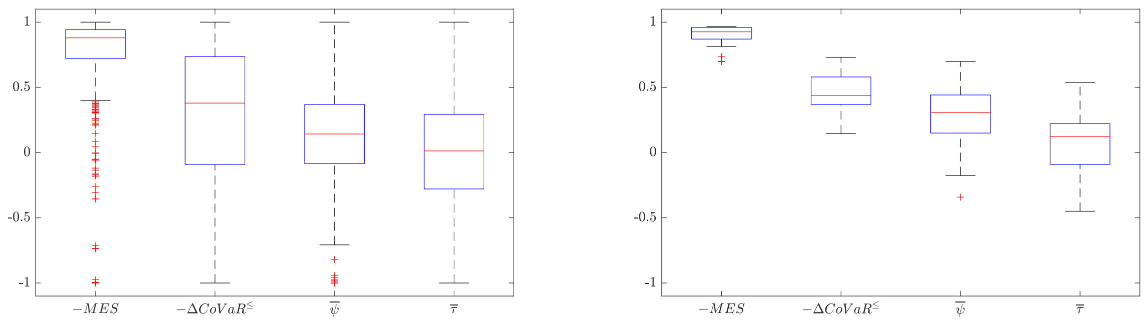
Table 2: Correlation coefficient between $\overline{\psi}$, $\overline{\tau}$, $-\Delta\text{CoVaR}^{\leq}$, $-MES$, $-VaR^M$, $-VaR^I$, and β based on all s.s.i. institutions.

These general findings do not change when distinguishing between the correlation over-time and cross-sectionally, i.e. the correlation for a single institution over time and the correlation between different institutions during a fixed time period, respectively. Figure 11 depicts the correlation of $-MES$, -$\Delta\text{CoVaR}^{\leq}$, $\overline{\psi}$, $\overline{\tau}$ with systematic risk, as given by β, over time and cross-sectionally for s.s.i. institutions.[19] In both cases, $-MES$ exhibits a significantly larger correlation with systematic risk than the other measures. While $-\Delta\text{CoVaR}^{\leq}$ has a smaller correlation, the correlation of $\overline{\psi}$

[18]Note, that $\Delta\text{CoVaR}^{\leq}$, MES and Value-at-Risks are inversely related to the risk they signal. Thus, we consider $-\Delta\text{CoVaR}^{\leq}$, $-MES$, and $-VaR$.

[19]The results are similar when considering all institutions in the sample, as shown in Figure 26 in Appendix E.3.

and $\overline{\tau}$ with systematic risk is still substantially smaller. Interestingly, for all systemic risk measures the cross-sectional correlation with β is larger than the correlation over time. This indicates, that systematic risk is better able to partly reflect rankings of systemic risk across institutions than to reflect the evolution of systemic risk over time.



(a) Correlation with β over time for each institution and market

(b) Cross-sectional correlation with β for each time period and market

Figure 11: Correlation coefficient between $-MES$, $-\Delta\text{CoVaR}^{\leq}$, $\overline{\psi}$, $\overline{\tau}$ and β, respectively, for s.s.i. institutions.

5 Conclusion

Since cash-flows and information may take time to spread within and across (financial) markets, systemic crises usually do not materialize instantaneously, but over time. Thus, systemic risk is not only the risk of simultaneous distress. It is also the risk of adverse systemic market (participants') reactions that occur with a time-lag subsequent to a distress event. With this in mind, the aim of our article is twofold: First, we address several shortcomings of common systemic risk measures, namely their large estimation error and correlation with systematic risk. For this purpose, we propose a new measure, the Conditional Shortfall Probability (CoSP), that exhibits a substantially smaller estimation error and correlation with systematic risk. Second, we employ the CoSP to measure the time-lagged dependence between the distress of institutions and markets. A large dependence indicates a contribution to systemic risk. In general, we find significant spillovers between institutions and markets at time-lags up to 50 days that are also robust to intra-market spillovers. Eventually, our article creates a broader basis for the understanding and measurement of systemic spillover risk.

In the empirical analysis we study all institutions with significant systemic spillover risk in the global banking, brokerage, insurance, and real estate subsectors, as well as the global financial market, and the American non-financial market. Hence, we are among the first to empirically compare the vulnerability of financial and non-financial markets. We classify an institution as significantly systemically important (s.s.i.) if its distress is significantly related to persistent market distress. This definition is an alternative to the methodology proposed by the Basel Committee on Banking Supervision (2013) and International Association of Insurance Supervisors (2016) to identify Systemically Important Financial Institutions (SIFIs). Our results are very much in line with the common perception of the systemic risk of different subsectors and the evolution of systemic crises. The number of significantly systemically important (s.s.i.) institutions, as implied by CoSP, shows that during the 2007-2008 financial crisis substantially more institutions are s.s.i. for the American real industry than in other years, both in absolute numbers and also relative to the financial sector. Moreover, we find a shift in the type of s.s.i. institutions: While prior to the year 2000 mainly non-financial companies are s.s.i., subsequent to 2000 and particularly during the 2007-2008 financial crisis mainly banks are s.s.i. for financial markets as well as the American real industry. In general, a larger market capitalization of an institution is related to an increase in its significant systemic importance. In particular, an increase in market capitalization by 200% increases the likelihood of being significantly systemically important by 5 percentage points. This is in line with the common understanding, that the size of an institution contributes to its systemic riskiness. Moreover, we find that less brokers than banks are significantly systemically important.

The Average Excess CoSP reflects the average level by which an institution's distress increases the likelihood of a market's distress. Thus, a large Average Excess CoSP indicates a large contribution of this institution to the systemic risk of the corresponding market. We find that brokers (i.e. non-depository credit institutions, investment banks, and security and commodity brokers) trigger the largest Average Excess CoSP, while the brokerage market is exposed to the smallest Average Excess CoSP. In contrast, insurance companies are exposed to the largest Average Excess CoSP, and trigger a smaller Average Excess CoSP than brokers. Non-financial companies trigger the smallest Average Excess CoSP, while the vulnerability of the American real industry towards systemic risk is similar to the vulnerability of the banking sector. The Spillover Duration indicates at what time horizon a market is affected by spillovers. The ranking of markets and institutions according to the Spillover Duration is very similar to that of Average Excess CoSP.

We compare our results with other measures of systemic and systematic risk. Interestingly, the dependence-consistent ΔCoVaR$^{\leq}$ of Ergün and Girardi (2013) and Mainik and Schaanning (2014) implies that non-financial companies trigger the largest and banks the smallest systemic risk. Guntay and Kupiec (2014) yield a similar result for ΔCoVaR developed by Adrian and Brunnermeier (2016). This result may partly be driven by a large correlation between ΔCoVaR$^{\leq}$ and systematic risk (approximately 51%). In contrast, the Average Excess CoSP and Spillover Duration exhibit a substantially smaller correlation with systematic risk (approximately 26% and -4%, respectively). Consequently, the CoSP-based measures are better able to distinguish between systemic and systematic risk than other systemic risk measures.

Several policy implications can be drawn from our study. Most importantly, we provide a very straightforward way to identify significantly systemically important institutions for a specific market. Our very robust ranking of the magnitude of systemic risk can be directly applied in macroprudential regulation by distinguishing between different types of institutions and financial subsectors. Finally, the Spillover Duration indicates that regulators may expect a significantly systemically important bank's distress to systemically impact the financial market on average for 28 days. However, this measure differs between different subsectors, being at largest 33 days for significantly systemically important brokers triggering systemic distress of insurers, and at smallest 22 days for significantly systemically important insurers triggering systemic distress of brokers. The Spillover Duration is also larger for larger institutions.

Our findings create a basis for further research in various forms. For example, preliminary results suggest that the Spillover Duration may serve as an early warning indicator in certain cases. Moreover, since our results differ from those implied by other systemic risk measures, different drivers for systemic risk may be identified. This would represent a way for regulators and managers to actively control and manage the systemic risk of institutions and markets. In this article we base the definition of a distress event on stock returns. Therefore, our results are crucially driven by the perception of market participants. Further works may apply other definitions of distress events, e.g. by employing balance sheet data. Due to the small reference level, it is necessary to base the estimation of CoSP on a large amount of data. Currently, the CoSP is computed with historical returns in rolling windows of 7 years. However, this limits the application to institutions that are not listed throughout the respective time period. Moreover, the dependence structure between institutions and the market may change during this period. Thus, the development of more sophisticated estimation approaches would contribute to the applicability of CoSP.

Appendix

A Properties of CoSP

The conditional shortfall probability (CoSP) is given as

$$\psi_\tau(q^M, q^I) = \mathbb{P}\left(r_\tau^M \leq VaR^M(q^M) \mid r^I \leq VaR^I(q^I)\right). \tag{10}$$

Thus, $\psi_\tau(q) = \psi_\tau(q, q)$ is very similar to the coefficient of lower tail dependence. In particular, the latter is the limit of $\psi_\tau(q)$ as q approaches 0, i.e.

$$\lambda_\tau = \lim_{q \to 0^+} \psi_\tau(q), \tag{11}$$

where λ_τ is the coefficient of lower tail dependence between r^I and r_τ^M (see McNeil et al. (2015, p.247)). CoSP for a time-lag $\tau = 0$ also resembles a property of the distributions' autocopula (see Rakonczai et al. (2012)).

A.1 Symmetry

In general, we have

$$\psi_\tau(q^M, q^I) = \mathbb{P}\left(MD_\tau \mid ID_0\right) = \mathbb{P}\left(r_\tau^M \leq VaR^M(q^M) \mid r^I \leq VaR^I(q^I)\right) \tag{12}$$

$$= \frac{\mathbb{P}\left(MD_\tau,\ ID_0\right)}{q^I} = \frac{q^M}{q^I}\mathbb{P}\left(ID_0 \mid MD_\tau\right). \tag{13}$$

Thus, $\psi_\tau(q^M, q^I)$ and $\mathbb{P}\left(ID_0 \mid MD_\tau\right)$ are proportional, whereas $\psi_\tau(q, q)$ is equal to $\mathbb{P}\left(ID_0 \mid MD_\tau\right)$. If $\tau > 0$, the latter probability, $\mathbb{P}\left(ID_0 \mid MD_\tau\right)$, cannot be interpreted in a causal sense, i.e. MD_τ can not have caused ID_0 since it happened later in time. Still, $\mathbb{P}\left(ID_0 \mid MD_\tau\right)$ is the likelihood that the institution exhibits an extraordinarily small return τ days before a systemic market event MD_τ. From this perspective, $\psi_\tau(q)$ may also be interpreted as the likelihood of a distress event of a specific institution τ days before a given systemic market event.

In contrast, the symmetry of $\psi_0(q)$ is very reasonable, since it is the result of co-movements between r^M and r^I. In other words, one can in general not identify a causal relationship between the events. This co-movement is also reflected in other systemic risk measures like MES or ΔCoVaR in the sense that these are proportional to the institution's firm-specific risk if the dependence between financial asset returns is linear.[20]

A.2 Third Causer

Between an institution's distress event $ID_0^{I_1}$ at time 0 and a market's distress event ME_τ at time τ there will typically occur other distress events of other institutions, that may also influence the market M. Therefore, it seems valid to question, if CoSP may (partly) be driven by the distress of a second institution I_2, that occurs between times 0 and τ.[21]

The following proposition shows, that in case the two institutions' distress is independent from each other, and the market's distress is not driven by I_1, CoSP correctly signals independence between the distress of I_1 and the market:

Proposition 1. *Let $ID_0^{I_1}$ and $ID_t^{I_2}$ be independent and $\mathbb{P}\left(MD_\tau \mid ID_0^{I_1}, ID_t^{I_2}\right) = \mathbb{P}\left(MD_\tau \mid ID_t^{I_2}\right)$. Then, $\mathbb{P}\left(MD_\tau \mid ID_0^{I_1}\right) = \mathbb{P}(MD_\tau)$.*

Proof.

$$
\begin{aligned}
\mathbb{P}\left(MD_\tau \mid ID_0^{I_1}\right) &= \mathbb{P}\left(MD_\tau, ID_t^{I_2} \mid ID_0^{I_1}\right) + \mathbb{P}\left(MD_\tau, \overline{ID_t^{I_2}} \mid ID_0^{I_1}\right) && (14)\\
&= \mathbb{P}\left(MD_\tau \mid ID_0^{I_1}, ID_t^{I_2}\right)\mathbb{P}\left(ID_t^{I_2} \mid ID_0^{I_1}\right) + \mathbb{P}\left(MD_\tau \mid ID_0^{I_1}, \overline{ID_t^{I_2}}\right)\mathbb{P}\left(\overline{ID_t^{I_2}} \mid ID_0^{I_1}\right) && (15)\\
&= \mathbb{P}\left(MD_\tau \mid ID_t^{I_2}\right)\mathbb{P}\left(ID_t^{I_2}\right) + \mathbb{P}\left(MD_\tau \mid \overline{ID_t^{I_2}}\right)\mathbb{P}\left(\overline{ID_t^{I_2}}\right) && (16)\\
&= \mathbb{P}\left(MD_\tau\right). && (17)
\end{aligned}
$$

□

If $ID_t^{I_2}$ is (partly) driven by and subsequent to $ID_0^{I_1}$, i.e. $t > 0$, we have $\mathbb{P}\left(ID_t^{I_2} \mid ID_0^{I_1}\right) > \mathbb{P}\left(ID_t^{I_2}\right)$. In this case, I_2 may serve as a channel between I_1 and the market. Consequently,

[20] This is a main finding of Benoit et al. (2013).
[21] Note that the following argument is also valid for other distress events of I_1.

CoSP may signal a positive dependence between $ID_0^{I_1}$ and MD_τ. If, however, $ID_0^{I_1}$ and $ID_t^{I_2}$ are dependent but occur simultaneously, i.e. $t = 0$, it is not possible to establish a direction of the spillovers.

A.3 Independence

By definition, the triggering event $ID_0 = \left\{r^I \leq VaR^I(q^I)\right\}$ and systemic event $MD_\tau = \left\{r_\tau^M \leq VaR^M(q^M)\right\}$ are stochastically independent if, and only if,

$$\mathbb{P}\left(MD_\tau,\ ID_0\right) = \mathbb{P}\left(MD_\tau\right)\ \mathbb{P}\left(ID_0\right), \tag{18}$$

which is equivalent to

$$\psi_\tau(q^M, q^I) = \frac{\mathbb{P}\left(MD_\tau,\ ID_0\right)}{\mathbb{P}\left(ID_0\right)} = \mathbb{P}\left(MD_\tau\right) = q^M. \tag{19}$$

In Figure 12 we show the estimate for CoSP with $q^M = q^I = q = 5\%$ for 1500 independent observations for r^M and r^I that were drawn from a student-t(5) distribution. Clearly, there exist numerous observations of events MD_τ and ID_0 for all lags τ. However, $\hat{\psi}_\tau$ fluctuates around the reference level q and is almost always below the confidence bound. In this case one would reason that r^I is not systemically important for r^M for any lag. This conclusion is also supported by the fitted CoSP, which stays constant at the reference level $q = 5\%$.

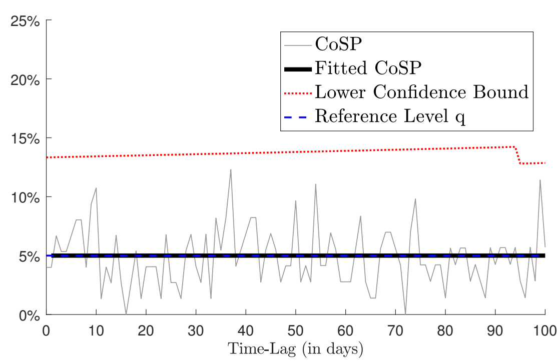


Figure 12: Estimated CoSP, $\hat{\psi}_\tau(0.05)$, for independent student-t(5) distributed returns.

A.4 Systemic Risk Rankings of CoSP and ΔCoVaR

$\text{CoVaR}_E(q)$ is defined as the Value-at-Risk (VaR) of the conditional distribution of the market return r^M, i.e.

$$\mathbb{P}\left(r^M \leq \text{CoVaR}_E(q) \mid E\right) = q. \tag{20}$$

Then, ΔCoVaR is the difference between the market's CoVaR conditional on a triggering event ID_0 and a benchmark event BM^I, i.e.

$$\Delta\text{CoVaR} = \text{CoVaR}_{ID_0}(q) - \text{CoVaR}_{BM^I}(q). \tag{21}$$

? define the triggering event as the institution's return being at the $VaR(q)$, i.e. $ID_0 = \left\{r^I = VaR^I(q)\right\}$, and the benchmark event as the institution's return being at the median state, i.e. $BM^I = \left\{r^I = VaR^I(0.5)\right\}$, which yields

$$\Delta\text{CoVaR}^{=}(q) = \text{CoVaR}_{r^I=VaR^I(q)}(q) - \text{CoVaR}_{r^I=VaR^I(0.5)}(q). \tag{22}$$

To also incorporate more severe losses than $VaR^I(q)$, Ergün and Girardi (2013) propose

$$\Delta\text{CoVaR}^{\leq}(q) = \text{CoVaR}_{r^I\leq VaR^I(q)}(q) - \text{CoVaR}_{r^I\in[\mu^I\pm\sigma^I]}(q), \tag{23}$$

where μ^I and σ^I are the mean and standard deviation for the return of the institution, respectively. The change in the triggering event definition from being exactly at the VaR to being at or below the VaR also effects the consistency of CoVaR: Mainik and Schaanning (2014) show that $\text{CoVaR}_{r^I\leq VaR^I(q)}(q)$ is a continuous and increasing function of the dependence parameter between r^I and r^M, while $\text{CoVaR}_{r^I=VaR^I(q)}(q)$ is not.

In the following we examine the relationship between two different returns r^{I_1} and r^{I_2} and a market return r^M. For simplicity, we focus on the case with $q^M = q^I = q$. Under the assumption that $r^M_\tau \mid r^{I_1} \leq VaR^{I_1}(q)$ first-order stochastically dominates $r^M_\tau \mid r^{I_2} \leq VaR^{I_2}(q)$, i.e. for all

$x \in \mathbb{R}$

$$\mathbb{P}\left(r_\tau^M \leq x \mid r^{I_1} \leq VaR^{I_1}(q)\right) \;\leq\; \mathbb{P}\left(r_\tau^M \leq x \mid r^{I_2} \leq VaR^{I_2}(q)\right), \tag{24}$$

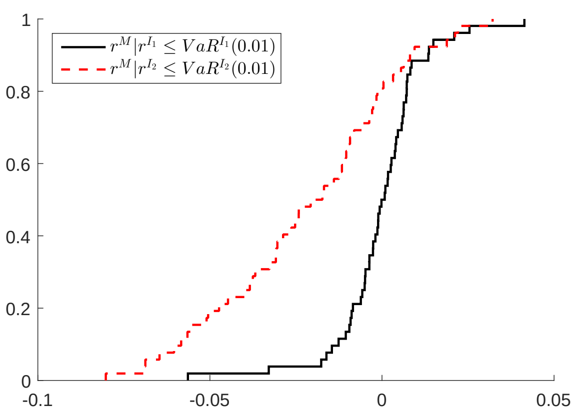
we have $\psi_\tau^{I_1}(q) \leq \psi_\tau^{I_2}(q)$. Moreover, for CoVaR^τ we have

$$\mathrm{CoVaR}^\tau_{r^{I_1} \leq VaR^{I_1}(q)}(q) \;\geq\; \mathrm{CoVaR}^\tau_{r^{I_2} \leq VaR^{I_2}(q)}(q). \tag{25}$$

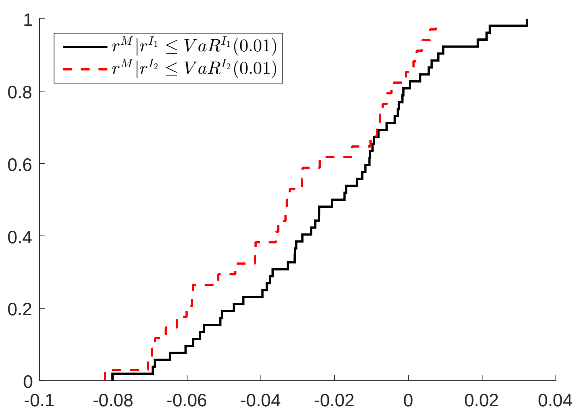
Hence, with respect to both risk measures I_2 is more systemically important than I_1. Also, if the market risk conditional on the benchmark events is approximately equal, i.e. $\mathrm{CoVaR}^\tau_{BM^{I_1}}(q) \approx \mathrm{CoVaR}^\tau_{BM^{I_2}}(q)$, for $\Delta\mathrm{CoVaR}^{\leq}_\tau$ we have

$$\Delta\mathrm{CoVaR}^{\leq, I_1}_\tau(q) \;\geq\; \Delta\mathrm{CoVaR}^{\leq, I_2}_\tau(q). \tag{26}$$

The condition that $r_\tau^M \mid r^{I_1} \leq VaR^{I_1}(q)$ first-order stochastically dominates $r_\tau^M \mid r^{I_2} \leq VaR^{I_2}(q)$ can often be observed for financial return series. In Figure 13 we show two exemplary empirical cumulative density functions (ecdf) for lag $\tau = 0$ for the unconditional and conditional returns of the financial index. Particularly in the lower tail $r^M | r^{I_1} \leq VaR^{I_1}(0.01)$ stochastically dominates $r^M | r^{I_2} \leq VaR^{I_2}(0.01)$.[22]



(a) I_1 is Bank of Greece and I_2 is AIG



(b) I_1 is AIG and I_2 is CME Group

Figure 13: Empirical CDF of returns from the financial index conditional on institutions' financial distress.

[22] Note that stochastic dominance in the lower tail is sufficient to obtain the same ranking of the institutions.

B Estimation Procedure

B.1 Estimation of CoSP

An estimator for ψ_τ is given as

$$\hat{\psi}_\tau = \frac{1}{q(n-\tau)} \sum_{t=1}^{n-\tau} \mathbb{1}_{\left\{r_t^I \leq \widehat{VaR}^I(q^I),\, r_{t+\tau}^M \leq \widehat{VaR}^M(q^M)\right\}}, \tag{27}$$

where the Value-at-Risk estimate is the $[nq^x]$-th smallest observation for return r^x, $\widehat{VaR}^x(q^x) = r^x_{([q^x n])}$. To estimate $\psi_\tau(q^M, q^I)$ we employ historical simulation (HS).[23] The use of this simplified approach is particularly motivated by the fact that, as to our knowledge, this is the first study about the interdependence of lagged tail returns. Thus, it seems unreasonable to impose distributional or modeling assumptions.[24] Additionally, it seems intuitive that systemic market events mostly occur in times with large volatility. In other words, the maximum return level that corresponds to systemic market distress, $VaR^M(q^M)$, should not depend on the current volatility level but on the (time-)unconditional volatility. Therefore, we employ the (time-)unconditional Value-at-Risk in one time period.

To smooth the estimation error of $\hat{\psi}_\tau$, we employ a Generalized Linear Model (GLM; see Nelder and Wedderburn (1972)). To this end, we assume that $\psi_\tau(q)$ has the following form for $\tau = 1, 2, ...$:

$$\psi_\tau^{\mathrm{GLM}}(q^M, q^I) = d + e^{b\tau + c}. \tag{28}$$

In other words, we assume that ψ_τ declines exponentially, which we also find confirmed in the empirical analysis. We do not assume this form for co-movements at the time-lag $\tau = 0$ in the fitting procedure, since these do not reflect persistence and, particularly, do not steadily continue ψ_τ, as the results in Section 4 suggest.

[23]There exist several studies discussing and improving the statistical properties of HS and other estimation approaches for time series of returns, for example Danielsson and Zhou (2015), Hendricks (1996), Hull and White (1998), Kuester et al. (2006) or Pritsker (2001). However, these focus on quantile or moment estimation and do not consider a time-lag and, thus, cannot be applied for the estimation of CoSP.

[24]Note, that by employing HS we do not need to assume that the full bivariate return distribution is stationary. In contrast, it is sufficient to assume that solely the dependence between lagged tail returns is stationary.

In order to compute the Average Excess CoSP and spillover duration, we are only interested in values of $\psi_\tau(q^M, q^I) > q^M$. Therefore, we assume that $d \equiv q^M$. In this case $\psi_\tau^{\text{GLM}}(q^M, q^I)$ equals the reference level q^M if $\hat{\psi}_\tau(q^M, q^I) \leq q^M$ for many lags τ, which indicates that the systemic spillover risk is zero for the corresponding time-lags.

We compute the Maximum-Likelihood estimate for $\psi_\tau^{\text{GLM}}(q^M, q^I)$ under the assumption that $\mathbb{1}_{\left\{r^M_{t+\tau} \leq VaR^M(q^M),\, r^I_t \leq VaR^I(q^I)\right\}}$ are iid for $t = 1, .., n_\tau$. Then, it follows

$$Y_\tau := \sum_{t=1}^{n_\tau} \mathbb{1}_{\left\{r^M_{t+\tau} \leq \widehat{VaR}^M(q^M),\, r^I_t \leq \widehat{VaR}^I(q^I)\right\}} \sim Bin\left(n_\tau, \psi_\tau q^I\right), \tag{29}$$

where $Bin(n, p)$ is the Binomial distribution. Moreover, we assume that $Y_1, Y_2, ...$ are independently distributed. Then, the log-likelihood function for $y_1, y_2, ...$ is given by

$$\mathcal{L} = \sum_{\tau=1}^{\tau^{max}} \log \binom{n-\tau}{y_\tau} + y_\tau \log\left(q^I \psi_\tau^{\text{GLM}}\right) + (n - \tau - y_\tau) \log\left(1 - q^I \psi_\tau^{\text{GLM}}\right) \tag{30}$$

and the score functions as

$$\frac{\partial \mathcal{L}}{\partial b} = \sum_{\tau=1}^{\tau^{max}} \frac{\tau y_\tau}{q^I + e^{b\tau+c}} e^{b\tau+c} - q^I \frac{\tau(n - \tau - y_\tau)}{q^I + e^{b\tau+c}} e^{b\tau+c} \overset{!}{=} 0, \tag{31}$$

$$\frac{\partial \mathcal{L}}{\partial c} = \sum_{\tau=1}^{\tau^{max}} \frac{y_\tau}{q^I + e^{b\tau+c}} e^{b\tau+c} - q^I \frac{n - \tau - y_\tau}{q^I + e^{b\tau+c}} e^{b\tau+c} \overset{!}{=} 0. \tag{32}$$

Finally, b and c are estimated by numerically solving equations (31) and (32).

B.2 Lower Bound of Significance for $\hat{\psi}_\tau$

Denote by $n_\tau = n - \tau$ the number of available observations for lag τ. As before, we assume that $\mathbb{1}_{\left\{r^M_{t+\tau} \leq VaR^M(q^M),\, r^I_t \leq VaR^I(q^I)\right\}}$ are iid for $t = 1, .., n_\tau$, thus,

$$Y_\tau = \sum_{t=1}^{n_\tau} \mathbb{1}_{\left\{r^M_{t+\tau} \leq \widehat{VaR}^M(q^M),\, r^I_t \leq \widehat{VaR}^I(q^I)\right\}} \sim Bin(n_\tau, \psi_\tau q^I), \tag{33}$$

where $Bin(n,p)$ is the Binomial distribution. Hence, under the null hypothesis $H_0 : \psi_\tau = q^M$, i.e. that systemic event MD_τ and triggering event ID_0 are independent, we have

$$n_\tau q^I \hat{\psi}_\tau \sim Bin(n_\tau, q^M q^I). \tag{34}$$

The null hypothesis if $\hat{\psi}_\tau \geq k^*_\tau$ is rejected with a significance level of $\alpha \in (0,1)$. Thus, a lower bound for the rejection area, k^*_τ, can be computed as follows:

$$\begin{aligned}
\alpha &= \mathbb{P}_{H_0}\left(\hat{\psi}_\tau \geq k^*_\tau\right) = \mathbb{P}_{H_0}\left(Y_\tau \geq n_\tau q^I k^*_\tau\right) && (35)\\
&= 1 - F_{Bin(n_\tau, q^M q^I)}(n_\tau q^I k^*_\tau - 1) && (36)\\
\Leftrightarrow \quad 1-\alpha &= F_{Bin(n_\tau, q^M q^I)}(n_\tau q^I k^*_\tau - 1) && (37)\\
\Leftrightarrow \quad n_\tau q^I k^*_\tau - 1 &= F^{-1}_{Bin(n_\tau, q^M q^I)}(1-\alpha) && (38)\\
\Leftrightarrow \quad k^*_\tau &= \frac{1}{n_\tau q^I}\left(F^{-1}_{Bin(n_\tau, q^M q^I)}(1-\alpha) + 1\right), && (39)
\end{aligned}$$

where $F^{-1}_{Bin(n_\tau, q^M q^I)}$ is the (lower) inverse cumulative distribution of the Binomial distribution.

By accounting for estimation errors, we employ the smoothed CoSP, ψ^{GLM}_τ, instead of $\hat{\psi}_\tau$ to assess the significance of systemic importance. Therefore, an institution is classified as significantly systemically important if $\psi^{\text{GLM}}_\tau \geq k^*_\tau$ for at least one time-lag $\tau > 0$. We do not consider co-movements at $\tau = 0$, since these are solely due to comovement. In contrast, for non-zero time-lags triggering events cannot be caused by systemic events.

B.3 Estimation of the Average Excess CoSP

To account for estimation errors, we employ the fitted CoSP ψ^{GLM}_τ (as described in Section B.1) for lags $\tau \geq 1$ to estimate the Average Excess CoSP. For the CoSP at lag $\tau = 0$ we include $\hat{\psi}_0$. Then, the estimator for the Average Excess CoSP is given as

$$\bar{\psi}_0 = \frac{1}{\tau^{\max}}\left(\hat{\psi}_0(q^M, q^I) - q^M + \int_1^{\tau^{\max}} \psi^{\text{GLM}}_\tau - q^M \, d\tau\right). \tag{40}$$

Firstly, note that

$$\int \psi_\tau^{\mathrm{GLM}} - q^M \, d\tau = \int e^{b\tau+c} \, d\tau = \frac{1}{b} e^{b\tau+c}, \tag{41}$$

thus, if $b < 0$,

$$\int_1^{\tau^{\max}} e^{b\tau+c} \, d\tau = \frac{1}{b} \left(e^{b\tau^{\max}+c} - e^{b+c} \right) \tag{42}$$

and

$$\overline{\psi} = \frac{1}{\tau^{\max}} \left(\hat{\psi}_0(q^M, q^I) - q^M + \frac{1}{b} \left(e^{b\tau^{\max}+c} - e^{b+c} \right) \right). \tag{43}$$

B.4 Estimation of the Spillover Duration

To account for estimation errors, we employ the fitted CoSP ψ_τ^{GLM} (as described in Section B.1) for lags $\tau \geq 1$ to estimate the spillover duration. Then, the estimator for the spillover duration is given as

$$\bar{\tau} = \frac{1}{\bar{\psi} \tau^{\max}} \int_1^{\tau^{\max}} \tau \, (\psi_\tau^{\mathrm{GLM}} - q^M) \, d\tau. \tag{44}$$

Firstly, note that

$$\int \tau (\psi_\tau^{\mathrm{GLM}} - q^M) \, d\tau = \int \tau e^{b\tau+c} \, d\tau = \left(\frac{\tau}{b} - \frac{1}{b^2} \right) e^{b\tau+c}, \tag{45}$$

thus,

$$\overline{\tau} = \frac{1}{\bar{\psi} \tau^{\max}} \int_1^{\tau^{\max}} \tau e^{b\tau+c} d\tau \tag{46}$$

$$= \frac{1}{\bar{\psi} \tau^{\max}} \left(\left(\frac{\tau^{\max}}{b} - \frac{1}{b^2} \right) e^{b\tau^{\max}+c} - \left(\frac{1}{b} - \frac{1}{b^2} \right) e^{b+c} \right). \tag{47}$$

C Standard Errors and Reliability of ΔCoVaR and CoSP

In this section we examine the standard errors and reliability of HS estimators for $\Delta\text{CoVaR}^{\leq}$ and ψ_τ. For simplicity, we focus on lag $\tau = 0$ (i.e. co-movements), since the computation and results for all other lags are equivalent. As in the empirical analysis in Section 4, the VaR-level is set to 5% for both measures.

C.1 Standard Errors

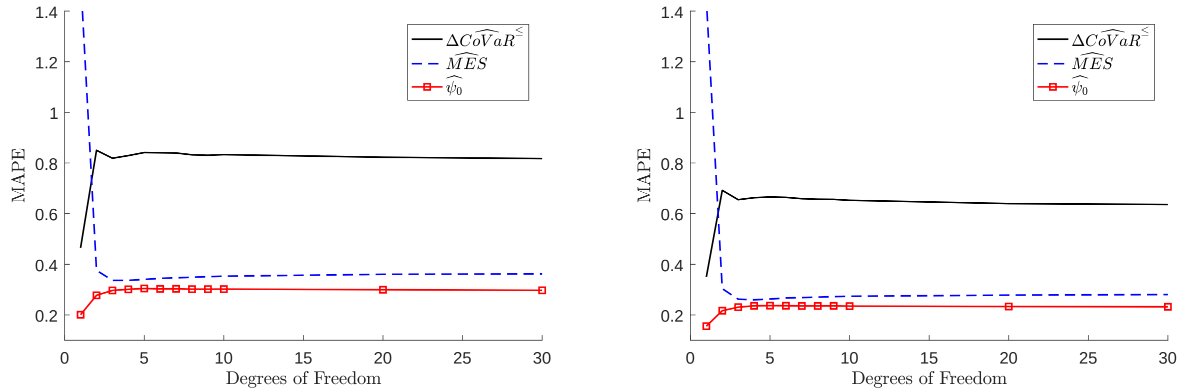
Firstly, we perform a Monte-Carlo analysis in two steps: In the first step, we study the mean absolute percentage errors (MAPE) of the risk measures for returns that are student t-distributed. To this end, we estimate the covariance matrix of the firm's and financial index' returns from our data sample by means of the method of moments (see Section D.2).[25] We draw samples from the student-distribution by employing the Cholesky composition of the resulting covariance matrix. The number of samples per iteration of the Monte-Carlo algorithm is set to $n = 1500$, but we also study the standard error for a larger sample size $n = 2500$. For N realizations (Monte-Carlo iterations) of the estimator ϑ the mean absolute percentage error (MAPE) of the estimator is given as (for example see Tsay (2010, p.217))

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{\hat{\vartheta}_i^{(n)} - \bar{\vartheta}^{(n)}}{\bar{\vartheta}^{(n)}} \right|, \tag{48}$$

where $\hat{\vartheta}_i^{(n)}$ is the i-th realization of the estimator (either $\widehat{\Delta\text{CoVaR}}^{\leq}$ or $\hat{\psi}_0$) and $\bar{\vartheta}^{(n)}$ the average realized value of the estimator. The MAPE can be interpreted as the average absolute deviation relative to the true value of ϑ. Since the latter is not known, we approximate this true value by $\bar{\vartheta}^{(n)}$.

We show the resulting MAPE for different degrees of freedom (which inversely correspond to the tail size of the distribution) in Figure 14. Clearly, the MAPE of $\hat{\psi}$ is substantially smaller than the MAPE of $\widehat{\Delta\text{CoVaR}}^{\leq}$. Interestingly, for very small degrees of freedom (i.e. a very heavy tail) the estimation error for $\widehat{\Delta\text{CoVaR}}^{\leq}$ is particularly large and decreases with increasing degrees of freedom, while the estimation error for $\hat{\psi}_0$ does not substantially change with the degrees of freedom.

[25] This results in the following estimates: $\sqrt{\text{var}(r^I)} = 0.0199$, $\sqrt{\text{var}(r^M)} = 0.0098$ and the correlation to 0.25.



(a) Sample size: 1500

(b) Sample size: 2500

Figure 14: MAPE of $\Delta\widehat{\text{CoVaR}}^{\leq}$ and $\hat{\psi}_0$ for student-distributed returns.

Since stock returns are not necessarily student-t distributed, we also apply a nonparametric bootstrap algorithm to draw samples from the historical returns of exemplary institutions and the financial index. As before, the sample size in each bootstrap step is set to $n = 1500$ and we take $N = 100000$ bootstrap samples. In Table 3 we show the resulting MAPE for $\Delta\widehat{\text{CoVaR}}^{\leq}$, $\widehat{\text{CoVaR}}_{r^I \leq VaR(0.05)}$, $\widehat{\text{CoVaR}}_{r^I \in [\mu^I \pm \sigma^I]}$ and $\hat{\psi}_0$. Clearly, the estimation error of $\hat{\psi}_0$ is substantially smaller for all considered institutions. Moreover, $\widehat{\text{CoVaR}}_{r^I \leq VaR(0.05)}$ has an enormously large estimation error: For some institutions the mean absolute error is 100 times as large as the mean value of the systemic risk measure. This result highly questions the use of $\widehat{\text{CoVaR}}_{r^I \leq VaR(0.05)}$ and, thus, is in line with the findings of Castro and Ferrari (2012), Danielsson et al. (2016) and Guntay and Kupiec (2014). Also, the estimation error of $\widehat{MES}$ is larger than that of CoSP for most institutions.

C.2 Reliability

In this section we compare the reliability of $\Delta\widehat{\text{CoVaR}}^{\leq}$, $\widehat{MES}$, and $\widehat{\psi}_0$. For this purpose we employ the framework proposed by Danielsson et al. (2016). In this framework an institution is classified as causing systemic risk if its probability to be among the most risky institutions is larger than 90% according to a given systemic risk measure. Then, the reliability of this risk measure is given as the fraction of institutions identified as *guilty* among all most risky institutions. More

	$\widehat{MES}$	$\Delta\widehat{\text{CoVaR}}^{\leq}$	$\widehat{\text{CoVaR}}_{r^I \leq VaR(0.05)}$	$\widehat{\text{CoVaR}}_{r^I \in [\mu^I \pm \sigma^I]}$	$\hat{\psi}_0$
ALLIANZ	0.095	0.177	0.138	0.050	0.093
AMAZON.COM	0.172	0.267	0.164	0.045	0.176
AMERICAN INTL.GP.	0.193	0.225	0.162	0.041	0.112
APPLE	0.213	0.243	0.172	0.043	0.138
AXA	0.096	0.172	0.131	0.053	0.092
BANK OF AMERICA	0.148	0.221	0.162	0.042	0.108
BLACKROCK	0.129	0.231	0.165	0.047	0.127
BP	0.155	0.233	0.167	0.042	0.137
CHARLES SCHWAB	0.112	0.197	0.146	0.045	0.124
CITIGROUP	0.133	0.183	0.140	0.051	0.095
CME GROUP	0.153	0.135	0.102	0.037	0.115
COCA COLA	0.240	0.236	0.166	0.039	0.152
DEUTSCHE BANK	0.091	0.159	0.124	0.048	0.081
GENERAL ELECTRIC	0.131	0.200	0.149	0.045	0.111
GOLDMAN SACHS GP.	0.107	0.148	0.111	0.035	0.097
JP MORGAN CHASE & CO.	0.132	0.200	0.151	0.051	0.102
MORGAN STANLEY	0.114	0.158	0.120	0.048	0.088
WELLS FARGO & CO	0.157	0.230	0.166	0.041	0.121
ZURICH INSURANCE GROUP	0.108	0.173	0.131	0.047	0.098

Table 3: MAPE of $\widehat{MES}$, $\Delta\widehat{\text{CoVaR}}^{\leq}$, $\widehat{\text{CoVaR}}_{r^I \leq VaR(0.05)}$, $\widehat{\text{CoVaR}}_{r^I \in [\mu^I \pm \sigma^I]}$ and $\hat{\psi}_0$ based on bootstrap samples of size $n = 1500$ for exemplary institutions.

specifically, in the baseline calibration 10% of the institutions are assumed to be *most risky*. Thus, the reliability is given as the fraction of institutions identified to be among the most 10% risky institutions with a probability larger than 90%. For a motivation for this framework and details regarding the computational implementation we refer to Danielsson et al. (2016).

To compare the reliability of $\Delta\widehat{\text{CoVaR}}^{\leq}$, $\widehat{MES}$, and CoSP we mainly follow the calibration of Danielsson et al. (2016): The reliability is computed for returns in rolling windows of 5 years, for each window we only consider the 200 firms with the highest market capitalization at the end of the time window, and 10% of the institutions are assumed to be *guilty*. In contrast to Danielsson et al. (2016), we use a simple non-parametric bootstrap with 100000 iterations and blocks with a sample size of 1500 observations. The resulting reliability of the risk measures is shown in Figure 15. Clearly, CoSP is substantially more reliable than $\Delta\widehat{\text{CoVaR}}^{\leq}$. Moreover, subsequent to 1998 CoSP is also at least as reliable as MES in most years and particularly during crises.

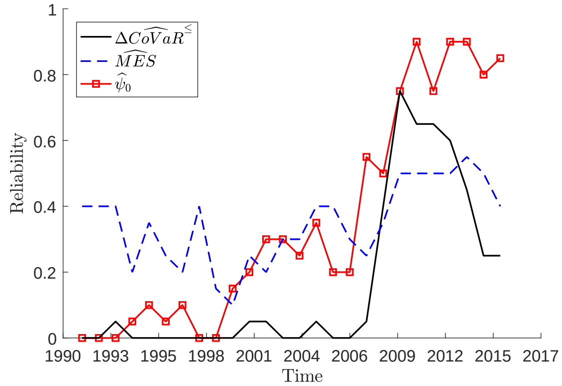


Figure 15: Reliability of $\hat{\psi}_0$, $\widehat{MES}$, and $\Delta\widehat{\text{CoVaR}}^{\leq}$ for a sample size of 1500 observations. The dates correspond to the last year in the respective time period that the estimates are based on.

D Data and Methodology

D.1 Market Indices

To account for endogeneity of publicly available market indices, i.e. the issue that institutions may already be incorporated in the index, we compute own market indices similarly to Chan-Lau (2010). To this end, we denote by $MC_t^{(i)}$ the market capitalization of institution i at time t, i.e. $MC_t^{(i)} = P_t^{(i)} \cdot Shares_t^{(i)}$, where $P_t^{(i)}$ is the stock price and $Shares_t^{(i)}$ the number of shares at time t. Moreover, by $TR_t^{(i)}$ we denote the total (dividend-adjusted) return index of institution i.[26] A market is denoted by a subset $\mathbb{S} \subseteq \{1, ..., M\}$, i.e. the institutions that are included in the market. Then, the index for market $\mathbb{S}$ excluding institution j is given as the weighted average of the total return indices:

$$INDEX_t^{\mathbb{S}|j} = INDEX_{t-1}^{\mathbb{S}|j} \sum_{s \in \mathbb{S} \setminus \{j\}} \frac{MC_{t-1}^{(s)}}{\sum_{s \in \mathbb{S} \setminus \{j\}} MC_{t-1}^{(s)}} \frac{TR_t^{(s)}}{TR_{t-1}^{(s)}}. \tag{49}$$

To adjust for different currencies, we calculate the market capitalization in US dollar. Therefore, the time t price of institution s is given by

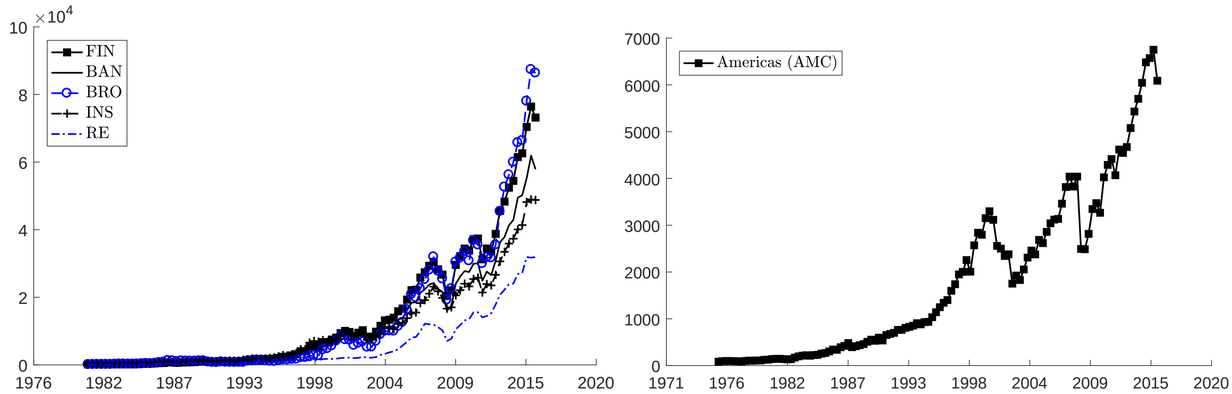
$$P_t^{(s)} = \tilde{P}_t^{(s)} / ER_t^{(s)}, \tag{50}$$

[26] The total return index reflects the evolution of the stock price assuming that dividends are re-invested to purchase additional units of equity.

where $\tilde{P}_t^{(s)}$ is the time t price in currency $\tilde{C}$ and $ER_t^{(s)}$ is the exchange rate from currency $\tilde{C}$ to US Dollar at time t. Finally, the market return is computed as

$$r_t^M = r_t^{\mathbb{S}|j} = \log\left(\frac{INDEX_t^{\mathbb{S}|j}}{INDEX_{t-1}^{\mathbb{S}|j}}\right). \tag{51}$$

D.2 Data and Descriptive Statistics

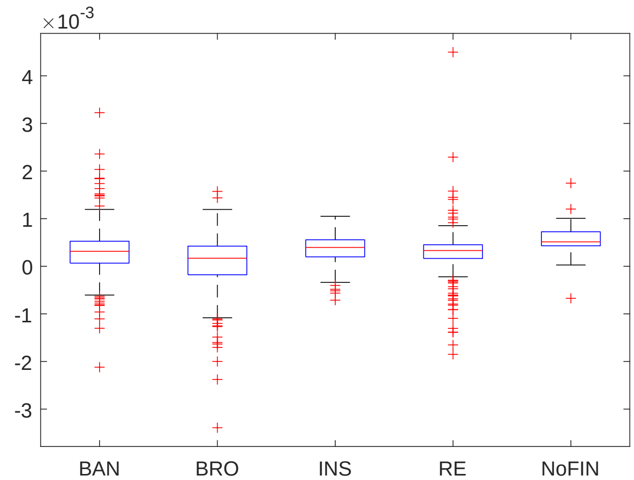


(a) Financial indices. (b) Non-financial index.

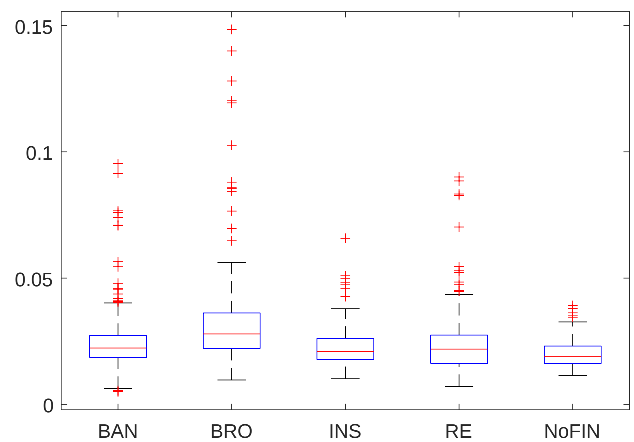
Figure 16: Financial and non-financial indices.

Banks	**Brokers**	**Insurers**	**Real Estate Firms**	**Non-Financial Companies**
WELLS FARGO & CO	BLACKROCK	BERKSHIRE HATHAWAY 'A'	BROOKFIELD ASSET MAN.'A' LTD.VTG.SHRE.	MICROSOFT
INDL.& COML.BK.OF CHINA 'H'	CHARLES SCHWAB	BERKSHIRE HATHAWAY 'B'	MITSUBISHI ESTATE	APPLE
JP MORGAN CHASE & CO.	INTERCONTINENTAL EX.	CHINA LIFE INSURANCE 'H'	UNIBAIL-RODAMCO	AMAZON.COM
CHINA CON.BANK 'H'	HONG KONG EXS.& CLEAR.	PING AN INSURANCE 'H'	MITSUI FUDOSAN	JOHNSON & JOHNSON
BANK OF CHINA 'H'	HOUSING DEVELOPMENT FIN.	ALLIANZ	WHARF HOLDINGS	PETROCHINA 'A'
BANK OF AMERICA	ORIX	AMERICAN INTL.GP.	HONG KONG LAND HDG.	ROCHE HOLDING
HSBC HOLDINGS	TD AMERITRADE HOLDING	AXA	WESTFIELD	CHINA MOBILE
CITIGROUP	MACQUARIE GROUP	METLIFE	SUMITOMO REAL.&DEV.	NESTLE 'R'
COMMONWEALTH BK.OF AUS.	NOMURA HDG.	CHINA PAC.IN.(GROUP) 'H'	KLEPIERRE	AT&T
ROYAL BANK OF CANADA	DAIWA SECURITIES GROUP	ZURICH INSURANCE GROUP	SM PRIME HOLDINGS	NOVARTIS 'R'
MERCANTIL SERVICIOS FINANCIEROS CA 'A'	NASDAQ	TRAVELERS COS.	LINK RL.EST.INV.TST.	ANHEUSER-BUSCH INBEV
MERCANTIL SERVICIOS FINANCIEROS CA 'B'	SEI INVESTMENTS	SWISS RE	EZDAN REAL ESTATE	PFIZER
TORONTO-DOMINION BANK	JAPAN EXCHANGE GROUP	MUENCHENER RUCK.	CBRE GROUP CLASS A	WAL MART STORES
US BANCORP	RAYMOND JAMES FINL.	MANULIFE FINANCIAL	EMAAR PROPERTIES	VERIZON COMMUNICATIONS
BANK OF COMMS.'H'	CIT GROUP	PICC PROPERTY & CLTY.'H'	DAITO TST.CONSTRUCTION	TENCENT HOLDINGS
UBS GROUP	ACOM	ASSICURAZIONI GENERALI	AYALA LAND	CHEVRON
BCO PROVINCIAL	INVESTEC	SAMPO 'A'	HANG LUNG PROPERTIES	WALT DISNEY
BANCO SANTANDER	ASX	TOKIO MARINE HOLDINGS	GOODMAN GROUP	HOME DEPOT
BNP PARIBAS	SINGAPORE EXCHANGE	AFLAC	DEUTSCHE WOHNEN BR.SHS.	INTEL
CHINA MERCHANTS BANK 'H'	BAJAJ FINANCE	GREAT WEST LIFECO	WHEELOCK AND CO.	TOYOTA MOTOR

Table 4: Names of the twenty largest institutions (by median market capitalization in 2015) in each subsector.



(a) Empirical mean return for different subsectors



(b) Empirical standard deviation for different subsectors

Figure 17: Distribution of mean and standard deviation of individual institutions' returns over the full data sample.

D.3 Regressions

Regression 1. *We regress the property of being significantly systemically important (s.s.i.) at the 1% level of all institutions in the subsectors BAN, BRO, INS, RE, and NoFIN w.r.t. the BAN, BRO, INS, RE, FIN, and American non-financial market based on the following model:*

$$f\left(\mathbb{P}\left[ssi_{t,market,institution}\right]\right) = \beta_0 + \beta_{subsector} + \beta_{market} + \beta_{MC} ln\left(MC_{institution,t}\right) + \beta_t, \qquad (52)$$

where $MC_{institution,t}$ is the median market capitalization (in Mio USD) of an institution in time period t. Model (1) is a Linear Model, where f is the identity. Model (2) is a Binomial Generalized

Linear Model logit link-function $f = log$. Model (3) is a Binomial Generalized Linear Model with probit link-function $f = log$. In the reference setting the subsector is the banking sector (BAN) w.r.t. banking market (BAN).

Significant Systemical Importance		Linear Model	GLM 1	GLM 2
		(1)	(2)	(3)
Intercept		0.108***	−1.656***	−2.966***
		(0.004)	(0.026)	(0.047)
Subsector	BRO	0.039***	0.206***	0.34***
		(0.003)	(0.019)	(0.034)
	INS	0.079***	0.483***	0.901***
		(0.003)	(0.016)	(0.028)
	RE	0.054***	0.461***	0.864***
		(0.002)	(0.016)	(0.028)
	NoFIN	0.022***	−0.124***	−0.212***
		(0.003)	(0.019)	(0.035)
Market	BRO	−0.047***	−0.36***	−0.601***
		(0.003)	(0.019)	(0.033)
	INS	−0.031***	−0.214***	−0.378***
		(0.003)	(0.018)	(0.033)
	RE	−0.012***	−0.092***	−0.144***
		(0.003)	(0.018)	(0.032)
	FIN	−0.006**	−0.047***	−0.075**
		(0.003)	(0.018)	(0.032)
	AMC	−0.042***	−0.313***	−0.526***
		(0.003)	(0.018)	(0.033)
MarketCap		0.056***	0.428***	0.762***
		(0)	(0.004)	(0.007)
Time Fixed Effects		yes	yes	yes
R^2/Degrees of Freedom		0.286	138543	138543
Adj. R^2/Deviance		0.286	70813.235	70920.764
Number of observations		138582	138582	138582

Table 5: Summary of Regression 1:
$f\left(\mathbb{P}\left[ssi_{t,market,institution}\right]\right) = \beta_0 + \beta_{\text{subsector}} + \beta_{\text{market}} + \beta_{MC} ln\left(MC_{institution,t}\right) + \beta_t$ for s.s.i. institutions. In the reference setting the subsector is the banking sector (BAN) w.r.t. the banking market (BAN). For the Linear Model we report R^2 and Adjusted R^2. For Generalized Linear Models we report the Degrees of Freedom and Deviance. Standard errors are shown in parentheses. $***$, $**$, $*$ denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

Regression 2. *We regress the Average Excess CoSP and Spillover Duration of all s.s.i. institutions in the subsectors BAN, BRO, INS, RE, and NoFIN w.r.t. the BAN, BRO, INS, RE, FIN, and American non-financial market based on the following model:*

$$f\left(\mathbb{E}\left[\overline{(\cdot)}_{t,market,institution}\right]\right) = \beta_0 + \beta_{subsector} + \beta_{market} + \beta_{MC} ln\left(MC_{institution,t}\right) + \beta_t, \qquad (53)$$

where $MC_{institution,t}$ is the median market capitalization (in Mio USD) of an institution in time period t. Model (1) is a Linear Model with normal errors, where f is the identity. Model (2) is a Generalized Linear Model with normal errors and logarithmic link-function $f = log$. Model (3) is a Generalized Linear Model with gamma-distributed errors and logarithmic link-function $f = log$. In the reference setting the subsector is the banking sector (BAN) w.r.t. banking market (BAN).

Average Excess CoSP		Linear Model	GLM 1	GLM 2
		(1)	(2)	(3)
Intercept		3.399^{***}	1.263^{***}	1.263^{***}
		(0.055)	(0.013)	(0.013)
Subsector	BRO	0.24^{***}	0.044^{***}	0.044^{***}
		(0.04)	(0.007)	(0.007)
	INS	0.001	-0.006	-0.006
		(0.029)	(0.005)	(0.005)
	RE	0.184^{***}	0.025^{***}	0.025^{***}
		(0.034)	(0.006)	(0.006)
	NoFIN	-0.69^{***}	-0.135^{***}	-0.135^{***}
		(0.033)	(0.006)	(0.006)
Market	BRO	-1.66^{***}	-0.305^{***}	-0.305^{***}
		(0.036)	(0.007)	(0.007)
	INS	0.905^{***}	0.144^{***}	0.144^{***}
		(0.035)	(0.005)	(0.005)
	RE	-0.863^{***}	-0.142^{***}	-0.142^{***}
		(0.034)	(0.006)	(0.006)
	FIN	-0.109^{***}	-0.018^{***}	-0.018^{***}
		(0.033)	(0.006)	(0.006)
	AMC	-0.008	-0.005	-0.005
		(0.036)	(0.006)	(0.006)
MarketCap		0.202^{***}	0.036^{***}	0.036^{***}
		(0.008)	(0.001)	(0.001)
Time Fixed Effects		yes	yes	yes
R^2/Degrees of Freedom		0.563	20881	20881
Adj. R^2/Deviance		0.562	44463.221	44463.221
Number of observations		20920	20920	20920

Table 6: Summary of Regression 2:
$f\left(\mathbb{E}\left[100\overline{\psi}_t\right]\right) = \beta_0 + \beta_{\text{subsector}} + \beta_{\text{market}} + \beta_{MC} ln\left(MC_{institution,t}\right) + \beta_t$ for s.s.i. institutions. In the reference setting the subsector is the banking sector (BAN) w.r.t. the banking market (BAN). For the Linear Model we report R^2 and Adjusted R^2. For Generalized Linear Models we report the Degrees of Freedom and Deviance. Standard errors are shown in parentheses. $***$, $**$, $*$ denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

Spillover Duration				
		Linear Model	GLM 1	GLM 2
		(1)	(2)	(3)
Intercept		27.926***	3.335***	3.335***
		(0.223)	(0.007)	(0.007)
Subsector	BRO	0.842***	0.028***	0.028***
		(0.164)	(0.005)	(0.005)
	INS	−0.652***	−0.025***	−0.025***
		(0.118)	(0.003)	(0.003)
	RE	0.448***	0.007*	0.007*
		(0.137)	(0.004)	(0.004)
	NoFIN	−0.347**	−0.012***	−0.012***
		(0.136)	(0.004)	(0.004)
Market	BRO	−4.94***	−0.138***	−0.138***
		(0.147)	(0.004)	(0.004)
	INS	3.76***	0.103***	0.103***
		(0.141)	(0.004)	(0.004)
	RE	−3.257***	−0.078***	−0.078***
		(0.137)	(0.004)	(0.004)
	FIN	−0.199	−0.007*	−0.007*
		(0.135)	(0.004)	(0.004)
	AMC	1.566***	0.041***	0.041***
		(0.145)	(0.004)	(0.004)
MarketCap		0.112***	0.002**	0.002**
		(0.033)	(0.001)	(0.001)
Time Fixed Effects		yes	yes	yes
R^2/Degrees of Freedom		0.587	20881	20881
Adj. R^2/Deviance		0.587	757787.709	757787.709
Number of observations		20920	20920	20920

Table 7: Summary of Regression 2:
$f\left(\mathbb{E}\left[\overline{\tau}_t\right]\right) = \beta_0 + \beta_{\text{subsector}} + \beta_{\text{market}} + \beta_{MC} ln\left(MC_{institution,t}\right) + \beta_t$ for s.s.i. institutions. In the reference setting the subsector is the banking sector (BAN) w.r.t. the banking market (BAN). For the Linear Model we report R^2 and Adjusted R^2. For Generalized Linear Models we report the Degrees of Freedom and Deviance. Standard errors are shown in parentheses. $***$, $**$, $*$ denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

Regression 3. *We regress the Average Excess CoSP and Spillover Duration of all s.s.i. institutions in the subsectors BAN, BRO, INS, RE, and NoFIN w.r.t. the BAN, BRO, INS, RE, FIN, and American non-financial market based on the following model:*

$$f\left(\mathbb{E}\left[\overline{(\cdot)}_{t,market,institution}\right]\right) = \beta_0 + \beta_{market} + \beta_{liqI} LIQ_{institution,t} + \beta_{liqM} LIQ_{market,t} + \beta_{institution} + \beta_t, \tag{54}$$

where $LIQ_{institution,t}$ and $LIQ_{market,t}$ are the median turnover by value (VA) or by volume (VO) of the institution and market in time period t, respectively. Models (1) and (4) are Linear Models with normal errors, where f is the identity. Models (2) and (5) are Generalized Linear Models with normal errors and logarithmic link-function $f = log$. Models (3) and (6) are Generalized Linear Models with gamma-distributed errors and logarithmic link-function $f = log$. In the reference setting the subsector is the banking sector (BAN) w.r.t. banking market (BAN).

Average Excess CoSP		Linear Model (1)	GLM 1 (2)	GLM 2 (3)	Linear Model (4)	GLM 1 (5)	GLM 2 (6)
Intercept		2.194***	1.023***	1.038***	3.101***	1.167***	1.232***
		(0.141)	(0.029)	(0.028)	(0.138)	(0.027)	(0.031)
Market	BRO	−1.467***	−0.269***	−0.284***	−2.133***	−0.379***	−0.426***
		(0.033)	(0.006)	(0.006)	(0.035)	(0.006)	(0.008)
	INS	0.874***	0.121***	0.138***	0.34***	0.039***	0.015*
		(0.04)	(0.006)	(0.008)	(0.034)	(0.005)	(0.008)
	RE	−0.494***	−0.084***	−0.11***	−1.321***	−0.214***	−0.313***
		(0.034)	(0.006)	(0.007)	(0.034)	(0.005)	(0.008)
	FIN	−0.071**	−0.012**	−0.015**	−0.246***	−0.041***	−0.051***
		(0.031)	(0.005)	(0.006)	(0.025)	(0.004)	(0.006)
	AMC	−0.075*	−0.016**	−0.029***	−0.585***	−0.1***	−0.132***
		(0.044)	(0.007)	(0.009)	(0.035)	(0.005)	(0.008)
Liquidity (VA)	$LIQ_{\text{institution}}$	−0.332***	−0.058***	−0.063***			
		(0.085)	(0.014)	(0.017)			
	LIQ_{market}	1.551***	0.255***	0.027			
		(0.405)	(0.067)	(0.08)			
Liquidity (VO)	$LIQ_{\text{institution}}$				−16.205***	−3.135***	−2.432**
					(4.189)	(0.686)	(0.958)
	LIQ_{market}				−53.731***	−8.652***	−12.754***
					(2.598)	(0.409)	(0.594)
Time Fixed Effects		yes	yes	yes	yes	yes	yes
Institution Fixed Effects		yes	yes	yes	yes	yes	yes
R^2/Degrees of Freedom		0.751	11346	11346	0.775	20781	20781
Adj. R^2/Deviance		0.738	10615.371	544.901	0.767	20568.386	1661.5
Number of observations		11953	11953	11953	21499	21499	21499

Table 8: Summary of Regression 3: $f\left(\mathbb{E}\left[100\overline{\psi}_t\right]\right) = \beta_0 + \beta_{\text{market}} + \beta_{liqI} LIQ_{\text{institution},t} + \beta_{liqM} LIQ_{\text{market},t} + \beta_{\text{institution}} + \beta_t$ for s.s.i. institutions. In the reference setting the subsector is the banking sector (BAN) w.r.t. the banking market (BAN). For the Linear Model we report R^2 and Adjusted R^2. For Generalized Linear Models we report the Degrees of Freedom and Deviance. Standard errors are shown in parentheses. $***$, $**$, $*$ denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

Spillover Duration							
		Linear Model (1)	GLM 1 (2)	GLM 2 (3)	Linear Model (4)	GLM 1 (5)	GLM 2 (6)
Intercept		25.908***	3.28***	3.263***	28.794***	3.348***	3.39***
		(0.579)	(0.017)	(0.021)	(0.607)	(0.018)	(0.027)
Market	BRO	−4.361***	−0.117***	−0.137***	−6.12***	−0.157***	−0.22***
		(0.134)	(0.004)	(0.005)	(0.155)	(0.005)	(0.007)
	INS	4.263***	0.108***	0.113***	2.067***	0.058***	0.025***
		(0.163)	(0.004)	(0.006)	(0.149)	(0.004)	(0.007)
	RE	−2.08***	−0.05***	−0.074***	−4.732***	−0.11***	−0.205***
		(0.139)	(0.004)	(0.005)	(0.15)	(0.004)	(0.007)
	FIN	−0.139	−0.004	−0.004	−0.68***	−0.018***	−0.027***
		(0.125)	(0.004)	(0.004)	(0.109)	(0.003)	(0.005)
	AMC	1.823***	0.049***	0.042***	−0.168	0	−0.039***
		(0.179)	(0.005)	(0.006)	(0.154)	(0.004)	(0.007)
Liquidity (VA)	$LIQ_{\text{institution}}$	−1.692***	−0.052***	−0.043***			
		(0.348)	(0.01)	(0.013)			
	LIQ_{market}	4.132**	0.131***	0.011			
		(1.659)	(0.046)	(0.06)			
Liquidity (VO)	$LIQ_{\text{institution}}$				−34.261*	−0.725	−1.219
					(18.466)	(0.555)	(0.834)
	LIQ_{market}				−175.68***	−3.961***	−8.141***
					(11.453)	(0.333)	(0.517)
Time Fixed Effects		yes	yes	yes	yes	yes	yes
Institution Fixed Effects		yes	yes	yes	yes	yes	yes
R^2/Degrees of Freedom		0.742	11346	11346	0.747	20781	20781
Adj. R^2/Deviance		0.729	195774.076	383.456	0.738	469229.315	1590.097
Number of observations		11953	11953	11953	21499	21499	21499

Table 9: Summary of Regression 3: $f\left(\mathbb{E}\left[\overline{\tau}_t\right]\right) = \beta_0 + \beta_{\text{market}} + \beta_{liqI} LIQ_{\text{institution},t} + \beta_{liqM} LIQ_{\text{market},t} + \beta_{\text{institution}} + \beta_t$ for s.s.i. institutions. In the reference setting the subsector is the banking sector (BAN) w.r.t. the banking market (BAN). For the Linear Model we report R^2 and Adjusted R^2. For Generalized Linear Models we report the Degrees of Freedom and Deviance. Standard errors are shown in parentheses. $***$, $**$, $*$ denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

Regression 4. *We regress the Average Excess CoSP and Spillover Duration of all s.s.i. institutions in the subsectors BAN, BRO, INS, RE, and NoFIN w.r.t. the BAN, BRO, INS, RE, FIN, and American non-financial market based on the following model:*

$$\begin{aligned} f\left(\mathbb{E}\left[\overline{(\cdot)}_t\right]\right) =& \beta_0 + \beta_{subsector} + \beta_{market} \\ &+ \beta_{MC} ln(MC_{institution,t}) + \beta_{liqI} LIQ_{institution,t} + \beta_{liqM} LIQ_{market,t} + \beta_t, \end{aligned} \tag{55}$$

where $LIQ_{institution,t}$ and $LIQ_{market,t}$ are the median turnover by value (VA) or by volume (VO) of the institution and market in time period t, respectively. Models (1) and (4) are Linear Models with normal errors, where f is the identity. Models (2) and (4) are Generalized Linear Models with normal errors and logarithmic link-function $f = log$. Models (3) and (6) are Generalized Linear Models with gamma-distributed errors and logarithmic link-function $f = log$. In the reference setting the subsector is the banking sector (BAN) w.r.t. banking market (BAN).

Average Excess CoSP		Linear Model (1)	GLM 1 (2)	GLM 2 (3)	Linear Model (4)	GLM 1 (5)	GLM 2 (6)
Intercept		2.812***	1.165***	1.165***	3.969***	1.346***	1.346***
		(0.097)	(0.019)	(0.019)	(0.069)	(0.015)	(0.015)
Subsector	BRO	0.258***	0.042***	0.042***	0.234***	0.043***	0.043***
		(0.056)	(0.009)	(0.009)	(0.04)	(0.007)	(0.007)
	INS	0.233***	0.036***	0.036***	−0.004	−0.007	−0.007
		(0.038)	(0.007)	(0.007)	(0.029)	(0.005)	(0.005)
	RE	0.61***	0.096***	0.096***	0.181***	0.026***	0.026***
		(0.04)	(0.007)	(0.007)	(0.034)	(0.006)	(0.006)
	NoFIN	−0.468***	−0.08***	−0.08***	−0.708***	−0.137***	−0.137***
		(0.049)	(0.008)	(0.008)	(0.034)	(0.006)	(0.006)
Market	BRO	−1.499***	−0.277***	−0.277***	−2.104***	−0.369***	−0.369***
		(0.046)	(0.009)	(0.009)	(0.049)	(0.009)	(0.009)
	INS	1.074***	0.168***	0.168***	0.496***	0.082***	0.082***
		(0.056)	(0.009)	(0.009)	(0.047)	(0.008)	(0.008)
	RE	−0.516***	−0.086***	−0.086***	−1.312***	−0.207***	−0.207***
		(0.048)	(0.008)	(0.008)	(0.047)	(0.008)	(0.008)
	FIN	−0.065	−0.01	−0.01	−0.243***	−0.037***	−0.037***
		(0.044)	(0.007)	(0.007)	(0.035)	(0.006)	(0.006)
	AMC	0.095	0.017*	0.017*	−0.45***	−0.07***	−0.07***
		(0.062)	(0.01)	(0.01)	(0.048)	(0.008)	(0.008)
MarketCap		0.219***	0.036***	0.036***	0.204***	0.036***	0.036***
		(0.011)	(0.002)	(0.002)	(0.008)	(0.001)	(0.001)
Liquidity (VA)	$LIQ_{\text{institution}}$	−0.194***	−0.038***	−0.038***			
		(0.034)	(0.006)	(0.006)			
	LIQ_{market}	2.579***	0.492***	0.492***			
		(0.578)	(0.1)	(0.1)			
Liquidity (VO)	$LIQ_{\text{institution}}$				−0.031	−0.009	−0.009
					(0.129)	(0.02)	(0.02)
	LIQ_{market}				−48.782***	−7.27***	−7.27***
					(3.611)	(0.622)	(0.622)
Time Fixed Effects		yes	yes	yes	yes	yes	yes
R^2/Degrees of Freedom		0.47	11695	11695	0.56	20686	20686
Adj. R^2/Deviance		0.469	23615.071	23615.071	0.559	44017.946	44017.946
Number of observations		11953	11953	11953	21499	21499	21499

Table 10: Summary of Regression 4:
$f\left(\mathbb{E}\left[100\overline{\psi}_t\right]\right) = \beta_0 + \beta_{\text{subsector}} + \beta_{\text{market}} + \beta_{MC} ln(MC_{institution,t}) + \beta_{liqI} LIQ_{\text{institution},t} + \beta_{liqM} LIQ_{\text{market},t} + \beta_t$ for s.s.i. institutions. In the reference setting the subsector is the banking sector (BAN) w.r.t. the banking market (BAN). For the Linear Model we report R^2 and Adjusted R^2. For Generalized Linear Models we report the Degrees of Freedom and Deviance. Standard errors are shown in parentheses. $***$, $**$, $*$ denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

Spillover Duration							
		Linear Model (1)	GLM 1 (2)	GLM 2 (3)	Linear Model (4)	GLM 1 (5)	GLM 2 (6)
Intercept		24.976***	3.25***	3.25***	29.97***	3.382***	3.382***
		(0.389)	(0.011)	(0.011)	(0.281)	(0.009)	(0.009)
Subsector	BRO	2.214***	0.063***	0.063***	0.847***	0.028***	0.028***
		(0.223)	(0.006)	(0.006)	(0.164)	(0.005)	(0.005)
	INS	0.557***	0.012***	0.012***	−0.7***	−0.026***	−0.026***
		(0.152)	(0.004)	(0.004)	(0.118)	(0.003)	(0.003)
	RE	2.098***	0.052***	0.052***	0.433***	0.007*	0.007*
		(0.159)	(0.004)	(0.004)	(0.137)	(0.004)	(0.004)
	NoFIN	0.456**	0.017***	0.017***	−0.402***	−0.014***	−0.014***
		(0.198)	(0.005)	(0.005)	(0.137)	(0.004)	(0.004)
Market	BRO	−4.887***	−0.137***	−0.137***	−6.507***	−0.174***	−0.174***
		(0.186)	(0.005)	(0.005)	(0.199)	(0.006)	(0.006)
	INS	4.768***	0.126***	0.126***	2.304***	0.068***	0.068***
		(0.227)	(0.006)	(0.006)	(0.19)	(0.005)	(0.005)
	RE	−2.057***	−0.051***	−0.051***	−4.856***	−0.115***	−0.115***
		(0.194)	(0.006)	(0.006)	(0.192)	(0.006)	(0.006)
	FIN	−0.127	−0.004	−0.004	−0.707***	−0.019***	−0.019***
		(0.176)	(0.005)	(0.005)	(0.141)	(0.004)	(0.004)
	AMC	2.23***	0.062***	0.062***	−0.03	0.004	0.004
		(0.249)	(0.007)	(0.007)	(0.197)	(0.006)	(0.006)
MarketCap		0.361***	0.008***	0.008***	0.119***	0.002**	0.002**
		(0.044)	(0.001)	(0.001)	(0.033)	(0.001)	(0.001)
Liquidity (VA)	$LIQ_{\text{institution}}$	−0.307**	−0.007*	−0.007*			
		(0.138)	(0.004)	(0.004)			
	LIQ_{market}	8.58***	0.288***	0.288***			
		(2.322)	(0.064)	(0.064)			
Liquidity (VO)	$LIQ_{\text{institution}}$				−0.696	−0.019	−0.019
					(0.523)	(0.015)	(0.015)
	LIQ_{market}				−173.167***	−3.896***	−3.896***
					(14.698)	(0.429)	(0.429)
Time Fixed Effects		yes	yes	yes	yes	yes	yes
R^2/Degrees of Freedom		0.477	11695	11695	0.584	20686	20686
Adj. R^2/Deviance		0.475	383460.835	383460.835	0.583	746415.576	746415.576
Number of observations		11953	11953	11953	21499	21499	21499

Table 11: Summary of Regression 4:
$f\left(\mathbb{E}\left[\overline{\tau}_t\right]\right) = \beta_0 + \beta_{\text{subsector}} + \beta_{\text{market}} + \beta_{MC} ln(MC_{institution,t}) + \beta_{liqI} LIQ_{\text{institution},t} + \beta_{liqM} LIQ_{\text{market},t} + \beta_t$ for s.s.i. institutions. In the reference setting the subsector is the banking sector (BAN) w.r.t. the banking market (BAN). For the Linear Model we report R^2 and Adjusted R^2. For Generalized Linear Models we report the Degrees of Freedom and Deviance. Standard errors are shown in parentheses. $***$, $**$, $*$ denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

Regression 5. *We regress $\Delta CoVaR^{\leq}$ of all s.s.i. institutions in the subsectors BAN, BRO, INS, RE, and NoFIN w.r.t. the BAN, BRO, INS, RE, FIN, and American non-financial market based on the following model:*

$$f\left(\mathbb{E}\left[\exp\left(-100\Delta CoVaR^{\leq}_{t,market,institution}\right)\right]\right) = \beta_0 + \beta_{subsector} + \beta_{market} + \beta_{MC} ln(MC_{institution,t}) + \beta_t. \tag{56}$$

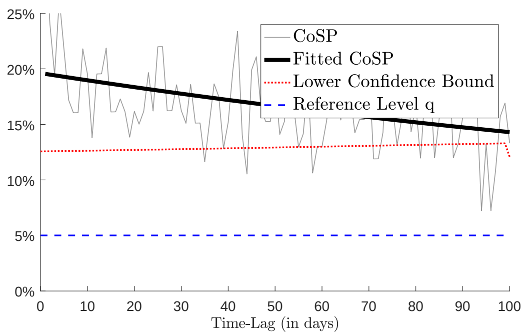
Model (1) is a Linear Model with normal errors, where f is the identity. Model (2) is a Generalized Linear Model with normal errors and logarithmic link-function $f = log$. Model (3) is a Generalized Linear Model with gamma-distributed errors and logarithmic link-function $f = log$. In the reference setting the subsector is the banking sector (BAN) w.r.t. banking market (BAN).

$\exp(-100\Delta\text{CoVaR}^{\leq})$				
		Linear Model	GLM 1	GLM 2
		(1)	(2)	(3)
Intercept		7.061***	2.757***	2.757***
		(1.083)	(0.039)	(0.039)
Subsector	BRO	6.86***	0.121***	0.121***
		(0.796)	(0.014)	(0.014)
	INS	8.125***	0.193***	0.193***
		(0.575)	(0.009)	(0.009)
	RE	3.767***	0.04***	0.04***
		(0.667)	(0.012)	(0.012)
	NoFIN	0.242	0.06***	0.06***
		(0.662)	(0.01)	(0.01)
Market	BRO	−2.864***	−0.057***	−0.057***
		(0.717)	(0.013)	(0.013)
	INS	11.498***	0.204***	0.204***
		(0.687)	(0.011)	(0.011)
	RE	−22.438***	−0.607***	−0.607***
		(0.667)	(0.018)	(0.018)
	FIN	0.531	0.006	0.006
		(0.657)	(0.012)	(0.012)
	AMC	28.403***	0.458***	0.458***
		(0.707)	(0.01)	(0.01)
MarketCap		5.32***	0.097***	0.097***
		(0.162)	(0.003)	(0.003)
Time Fixed Effects		yes	yes	yes
R^2/Degrees of Freedom		0.432	20881	20881
Adj. R^2/Deviance		0.431	16439901.563	16439901.563
Number of observations		20920	20920	20920

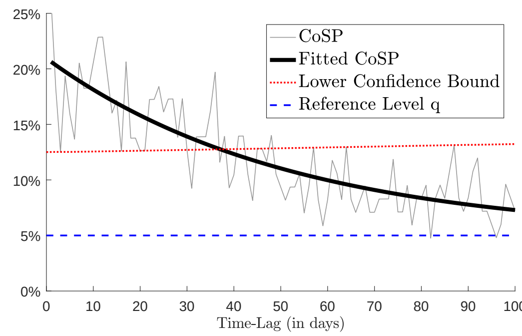
Table 12: Summary of Regression 5:
$f\left(\mathbb{E}\left[\exp\left(-100\Delta\text{CoVaR}^{\leq}_{t,market,institution}\right)\right]\right) = \beta_0+\beta_{\text{subsector}}+\beta_{\text{market}}+\beta_{MC}ln(MC_{institution,t})+\beta_t$ for s.s.i. institutions. In the reference setting the subsector is the banking sector (BAN) w.r.t. the banking market (BAN). For the Linear Model we report R^2 and Adjusted R^2. For Generalized Linear Models we report the Degrees of Freedom and Deviance. Standard errors are shown in parentheses. $***$, $**$, $*$ denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

E Additional Figures

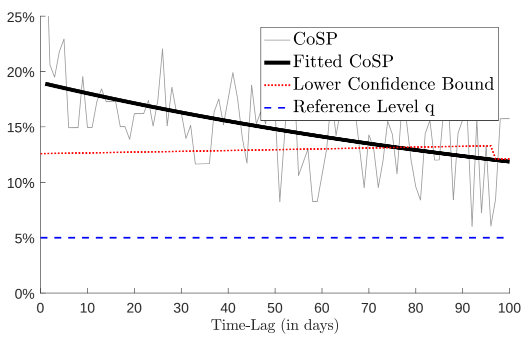
E.1 Time-Conditional Analysis



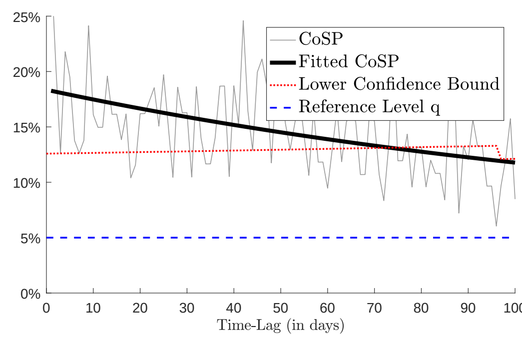
(a) Bank of America (BAN)



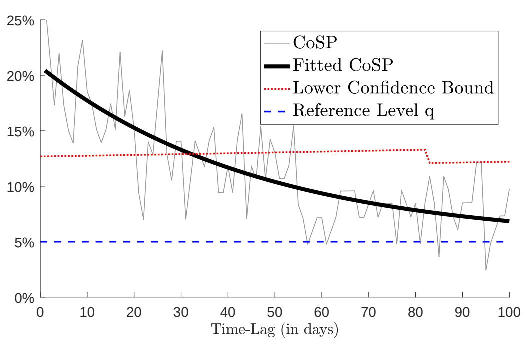
(b) Deutsche Bank (BAN)



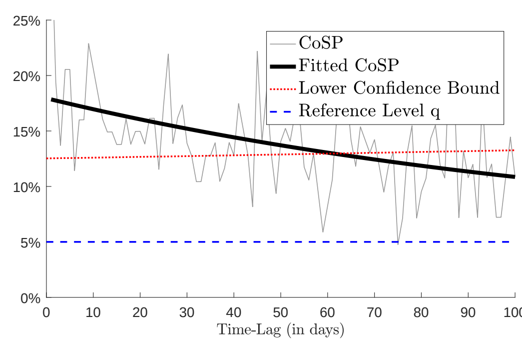
(c) Citigroup (BAN)



(d) Wells Fargo (BAN)

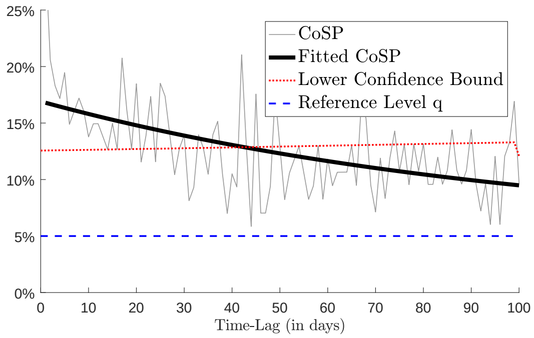


(e) Scharles Schwab (BRO)

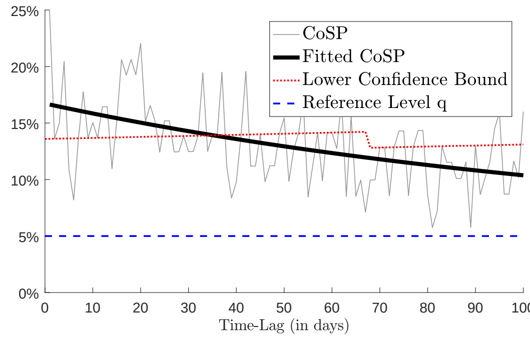


(f) Morgan Stanley (BRO)

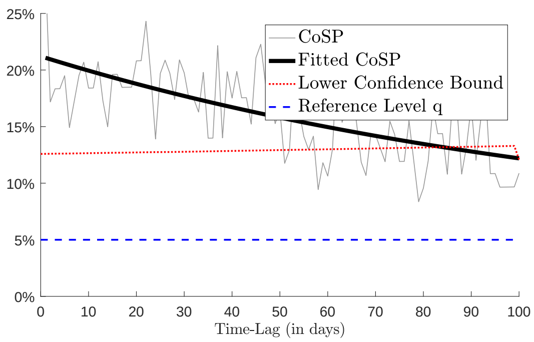
Figure 18: CoSP during 2003-2008 triggered by exemplary banks and brokers w.r.t. the FIN index.



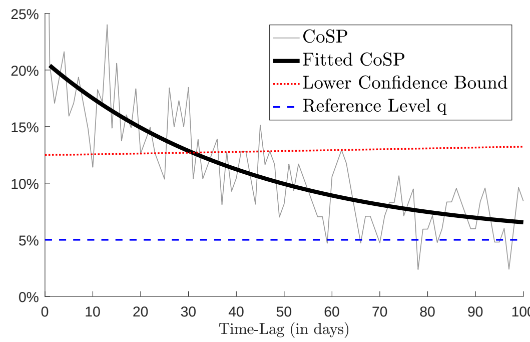
(a) Blackrock (BRO)



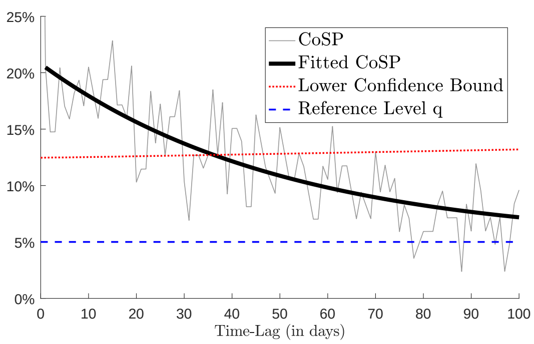
(b) CME Group (BRO)



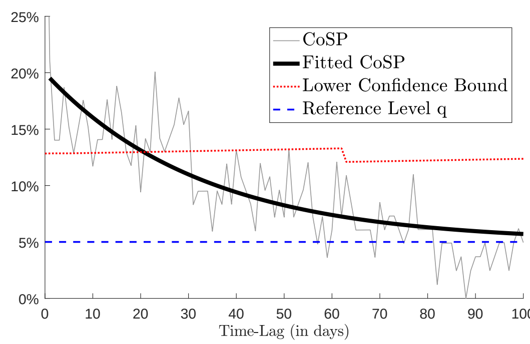
(c) AIG (INS)



(d) Allianz (INS)

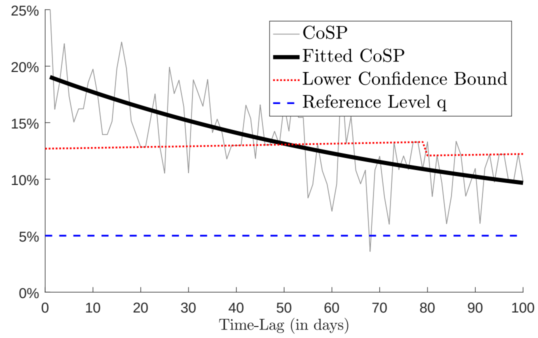


(e) AXA (INS)

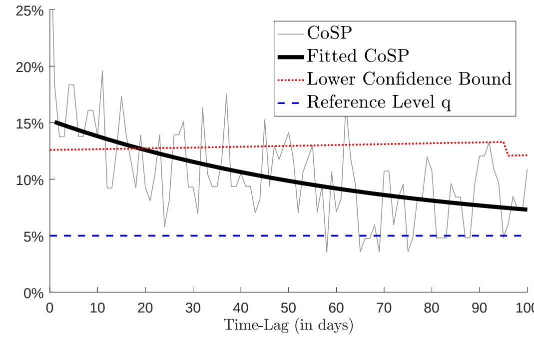


(f) Zurich Group (INS)

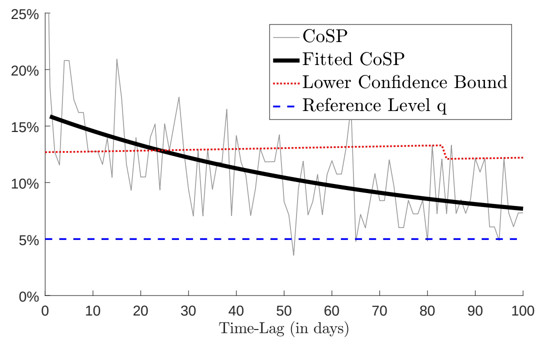
Figure 19: CoSP during 2003-2008 triggered by exemplary brokers and insurers w.r.t. the FIN index.



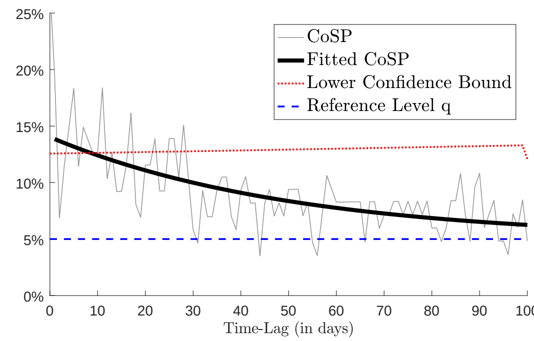
(a) General Electric (NoFIN)



(b) Apple (NoFIN)

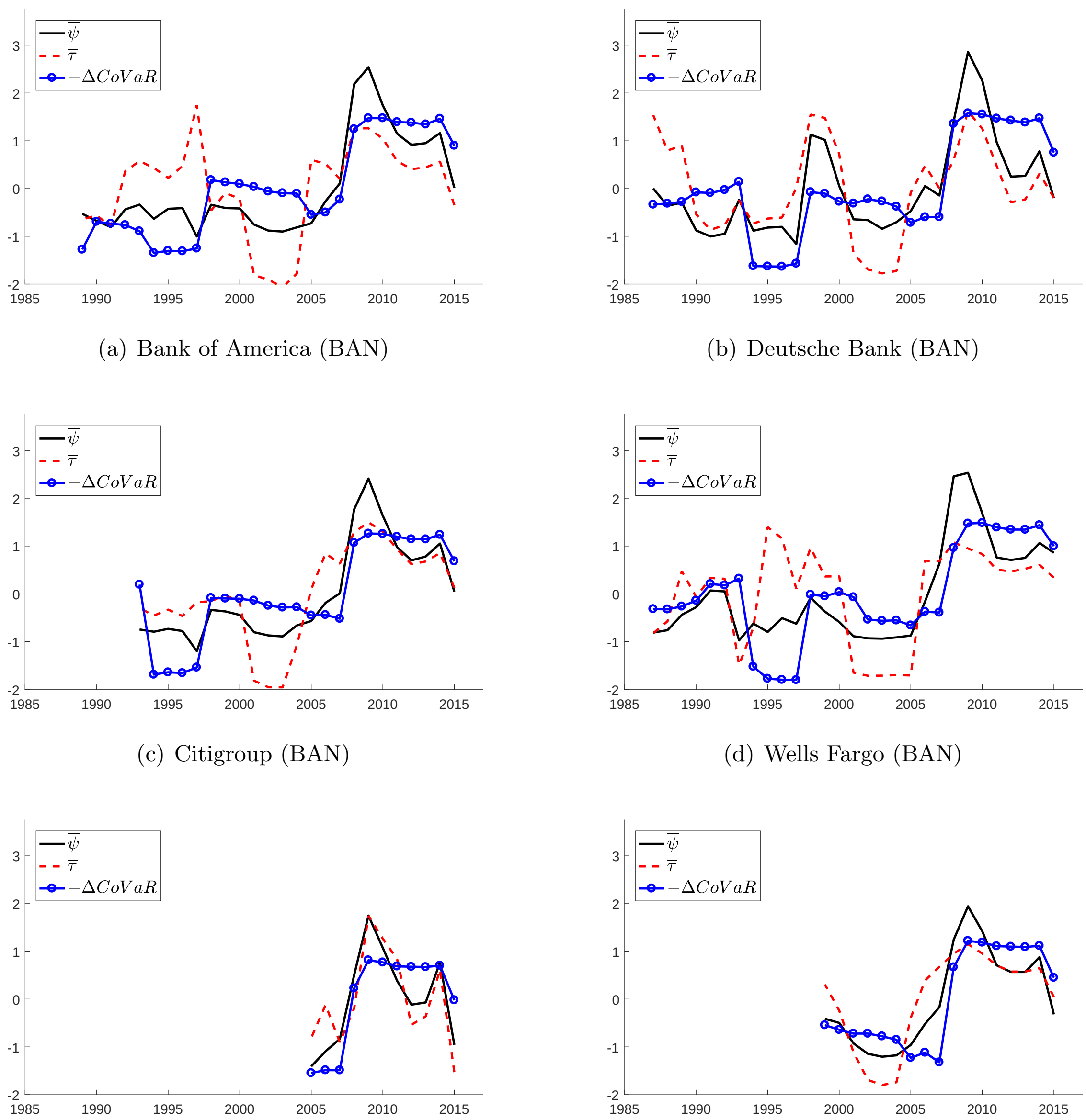


(c) BP (NoFIN)



(d) Amazon.com (NoFIN)

Figure 20: CoSP during 2003-2008 triggered by exemplary non-financial companies w.r.t. the FIN index.



(a) Bank of America (BAN)

(b) Deutsche Bank (BAN)

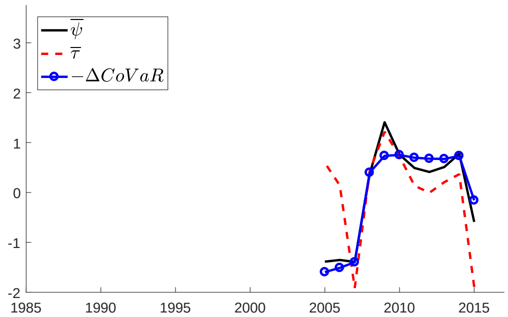
(c) Citigroup (BAN)

(d) Wells Fargo (BAN)

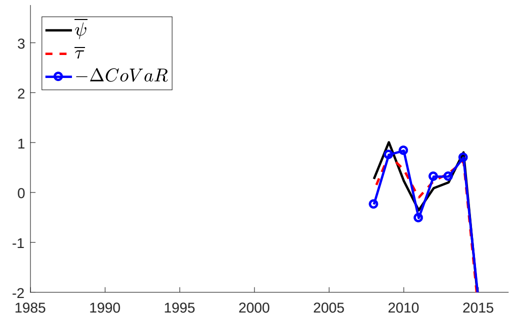
(e) Goldman Sachs (BRO)

(f) Morgan Stanley (BRO)

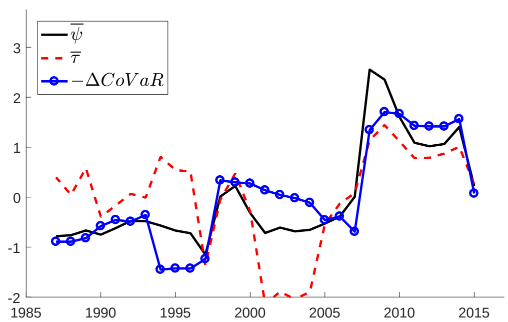
Figure 21: Standardized Average Excess CoSP, Spillover Duration, and $-\Delta\text{CoVaR}^{\leq}$ triggered by exemplary banks and brokers w.r.t. the FIN index.



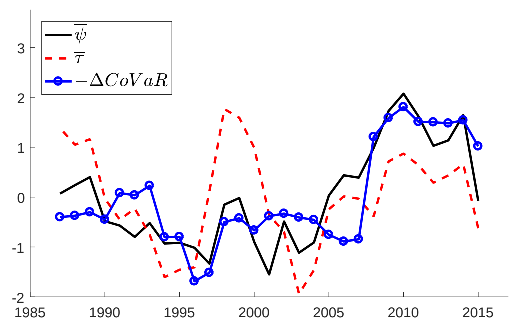
(a) Blackrock (BRO)



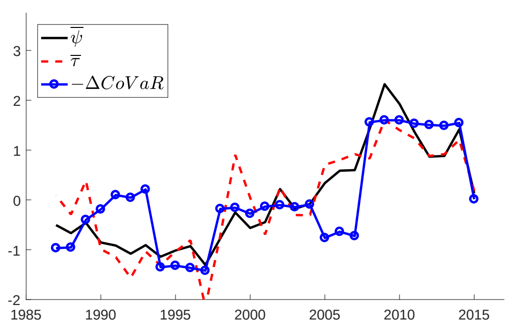
(b) CME Group (BRO)



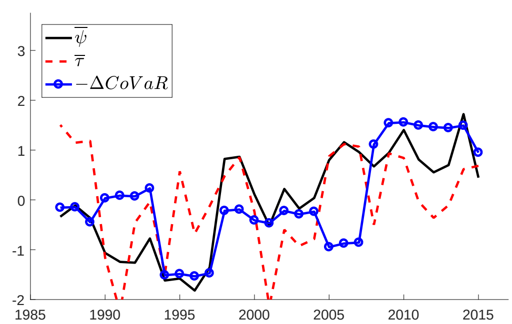
(c) AIG (INS)



(d) Allianz (INS)

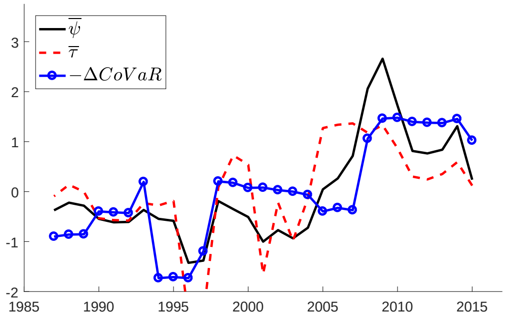


(e) AXA (INS)

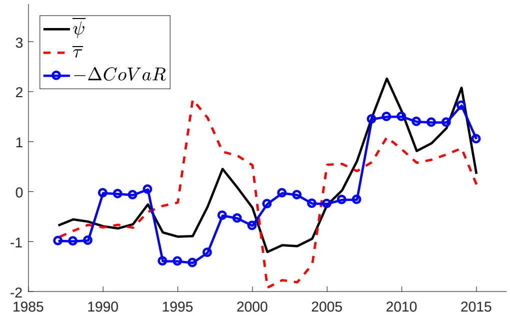


(f) Zurich Group (INS)

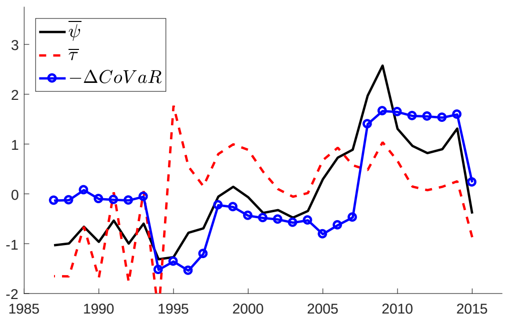
Figure 22: Standardized Average Excess CoSP, Spillover Duration, and $-\Delta\text{CoVaR}^{\leq}$ triggered by exemplary brokers and insurers w.r.t. the FIN index.



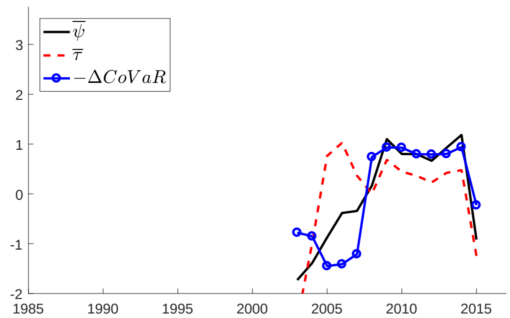
(a) General Electric (NoFIN)



(b) Apple (NoFIN)



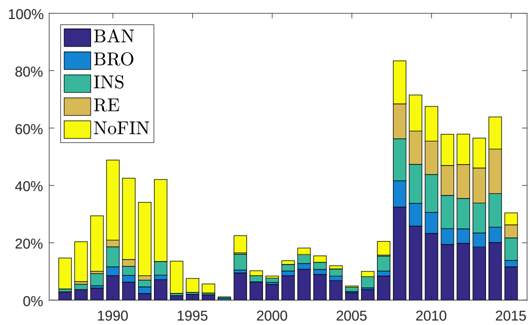
(c) BP (NoFIN)



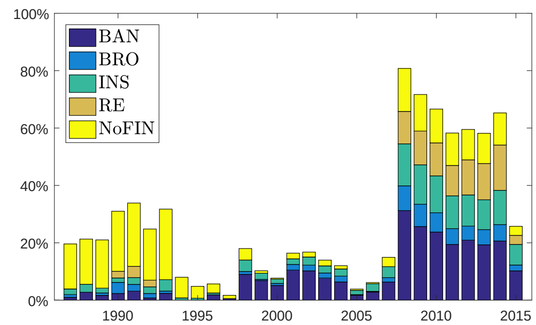
(d) Amazon.com (NoFIN)

Figure 23: Standardized Average Excess CoSP, Spillover Duration, and $-\Delta \text{CoVaR}^{\leq}$ triggered by exemplary non-financial companies w.r.t. the FIN index.

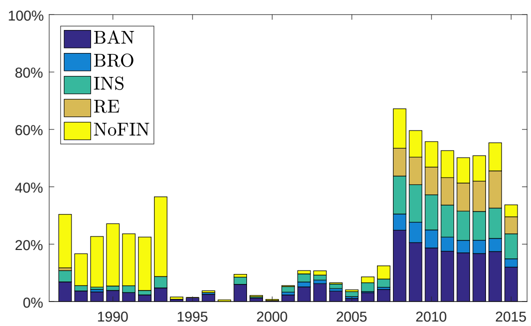
E.2 Cross-Sectional Analysis



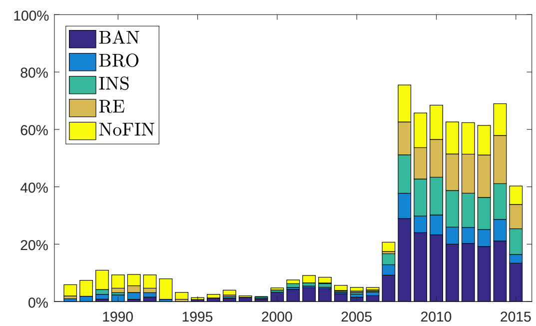
(a) w.r.t. the BAN index



(b) w.r.t. the BRO index

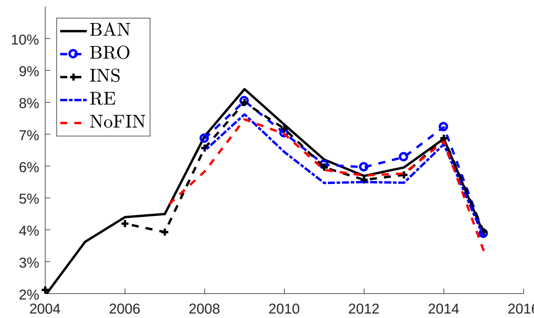


(c) w.r.t. the INS index

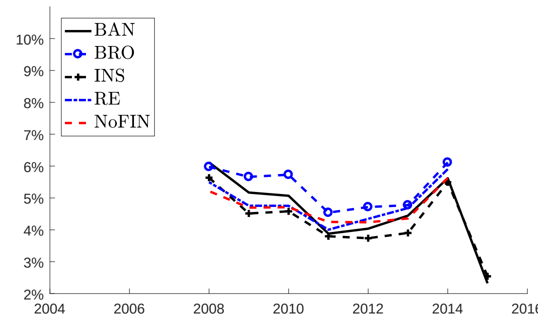


(d) w.r.t. the RE index

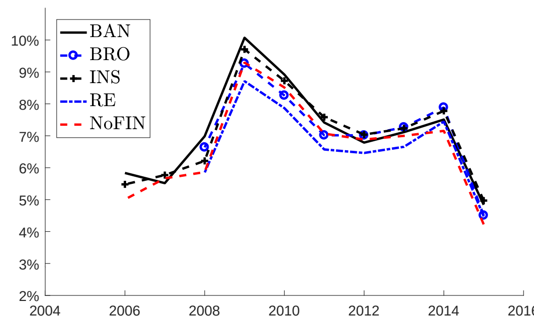
Figure 24: Fraction of significantly systemically important institutions on the 1% level relative to the total number of institutions in the sample w.r.t. the BAN, BRO, INS, and RE market.



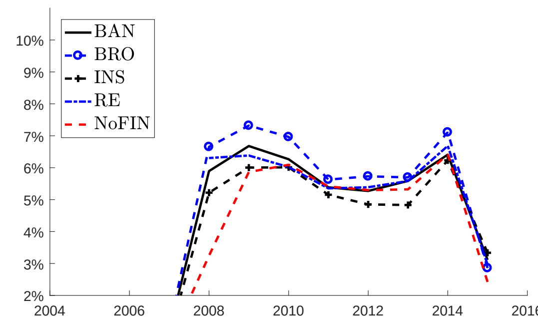
(a) w.r.t. the BAN index



(b) w.r.t. the BRO index



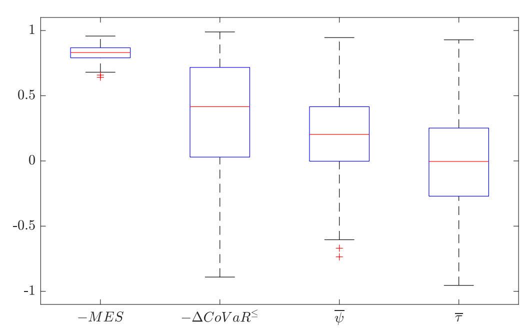
(c) w.r.t. the INS index



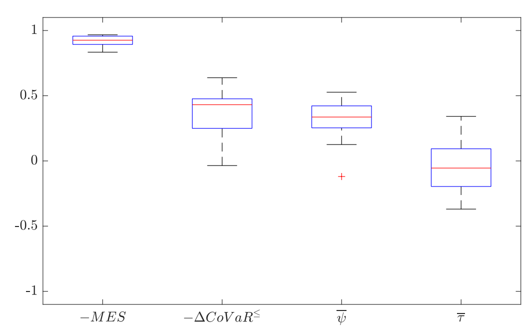
(d) w.r.t. the RE index

Figure 25: Median Average Excess CoSP triggered by systemically important institutions in the subsectors BAN, BRO, INS, RE, and NoFIN w.r.t. the BAN, BRO, INS, and RE market.

E.3 Other Figures



(a) Correlation with β over time for each institution and market



(b) Cross-sectional correlation with β for each time period and market

Figure 26: Correlation between $-MES$, ΔCoVaR$^{\leq}$, $\overline{\psi}$, $\overline{\tau}$ and β, respectively, for all institutions.

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