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Systemic Risk and Contagion beyond the Banking Sector

Empirical Studies on Insurers and Real Sector Firms

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ABSTRACT

In the aftermath of the financial crisis of 2007–2009, financial regulators have increased their scrutiny of potential threats to financial stability, in particular those beyond the banking sector. This thesis contributes to a better understanding of systemic risk and contagion outside the banking sector via an empirical assessment of such risks in the insurance sector and the real economy. The analysis of systemic risk in the insurance sector shows that overall, the insurance industry gives rise to notably lower financial stability concerns than the banking sector. Several individual multi-line and life insurers, however, are found to be systemically important financial institutions. Furthermore, distress in life insurers may spill over to banks. By contrast, contagion among different types of insurers is found to be relatively weak. The analysis of distress risk in the real economy shows that the real sector is much less vulnerable to widespread losses than the financial system. Real sector firms that expand beyond their traditional nonfinancial businesses by offering financial services may still contribute to systemic risk. Collectively, these findings offer important insights into threats to financial stability beyond the banking sector and thus inform the design of effective regulatory policies for the mitigation of systemic risk.

ZUSAMMENFASSUNG

Die Finanzmarktaufsicht hat im Nachgang zur Finanzkrise von 2007–2009 die Überwachung potenzieller Bedrohungen der Finanzstabilität ausgeweitet. Dabei sind verstärkt Risiken in den Fokus gerückt, die außerhalb des Bankensektors erwachsen. Die vorliegende Dissertation trägt zu einem besseren Verständnis von systemischen Risiken und Ansteckungseffekten jenseits des Bankensektors bei. Hierzu wird eine empirische Untersuchung solcher Risiken in der Versicherungs- und der Realwirtschaft vorgenommen. Die Analyse des systemischen Risikos in der Versicherungswirtschaft zeigt, dass der Versicherungssektor insgesamt eine weit geringere Bedrohung der Finanzstabilität darstellt als der Bankensektor. Für sich betrachtet sind jedoch mehrere Universal- und Lebensversicherer systemisch relevante Finanzinstitute. Zudem können sich finanzielle Schwierigkeiten von Lebensversicherern auf Banken übertragen. Innerhalb des Versicherungssektors hingegen spielen solche Ansteckungseffekte eine untergeordnete Rolle. Die Analyse von Risiken in der Realwirtschaft zeigt, dass diese ein geringeres Risiko aufweist, industrieweite Verluste zu erleiden als das Finanzsystem. Firmen der Realwirtschaft können dennoch systemische Risiken bedingen, wenn sie über ihr nichtfinanzielles Kerngeschäft hinaus in Finanzdienstleistungen expandieren. Diese Forschungsergebnisse liefern in ihrer Gesamtheit wichtige Erkenntnisse zu Bedrohungen der Finanzstabilität von außerhalb des Bankensektors und unterstützen dadurch die Ableitung effektiver regulatorischer Maßnahmen zur Eindämmung systemischer Risiken.

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LIST OF ABBREVIATIONS

ADF	augmented Dickey–Fuller
AIG	American International Group
AUD	Australian dollar
BIC	Bayesian information criterion
bp	basis point
CDS	credit default swap
CoPD	conditional probability of default
CoPSD	conditional probability of systemic distress
CRSP	Center for Research in Security Prices
DIP	distress insurance premium
ETL	expected tail loss
EUR	Euro
FDIC	Federal Deposit Insurance Corporation
FSB	Financial Stability Board
FSOC	Financial Stability Oversight Council
G-SIB	global systemically important bank
G-SIFI	global systemically important financial institution
G-SII	global systemically important insurer
GARCH	generalized autoregressive conditional heteroscedasticity
GBP	pound sterling
GDP	gross domestic product
IAIS	International Association of Insurance Supervisors
ICB	Industry Classification Benchmark
MES	marginal expected shortfall
P/C	property–casualty
PSD	probability of systemic distress
U.S.	United States
USD	U.S. dollar
VAR	vector autoregression
VaR	value at risk
VARX	vector autoregression with exogenous component
VIF	variance inflation factor

1 INTRODUCTION

In normal times, when markets are calm, financial institutions are key enablers of economic activity and growth. Banks, for example, operate payment systems and provide funding for business expansions and individual consumption by granting loans. Insurers, in turn, offer protection against individual losses by sharing risks across businesses and households and act as important investors in financial markets. To pursue opportunities that would otherwise be foregone, firms and households depend on a well-functioning financial system providing these and a broad array of other financial services (see, e.g., Trichet, 2005).

The financial crisis of 2007–2009, however, revealed that the financial system is vulnerable to shocks and that financial institutions may pose significant negative externalities for the wider economy. What started as a limited crisis in the U.S. subprime mortgage market contagiously spread to other markets (see, e.g., Gorton and Metrick, 2012; Covitz et al., 2013), and eventually unfolded into global financial turmoil. Asset prices dropped as confidence in the financial system eroded, and a number of financial institutions failed, were taken over, or received government support. In response to weakening balance sheets, banks reduced their supply of credit, thereby imposing financial constraints on real sector firms (see, e.g., Campello et al., 2010; Puri et al., 2011; Almeida et al., 2012). These constraints played an important role in stalling economic activity, and despite unprecedented fiscal and monetary interventions to mitigate the financial crisis (see, e.g., IMF, 2009), its aftermath was a period of reduced aggregate output and higher unemployment rates across a range of countries.

The decade after the financial crisis has thus witnessed considerable effort on the part of policymakers, regulators, and supervisors to restore and enhance financial stability. As opposed to microprudential regulation, which focuses on individual financial institutions in isolation, policies targeting financial stability are macroprudential in the sense that they focus on the negative externalities of financial institutions. Microprudential regulation aims at limiting the distress potential of individual financial institutions with the ultimate goal of consumer protection. Macroprudential regulation, by contrast, aims at limiting system-wide distress with the ultimate goal of avoiding the high economic costs of financial crises (see, e.g., Borio, 2003).

At the international level, the post-crisis effort to strengthen macroprudential regulation has resulted in the designation of global systemically important financial institutions (G-SIFIs) by the Financial Stability Board (FSB). These institutions are deemed to be of such importance that their failure would likely have severe repercussions for the financial system and the global economy at large. G-SIFIs are thus subject to stricter oversight and additional regulatory measures, such as tighter capital standards and recovery and resolution planning. Whereas regulators initially focused on the banking sector, designating global systemically important banks (G-SIBs), they later also turned to the insurance sector, designating global systemically important insurers (G-SIIs). G-SIBs and G-SIIs are identified based on a set of indicators derived from public and confidential accounting information and supervisory judgment. Additionally, regulators at the national and international levels have scrutinized—and continue to assess—potential systemic risks in nonbank noninsurer financial institutions, such as asset managers and real sector firms' financing arms.

Systemic risks in the banking sector are widely acknowledged and backed by extensive anecdotal and empirical evidence. Policy initiatives targeting potential systemic risks in other parts of the financial system, however, have given rise to considerable controversy, in particular those initiatives targeting the insurance industry (see, e.g., Harrington, 2009; Kessler, 2014; Weiß and Mühlnickel, 2014; Bierth et al., 2015). The important issue, then, is how to robustly and reliably assess systemic risks outside the banking sector. Systemic risks are arguably less obvious in nonbank financial institutions than they are in banks. The business model and balance sheet structure of banks and other financial institutions differ in important ways, and arguments regarding systemic vulnerabilities in banks, such as bank runs, thus do not apply directly and fully to other firms (see, e.g., Kessler, 2014). Nevertheless, nonbank financial institutions are an integral part of the financial system and may pose negative externalities for the real economy upon their failure (see, e.g., Acharya et al., 2016). In light of this ambiguity, conducting an empirical assessment of the potential risks posed by nonbank financial firms is all the more important to identifying potential vulnerabilities in the financial system and to guiding the effective regulation of systemic risk. As national and international regulators reconsider their approaches to identifying and regulating systemic risks in nonbank financial institutions,[1] however, empirical research on the subject remains surprisingly limited.

Against this background, this thesis sets out to improve the understanding of systemic risk and contagion beyond the banking sector. It is organized around three empirical studies that address specific threats to financial stability originating outside the banking sector. Two of the three studies focus on insurance companies. In the first study, I investigate to what extent insurance as an industry as well as individual insurers are systemically risky. The second study analyzes financial contagion between the insurance industry and the banking industry and among different types of insurers. In the third study, I address potential financial stability concerns in the real sector.[2]

1 For example, the International Association of Insurance Supervisors, a regulatory body involved in the designation of G-SIIs, has recently suggested suspending and potentially discontinuing such designations in favor of a new framework to be applied to a broader set of insurers (see IAIS, 2018).

2 In the introduction and conclusion, I use the first person singular pronoun to refer to the author(s) of the empirical studies. However, it does not always refer to me exclusively as the first study is based on joint work with a coauthor. For expositional convenience, in the introduction and conclusion, I shall use ideas and language from the three studies without explicit reference.

1.1 SYSTEMIC RISK AND CONTAGION IN FINANCIAL MARKETS

In this section, I introduce the concepts of systemic risk and contagion in financial markets. Importantly, rather than being separate concepts, the notions of systemic risk and contagion are closely related. Systemic risk may be defined as the risk of a financial crisis so disruptive that it may have substantial negative effects on the real economy (see, e.g., IMF, BIS, and FSB, 2009). Systemic crises may result either from a broad shock impairing a substantial part of the financial system at once or from a narrow shock to a limited part of the financial system that then spreads to other institutions and markets (see, e.g., de Bandt and Hartmann, 2000; Group of Ten, 2001). Financial contagion may be defined as a state of increased interconnectedness among financial institutions and markets following a distress event (see, e.g., Forbes and Rigobon, 2002; Longstaff, 2010) and thus refers to a mechanism through which a shock to a limited part of the financial system may turn systemic.

1.1.1 *Defining and Measuring Systemic Risk*

The financial crisis of 2007–2009 has sparked a tremendous increase in the interest in systemic risk. Regulators have set out to identify systemically important financial institutions, and researchers have endeavored to develop empirical measures of systemic risk. In this section, I review regulatory definitions of systemic risk and introduce selected empirical measures of systemic risk that have been proposed in the literature.

1.1.1.1 *Definitions of Systemic Risk*

Systemic risk, in a way, is an elusive concept (Bisias et al., 2012). To date, there is no consensus on what precisely constitutes systemic risk, and a broad array of working definitions has emerged. Eling and Pankoke (2016) identify three key elements of systemic risk definitions: (i) the occurrence of a distress event, (ii) the causes of the event, and (iii) the effect of such an event. In the following, I discuss regulators' definitions of systemic risk along these dimensions.

The concept of systemic risk is not new but had been recognized and debated long before the events of the financial crisis of 2007–2009. In a pre-crisis definition, the BIS (1992) describes systemic risk as

> the risk that a disruption (at a firm, in a market segment, to a settlement system etc.) causes widespread difficulties at other firms, in other market segments or in the financial system as a whole. (p. 69)

Contagion is at the heart of this definition. A systemic crisis corresponds to solvency or liquidity problems that cascade through financial institutions and markets and eventually lead to a malfunctioning of a substantial part or even the entirety of the financial system. The definition is, however, rather broad in that it does not place limitations on the consequences of a systemic crisis. In fact, a financial crisis would qualify as an instance of systemic risk even if it affected the real economy only marginally or not at all.

With respect to the effect of systemic problems, the Group of Ten (2001) proposes a more restrictive working definition of systemic risk:

> *Systemic financial risk* is the risk that an event will trigger a loss of economic value or confidence in [...] a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy. [...] The adverse real economic effects from systemic problems are generally seen as arising from disruptions to the payment system, to credit flows, and from the destruction of asset values. (p. 126, emphasis in original)

According to this definition, financial crises can be considered systemic only if there is an expectation of severe negative consequences for the real economy. Financial crises that are limited to the financial system and are unlikely to affect the real economy would thus not constitute a materialization of systemic risk. In its discussion of the above definition, the Group of Ten (2001) further points out that the original cause of a systemic crisis may lie within the financial system, in financial markets, or in the real economy.

After the financial crisis of 2007–2009, the IMF, BIS, and FSB (2009) proposed a closely related definition that also predicates systemic risk on the potential for negative externalities. Accordingly, the FSB (2010) incorporated the requirement of negative real consequences into the definition that underlies the ongoing regulatory efforts to identify and regulate G-SIFIs:

> [These] are institutions of such size, market importance, and global interconnectedness that their distress or failure would cause significant dislocation in the global financial system and adverse economic consequences across a range of countries. (p. 2)

Although there is no universally accepted academic definition of systemic risk, an important strand of the literature has taken an empirical perspective, which I also adopt in this thesis. In this literature, systemic risk has been measured mostly based on shortfalls or losses in the financial system. Empirical measures such as those introduced in the next section, however, have typically sought neither to explicitly quantify the negative externalities of financial institutions nor to place limitations on what precisely may trigger systemic events.

1.1.1.2 *Empirical Measures of Systemic Risk*

The empirical literature on measuring systemic risk has grown explosively following the financial crisis and has become far too extensive to fully review here. Bisias et al. (2012), however, provide a comprehensive survey.

Empirical measures of systemic risk fall into two broad groups: *contagion* measures and *contemporaneous* measures. Approaches relating to the first group analyze the dynamics of systemic risk spillovers in the financial system. To this end, they model financial institutions' mutual balance sheet exposures (see, e.g., van Lelyveld et al., 2011; Park and Xie, 2014) or apply econometric methods to time series data (see, e.g., Billio et al., 2012; Chen et al., 2014). Approaches relating to the second group as such do not take a stand on how shocks propagate through the system. The focus of these measures is on the level of systemic risk in individual financial institutions or the financial system as a whole.

The empirical analysis in this thesis employs both contagion and contemporaneous measures of systemic risk. In this section, I briefly introduce and compare influential measures of contemporaneous systemic risk.[3] To ease the exposition, I use the following notation. Consider a market or financial system m of institutions $i \in \{1, \ldots, N\}$. Further define:

- R_m – return of the financial system m
- R_i – return of an individual institution i
- E_i – market value of equity of institution i
- X_i – book value of liabilities of institution i
- r – risk-free rate of return

Systemic risk can be measured in terms of systemic importance, at the level of individual financial institutions, or in terms of aggregate systemic risk, at the level of the financial system. Acharya et al. (2017) propose to measure the systemic risk of individual financial institutions by the marginal expected shortfall (MES), an institution's loss when the financial system is in crisis. MES is defined as an institution's return conditional on a significant market decline, breaching the value at risk (VaR) at the confidence level α:[4]

$$\mathrm{MES}_{\alpha}^{i} = -\,\mathrm{E}\left(R_i \mid R_m < -\mathrm{VaR}_{\alpha}^{m}\right). \tag{1.1}$$

Adrian and Brunnermeier (2016) introduce CoVaR, an alternative measure of individual financial institutions' systemic importance, which is based on firms' tail interdependence with the broader financial system. CoVaR is defined as the market's VaR at the confidence level α conditional on a quantile of an institution's return distribution. The institution's systemic importance is then measured by the change in CoVaR as the firm moves from its median state to a state of distress, given by its α-quantile:

$$\Delta\mathrm{CoVaR}_{\alpha}^{m|i} = \mathrm{CoVaR}_{\alpha}^{m|R_i=-\mathrm{VaR}_{\alpha}^{i}} - \mathrm{CoVaR}_{\alpha}^{m|R_i=-\mathrm{VaR}_{0.5}^{i}}. \tag{1.2}$$

Although both indicators, MES and CoVaR, measure the systemic risk of individual financial institutions, they take different perspectives on systemic risk

3 The discussion is based on Kaserer and Klein (2018). See also Huang et al. (2012a,b) and Black et al. (2016) for related discussions of the systemic risk measures presented in this section.
4 Here and throughout, I adopt the sign convention that a positive VaR indicates a loss.

and thus offer complementary insights. MES conditions on the occurrence of a financial crisis and in this sense assesses the *exposure* of an individual institution to turmoil in the broader financial system. CoVaR conditions on the distress of an individual institution and in this sense gauges the *contribution* of the institution to systemic risk in the financial system. Importantly, neither of these two measures can be aggregated to deliver a meaningful assessment of the total level of systemic risk in the financial system. The two risk measures discussed below bridge the gap between individual firms' systemic importance and the aggregate level of systemic risk in the financial system.

Brownlees and Engle (2017) propose the SRISK measure, which builds on MES and additionally incorporates the size and leverage of financial institutions. The marginal contribution of a financial institution to aggregate systemic risk is defined as its capital shortfall conditional on a major market decline:

$$\mathrm{SRISK}_i = E\left(k\left(X_i + E_i\right) - E_i \mid R_m < C\right), \tag{1.3}$$

where k is a prudent capital ratio and C is the return level defining a crisis. The total level of systemic risk in the financial system, then, is the aggregate of positive capital shortfalls across all financial institutions:

$$\mathrm{SRISK} = \sum_{i=1}^{N} \max\{\mathrm{SRISK}_i, 0\}, \tag{1.4}$$

as capital surpluses at individual institutions most likely would not be available to stabilize the financial system in times of crisis.

Huang et al. (2009) define systemic crises as situations in which a sizable share of the financial system's liabilities is in default. Building on this definition, they measure aggregate systemic risk by the distress insurance premium (DIP). DIP is the premium to be paid at time t for a hypothetical insurance contract covering distressed losses of the financial system at time T:

$$\mathrm{DIP}_t = E^Q\left(L_T \cdot \mathcal{I}\left(L_T > \mathrm{SLT}\right)\right) \cdot e^{-r(T-t)}. \tag{1.5}$$

L_T denotes the aggregate defaulted liabilities of the financial system. SLT defines the systemic loss threshold, the minimum level of catastrophic losses triggering a systemic crisis. $\mathcal{I}(x)$ takes the value 1 if condition x is true, and 0 otherwise. The expectation is calculated under the risk-neutral measure Q. Huang et al. (2012a,b) extend the approach to measure the systemic importance of individual institutions based on their marginal loss contributions:

$$\mathrm{DIP}_{i,t} = E^Q\left(L_{i,T} \cdot \mathcal{I}\left(L_T > \mathrm{SLT}\right)\right) \cdot e^{-r(T-t)}, \tag{1.6}$$

where $L_{i,T}$ is the loss to the creditors of financial institution i.

Both SRISK and DIP are additive measures of aggregate systemic risk and individual systemic importance. An important difference, however, is that SRISK is a conditional measure of capital shortfall in a financial crisis, whereas DIP is an unconditional measure of distressed losses. Therefore, whereas SRISK reflects only the severity of a financial crisis should it occur, DIP is a condensed indicator of both the propensity for and the severity of a financial crisis. Moreover, SRISK is a physical measure of systemic risk. DIP, by contrast, is calculated under the risk-neutral measure and thus reflects the physical probability of a financial crisis and an additional risk premium component. Via this risk premium component, DIP will capture a potential increase in market participants' risk aversion in times of financial turmoil.

All measures of systemic risk discussed in this section draw on publicly available market data, and SRISK and DIP additionally draw on publicly available accounting information. Risk measures derived from market data are forward-looking in the sense that market prices reflect market participants' aggregate expectation about future events. They thus complement indicators derived solely from financial statements data, which essentially reflect the result of contractual agreements that were made in the past.

1.1.2 *Tracing Financial Contagion*

This section provides a brief overview of channels of contagion in financial markets. Following Forbes and Rigobon (2002), Longstaff (2010), and others, I define financial contagion as a period of increased interconnectedness among financial institutions and markets following a shock to a particular firm or market segment. Such shocks may spread through the financial system through various linkages, and they can be traced using exposure data or by analyzing the lead–lag relationships of financial market variables.

1.1.2.1 *Direct and Indirect Contagion*

The literature has identified two broad types of channels by which shocks may propagate: *direct* and *indirect* channels of contagion (see, e.g., Trichet, 2005; van Lelyveld et al., 2011). Direct contagion occurs through direct exposures introduced by contractual relationships or other fundamental links. As one market participant comes under stress, other market participants may see their financial strength erode as the distressed counterparty becomes more likely to fail to deliver on its obligations. Financial institutions' balance sheets introduce the most prominent form of such links. On the asset side, financial institutions are exposed to other market participants' credit risk, and on the liability side, they depend on the availability of funding from other market participants.[5]

In the banking sector, the interbank market introduces close links among banks' balance sheets. Liquidity preference shocks may disrupt the banking

5 Beyond balance sheet exposures, providing critical functions and services is another channel through which direct contagion can occur. Financial institutions may become distressed if certain functions or services that are vital to their operations are disrupted. An example of such a critical function provided by banks is the payment system (FSB, 2013b).

system when distressed banks cancel their positions in that market, thereby denying critical funding to other banks. Allen and Gale (2000) illustrate this mechanism in a model with cross-regional interbank holdings.

Some authors have argued that the reinsurance market may play a similar role in the insurance sector. Insurers ceding part of their underwriting risks to reinsurers expose themselves to the assuming reinsurers' credit risk and, therefore, may come under stress if reinsurers fail (Cummins and Weiss, 2014). Regulators and industry representatives, however, have maintained that the topology of interbank and reinsurance networks differs: whereas the interbank market closely links all parts of the banking sector, the reinsurance market introduces primarily hierarchical links between reinsurers and primary insurers. This hierarchical structure is expected to limit cascading failures in the insurance sector (IAIS, 2011; Kessler, 2014). Indeed, analyzing reinsurance exposures, van Lelyveld et al. (2011), Park and Xie (2014), and Chen et al. (2018) find only limited evidence that the failure of reinsurers may spread contagiously to primary insurers and induce widespread losses.

Contagion may also occur if market participants are linked only indirectly rather than being directly exposed to one another. Following Longstaff (2010), indirect contagion may spread via at least three channels: *correlated information*, *liquidity spirals*, and *risk premiums*.[6]

Indirect contagion due to correlated information occurs if market participants try to infer information on the state of the broader financial system from negative news on an individual financial institution or market. As market participants act on this information, herding behavior and panics may ensure, and asset prices will be affected in parts of the financial system that were spared by the initial distress event. King and Wadhwani (1990), for example, present a related model where investors attempt to deduce information from price changes.

Liquidity spirals may arise if distressed financial institutions rapidly unwind their positions to free up liquidity. These fire sales may adversely affect asset prices and thus induce write-downs at other, initially unaffected institutions. In turn, these financial institutions may face liquidity problems and engage in asset sales as well, giving rise to a downward spiral of asset sales, price declines, and liquidity shortages. Kodres and Pritsker (2002) present a related model according to which investors transmit shocks by adjusting their portfolios across markets, and Brunnermeier and Pedersen (2009) describe the downward spiral in a model that links funding liquidity and market liquidity.

Finally, following a distress event affecting a particular financial market, market participants may demand higher compensation for risk-taking across all financial markets. This reassessment of the risk premium will affect asset prices across the entire economy. Theoretical frameworks relating to this channel include those of Vayanos (2004) and Acharya and Pedersen (2005), which accommodate shocks, risk premiums, and expected returns.

6 In Longstaff (2010), these three channels describe both direct and indirect contagion. As I discuss direct contagion separately, the following discussion relates only to indirect contagion.

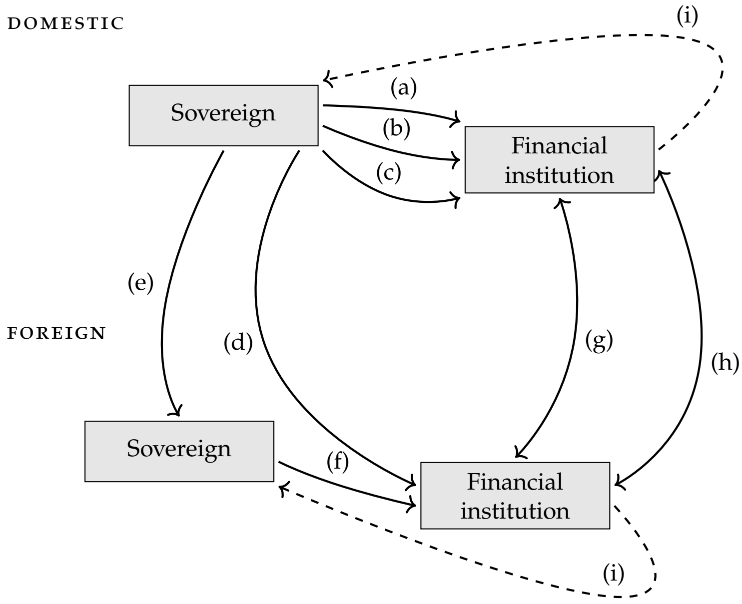

FIGURE 1.1: Contagion between sovereigns and financial institutions
This figure shows channels of contagion between sovereigns and financial institutions. The arrows represent the following channels: (a) decrease in the value of government bonds held by domestic financial institutions, (b) increase in domestic financial institutions' funding costs, (c) reduction of potential to support distressed domestic financial institutions, (d) decrease in the value of government bonds held by foreign financial institutions, (e) pressure on similar foreign sovereigns, (f) channels as at the domestic level, (g) direct contagion due to increase in counterparty credit risk or withdrawal of funding, (h) indirect contagion due to correlated information, liquidity spirals, and risk premium reassessments, and (i) increase in contingent government liabilities. *Source*: Modified from IMF (2010, p. 4).

Although the channels discussed above describe distinct mechanisms by which contagion may spread, they all affect asset prices. As contagion spreads, it thus introduces lead–lag relationships in time series of asset returns (Longstaff, 2010). This predictability can be exploited to measure contagion empirically by testing parameter restrictions in a suitable time series representation of asset returns (as in, e.g., Longstaff, 2010; Billio et al., 2012) or more sophisticated market-based systemic risk measures (as in, e.g., Chen et al., 2014).

1.1.2.2 *Sovereign Risk Spillovers*

Direct and indirect contagion is not confined to financial institutions. It may also emanate from—and adversely affect—sovereigns. Figure 1.1 illustrates the various channels of contagion between sovereigns and financial institutions. Following IMF (2010), these channels can be summarized as follows.

As a particular sovereign comes under stress, the value of government bonds held by financial institutions declines while domestic institutions' funding costs increase. This double hit impairs financial institutions' credit quality. As financial institutions move closer to the brink of failure, they pose an increasing contingent liability to the sovereign. Governments may be pressured to intervene and provide official support to prevent an impairment of the broader financial system upon the institutions' ultimate default. This contingent liability to the sovereign impairs the sovereign's credit quality, giving rise to a negative feedback loop between financial institutions and the sovereign. Eventually, this downward spiral of mutual credit quality impairment may deplete the government's potential to support distressed financial institutions.

Foreign sovereigns may come under pressure as market participants rationally or irrationally assume that sovereign distress abroad is indicative of the situation in their own country. Foreign financial institutions may need to write down bonds of the initially distressed sovereign, and a feedback loop similar to the one abroad can emerge in their home country. Within the financial sector, the situation may be exacerbated both domestically and across borders through the various channels of contagion described in the last section.

1.2 RESEARCH QUESTIONS

Banking is widely recognized as a source of systemic risk. Several factors contribute to systemic risk in banks (see, e.g., Trichet, 2005; Kessler, 2014). First, banks are vulnerable to shocks as they are typically highly leveraged and prone to runs on their liabilities (see, e.g., Diamond and Dybvig, 1983). Second, distress may contagiously spread among banks due to strong links between individual institutions, such as those in the interbank market (see, e.g., Allen and Gale, 2000). Third, distressed banks may exert negative externalities on the real economy, for example by rationing credit supply (see, e.g., Campello et al., 2010; Puri et al., 2011). In this sense, the size of a bank's balance sheet may be seen as an indicator of systemic risk concentration.

These characteristics have traditionally been less obvious in nonbank financial institutions due to differing business models and balance sheet structures (see, e.g., Trichet, 2005; Kessler, 2014). Insurers operating within the traditional business model, for example, do not rely on leverage in the same sense as banks as their liabilities are unlikely to be run on; their size may be seen as a measure of risk diversification rather than concentration; and the impact of their failure on the broader financial system should be limited due to weak interconnections and orderly resolution procedures (Kessler, 2014). Industry representatives have put forward related arguments against systemic risks in other nonbank financial institutions, such as asset managers (Stevens, 2014).

Unsurprisingly, in light of these arguments, global regulators' scrutiny of potential systemic risks in nonbank financial institutions has occasioned considerable debate. Whereas the traditional business model of nonbank financial institutions is arguably less likely to pose systemic risks, the boundaries between banking and other financial services are blurring (see, e.g., Trichet, 2005). After all, the systemic risk of nonbank financial institutions needs to be assessed empirically (see, e.g., IAIS, 2011). Whereas there is extensive empirical research on systemic risk in the banking industry, few empirical studies have investigated systemic risk in nonbank financial institutions, even less so in a global context.[7]

Against this background, the three studies in this thesis conduct an empirical analysis of systemic risk and contagion beyond the banking sector. Each of the three studies focuses on a specific aspect of systemic risk in nonbank financial institutions. Two studies assess systemic risk in insurance. The first of these studies analyzes the contribution of insurers to systemic risk in the global financial system, and the second examines contagion between and within the global insurance and banking industries. The third study addresses the issue of systemic risk caused by U.S. nonfinancial firms.

The empirical analysis in this thesis employs the general modeling framework of Huang et al. (2009, 2012a,b). The aggregate level of systemic risk in an industry and the systemic importance of individual firms are assessed by the aggregate and marginal DIP indicators, which refer to the market value of catastrophic losses at the industry and firm levels. DIP indicators have recently been applied to the analysis of systemic risk in the banking sector (Huang et al., 2009, 2012a,b; Lahmann and Kaserer, 2011; Black et al., 2016) and of contagion in the financial system (Lahmann, 2012; Chen et al., 2014).

Whereas the DIP frameworks implemented in previous studies require both equity and credit default swap (CDS) data to estimate the credit risk parameters of the firms in the sample, in the first two studies in this thesis, I implement an alternative estimation procedure that infers these parameters exclusively from CDS spreads. This approach enables, for the first time, a systematic analysis of the systemic risk contribution of nonpublic financial institutions. The third study implements the original DIP methodology. Importantly, as all risk measures I consider are derived from publicly available market data, they provide a transparent, timely, and forward-looking assessment of systemic distress.

1.2.1 *Systemic Risk in the Insurance Industry*

During the financial crisis of 2007–2009, the U.S. government saved the insurer American International Group from failure based on the fear that the firm's collapse would impair the broader financial system (Harrington, 2009). In the aftermath of the crisis, global regulators set out to scrutinize those insurers that, according to their assessment, pose such risks (FSB, 2013a).

Despite the events of the financial crisis and the policy responses that followed, the issue of systemic risk in insurance remains disputed. In particular, whether insurance poses a systemic risk (Kessler, 2014), whether the regulatory assessment approach is a suitable indicator of systemic risk in the insurance industry

7 Notable exceptions are a limited number of empirical studies on systemic risk in insurance, including Weiß and Mühlnickel (2014), Bierth et al. (2015), and Chen et al. (2014). Weiß and Mühlnickel (2014) analyze predictors of systemic risk in U.S. insurers. Bierth et al. (2015) provide a related study in a global context. Chen et al. (2014) analyze contagion between U.S.-listed insurers and banks. Other studies that consider nonbank financial institutions as part of analyses of systemic risk in regional financial systems include Billio et al. (2012), Engle et al. (2015), Adrian and Brunnermeier (2016), Acharya et al. (2017), and Brownlees and Engle (2017).

(Weiß and Mühlnickel, 2014; Bierth et al., 2015), and whether there should be a central regulator overseeing individual insurers considered systemically risky (Harrington, 2009) are issues of ongoing debate.

Indeed, it is not immediately obvious how insurers may pose a systemic risk. Kessler (2014) argues that overall, insurers' traditional business model enhances financial stability rather than instigates financial turmoil. Acharya et al. (2010) and Cummins and Weiss (2014), among others, agree that traditional insurance is unlikely to pose a systemic risk but point out that insurers have expanded into systemically risky nontraditional business activities. Regulators have thus argued that, ultimately, conclusions about systemic risk in the insurance industry need to be drawn based on empirical assessments (IAIS, 2011).

The first study, presented in Chapter 2, contributes to the discussion on systemically important insurers by providing such an empirical assessment. It addresses two pivotal questions. First, how much does the insurance sector contribute to systemic risk in the global financial system? Second, to what degree are individual insurers systemically risky?

The analysis is based on a sample of 183 public and nonpublic financial institutions from around the world. The panel includes 133 banks and 50 insurers over the period from January 2004 through December 2014. The sample represents many of the largest financial institutions in the global banking and insurance industries, including most of the institutions designated as G-SIBs and G-SIIs by the FSB. Collectively, the financial institutions in the sample account for almost half of the global banking and insurance assets.

I measure the aggregate level of systemic risk in the financial system and individual financial institutions' systemic importance by implementing the aggregate and marginal DIP indicators of Huang et al. (2009, 2012a,b). Additionally, I assess financial institutions' systemic importance by a set of complementary tail interdependence measures, which measure an institution's propensity to be distressed when the financial system is in crisis, and vice versa.

As my main result, I point out an important ambiguity between the insurance industry's aggregate systemic risk and individual insurers' systemic importance. On the one hand, the results indicate that the aggregate contribution of the insurance sector to systemic risk is relatively limited. During the financial crisis and the European sovereign debt crisis, the insurance sector's systemic risk share averaged only 9 percent. On the other hand, I provide evidence that individual insurers may still be systemically important financial institutions. In particular, the riskiest multi-line and life insurers individually exhibit similar systemic risk shares as the riskiest banks in the sample. Moreover, distress in several individual multi-line insurers, life insurers, and reinsurers is associated with turmoil in the broader financial system.

Furthermore, beyond shedding light on systemic risk in insurance, I also provide evidence that nonpublic financial institutions are an economically relevant source of systemic risk. During the crisis episodes, the nonpublic banks in the sample collectively accounted for a higher systemic risk share than the entire insurance sector. Moreover, several nonpublic firms are represented among the most systemically risky firms in the sample.

1.2.2 *Interconnectedness of Banks and Insurers*

The analysis in the first study focuses on contemporaneous systemic risk and does not take a stand on how shocks to banks and insurers spread through the financial system. Indeed, the previous evidence of systemic risk spillovers between banks and insurers is at least partly inconclusive. As for the inter-sector connectedness of insurers, Billio et al. (2012) identify insurance companies as a highly interconnected part of the financial system and as potential propagators of shocks to other institutions. By contrast, Chen et al. (2014) find that distress in the banking sector impairs insurers much more significantly and over a longer horizon than vice versa. As for the intra-sector connectedness of insurers, Cummins and Weiss (2014) argue that reinsurance crises might spill over to primary insurers. In analyses of exposures in the reinsurance market, however, van Lelyveld et al. (2011), Park and Xie (2014), and Chen et al. (2018) find that the effect of reinsurance defaults on primary insurers is relatively contained. Nonetheless, as their default analyses focus on direct contagion, they leave open the possibility of cascading failures induced by indirect contagion.

The second study, presented in Chapter 3, sets out to shed further light on the interconnectedness of banks and insurers. It thus complements the analysis of contemporaneous systemic risk in the first study. In particular, I address three important questions. First, which individual insurance segments are most interconnected with the banking sector? Second, how interconnected are different types of insurers with one another? Third, what is the role of sovereign risk in contagion between banks and insurers?

The empirical analysis is based on the sample of 183 financial institutions from around the world analyzed in the first study. In a first step, I measure systemic risk in the banking and insurance sectors using the aggregate DIP indicator of Huang et al. (2009). In essence, whereas the first study modeled the financial system in its entirety to analyze the risk of system-wide crises, the second study models individual banking and insurance sectors to analyze the risk of sector-wide crises. In a second step, based on these indicators, I test for systemic risk spillovers in the banking and insurance sectors using Granger causality analysis. As the systemic risk indicators are derived from market data, to the extent that financial markets are informationally efficient, the analysis should capture both direct and indirect channels of contagion.

I find that overall, the impact of the banking sector on the insurance sector is indeed more significant than in the other direction. However, analyzing contagion between the banking and insurance sectors at the level of individual lines of business, I provide novel evidence of a feedback loop between the banking sector and the life insurance sector. This bidirectional dependency between the banking and insurance industries is robust when controlling for a common exposure to sovereign risk. The results thus indicate that insurers are not only victims of systemic risk in the banking sector but may also contribute to financial turmoil by propagating shocks to the broader financial system.

By contrast, interconnectedness within the insurance sector is relatively weak, and there are no feedback loops between different lines of business. Multi-line insurers, life insurers, and reinsurers all Granger-cause property–casualty insurers but not vice versa. Additionally, bond and mortgage insurers lead life insurers. Interestingly, these interconnections appear to be mediated by a common exposure of insurers to distress in the banking sector, as the interconnections in the insurance sector largely break down when insurers' common exposure to the banking sector is taken into account.

1.2.3 *Systemic Risk in the Real Sector*

In a regulatory context, systemic risk is typically defined as the risk of an impairment of the financial system that likely has severe real consequences.[8] This definition is restrictive in that it excludes the possibility of systemic risk beyond the financial system. Alternatively, systemic risk could be defined in more general terms as the risk of an economic event that causes substantial declines in aggregate output and employment levels. This definition would encompass financial systemic risk in the financial system as well as nonfinancial systemic risk in the real economy. Indeed, Trapp and Wewel (2013) argue that economic downturns are more likely to be caused by the default of a large real sector firm than by the failure of a major bank.

In line with the above definition, indicators of systemic risk proposed in the empirical literature are typically premised on the implicit assumption that they measure a unique characteristic of the financial system. It is, however, not immediately clear whether these metrics indeed measure systemic risk in the intended sense or reflect a more generic type of distress risk in the sense of the generalized definition of systemic risk. The implications of systemic risk in the generalized sense would be twofold. First, empirical evidence of systemic risk in financial institutions would need to be interpreted with caution, especially for nonbank financial institutions. Moreover, it would be instructive to identify the drivers of nonfinancial systemic risk to enable the design, implementation, and enforcement of effective measures to mitigate such risk.

Very few prior studies have employed empirical indicators of systemic risk to analyze sector-wide distress in the real economy. As a notable exception, using SRISK, Brownlees and Engle (2017) provide evidence that the nonfinancial sector suffered much less from an increase in aggregate capital shortfall during the financial crisis than the financial sector did. Importantly, however, their study does not address the drivers of sector-wide distress in nonfinancial firms.

8 For a discussion of regulatory definitions of systemic risk, see Section 1.1.1.1.

The third study, presented in Chapter 4, analyzes the performance of empirical measures of systemic risk for nonfinancial firms and the potential threats to financial stability caused by such firms. In particular, it addresses two questions. First, do empirical measures of systemic risk pick up characteristics unique to the financial system? Second, if there is economically relevant systemic risk in the nonfinancial sector, what causes such risk?

To investigate these issues, I apply the aggregate and marginal DIP indicators of Huang et al. (2009, 2012a,b) to samples of U.S. financial and nonfinancial firms. The financial sample includes 53 firms, and the nonfinancial sample includes 207 firms, representing most of the largest firms in their respective industries. The analysis spans the period from April 2002 through September 2016.

The results confirm that sector-wide distress risk is indeed substantially higher for financial firms than for nonfinancial firms. Over the full sample period, systemic risk averages USD 63 billion in the financial sample, whereas it averages USD 9 billion in the nonfinancial sample. At the height of the financial crisis, however, the nonfinancial sector experienced economically relevant levels of distress risk. Moreover, a small number of nonfinancial firms exhibited distressed losses similar to those of systemically risky financial institutions. I show that systemic risk in nonfinancial firms is driven by these firms' engagement in financial services at the subsidiary level. Empirical measures of systemic risk, therefore, appear to capture systemic risk in the intended sense.

1.3 CONTRIBUTIONS

Overall, this thesis contributes to a better understanding of systemic risk and contagion beyond the banking sector. In particular, I enrich the literature along the following important dimensions.

First, I provide a comprehensive assessment of systemic risk in insurance. Using a set of aggregate and firm-level indicators derived from CDS spreads, I point out an important ambiguity between the systemic risk posed by the insurance sector as a whole and the systemic importance of individual insurers. On the one hand, the insurance sector is found to account for a relatively small share of the systemic risk in the global financial system. On the other hand, several individual insurers exhibit elevated levels of systemic risk and may, therefore, be considered systemically important. The findings inform the controversial discussion of the designation and regulation of systemically important insurers (see, e.g., Harrington, 2009; Acharya et al., 2010; Kessler, 2014; Weiß and Mühlnickel, 2014; Bierth et al., 2015). Although the empirical evidence suggests that most of the effort to enhance financial stability should be directed toward the banking sector, regulators may still want to selectively target systemic risk in insurance using a combination of entity- and activity-based measures.

Second, I improve the understanding of contagion in the banking and insurance industries. To this end, I exploit the lead–lag relationships in market-based indicators of the industries' systemic risk. I thus extend the lines of inquiry in the recent studies of Billio et al. (2012), Chen et al. (2014), Hautsch et al. (2015), and others, which try to identify the sources and sinks of systemic risk in the financial system. In partial contrast to the findings of Chen et al. (2014), who argue that the insurance sector is a sink rather than a source of systemic risk, I identify a feedback loop between banks and life insurers. Interconnectedness among the insurance sector's different lines of business, however, is found to be low. In particular, in line with the findings of van Lelyveld et al. (2011), Park and Xie (2014), and Chen et al. (2018), distress in the reinsurance sector does not appear to entail widespread insurance crises. The insurance sector thus appears to have sufficient shock-absorbing capacity to prevent both direct and indirect contagion and hence cascading failures in times of crisis.

Third, I shed light on sector-wide distress risk in the broader economy by providing an empirical assessment of systemic risk in real sector firms. The analysis confirms that systemic risk is generally low for real sector firms, but also reveals elevated levels of systemic risk for some nonfinancial firms. Whereas this finding is seemingly inconsistent with the common notion that systemic risk is a unique characteristic of the financial system, nonfinancial firms' systemic risk contributions appear to be driven by their engagement in financial services at the subsidiary level. These findings have two important implications. First, they reassure regulators and researchers that empirical measures of systemic risk capture systemic risks inherent in financial services rather than a generic type of distress risk. Second, they highlight the need for regulators to duly monitor shadow-banking activities of real sector firms.

Finally, I show that nonpublic financial institutions are an economically relevant source of systemic risk. Empirical measures of systemic risk implemented in the literature typically rely on equity data. I implement an alternative modeling approach that only requires CDS spreads. As an innovation on the prior literature, I provide an analysis of sources of systemic risk not accounted for by equity-based measures, such as privately held firms, state-owned firms, and subsidiaries of public firms. I expect such a modeling approach to benefit future analyses of systemic risk in financial systems with a comparatively high share of nonpublic firms, as is the case in several European countries. Furthermore, it enables more fine-grained analyses of systemic risk at the subsidiary level of diversified financial and nonfinancial firms.

1.4 OUTLINE

The remainder of this thesis proceeds as follows. Chapter 2 assesses the contribution of insurers to systemic risk in the financial system. Chapter 3 explores contagion among insurers, banks, and sovereigns. Chapter 4 analyzes systemic risk in real sector firms. Chapter 5 offers concluding remarks and outlines avenues for future research.

2

SYSTEMIC RISK IN FINANCIAL MARKETS: HOW SYSTEMICALLY IMPORTANT ARE INSURERS?

ABSTRACT

This study investigates how insurers contribute to systemic risk in the global financial system. In a modeling framework embracing publicly traded and non-public firms, the financial system is represented by 183 major banks and insurers over the period from 2004 through 2014. In the aggregate, the insurance sector contributes relatively little to systemic losses; during the financial crisis and the European sovereign debt crisis, its risk share averaged 9 percent. Individually, however, several multi-line and life insurers appear to be as systemically risky as the riskiest banks. Our results, therefore, affirm that some insurers are systemically important and indicate that insurers' level of systemic risk varies by line of business. We discuss several important implications of our results for managing systemic risk in insurance, arguing for a combination of entity- and activity-based regulation.

KEYWORDS:	Financial crisis, European sovereign debt crisis, systemic risk, global systemically important insurer, credit default swap
JEL CLASSIFICATION:	G01, G17, G21, G22, G28
AUTHORS:	Christoph Kaserer and Christian Klein
FIRST AUTHOR:	Christian Klein
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1 For the published version, see Kaserer and Klein (2019). The main differences between the working paper included in this thesis and the published version are that the working paper (i) presents additional details on the modeling approach, empirical findings, and policy and analysis implications, (ii) uses a different data source for the CDS spreads, and (iii) uses a different methodology for determining recovery rates in default scenarios. The working paper is based on CDS data provided by Thomson Reuters Datastream and uses deterministic recovery rates. The published version is based on CDS data provided by Markit and uses stochastic recovery rates. The published version covers a slightly broader sample of financial firms than the working paper; however, both studies yield qualitatively and quantitatively similar results.

2.1 INTRODUCTION

Insurers experienced distress in the financial crisis of 2007–2009; however, their status as systemically important financial institutions is disputed. During the crisis, the insurance company American International Group (AIG) was brought to the brink of failure by severe losses in its financial markets businesses. The firm's ultimate rescue from bankruptcy illustrates the fact that an insurer's default may have such powerful repercussions for the wider financial system that it provokes government interventions (Harrington, 2009). More recently, supervisors have feared that European life insurers are prone to fail en masse in a double-hit scenario involving sustained low interest rates compounded by a sudden decline in asset prices. Under this scenario, widespread loss of trust in financial institutions could easily ensue (ESRB, 2015).

In the aftermath of the financial crisis, regulators set out to identify global systemically important financial institutions (G-SIFIs) and subject them to closer regulatory scrutiny.[2] As part of this general initiative, following the designation of global systemically important banks (G-SIBs), the Financial Stability Board (FSB) and the International Association of Insurance Supervisors (IAIS) embarked on a joint effort to identify and regulate global systemically important insurers (G-SIIs). In July 2013, the FSB first published a list of systemically important insurers based on an initial assessment methodology developed by the IAIS. This list is subject to annual review, and the designated insurers are required to comply with a range of additional policy measures, including increased group-wide supervision, group-wide recovery and resolution planning, and higher loss absorbency requirements.[3]

Although policy measures for systemically important insurers are now being phased in, much controversy still exists about whether the insurance sector poses a systemic risk and, if so, how this risk should be measured, and how systemically important insurers should be regulated. Industry representatives have argued that overall, insurers enhance financial stability rather than pose a systemic risk (Kessler, 2014). Previous research has criticized the regulatory assessment methodology (Weiß and Mühlnickel, 2014; Bierth et al., 2015), and researchers have argued that a systemic risk regulator for insurance companies would erode market discipline (Harrington, 2009). The future status of today's G-SIIs is meanwhile uncertain, as MetLife has successfully challenged its systemic risk label assigned by U.S. regulators in court. As noted by the IAIS (2011), systemic risk in insurance ultimately needs to be judged on empirical grounds. Surprisingly, despite its pivotal role in the regulation of financial

2 G-SIFIs are defined as "institutions of such size, market importance, and global interconnectedness that their distress or failure would cause significant dislocation in the global financial system and adverse economic consequences across a range of countries" (FSB, 2010, p. 2).

3 The initial list of systemically important insurers published in July 2013 included Allianz, AIG, Assicurazioni Generali, Aviva, AXA, MetLife, Ping An, Prudential Financial, and Prudential. The November 2014 update left the G-SII list unchanged. In November 2015, Aegon replaced Assicurazioni Generali. Reinsurers were not included in the underlying assessments.

markets, empirical evidence on the subject remains relatively limited.

Against this background, we set out to contribute to better-informed regulation of systemic risk via an empirical assessment of insurers' systemic importance. We model the global insurance sector in the context of the global financial system and analyze systemic risk in insurance relative to systemic risk in banking. Our sample is a set of 183 financial institutions over the period from January 2004 through December 2014. The sample includes 133 banks and 50 insurers, which account for almost half of the global banking and insurance assets and almost all G-SIFIs. In our analysis, we address two main questions: First, what contribution does the insurance sector make to the aggregate level of systemic risk in the global financial system? Second, to what degree are individual insurers systemically important?

Our analysis employs the general modeling framework of Huang et al. (2009, 2012a,b). The financial system is represented by a portfolio of debts, and financial crises are modeled as catastrophic portfolio losses. The financial system's aggregate systemic risk is measured by the distress insurance premium (DIP), defined as the premium of a hypothetical insurance contract covering such losses. The systemic importance of individual financial institutions is measured as their marginal contribution to aggregate systemic risk and in terms of tail interdependence with the broader financial system. We conduct a forward-looking assessment of systemic risk by estimating these risk measures from credit default swap (CDS) spreads.

As our main result, we point out an important ambiguity between the systemic risk posed by the insurance sector as a whole and the systemic importance of individual insurers. Indeed, the insurance sector contributes a relatively small share to the aggregate level of systemic risk in the global financial system, averaging only 9 percent over the period of the financial crisis and the ensuing European sovereign debt crisis. On the level of individual financial institutions, however, a number of multi-line and life insurers exhibit levels of systemic risk similar to those of the riskiest banks in the sample. Our results, therefore, indicate that some insurers are indeed systemically important financial institutions.

In summary, we make both empirical and methodological contributions to the literature. On the empirical side, we document a rich set of stylized facts on systemic risk in insurance. We differentiate between life, nonlife, and reinsurance, and examine aggregate systemic risk contributions as well as individual systemic importance. To the best of our knowledge, our study is the first to measure the actual systemic risk share of the insurance industry in a global context, and provides the broadest available cross-sectional analysis of financial institutions' systemic risk based on CDSs to date.[4]

On the methodological side, we provide an extended framework for measuring systemic risk. Our implementation includes a diverse set of complementary risk measures in a unifying modeling framework. The model applies to both publicly

4 Note that the published version of this study covers an even broader sample than the working paper version presented here. For the published version, see Kaserer and Klein (2019).

traded and nonpublic firms, such as privately held firms, state-owned firms, and subsidiaries of public firms. Including nonpublic firms enables us to cover a broader sample and, as an innovation relative to the prior literature, to analyze the systemic importance of nonpublic financial institutions. We expect that modeling frameworks embracing nonpublic firms will benefit future analyses of systemic risk in financial markets with a large share of privately held or state-owned financial institutions. Modeling subsidiaries of public firms will further enable more accurate analyses of systemic risk in diversified holding companies, such as financial firms operating both banking and insurance businesses.

The remainder of this paper proceeds as follows. Section 2.2 reviews the literature on systemic risk in insurance. Sections 2.3 and 2.4 describe the modeling framework and the sample, respectively. Section 2.5 presents our empirical findings. We discuss policy implications and recommendations in Section 2.6 and offer concluding remarks in Section 2.7.

2.2 RELATED LITERATURE

Research on systemic risk in insurance broadly addresses the issues of whether the insurance sector poses a systemic risk and, if so, how systemically important insurers should be identified and regulated. To frame the analysis in the main part of our paper, we briefly review this literature below. For a comprehensive survey of the existing literature on systemic risk in insurance, see Eling and Pankoke (2016).

Whether the insurance sector poses a systemic risk is a fundamental issue, and varying opinions have emerged. Kessler (2014) adheres to the traditional view that insurers are not systemically risky. The argument is premised largely on the observation that the traditional insurance balance sheet lacks those characteristics typically associated with systemic risk in other financial institutions. Insurers' size stems from a well-diversified portfolio of idiosyncratic risks, insurers rely less on leverage in the traditional sense, and they engage less in maturity transformation. Even if an individual insurance company were to fail, weak interconnectedness and orderly resolution processes should attenuate the impact on the wider financial system.

Acharya et al. (2010) and Cummins and Weiss (2014) look more closely at insurers' business activities. They agree that little, if any, systemic risk is associated with insurers' traditional underwriting, financing, and investment activities. However, these authors argue that noncore business activities such as providing financial guarantees, excessive short-term financing, and investing in structured securities are systemically risky. These activities interconnect insurers more closely with financial markets, enabling them to propagate distress to the wider financial system.

Insurers' noncore activities share many characteristics with the type of business that banks usually undertake. Even before the financial crisis, Trichet (2005) identified blurred boundaries between banks and insurers as a potential source of new risks that needs to be duly monitored. More recently, Acharya and Richardson (2014) have argued that some insurers have shifted away from their traditional business model to such an extent that the insurance sector does indeed pose a systemic risk. According to their study, insurers now offer products containing systematic risks or protecting against macroeconomic shocks, have increased their capital markets businesses, and have become more prone to runs. Baluch et al. (2011) agree that systemic risk in insurance has become nonnegligible, but argue that it is contained relative to the banking sector.

Few prior studies have modeled systemic risk in insurance in the context of the wider financial system. Brownlees and Engle (2017) and Engle et al. (2015) respectively investigate systemic risk in the U.S. financial system and Europe using the SRISK indicator. Their results provide empirical evidence that systemic risk in insurance has increased during the recent crisis episodes, but is generally dominated by systemic risk in banking.

Billio et al. (2012) investigate the interconnectedness of large financial institutions during episodes of tranquility and of turmoil. Granger causality tests among financial institutions' returns highlight insurance companies as a highly interconnected part of the financial system, and as potential propagators of shocks during financial crises. Chen et al. (2014) are more skeptical of contagion emanating from insurers. They measure systemic risk in the banking and insurance sectors using the DIP indicator of Huang et al. (2009), and establish by means of Granger causality tests and stress test scenarios that the impact of banks' distress on insurers is overall more significant and longer-lived than in the other direction. Bégin et al. (2019) document similar results on banks' and insurers' interconnectedness.

If one sees the insurance sector as a source of systemic risk, then the important issue becomes how to identify those insurers that might contribute to dislocation in the financial system. The initial regulatory assessment methodology proposed in IAIS (2013) relies on a set of indicators describing five assessment categories: size, global activity, interconnectedness, nontraditional and noninsurance activities, and substitutability.

Weiß and Mühlnickel (2014) and Bierth et al. (2015) subject this methodology to empirical scrutiny. Their studies analyze the impact of firm characteristics in the five assessment categories on insurers' contribution and exposure to systemic risk. Insurers' contribution to systemic risk is measured by the ΔCoVaR measure of Adrian and Brunnermeier (2016), and their exposure to systemic risk is measured by the marginal expected shortfall (MES) measure of Acharya et al. (2017). The results lend only partial support to the initial regulatory assessment methodology. Weiß and Mühlnickel (2014) analyze a sample of U.S. insurers during the financial crisis. They conclude that size predicts insurers' contribution and exposure to systemic risk. Insurers' exposure to systemic risk additionally depends on nontraditional and noninsurance activities as well as investment income. Factors relating to the other categories do not appear to be main drivers of systemic risk. Bierth et al. (2015) consider a global panel of insurers over the financial crisis and the European sovereign debt crisis. They find that insurers' contribution to systemic risk is mainly driven by leverage, whereas large insurers' exposure to systemic risk is accounted for by their interconnectedness within the industry. According to this study, size drives neither insurers' contribution nor exposure to systemic risk.[5]

A final issue concerns how systemically risky insurers should be regulated. Harrington (2009) opposes a systemic risk regulator for insurance companies, as designating an insurer as systemically important would generate a negative externality and reduce market efficiency. The explicit or implicit bailout guarantee associated with a systemic risk label would encourage institutions designated systemically important to take more risk, and would likely result in a competitive advantage through lower funding costs. Acharya et al. (2010), in contrast, call for a dedicated regulator overseeing systemically important insurers.

Of this literature, the recent work by Chen et al. (2014) is closest to ours. Like these authors, we provide an empirical assessment of systemic risk in insurance based on the DIP indicator. There are, however, several important differences between their analyses and ours, which collectively also distinguish our work from other contributions.

First, we approach systemic risk from a different perspective. Chen et al. (2014) take a time-series perspective and analyze the lead–lag relationships between total systemic risk in the banking and insurance industries. These authors highlight analyzing the systemic importance of individual insurers as an important avenue for further research. The present paper takes such a cross-sectional perspective and analyzes the contemporaneous relationships among banks, different types of insurers, and the overall financial system. Whereas previous research indicates that systemic risk in insurance is lower than it is in banking, a subset of insurance companies might still be systemically important.

Second, we implement an adapted modeling approach, which applies to publicly traded as well as to nonpublic firms. As opposed to the approach taken in Chen et al. (2014), which requires both CDS and equity data, we only require CDS data. This allows us to include privately held firms, state-owned firms, and subsidiaries of public firms in the systemic risk analysis, addressing potential sources of systemic risk not accounted for by equity-based measures.

Third, we provide a global analysis spanning the entirety of the financial crisis and the ensuing European sovereign debt crisis. This complements the study of Chen et al. (2014), who base their analysis on a sample of U.S.-listed banks and insurers covering the early stages of the financial crisis up to May 2008.

5 The regulatory assessment methodology has recently been updated. The updated assessment methodology and the changes over the initial methodology are described in IAIS (2016). Among other revisions, the nontraditional and noninsurance activities category has been eliminated. The respective indicators have been collapsed into the interconnectedness category and a newly established asset liquidation category. How the updated assessment methodology performs vis-à-vis empirical risk measures, however, remains an open question.

2.3 MODELING FRAMEWORK

This section introduces our modeling framework. We define and analyze systemic risk in terms of losses to financial institutions' creditors. First, the financial system is set in a structurally founded model for portfolio credit risk. We then define financial crises as a major portfolio loss and, based on this definition, implement measures for the time series of aggregate systemic risk and the cross section of individual systemic importance. Finally, we estimate the default probabilities and correlations underpinning our model from CDS data.

2.3.1 *Modeling Financial Institutions' Losses*

In this section, we model losses to financial institutions' creditors, including losses to their depositors, policyholders, and investors. We construct a portfolio of firms $i = 1, \dots, N$, which represents the financial system. Each firm i has a portfolio weight equal to the book value of its liabilities, X_i. If the firm defaults at time t, its creditors recover a fraction of their claims as determined by the recovery rate $RR_{i,t} \in [0, 1]$, and the portfolio incurs a marginal loss $(1 - RR_{i,t}) \cdot X_i$. In the following, we focus on modeling the portfolio's aggregate loss, which we will use in the next section to define financial crises.

The underlying model for portfolio credit risk is based on the Merton (1974) model. This framework establishes a structural link between the market value of individual firms' assets and defaults by those firms. We implement a multi-firm extension that accounts for default dependence between the individual firms in the portfolio through a set of common factors driving the firms' asset values. Our implementation corresponds to the normal copula model widely used in practical credit risk applications (see, e.g., Glasserman and Li, 2005).

Following the Merton (1974) model, firm i's market value of assets $A_{i,t}$ is given by a geometric Brownian motion. We capture dependence among firms by modeling the stochastic part of the asset returns by a multi-factor model of M systematic risk factors $Y_t = [Y_{1,t}, \dots, Y_{M,t}]^\top$ common to all firms and an idiosyncratic risk factor $Z_{i,t}$ specific to firm i. Under the risk-neutral measure Q, the asset value dynamic is of the form

$$dA_{i,t} = rA_{i,t}\, dt + \sigma_i A_{i,t}\, dW_{i,t}, \tag{2.1}$$

$$dW_{i,t} = F_i\, dY_t + \sqrt{1 - F_i F_i^\top}\, dZ_{i,t}, \tag{2.2}$$

where r is the risk-free rate, σ_i is the volatility, and $W_{i,t}$ is a Wiener process. All risk factors are given by Wiener processes and, without loss of generality, are assumed to be mutually independent.[6] The common factor loadings $F_i =$

6 The systematic risk factors can be motivated by market or country risk factors, such as interest rates or inflation. Note that we can allow for correlation among such market or country factors and transform them into a set of independent random variables based on a Cholesky decomposition of their covariance matrix.

$[F_{i,1}, \ldots, F_{i,M}]$, $F_i F_i^\top \leqslant 1$, drive the asset return correlations: for two firms $i \neq j$, the asset returns are correlated by $\rho_{ij} = \text{corr}\left(d \ln A_{i,t}, d \ln A_{j,t}\right) = F_i F_j^\top$.

In this setting, firm i defaults if its asset value falls below a solvency requirement D_i. The time-t probability of default h periods into the future is

$$\begin{aligned} PD_{i,t}(h) &= P^Q \left(A_{i,t+h} < D_i\right) \\ &= P^Q \left(A_{i,t} \cdot \exp\left[\left(r - \sigma_i^2/2\right) \cdot h + \sigma_i \cdot \sqrt{h} \cdot R_{i,t:t+h}\right] < D_i\right) \\ &= \Phi\left(-DTD_{i,t}(h)\right), \end{aligned} \tag{2.3}$$

$R_{i,t:t+h}$ is the standardized asset return of firm i between times t and $t+h$,

$$R_{i,t:t+h} = \frac{W_{i,t+h} - W_{i,t}}{\sqrt{h}}, \tag{2.4}$$

and Φ is the cumulative standard normal distribution function. Furthermore, we introduce the distance-to-default as a measure of firm i's credit quality:

$$DTD_{i,t}(h) = \frac{\ln A_{i,t} - \ln D_i + \left(r - \sigma_i^2/2\right) \cdot h}{\sigma_i \sqrt{h}}. \tag{2.5}$$

The portfolio credit risk model for default of individual firms, indicated by $I_{i,t+h}$, the loss incurred by individual firms, measured by $L_{i,t+h}$, and the total loss incurred by the portfolio, measured by L_{t+h}, can now be written as follows:

$$I_{i,t+h} = \mathcal{I}\left(R_{i,t:t+h} < -DTD_{i,t}(h)\right), \tag{2.6}$$

$$L_{i,t+h} = \left(1 - RR_{i,t+h}\right) \cdot X_i \cdot I_{i,t+h}, \tag{2.7}$$

$$L_{t+h} = \sum_{i=1}^{N} L_{i,t+h}. \tag{2.8}$$

The recovery rates, $RR_{i,t+h}$, are assumed to be independent of the default probabilities, $PD_{i,t}(h)$. We define $\mathcal{I}(x) = 1$ if condition x is true and 0 otherwise.

In the following sections, we will implement the systemic risk measures and estimate the underlying credit risk parameters. Two concluding remarks on the credit risk model are in order. First, firms either default or survive at time $t+h$. No default will occur if $A_{i,\tau}$ has fallen below D_i for some $\tau \in (t, t+h)$ but has recovered at time $t+h$. Second, although the model implicitly depends on the risk-free rate r, the volatility σ_i, the asset value $A_{i,t}$, and the solvency requirement D_i, none of these quantities has to be estimated explicitly. The model is fully specified given the default probabilities, asset return correlations, liability weights, and recovery rates.

2.3.2 *Implementing the Systemic Risk Measures*

In this section, we implement our systemic risk measures. Within the above setting and notation, financial crises can be defined as catastrophic portfolio losses. For a system-wide crisis, referred to as a *systemic event*, we consider a scenario where the portfolio loss exceeds a fraction $SLT^{rel} \in (0, 1]$ of the portfolio liabilities:

$$\sum_{i=1}^{N} L_{i,t+h} = L_{t+h} > SLT = SLT^{rel} \cdot \sum_{i=1}^{N} X_i. \tag{2.9}$$

The systemic loss threshold SLT is the maximum loss the financial system can absorb without becoming distressed. Losses greater than SLT trigger systemic events with potentially severe consequences for the real economy.

Starting from this definition, we measure systemic risk using a diverse set of metrics. We first implement the DIP indicators originally proposed by Huang et al. (2009, 2012a,b), which have also been applied by, for example, Chen et al. (2014) and Black et al. (2016). These measure aggregate systemic risk and financial institutions' marginal contributions as the market value of losses during a systemic event. We further implement measures of tail interdependence between the broader financial system and individual financial institutions, as suggested by Malz (2013). These measure the propensity for an individual institution's distress if the financial system is under stress, and vice versa.

We implement all risk measures using Monte Carlo methods. For each time t, we simulate 500,000 default scenarios of failing and surviving firms. Systemic events are rarely observed by definition, and plain Monte Carlo methods may therefore be slow to converge. To enhance the efficiency of the estimators, we implement the mean-shifting importance sampling procedure of Glasserman and Li (2005) and Glasserman (2005), which adjusts the mean of the common factors underpinning the asset returns.

2.3.2.1 *Distress Insurance Premium*

Intuitively, the DIP framework measures aggregate systemic risk as the premium of a hypothetical insurance policy covering distressed losses to financial institutions' creditors—hence its name. More formally, this premium is the market value of a contingent claim that pays the loss in the financial systems' liabilities if a systemic event occurs at maturity and nothing otherwise. Taking a forward-looking perspective, the level of aggregate systemic risk over the next h periods as seen at time t is given by (Huang et al., 2009):

$$\begin{aligned} DIP_t(h) &= E^Q\left(L_{t+h} \cdot \mathcal{I}\left(L_{t+h} > SLT\right)\right) \cdot e^{-r_t h} \\ &= \underbrace{P^Q\left(L_{t+h} > SLT\right)}_{=PSD_t(h)} \cdot \underbrace{E^Q\left(L_{t+h} \mid L_{t+h} > SLT\right)}_{=ETL_t(h)} \cdot e^{-r_t h}. \end{aligned} \tag{2.10}$$

$PSD_t(h)$ defines the risk-neutral probability of systemic distress (PSD), and $ETL_t(h)$ defines the expected tail loss (ETL).[7] As it is risk-neutral, the PSD incorporates the physical probability of a systemic event and an additional

7 The decomposition of the DIP indicator into PSD and ETL follows Lahmann and Kaserer (2011).

risk premium. The ETL is closely related to the notion of expected shortfall in financial risk management. Both measure the expected loss of a portfolio under extreme conditions. The subtle difference is that we define ETL conditional on a loss threshold, whereas the expected shortfall is defined in terms of a probability threshold. In the context of DIP, the risk-neutral PSD corresponds to the compounded insurance premium per unit of ETL.

The aggregate systemic risk of the financial system can be fully allocated to individual financial institutions in an additive fashion. The marginal contribution of firm i to the financial system's systemic risk amounts to (Huang et al., 2012a,b):

$$\begin{aligned} \mathrm{DIP}_{i,t}(h) &= E^{Q}\left(L_{i,t+h} \cdot \mathcal{I}\left(L_{t+h} > \mathrm{SLT}\right)\right) \cdot e^{-r_t h} \\ &= \underbrace{P^{Q}\left(L_{t+h} > \mathrm{SLT}\right)}_{=\mathrm{PSD}_t(h)} \cdot \underbrace{E^{Q}\left(L_{i,t+h} \mid L_{t+h} > \mathrm{SLT}\right)}_{=\mathrm{ETL}_{i,t}(h)} \cdot e^{-r_t h}, \end{aligned} \tag{2.11}$$

where $\mathrm{ETL}_{i,t}(h)$ defines the firm's marginal ETL. We can now determine the marginal contribution $\mathrm{DIP}_{\mathcal{S},t}(h)$ of an arbitrary segment $\mathcal{S} \subseteq \{1, \ldots, N\}$ of the financial system to total systemic risk by aggregating the marginal contributions $\mathrm{DIP}_{i,t}(h)$ of each firm $i \in \mathcal{S}$,

$$\mathrm{DIP}_{\mathcal{S},t}(h) = \sum_{i \in \mathcal{S}} \mathrm{DIP}_{i,t}(h). \tag{2.12}$$

DIP, as defined above, measures systemic risk in nominal terms. Rather than measuring systemic risk in nominal price, we will occasionally find it more convenient to express systemic risk in relative terms, per unit of exposure, $\mathrm{DIP}^{unit}_{\mathcal{S},t}(h)$, or as a share of aggregate systemic risk, $\mathrm{DIP}^{share}_{\mathcal{S},t}(h)$:

$$\mathrm{DIP}^{unit}_{\mathcal{S},t}(h) = \frac{\mathrm{DIP}_{\mathcal{S},t}(h)}{\sum_{i=1}^{N} X_i}, \qquad \mathrm{DIP}^{share}_{\mathcal{S},t}(h) = \frac{\mathrm{DIP}_{\mathcal{S},t}(h)}{\mathrm{DIP}_t(h)}, \tag{2.13}$$

where we define $\mathrm{DIP}^{share}_{\mathcal{S},t}(h)$ to be zero if $\mathrm{DIP}_t(h)$ is zero.

2.3.2.2 *Tail Interdependence Measures*

We use two conditional tail probability measures to analyze interdependence between individual financial institutions and the broader financial system. The measures differ according to the direction of conditioning: the conditional probability of default (CoPD) measures stress at the firm level conditional on stress at the level of the financial system. Reversing the conditioning, the conditional probability of systemic distress (CoPSD) measures stress at the level of the financial system conditional on stress at the firm level. We define the CoPD associated with firm i as the risk-neutral probability of a default by the firm contingent on a systemic event,

$$\mathrm{CoPD}_{i,t}(h) = P^{Q}\left(R_{i,t:t+h} < \Phi^{-1}\left(\mathrm{PD}_{i,t}(h)\right) \mid L_{t+h} > \mathrm{SLT}\right), \tag{2.14}$$

and the CoPSD associated with firm i as the risk-neutral probability of a systemic event conditional on the firm's asset return falling short of its α-quantile,

$$\mathrm{CoPSD}_{i,t}^{\alpha}(h) = P^{Q}\left(L_{t+h} > SLT \mid R_{i,t:t+h} < \Phi^{-1}(\alpha)\right). \tag{2.15}$$

Note that we define CoPSD conditional on the α-quantile of the asset return distribution rather than conditional on firm default, and the firm-level event therefore differs from CoPD. Conditioning on the α-quantile ensures that the conditioning event has the same probability, α, across all institutions by definition. Conditioning on firm default would correspond to conditioning on a firm-specific return level, and the probability of the conditioning event would then vary across firms. In this case, firms with a lower default risk might show a higher CoPSD simply because they have been conditioned on a more extreme event.[8]

The two risk metrics implemented above measure tail interdependence in the financial system from different perspectives. CoPD measures a firm's resilience in times of severe turmoil in the broader financial system, that is, its *exposure* to systemic risk. CoPSD, on the other hand, measures a firm's potentially destabilizing effect on the financial system as a whole, that is, its *contribution* to systemic risk. Importantly, managing these risk measures mandates different regulatory actions. Regulatory measures addressing CoPD will aim to limit an individual firm's distress potential by shielding it against exogenous crises. The ultimate goal is mitigation of potential losses to the firm's depositors, policyholders, and investors. Regulatory measures governed by CoPSD will aim at reducing the impact of an individual firm's distress on the broader financial system. The ultimate goal is mitigation of potential losses to the economy in terms of aggregate output.

Comparing CoPD and CoPSD to marginal DIP, an important difference is that the marginal DIP indicator directly incorporates firm size as a liability weight, whereas the CoPD and CoPSD measures are size-free to the extent that financial institutions' size only enters their definition via the systemic event condition. The tail interdependence and marginal loss measures therefore provide complementary information on financial institutions' systemic risk. Marginal DIP will identify financial institutions that are systemically important on an individual basis. CoPSD will additionally identify groups of firms that are individually too small to be systemic, but that may be *systemic as a herd* in the sense of Adrian and Brunnermeier (2016).

Defining CoPD and CoPSD under the risk-neutral measure warrants a final remark about their interpretation. As they are risk-neutral, both measures incorporate not only physical probabilities but also an additional risk premium

8 See Adrian and Brunnermeier (2016, pp. 1710–1711) for a related discussion in the context of CoVaR. Note that requiring firm distress instead of firm default as the conditioning event in the definition of CoPSD is also consistent with the definition of G-SIFIs in FSB (2010, p. 2), which calls for "distress or failure" at the institution level to cause financial turmoil and economic consequences.

component reflecting market participants' aggregate risk preferences. CoPD and CoPSD therefore take into account the full set of market information on distress risk, and they are best interpreted as risk-adjusted likelihood indicators of the underlying events.[9]

2.3.2.3 *Brief Comparison with Other Measures*

A broad array of related metrics beyond the systemic risk measures we implement has been proposed in the literature. The approaches are far too numerous to fully review here; however, Bisias et al. (2012) provide a comprehensive survey. Below, we briefly discuss three frequently used measures of systemic risk and compare them to the metrics implemented in our study.[10] Generally speaking, different measures of systemic risk offer complementary insights. Our implementation integrates the different notions of systemic risk underlying other empirical measures in a unifying modeling framework.

Acharya et al. (2017) propose to measure the systemic risk of an individual financial institution by its MES, the institution's loss when the financial system is in crisis. MES is defined as the negative of institution i's expected return conditional on the financial system or market m breaching its value at risk (VaR) at the α-quantile:

$$MES_{\alpha}^{i} = -E\left(R_i \mid R_m < -VaR_{\alpha}^{m}\right), \tag{2.16}$$

where we adopt the sign convention that a positive VaR indicates a loss.[11]

Adrian and Brunnermeier (2016) also address the systemic risk of individual financial institutions. They introduce CoVaR, the financial system's VaR conditional on a particular return level of an individual firm. The systemic risk of the firm is then measured as the change in CoVaR as the firm moves from its median state to a state of distress:

$$\Delta CoVaR_{\alpha}^{m|i} = CoVaR_{\alpha}^{m|R_i=-VaR_{\alpha}^{i}} - CoVaR_{\alpha}^{m|R_i=-VaR_{0.5}^{i}}. \tag{2.17}$$

These metrics compare to our measures of tail interdependence as follows. MES is related to CoPD in that it measures a firm's exposure to systemic risk. ΔCoVaR is related to CoPSD in that it measures a firm's contribution to systemic risk, that is, its potentially destabilizing effect on the broader financial system.

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9 See also the discussion in Malz (2013, p. 2). The DIP framework offers an alternative interpretation of CoPD and CoPSD as conditional unit prices of systemic risk. Indeed, consider the marginal DIP of firm i in Equation (2.11) conditional on a systemic event:

$$DIP_{i,t\,|\,L_{t+h}>SLT}(h) = E^{Q}\left(\left(1 - RR_{i,t+h}\right) \cdot X_i\right) \cdot CoPD_{i,t}(h) \cdot e^{-r_t h}.$$

Conditional on a systemic event, the marginal DIP depends on CoPD and the expected loss at default. In this sense, CoPD is the compounded insurance premium for one unit of firm i's expected loss at default if a systemic event occurs. Likewise, CoPSD is the compounded insurance premium for one unit of the financial system's expected systemic loss if firm i is in distress.

10 Huang et al. (2012a,b) and Black et al. (2016) provide a related discussion for DIP.

11 That is, VaR_{α} is implicitly defined by $P\left(R < -VaR_{\alpha}\right) = \alpha$.

Importantly, however, MES and ΔCoVaR are physical measures expressing systemic risk in terms of return losses, whereas, as discussed above, CoPD and CoPSD are risk-neutral probability measures.

Brownlees and Engle (2017) propose SRISK, an alternative measure of systemic risk that is based on capital shortfall in times of crisis. At the firm level, SRISK is defined as

$$\mathrm{SRISK}_i = E\left(k\left(X_i + E_i\right) - E_i \mid R_m < C\right), \tag{2.18}$$

where X_i is the book value of debt, E_i is the market value of equity, k is a prudential capital ratio, and C is an adverse market return defining a financial crisis. SRISK is related to DIP in that it can be aggregated to the level of the financial system and explicitly incorporates financial institutions' sizes. However, there are a number of differences between SRISK and our implementation of DIP. First, SRISK is a physical measure, whereas DIP incorporates a risk premium component. Second, SRISK measures systemic risk as the severity of a financial crisis, whereas DIP is a condensed measure of both the propensity for and severity of a financial crisis. Finally, SRISK requires equity return data and hence can be applied only to publicly traded firms, whereas DIP, when estimated as outlined in the following section, can be applied to both publicly traded and nonpublic firms.

2.3.3 *Estimating the Credit Risk Parameters*

We base our analysis on probabilities of default and asset return correlations estimated from CDS spreads. CDSs offer protection against the risk that a firm will default on its debt. The entity underlying the contract is known as the *reference entity*. Default by that entity is referred to as a *credit event*. The protection buyer pays the protection seller a periodic spread until either the contract matures or a credit event occurs, whichever is first. The protection seller, in return, promises to cover losses should a credit event occur. These losses are measured as the difference between the nominal value and the post-default value of a particular bond issued by the reference entity.[12]

CDS spreads offer several advantages over other credit risk indicators such as bond or loan spreads and ratings. CDS spreads have been reported to be a relatively plain measure of credit risk compared to bond spreads (Longstaff et al., 2005)[13] while being only very marginally affected by counterparty risk due to collateralization (Arora et al., 2012). Moreover, the CDS market has been

12 CDSs thus mimic the payout profile of insurance contracts. However, CDSs are distinct from insurance in that they lack the notion of *insurable interest*: the protection buyer is not required to hold debt issued by the reference entity. Market participants can therefore use CDSs to trade the reference entity's credit risk. CDSs are not treated as insurance for regulatory purposes.

13 Nondefault components in bond prices are primarily driven by illiquidity (Longstaff et al., 2005). Other factors such as short-sale restrictions, taxes, and embedded options may add further to a distortion of bond prices (Blanco et al., 2005; Longstaff et al., 2005).

found to lead the bond market (Blanco et al., 2005; Zhu, 2006; Forte and Peña, 2009) and the loan market (Norden and Wagner, 2008) in the price discovery process, and to anticipate rating announcements (Hull et al., 2004). With regard to measuring systemic risk, Rodríguez-Moreno and Peña (2013) find that the CDS market is a better indicator of systemic distress than the stock market, even though evidence is not totally unanimous in this regard (Hilscher et al., 2015). Overall, we expect our CDS-implied systemic risk measures to reflect informational advantages relative to other instruments and markets.

Several recent studies using credit portfolio measures of systemic risk have relied on default probabilities estimated from CDS spreads; see, for example, Huang et al. (2009, 2012a,b), Chen et al. (2014), and Black et al. (2016). These studies have estimated asset return correlations from equity returns. We infer the asset return correlations from CDS spreads rather than from equity returns for two main reasons. First, estimating both credit risk parameters from the same financial instrument ensures that they are consistent. Within the Merton (1974) model, equity and debt can be interpreted as call and put options on a firm's assets, respectively. Equity and debt markets should thus comove with the asset value. However, whereas equity and debt markets theoretically convey equivalent information on asset values, they may behave differently in reality. The instruments traded in these markets refer to distinct parts of a firm's capital structure. Some parts of the capital structure may enjoy explicit or implicit guarantees, and the market prices of the corresponding instruments will reflect a level of credit risk net of such guarantees (Dwyer et al., 2010).

Moreover, estimating default probabilities and correlations from CDS spreads makes our modeling framework applicable to nonpublic entities such as privately held firms, state-owned firms, or subsidiaries of public firms, which enables us to cover a broader cross section of financial institutions. Modeling nonpublic firms is of particular practical relevance for the European banking sector, which has a relatively high share of privately held or state-owned savings and cooperative institutions.[14] Modeling subsidiaries of public firms further allows financial groups consolidating unlisted insurance and banking entities to be analyzed at the subsidiary level, hence enabling a more precise allocation of systemic risk among sectors.

2.3.3.1 *Probabilities of Default*

We estimate *risk-neutral* probabilities of default from CDS spreads using the reduced-form valuation framework described in the literature (see, e.g., Hull and White, 2000; Tarashev and Zhu, 2008). Under no-arbitrage, the expected present value of the protection buyer's spread payments in the premium leg (the left-hand side of Equation (2.19)) initially equals the expected present value of the protection seller's default loss payment in the protection leg (the right-hand

14 For Germany, for example, 7 of the 10 banks in the sample are not publicly traded. Six of these nonpublic banks are *Landesbanken*, the state-owned head institutions of the regional savings banks. For a complete list of all nonpublic firms in the sample, see Appendix 2.B.2.

side of the equation). The initial value of the CDS contract is zero:

$$\int_t^{t+T} s_{i,t} e^{-r_\tau(\tau-t)} \bar{q}_{i,\tau} d\tau = \int_t^{t+T} \left(1 - RR_{i,t}^{CDS}\right) e^{-r_\tau(\tau-t)} q_{i,\tau} d\tau. \tag{2.19}$$

$RR_{i,t}^{CDS} \in [0, 1]$ is the time-t expectation of the recovery rate on the underlying debt, $s_{i,t}$ is the annual spread, $q_{i,\tau}$ is the risk-neutral default intensity, $\bar{q}_{i,\tau} = 1 - \int_t^\tau q_{i,\nu} d\nu$ is the associated risk-neutral probability of survival up to time τ, and T is the tenor of the contract. We assume that the recovery rate is independent of the risk-free rate and the default intensity. As in Tarashev and Zhu (2008, p. 8), we solve for the 1-year risk-neutral probability of default under the common simplifying assumptions that the term structures of the risk-free rate and the default intensity are flat, $r_\tau = r_t$ and $q_{i,\tau} = q_{i,t}$ for all $\tau \in [t, t+T]$:

$$q_{i,t} = \frac{a s_{i,t}}{a(1 - RR_{i,t}^{CDS}) + b s_{i,t}}, \tag{2.20}$$

where $a = \int_t^{t+T} e^{-r_t(\tau-t)} d\tau$ and $b = \int_t^{t+T} (\tau - t) e^{-r_t(\tau-t)} d\tau$.

2.3.3.2 *Asset Return Correlations*

Following Düllmann et al. (2010), market-based estimation approaches for asset return correlations fall into two categories: *indirect* approaches that infer the correlations from prior estimates of the unobserved market value of assets, and *direct* approaches that calculate the correlations from observed market prices. In the literature, Lopez (2004) follows the indirect approach using asset values estimated from equity and financial statements data. Byström (2011) follows the indirect approach using an asset value proxy based on equity and CDS data. Huang et al. (2009) implement the direct approach based on equity returns, and Tarashev and Zhu (2008) apply the direct approach using CDS spreads.[15]

We implement the method of Tarashev and Zhu (2008). Following this approach, we infer *physical* asset return correlations from the CDS-implied risk-neutral probabilities of default estimated in the previous section (Tarashev and Zhu, 2008, p. 8):

$$\begin{aligned} \rho_{ij} &= \operatorname{corr}\left(\Delta \ln A_{i,t}, \Delta \ln A_{j,t}\right) \\ &= \operatorname{corr}\left(\Delta\Phi^{-1}\left(PD_{i,t}\left(h\right)\right), \Delta\Phi^{-1}\left(PD_{j,t}\left(h\right)\right)\right) \\ &\approx \operatorname{corr}\left(\Delta\Phi^{-1}\left(q_{i,t}\right), \Delta\Phi^{-1}\left(q_{j,t}\right)\right). \end{aligned} \tag{2.21}$$

In this equation, we make the transition to discrete time, where Δ is the usual difference operator. The third line serves as an approximation, because Equa-

15 As an alternative to the market-based approach, the correlation structure underpinning our modeling framework could theoretically also be estimated from historical default events. The correlation of corporate defaults has been analyzed in several empirical studies (e.g., Dietsch and Petey, 2004; Das et al., 2007). We do not pursue this approach as data on simultaneous defaults are scarce, even more so for investment-grade insurers and banks, which could lead to a potentially severe estimation bias in our setting. Düllmann et al. (2010) confirm the superiority of the market-based estimation approach in a simulation study.

tion (2.3) does not make the assumption of a flat term structure of default intensities used in Equation (2.20).[16]

Based on Equation (2.21), we first estimate nonparametric pairwise correlations $\hat{\rho}_{ij}$. Due to missing data for some firms, the outcome of the pairwise estimation process is not guaranteed to yield a consistent correlation structure. Specifically, the matrix $\hat{C}$ defined by $\left[\hat{C}\right]_{ij} = \hat{\rho}_{ij}$ may not be positive semi-definite and will then not be valid as a correlation matrix. This is resolved when fitting the factor model of Equation (2.2) to the raw estimates. Minimizing the sum of squared element-wise deviations, we obtain the following optimization problem for the M-factor correlation structure:

$$\begin{aligned} \min_{F_1,\ldots,F_N} \quad & \sum_{i=2}^{N}\sum_{j=1}^{i-1}\left(\hat{\rho}_{ij} - F_i F_j^\top\right)^2 \\ \text{s.t.} \quad & F_i F_i^\top \leqslant 1, \qquad\qquad i = 1,\ldots,N, \end{aligned} \tag{2.22}$$

where we recall that $F_i = [F_{i,1},\ldots,F_{i,M}]$ is a row vector of M factor loadings. We solve the optimization problem using the principal factors method of Andersen et al. (2003).[17]

2.4 EMPIRICAL DATA

The sample analyzed in our empirical study is a panel of banks and insurers from around the world over the period from January 2004 through December 2014. The data set includes CDS data available from Thomson Reuters Datastream and financial statements data collected from Bloomberg. We retrieve daily spreads for 5-year senior unsecured CDS contracts and annual total liabilities. We aggregate the daily spreads to weekly frequency and use linear interpolation to compute weekly portfolio weights from the annual liabilities. Appendix 2.A provides a detailed description of the data sources and definitions.

2.4.1 *Sample Selection*

We select our sample from the full list of reference entities with a 5-year senior unsecured CDS contract on Thomson Reuters Datastream. We first select an initial banking sample of all commercial banks and investment banks and an initial insurance sample of all primary insurance carriers and reinsurance carriers based on Industry Classification Benchmark (ICB) subsectors. To ensure that only firms with sufficient quote activity are included in our sample, we then restrict the selection to firms with a sample period worth at least 2 years of weekly

16 The approximation could be avoided by using Equation (2.3) directly in Equation (2.19). Tarashev and Zhu (2008), however, find that the correlation estimates are insensitive to this simplifying assumption. We thus stick to Equation (2.21) for the sake of parameter parsimony.

17 Note that Equation (2.22) defines a nonconvex optimization problem for $M > 1$. In the multi-factor case, we can thus generally expect to find only a local minimum. For a detailed discussion of the optimization problem and suitable solution approaches, see Borsdorf et al. (2010).

firm observations. Each firm in the sample is assigned to one of six sectors reflecting its main business activity: *banking*, *multi-line insurance*, *life insurance*, *property–casualty (P/C) insurance*, *bond and mortgage insurance*, and *reinsurance*.[18]

At the firm level, we adjust the sample periods for in-sample consolidation. CDS contracts may trade for all debt-issuing firms within a corporate group, and several firms in the initial sample are subsidiaries of other sample firms for at least part of the sample period. Including a parent company and one of its subsidiaries in the sample would engender concern due to potential double counting of losses. The consolidated balance sheet of the parent firm includes the liabilities of the subsidiary, and the impact of the corporate group on aggregate losses would be overstated if both, the parent and the subsidiary, were to default. To circumvent this bias, we exclude firms from the sample for any period in which they are direct or indirect subsidiaries of other firms in the sample. Following this approach, given sufficient data availability, we generally keep only the ultimate parent of a corporate group in the final sample.[19]

ING Groep of the Netherlands is a notable exception to this general rule. During the sample period, this financial holding company operated through two principal subsidiaries: a banking subsidiary, ING Bank, and an insurance subsidiary, NN Group. We opt to exclude the holding company in favor of the subsidiaries to allocate systemic risk as precisely as possible to the banking and insurance sectors.

The resulting sample represents an unbalanced panel, where firms enter and exit depending on mergers and acquisitions as well as data availability. Firms naturally exit the sample if they experience a credit event. For consistency across firms, and to eliminate any potential bias stemming from post-failure observations, we further exclude firms from the sample after they enter an orderly resolution process.[20]

2.4.2 *Data Set*

Table 2.1 shows descriptive statistics for the sample firms. There are 183 financial firms in the sample, including 133 banks and 50 insurers. The banking sample

18 The ICB subsector codes represented in the final sample are 8355, 8532, 8536, 8538, 8575, 8777, and 8779. We map the subsector codes into our sample sectors as follows: the banking sample includes all commercial banks from subsector 8355 and all investment banks from subsector 8777; the multi-line insurance sample includes all firms from subsector 8532; the life insurance sample includes all firms from subsector 8575; the P/C insurance sample includes all firms except financial guarantee insurers from subsector 8536; the bond and mortgage insurance sample includes all financial guarantee insurers from subsector 8536 and all private mortgage insurers from subsector 8779; and the reinsurance sample includes all firms from subsector 8538. We manually exclude central banks classified in subsector 8355, deposit insurance schemes classified in subsector 8536, nonbank financial firms such as market infrastructures and online brokers classified in subsector 8777, and noninsurer financial firms such as government-sponsored enterprises and building societies classified in subsector 8779 from the sample.

19 We recover the historical corporate group structures used in this exercise from data on current corporate group structures and mergers and acquisitions, which are taken from Bloomberg.

20 Data on credit events are available from the International Swaps and Derivatives Association. Data on orderly resolution processes are collected from the firms' investor relations Web sites.

TABLE 2.1: Summary statistics

		Liabilities[a]				CDS spreads[b]			
Sample	N	Min	Mean	Max	Sum	Sample	Per. 1	Per. 2	Per. 3
Panel A: Full sample									
All firms	183	3	410	2,834	68,467	182	31	283	235
Panel B: Sample by sector									
Banks	133	8	497	2,834	59,148	157	27	198	229
Insurers	50	3	194	943	9,318	239	38	472	251
Multi-line ins.	8	29	475	943	3,800	131	26	218	155
Life insurers	15	21	270	548	4,044	158	30	300	168
P/C insurers	12	21	56	116	614	91	63	140	81
Bond/mtge ins.	8	3	11	23	74	900	37	1,799	1,038
Reinsurers	7	12	112	288	786	91	24	121	122
Panel C: Sample by region									
North America	38	3	366	1,999	11,356	308	44	625	343
Banks	12	165	1,194	1,999	8,357	133	26	251	181
Insurers	26	3	125	749	2,998	379	53	764	399
Europe	91	27	528	2,834	44,381	151	17	162	243
Banks	73	27	583	2,834	38,498	166	16	163	279
Insurers	18	29	327	943	5,883	102	22	160	125
Other regions[c]	54	8	245	1,627	12,730	140	42	224	154
Banks	48	8	267	1,627	12,293	149	46	237	163
Insurers	6	31	73	128	437	79	21	124	95

[a] Total liabilities for 2009 in USD billion; adjusted for in-sample consolidation and failed firms.
[b] Mean spreads for 5-year senior unsecured CDS contracts in basis points. Averages are calculated as unweighted averages across weekly observations for the following periods: *sample* covers the full sample period from January 2004 through December 2014; *period 1* runs from January 2004 through July 2007; *period 2* runs from August 2007 through April 2010; and *period 3* runs from May 2010 through December 2014.
[c] South America, Russia, the Middle East, and Asia-Pacific.

covers 28 of the 34 banks that have been designated as G-SIBs based on data from the sample period. The insurance sample covers 9 of the 10 insurers that have received G-SII status based on data from the sample period.[21] The sample includes both public and nonpublic firms. In total, 132 banks and insurers have publicly traded equity for most of their sample period. The remaining 51 financial institutions include privately held firms, state-owned firms, and subsidiaries of public firms. Appendix 2.B.1 lists the firms in our sample, and Appendix 2.B.2 provides descriptive statistics for the nonpublic firms.

Based on financial statements data for 2009, the largest sample banks by total liabilities are BNP Paribas (USD 2,834 billion), Royal Bank of Scotland Group (USD 2,587 billion), and HSBC Holdings (USD 2,229 billion). The largest sample insurers are AXA (USD 943 billion), Allianz (USD 776 billion), and AIG (USD

21 We count a financial institution as G-SIFI if it either (i) has been included on one of the lists of G-SIBs published by the FSB from 2011 through 2015, (ii) has been included on one of the lists of G-SIIs published by the FSB from 2013 through 2015, or (iii) operates as a principal subsidiary of one of these firms. Each annual update of the G-SIFI lists is based on data as per the end of the previous year. The period considered by the FSB when designating these G-SIFIs is therefore consistent with the sample period.

749 billion). The sample's aggregate liabilities amount to USD 68,467 billion, with USD 59,148 billion owed by the banking sector and USD 9,318 billion owed by the insurance sector.[22]

For the year 2009, the sample banks account for 44 percent of the global banking assets, and likewise, the sample insurers account for 44 percent of the global insurance assets reported by the FSB.[23] This has two important implications for our analyses. First, the banking and insurance samples are representative of the industries' levels of systemic risk. Both samples cover a significant part of the industries' assets, including many of the industries' largest firms, among them most G-SIBs and G-SIIs. The samples should therefore capture most of the systemic risk in the respective industry. Second, the banking sample and the insurance sample scale the worldwide banking and insurance industry assets in virtually the same proportion. We can, therefore, validly infer the relative contribution of the banking and insurance sectors to the level of systemic risk in the financial system.

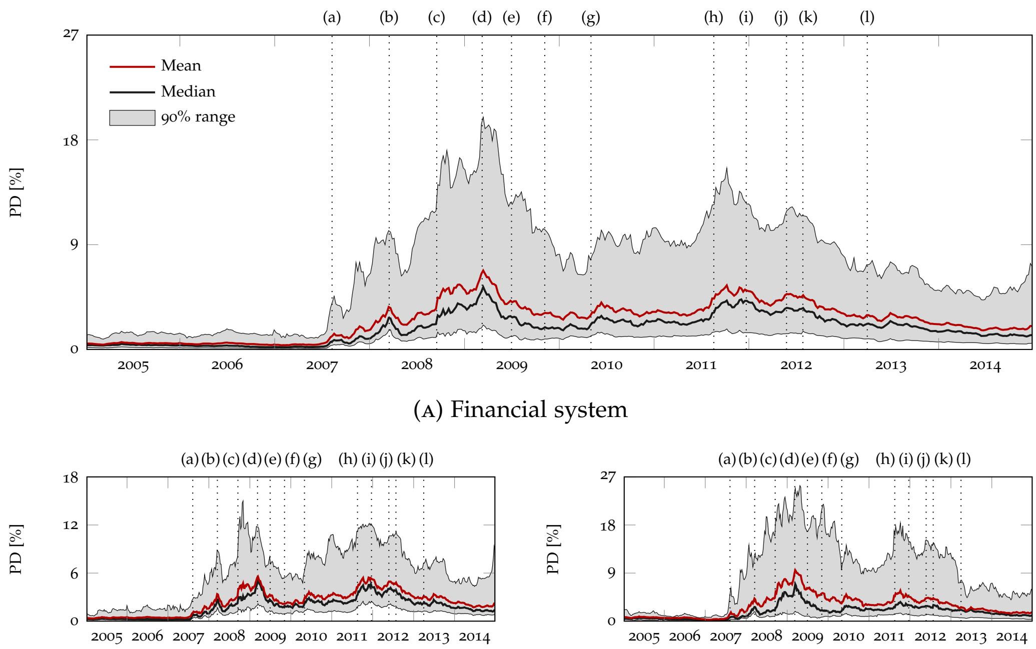
The CDS spreads reported in Table 2.1 offer initial insights into the time-series dynamics of banks' and insurers' credit risk. We report mean spreads for 5-year senior unsecured CDS contracts for four periods: the full sample period, spanning January 2004 through December 2014; the pre-crisis period, taken as January 2004 through July 2007; the period of the ensuing financial crisis and the intermittent recovery, taken as August 2007 through April 2010; and the period of the European sovereign debt crisis and the subsequent recovery, taken as May 2010 through December 2014.

The spreads show considerable time-series and cross-sectional variation. The mean spread of the full sample was at 31 basis points in the years leading up to the financial crisis. The period of the financial crisis saw a more than nine-fold increase of the mean spread level, then averaging 283 basis points. During the period of the European sovereign debt crisis, the mean spread receded mildly, then averaging 235 basis points, almost eight times the pre-crisis value.

Banks and insurers show different credit risk dynamics during the sample period. In the pre-crisis period, the sample banks had a mean spread of 27 basis points, fewer than the sample insurers, which averaged 38 basis points. The mean spread of the sample banks then increased to 198 basis points for the period of the financial crisis and, driven by European banks, increased further to 229 basis points for the period of the European sovereign debt crisis. The mean

22 To put the liability sizes into perspective, relative to gross domestic product (GDP) data for 2009 reported by the World Bank, BNP Paribas of France and Royal Bank of Scotland Group of the United Kingdom are larger than their home countries' GDP, and the banking sample as a whole is larger than the global GDP. This corroborates the too-big-to-fail concern, as the default of large financial institutions could result in losses equivalent to the GDP of entire countries.

23 The data set accompanying FSB (2017) reports the assets of different types of financial institutions for the euro area and 21 additional jurisdictions, including the United States, the United Kingdom, and Japan. The definition extends to financial assets where available and to total assets otherwise. In total, the data set covers more than 80 percent of the world's GDP (FSB, 2017, p. 1). We relate the assets of the banking sample to the assets reported for deposit-taking institutions, public financial institutions, and broker-dealers, and the assets of the insurance sample to the assets reported for insurance corporations.



(A) Financial system

(B) Banking

(C) Insurance

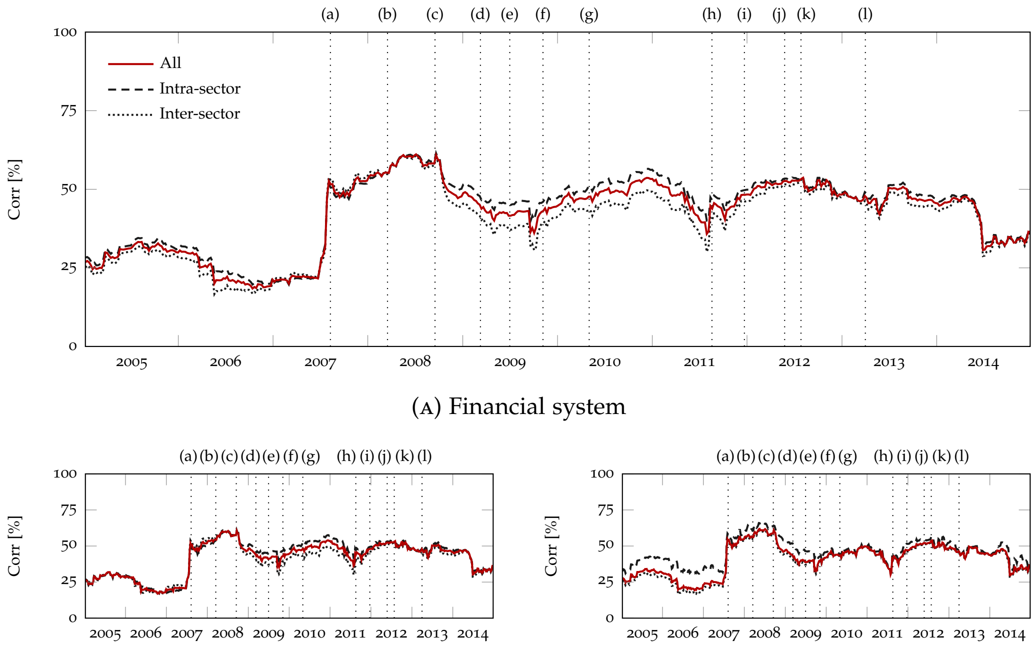
FIGURE 2.1: Probabilities of default by sector
This figure shows 1-year risk-neutral probabilities of default by sector. The risk-neutral probabilities of default are calculated at weekly frequency from 5-year senior unsecured CDS spreads. The vertical lines represent the following events: (a) BNP Paribas funds freeze, (b) Bear Stearns takeover, (c) Lehman Brothers failure, (d) U.S. stock market low, (e) U.S. leaves recession, (f) Greek government revises budget deficit, (g) first support package for Greece agreed upon, (h) global stock markets fall on uncertain world economic outlook, (i) European Central Bank conducts first round of 3-year longer-term refinancing operations, (j) Mario Draghi's "courageous leap" speech, (k) Mario Draghi's "whatever it takes" speech, and (l) euro area leaves recession.

spread of the sample insurers increased to 472 basis points for the period of the financial crisis, and receded to 251 basis points for the period of the European sovereign debt crisis. P/C insurers and reinsurers had the lowest overall spread levels, and bond and mortgage insurers had the highest overall spread levels.

2.4.3 *Model Estimation*

The full set of parameter estimates for each sample firm includes probabilities of default, asset return correlations, and expected recovery rates for the firm's liabilities. We estimate weekly time series of risk-neutral probabilities of default and asset return correlations from the CDS spreads described in the previous section. We calculate the risk-neutral probabilities of default for a 1-year horizon, adopting the market convention of a 40 percent recovery rate on the underlying senior unsecured debt. Further, we calculate the asset return correlations using a rolling window of 1 year. This effectively limits the horizon for our systemic risk analyses to the period from January 2005 through December 2014.

Figure 2.1 shows plots of the estimated risk-neutral probabilities of default. We report the mean, median, lower 5 percent quantile, and upper 5 percent



(A) Financial system

(B) Banking

(C) Insurance

FIGURE 2.2: Asset return correlations by sector
This figure shows the average of pairwise asset return correlations by sector. For each financial institution, pairwise correlations are calculated between the firm and all other firms in the sample (*all correlations*), between the firm and all other firms from the same sector (banking or insurance, *intra-sector correlations*), and between the firm and all firms from the respective other sector (*inter-sector correlations*). The correlations are calculated at weekly frequency from 5-year senior unsecured CDS spreads using a rolling window of 1 year. The vertical lines represent the same events as those in Figure 2.1.

quantile for the financial system, the banking sector, and the insurance sector. The default probabilities reflect the time-series and cross-sectional variation of the CDS spreads. Risk-neutral probabilities of default were low prior to the onset of the financial crisis and peaked at various occasions during the crisis periods. The banking sample's mean default probability averaged slightly higher during the European sovereign debt crisis than it did during the financial crisis, whereas the insurance sample's mean default probability averaged considerably higher during the financial crisis than it did during the European sovereign debt crisis.

Figure 2.2 shows plots of the estimated asset return correlations. For each financial institution, we compute the average asset return correlation between the firm and all other firms in the sample (*all correlations*), between the firm and all other firms from the same sector (banking or insurance; *intra-sector correlations*), and between the firm and all firms from the respective other sector (*inter-sector correlations*). The figure shows these pairwise correlations for the financial system, the banking sector, and the insurance sector. The onset of the financial crisis is marked by a surge in correlations: during the pre-crisis period, the mean asset return correlation of the full sample averaged 26 percent; during the remaining sample period, the mean asset return correlation averaged 48 percent.

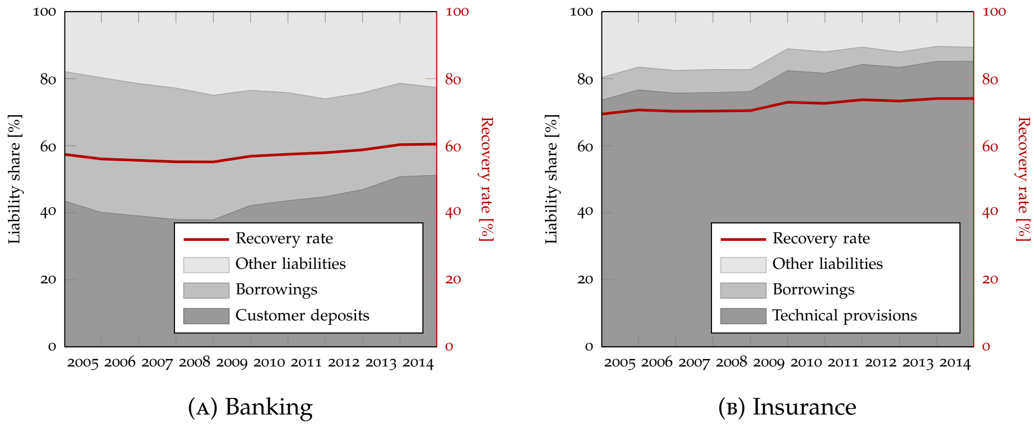


FIGURE 2.3: Liability structure and recovery rate by sector
This figure shows the liability structure and average recovery rate for the banking and insurance sectors. Average recovery rates are calculated assuming a recovery rate of 80 percent for *customer deposits* and *technical provisions* and a recovery rate of 40 percent for *borrowings* and *other liabilities*.

The recovery rates required for the default scenarios represent the share of total liabilities that the creditors of defaulted firms are expected to ultimately recover. They relate to the entire liability structure, as opposed to the recovery rates used in the estimation of the risk-neutral probabilities of default, which relate to a specific part of the liability structure, namely senior unsecured debt. The recovery rates of banks and insurers depend mainly on the individual firms' post-default asset quality. Insurers generally hold a higher share of liquid assets than banks do,[24] and can therefore reasonably be expected to realize higher average recovery rates.

Figure 2.3 shows the liability composition of the banking and insurance sectors. Broadly speaking, banks' liabilities comprise customer deposits, borrowings, and other liabilities, and insurers' liabilities comprise technical provisions, borrowings, and other liabilities. Technical provisions form the largest part of insurers' liabilities. They serve to cover unexpired risk from insurance policies and to meet unsettled policyholder claims. Insurance regulators are particularly concerned about the quality of the assets invested in support of the technical provisions, and these assets are generally more tightly regulated.[25] This should result in a particularly high post-default value for the relevant portion of insurers' assets.

The post-default value of individual financial institutions' assets is hard to estimate. Previous studies of systemic risk in the banking sector have therefore modeled recovery rates in accordance with regulatory capital requirement formulae (e.g., Huang et al., 2009), used market participants' expectation of

24 Banks' primary assets are loans, which are relatively illiquid, whereas in particular life insurers primarily invest in bonds and stocks, which are rather liquid; see also Paulson et al. (2014).

25 The first set of *Insurance Core Principles* explicitly required that "[s]tandards should be established with respect to the assets of companies [...] these should apply at least to an amount of assets equal to the total of the technical provisions" (IAIS, 2000, p. 9). In its report on *Insurance and Financial Stability*, the IAIS proclaimed that "ensuring the quality and safety of invested assets in support of these provisions comprise the core functions of the traditional insurance business. Under the model, insurers often pursue also an appropriate duration matching of assets to liabilities" (IAIS, 2011, p. 8).

recovery rates on senior unsecured debt (e.g., Huang et al., 2012a,b; Black et al., 2016), or modeled scenarios where creditors either suffer full loss given default or realize recovery rates depending on the share of banks' assets invested in different asset classes (e.g., Puzanova and Düllmann, 2013).

In the absence of reliable estimates of the recovery rates of individual banks and insurers, we use sector recovery rates, which we approximate as follows. For insurers, we assume a recovery rate of 80 percent for technical provisions. This recovery rate is generally consistent with existing evidence on large insurers' failures,[26] and has been confirmed as an adverse yet plausible scenario in talks with experts involved in regulatory affairs. We further assume a recovery rate of 40 percent for borrowings and other liabilities. This choice is guided by the market practice for senior unsecured debt. For banks, we follow a parallel procedure and assume an 80 percent recovery rate for customer deposits,[27] and a 40 percent recovery rate for borrowings and other liabilities. Using these liability-specific recovery rates, we then calculate value-weighted recovery rates for the insurance and banking sector.[28]

Figure 2.3 shows plots of the resulting time series of recovery rates used in the systemic event simulations. By construction, changes in the sectors' recovery rats are driven by changes in the sectors' liability structures rather than by the risk dynamics of firms' assets as determined by their investment strategies. The recovery rates are relatively constant over time, averaging 57 percent for the banking sample, and 72 percent for the insurance sample.[29]

26 Equitable Life of the United Kingdom and HIH Insurance of Australia represent two rare cases of the failure of large insurers. Equitable Life, a mutual life insurer, stopped writing new business in December 2000 and subsequently announced reductions in policy payouts. The resulting losses to policyholders have been estimated to be between GBP 2.9 and 3.7 billion (Towers Watson, 2010). Relative to technical provisions of GBP 31.5 billion reported for 2000, this translates into an 88 to 91 percent recovery rate on insurance claims. HIH Insurance was one of the largest P/C insurers in Australia, reporting assets of AUD 8.3 billion for 2000. The group collapsed in March 2001, and was placed in liquidation. According to the scheme administrators, as of May 2017, creditors with insurance liabilities in HIH Casualty & General Insurance, CIC Insurance, and FAI General Insurance Company, the group's largest operating subsidiaries, were expected to ultimately receive between 52 and 94 percent of their claims (HIH Insurance, 2017).

27 The recovery rate on banks' deposits is in line with the average loss of 21 percent on the claim of the Federal Deposit Insurance Corporation (FDIC) in U.S. bank failures over the period between 1986 and 2007, as reported in Bennett and Unal (2015, p. 378). The FDIC claim subsumes "any deposit claim that was covered by the deposit insurance fund. The FDIC claim also includes any other liability that the receivership has with the FDIC" (p. 378).

28 We note that, beyond a failed financial institution's asset quality, the average recovery rates realized by depositors, policyholders, investors, and other creditors will additionally depend on the seniority of their claims as determined by the bankruptcy law of the institution's jurisdiction. In this respect, the individual recovery rates we assume for the different classes of liabilities should be interpreted more generally as applying to the corresponding *share* of liabilities, rather than necessarily to the respective *type* of liability.

29 The recovery rates for banks compare well to the results of James (1991), who reports average costs of failure to assets of 40 percent for U.S. bank failures in the mid-1980s. Bennett and Unal (2015) document somewhat lower costs of failure of 33 percent for U.S. bank failures during the period from 1986 to 2007. We are not aware of a comparable study for multi-line insurers, life insurers, bond and mortgage insurers, or reinsurers. Hall (2000) and Grace et al. (2005) document very high costs to guaranty funds for U.S. P/C insurer failures in the 1980s and 1990s, which on average exceed the assets of the failed institutions. However, these results relate to very small insurers, and thus appear to be inapplicable to our study.

2.5 FINDINGS ON SYSTEMIC RISK

This section analyzes systemic risk in financial markets using our modeling framework. We organize our analysis in four parts. First, we examine the time series of systemic risk in the global financial system and determine the contributions of the different sectors and regions to aggregate systemic risk. Second, we analyze the cross section of systemic importance and determine the level of systemic risk associated with individual financial institutions. We then examine the input factor determinants of our systemic risk measures. As a final step, we establish the robustness of our results under alternative model specifications.

For the purpose of empirical illustration, we define systemic events as a loss in aggregate liabilities of more than 10 percent over a 1-year horizon. We further assume that a financial institution is under severe stress if it falls short of the lower 1 percent quantile of its asset return distribution over the same horizon. All risk measures are evaluated at weekly frequency to closely track the events during the financial crisis and the European sovereign debt crisis. To ease our exposition, we will sometimes report average values for the crisis periods. We define the financial crisis and intermittent recovery as the period from August 2007 through April 2010, and the European sovereign debt crisis and subsequent recovery as the period from May 2010 through December 2014.

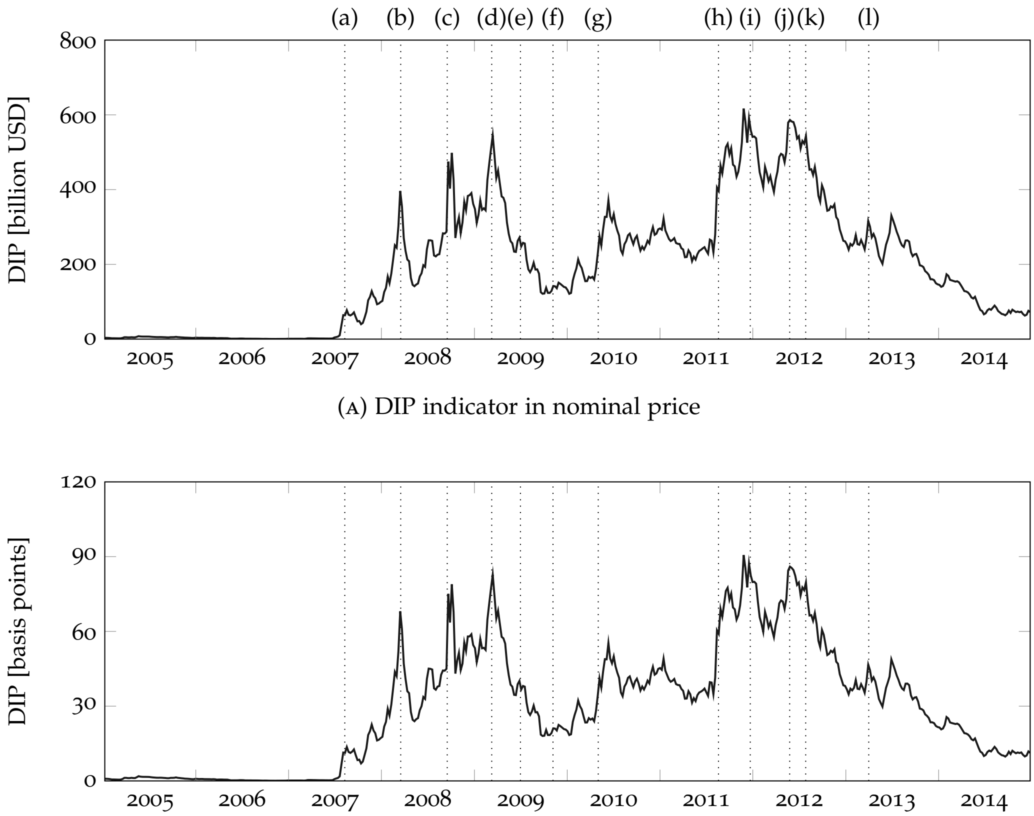
2.5.1 *Systemic Risk in the Financial System*

In this section, we consider the aggregate systemic risk of the global financial system. We first examine the time series of systemic risk over the sample period. We then analyze the marginal risk contributions by sector and region.

2.5.1.1 *Time Series of Systemic Risk*

Figure 2.4 shows plots of the time series of systemic risk in the financial system. Systemic risk is measured using the DIP indicator, defined as the premium of a hypothetical insurance contract protecting creditors against systemic losses. This premium is reported in nominal price expressed in U.S. dollars in Figure 2.4a and in unit price relative to aggregate total liabilities in Figure 2.4b. The nominal price of systemic risk scales with the aggregate liabilities in the sample. To compare systemic risk on a uniform scale over time, we focus on unit prices and report nominal prices in parentheses.

The level of systemic risk exhibits considerable time-series variation and reflects major events occurring during the financial crisis and the ensuing European sovereign debt crisis. In the early years of the sample, the level of systemic risk is low, averaging less than 1 basis point (USD 3 billion) during the pre-crisis period from January 2005 through July 2007. As the financial crisis begins to spill over from the U.S. subprime mortgage market to the wider financial system, the level of systemic risk increases remarkably. By August 10, 2007, one day after



(A) DIP indicator in nominal price

(B) DIP indicator in unit price

FIGURE 2.4: Systemic risk in the global financial system
This figure shows the level of systemic risk in the global financial system. Systemic risk is measured using the DIP indicator. This indicator is reported in nominal price in the upper panel and in unit price relative to aggregate total liabilities in the lower panel. The vertical lines represent the same events as those in Figure 2.1.

BNP Paribas froze three funds with exposure to the U.S. subprime mortgage market, the level of systemic risk has jumped to 11 basis points (USD 64 billion). There are three distinct peaks in the systemic risk indicator during the financial crisis. The first peak marks the week of March 14, 2008, immediately before the takeover of Bear Stearns by JPMorgan Chase. The second peak marks the period between the middle of September and the beginning of October 2008, when Lehman Brothers filed for bankruptcy, AIG received government support, and Washington Mutual was seized. The third and final peak marks the week of March 13, 2009, when systemic risk stands at its highest value during the financial crisis, 83 basis points (USD 545 billion), just when U.S. stock markets reached their financial crisis low. Following the last peak, the systemic risk indicator starts to trend downward. In the fourth quarter of 2009, during the intermittent recovery period, the level of systemic risk in the sample is valued at around 20 basis points (USD 137 billion).

Early warning signals of the European sovereign debt crisis became visible during the recovery period following the financial crisis, as the Greek government revised its budget deficit, and as major rating agencies downgraded long-term

Greek sovereign debt. The level of systemic risk increases again as the European sovereign debt crisis worsens. It reaches a temporary peak at 55 basis points (USD 371 billion) for the week of June 11, 2010, six weeks after the first support package for Greece was agreed upon between the European Commission, the European Central Bank, the International Monetary Fund, and the Greek government. The period between autumn 2011 and summer 2012 appears to mark the height of the European sovereign debt crisis. For the week of November 25, 2011, the systemic risk indicator reaches its highest value during our sample period with 91 basis points (USD 617 billion). In the following months, the systemic risk indicator trends downward again. In the second half of 2014, during the recovery from the core European sovereign debt crisis and toward the end of our sample period, systemic risk averages 11 basis points (USD 73 billion), about the same level as at the beginning of the financial crisis.

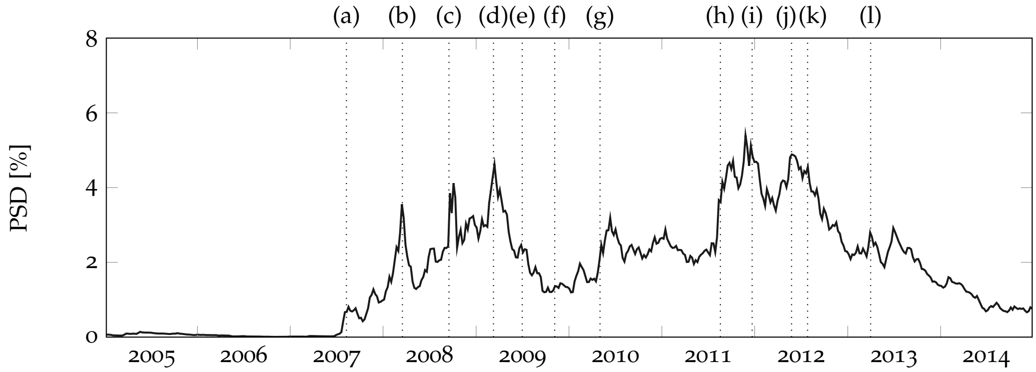
The financial crisis and the European sovereign debt crisis triggered a range of monetary and fiscal policy responses.[30] Central banks reduced interest rates and provided liquidity support. Governments recapitalized troubled financial institutions, guaranteed their liabilities, and engaged in asset purchases. For example, as part of their crisis interventions, the Federal Reserve Bank, the European Central Bank, and the Swiss National Bank announced a joint enhancement of liquidity-providing measures at the beginning of May 2008. Five months later, early in October 2008, the U.S. Congress passed the USD 700 billion Troubled Asset Relief Program, the British government announced a bank rescue package valued at GBP 400 billion, and the French government released a EUR 360 billion bank rescue plan. Other governments took similar action.

Two interesting observations can be made with respect to these exemplary policy responses. First, the level of systemic risk was lower around the time of both interventions, only to hike up again after several months. Therefore, whereas these policy measures may have succeeded in calming markets short-term, they did not succeed in reducing systemic risk over an extended period. Moreover, the total amount of government support for the financial system seemingly exceeds the level of systemic risk as measured by the DIP indicator. This apparent difference stems from the fact that the DIP indicator measures systemic risk as the present value of *expected* losses over a 1-year horizon, whereas the government support relates to *realized* funding needs or losses.

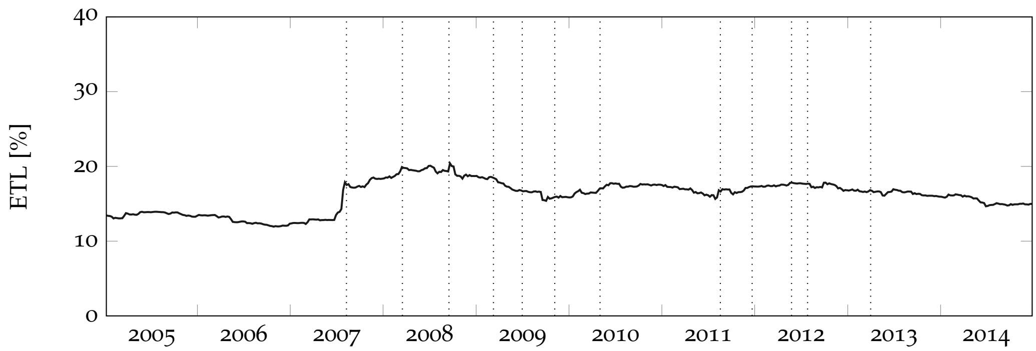
The level of systemic risk as measured by the DIP indicator factors into two components: the likelihood of a systemic event, measured by the risk-neutral PSD, and the expected severity of a systemic event, measured by the ETL. We will disentangle these drivers of aggregate systemic risk below.

Figure 2.5 shows plots of the time series of these systemic risk components. Figure 2.5a shows the risk-neutral PSD, and Figure 2.5b shows the ETL in unit price relative to aggregate liabilities. The PSD tracks the relative DIP indicator very closely: on its own, it accounts for 99 percent of the observed variation in

30 For an overview of policy measures taken during the financial crisis, see IMF (2009).



(A) Risk-neutral PSD



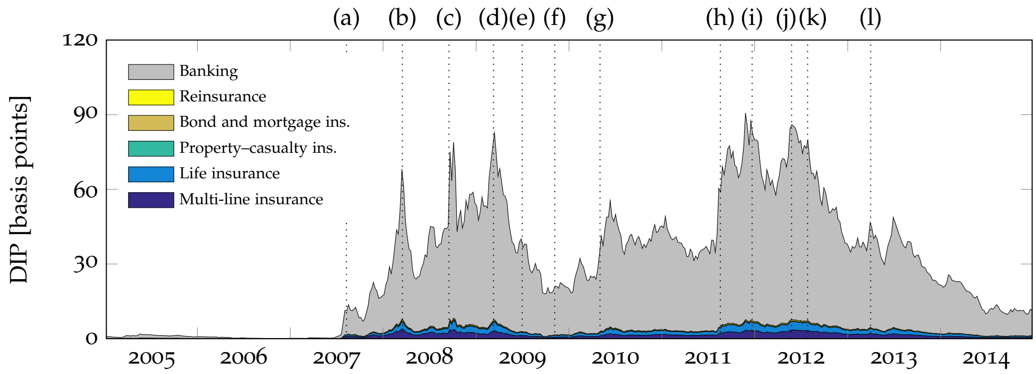
(B) ETL in unit price

FIGURE 2.5: Systemic risk components of the global financial system
This figure shows the systemic risk components of the global financial system. The risk-neutral PSD shown in the upper panel measures the risk-adjusted likelihood of a systemic event. The ETL shown in the lower panel measures the expected severity of systemic losses relative to aggregate total liabilities. The vertical lines represent the same events as those in Figure 2.1.

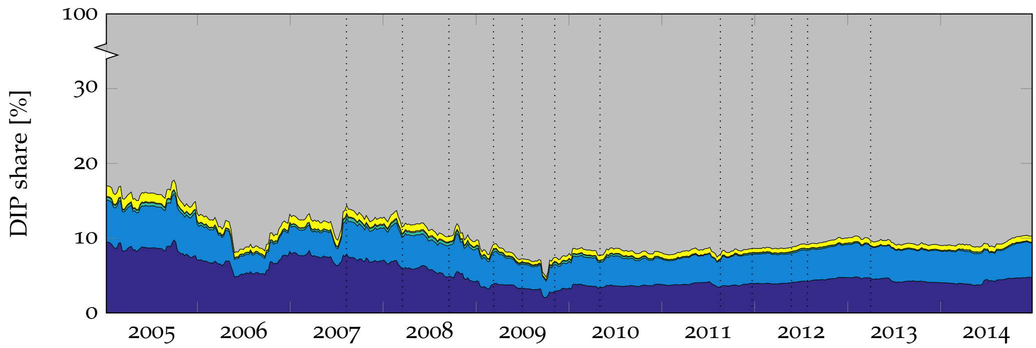
systemic risk. The risk-neutral PSD is virtually zero in the years leading up to the financial crisis, and surges following the onset of the crisis. The highest value during the financial crisis is reached with 4.6 percent for the week of March 13, 2009, when U.S. stock markets stood at their financial crisis low. The highest value during our sample period is assumed with 5.4 percent for the week of November 25, 2011, during the height of the European sovereign debt crisis.

The ETL shows considerably less time-series variation. On its own, it explains 58 percent of the observed variation in relative DIP. We observe a level shift in the ETL with the onset of the financial crisis. During the pre-crisis period, the ETL averages 13 percent, and during the period of the financial crisis and the European sovereign debt crisis, the ETL averages 17 percent. The ETL reaches its highest values of about 20 percent during the period from mid-March 2008, when Bear Stearns was taken over, through early October 2008, the immediate aftermath of the Lehman Brothers bankruptcy.

The dynamics of the PSD and the ETL shed light on the market assessment of systemic risk. Within our framework, the severity of systemic events increases only relatively moderately during the crisis episodes. The considerable increase



(A) DIP indicator sector contributions in unit price



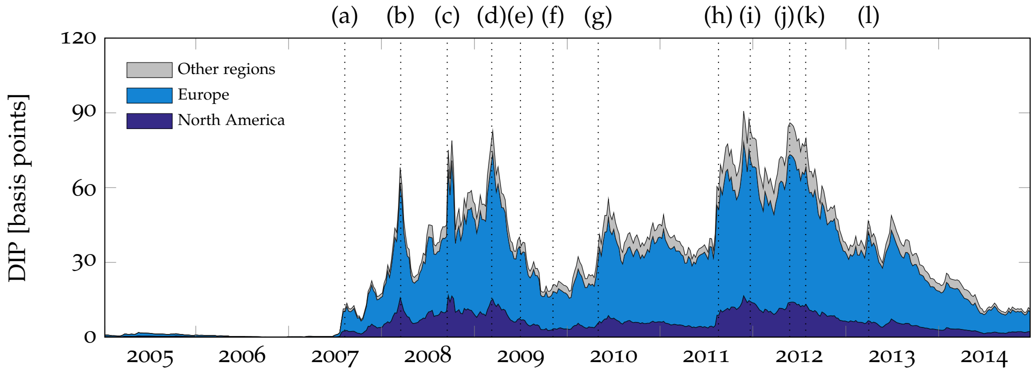
(B) DIP indicator sector contributions as share of total

FIGURE 2.6: Systemic risk in the global financial system by sector
This figure shows the level of systemic risk in the global financial system by sector. Systemic risk is measured using the DIP indicator. Sector contributions are shown in unit price in the upper panel and as shares of total systemic risk in the lower panel. The vertical lines represent the same events as those in Figure 2.1.

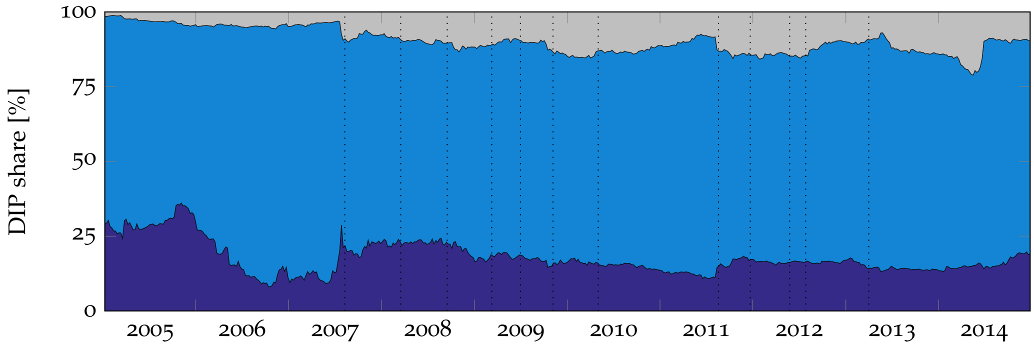
in systemic risk observed during the crisis periods is thus mainly driven by an increase in the risk-adjusted likelihood of a systemic event. This increase may be attributed to a combination of increased physical default probabilities and increased risk aversion in times of financial turmoil (see, e.g., Huang et al., 2012b; Black et al., 2016).

2.5.1.2 *Financial System Vulnerabilities*

For a given level of systemic risk, an interesting objective is to identify the vulnerabilities in the financial system, that is, the sectors contributing the most to systemic risk. Figure 2.6 shows plots of the systemic risk contributions of the different sample sectors over time. Figure 2.6a shows the marginal contributions in unit price, and Figure 2.6b shows the marginal contributions as shares of total risk. The marginal contributions of the banking and insurance sectors follow a similar trajectory, although at different levels. The banking sector contributes most to systemic risk throughout the sample period. During the financial crisis and the European sovereign debt crisis, the banking sector accounts for 91 percent of systemic losses on average, and the insurance sector accounts for



(A) DIP indicator sector contributions in unit price



(B) DIP indicator sector contributions as share of total

FIGURE 2.7: Systemic risk in the global financial system by region
This figure shows the level of systemic risk in the global financial system by region. Systemic risk is measured using the DIP indicator. Sector contributions are shown in unit price in the upper panel and as shares of total systemic risk in the lower panel. The vertical lines represent the same events as those in Figure 2.1.

9 percent. The systemic risk contribution of the insurance sector is mostly driven by multi-line insurance and life insurance. Each of these sectors accounts for about 4 percent of aggregate systemic losses during the crisis episodes, whereas the remaining insurance sectors collectively account for only about 1 percent. The marginal contributions of the banking and insurance sectors are relatively constant over time, with a somewhat higher systemic risk contribution of the insurance sector at the beginning of the financial crisis of about 14 percent. Overall, these results provide evidence that the insurance sector is not a major contributor to systemic risk. Nonetheless, whereas the insurance sector's aggregate contribution is relatively small, individual insurance companies may still be systemically important. We will discuss the systemic importance of individual financial institutions in Section 2.5.2.

We further assess the contribution to systemic risk by region. Figure 2.7 shows plots of the systemic risk contributions of the different sample regions over time. Figure 2.7a reports the marginal contributions in unit price, and Figure 2.7b reports the marginal contributions as shares of total risk. Europe contributes the highest share of systemic risk throughout the sample period. During the financial crisis and the European sovereign debt crisis, Europe accounts for 71 percent of systemic losses, North America for 17 percent, and the other regions combined for another 12 percent. We observe a gradual increase in Europe's relative systemic risk contribution over the period from May 2010, when the first support package for Greece was agreed upon, to August 2011, when global stock markets fell on uncertainty on the global economic outlook. This may be seen as evidence that a concentration of systemic risk built up in Europe during the early stages of the European sovereign debt crisis, and that this systemic risk subsequently spilled over to other economies.

Finally, we can use the same approach to compute the systemic risk shares of the public and the nonpublic financial institutions in the sample. During the crisis episodes, the public firms account for 86 percent of systemic losses, and the nonpublic firms account for 14 percent. Of the nonpublic firms' systemic losses, 37 percent are due to privately held firms and state-owned firms, and 63 percent are due to subsidiaries of publicly traded firms. The banking sector accounts for 95 percent of nonpublic systemic risk, and the insurance sector accounts for 5 percent. Whereas most systemic risk in our sample can be allocated to public firms, nonpublic firms are clearly an economically relevant source of distress in financial markets that is not captured by measures requiring equity data.

2.5.2 *Systemically Important Financial Institutions*

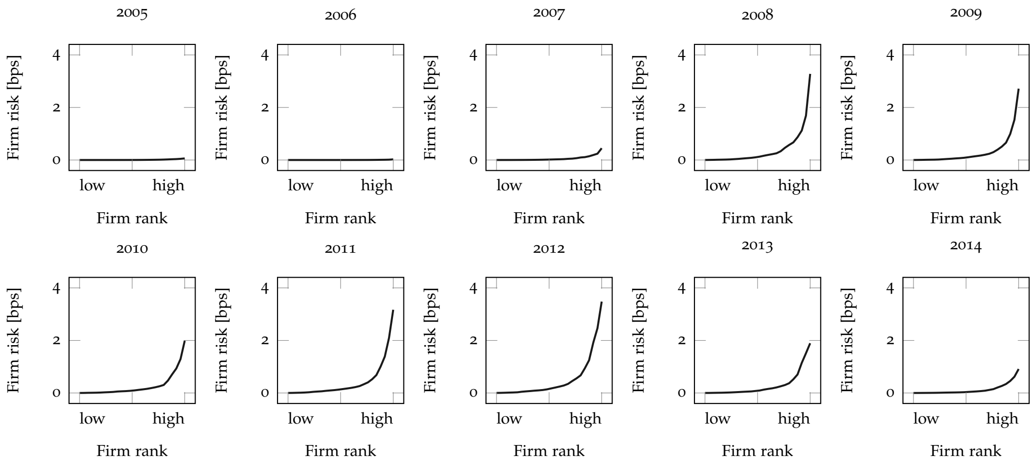
In this section, we analyze the systemic importance of the individual financial institutions in our sample. We measure the systemic risk of each firm using our three firm-level indicators: marginal DIP, the premium of a hypothetical insurance contract protecting the firm's creditors against losses during a systemic event; CoPD, the risk-neutral probability that the firm will default during a systemic event; and CoPSD, the risk-neutral probability of a systemic event if the firm is under severe stress, but does not necessarily default.

We organize our discussion in four parts. We first consider the general market perception of financial institutions' systemic importance. Next, we analyze the average systemic risk ranking of all firms from a given sector. We then turn to the systemic risk ranking of individual financial institutions. Finally, we discuss our findings.

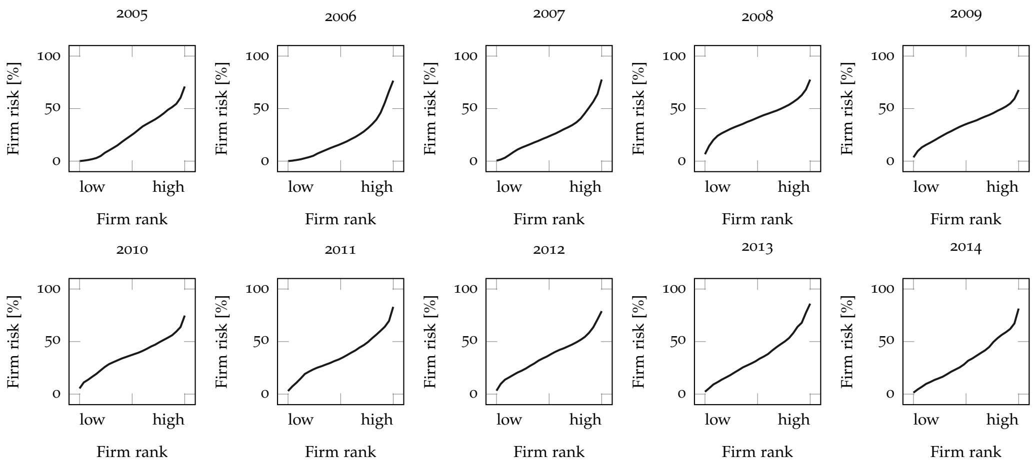
2.5.2.1 *Market Perception of Systemic Importance*

All our risk measures for the systemic importance of financial institutions are based on publicly available market data. As the following analysis confirms, the market perception of systemic importance changed significantly with the onset of the financial crisis.

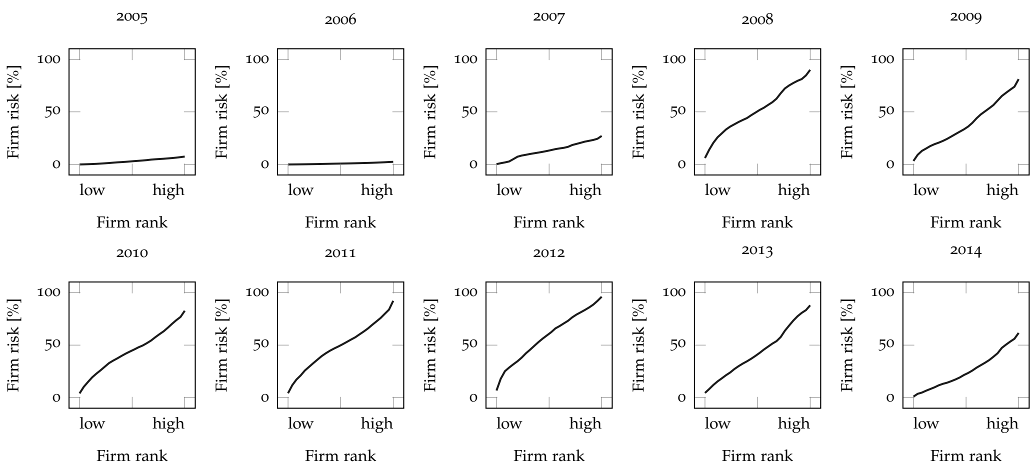
Figure 2.8 shows the level of systemic risk by firm rank for each risk measure and each year in our sample. The shapes of these risk rankings vary considerably across measures and over time. In the years leading up to the financial crisis, the



(A) Marginal DIP



(B) CoPD



(C) CoPSD

FIGURE 2.8: Systemic risk rankings over time
This figure shows the level of systemic risk by firm rank over time. We plot yearly risk rankings for three firm-level risk measures: the marginal DIP, the risk-neutral CoPD, and the risk-neutral CoPSD.

curves of the marginal DIP and the CoPSD are relatively flat. This indicates that financial markets' perception of systemic importance, that is, market prices of systemic risk, did not differ much between low-ranking firms and high-ranking firms in the period of relative tranquility preceding the crisis episodes. As the financial crisis unfolds, the curves grow steeper, providing evidence that financial markets discriminate more between systemically important financial institutions and non-systemically important financial institutions. At the peak of the financial crisis and at the height of the European sovereign debt crisis, the highest-ranking institutions have a marginal contribution to aggregate DIP of more than 2 basis points, and a CoPSD in the range of 80 to 95 percent. During this period, low-ranking institutions are associated with values close to zero in the case of the marginal DIP, and values of a few percentage points in the case of the CoPSD. Toward the end of our sample period, the curves of the marginal DIP and the CoPSD begin to flatten again, indicating that individual firms are less associated with systemic distress.

Two remarks on the marginal DIP and the CoPSD are in order. First, the CoPSD of high-ranking financial institutions consistently exceeds the unconditional PSD reported in Figure 2.5a. Distress of high-ranking firms therefore is clearly associated with an increased propensity for systemic distress. Second, the marginal DIP generally appears to discriminate more between high-ranking and medium-ranking financial institutions than the CoPSD. This is likely influenced by two aspects. First, the marginal DIP reflects the liability size distribution, where a small number of large firms accounts for a sizable share of the financial system's liabilities. Further, the CoPSD may identify a set of smaller financial institutions as systemic as a herd: the individual distress of an institution from this set is not sufficient to trigger a financial crisis, but the collective distress of several institutions from this set may engender financial turmoil.

The risk rankings of the CoPD show different dynamics than those of the marginal DIP and CoPSD. Throughout our sample period, the riskiest financial institutions are associated with a CoPD of more than 60 percent. Since this risk measure conditions on a crisis, the low time-series variation in the value associated with high-ranking institutions indicates that some firms are generally vulnerable during times of turmoil in the wider financial system. The differentiating element then is the severity of the crisis. Indeed, during the period of the financial crisis and the European sovereign debt crisis, we observe an increase in the level of risk associated with the firms in the lower tail of the distribution. Toward the end of our sample period, the level of risk decreases again. Overall, these observations reinforce the interpretation of CoPD as an indicator of financial institutions' exposure to systemic risk, measuring a firm's propensity to default during a crisis, and of CoPSD, by contrast, as an indicator of financial institutions' contribution to systemic risk, measuring the propensity for a crisis if a firm is distressed.

2.5.2.2 *Sector Ranking Distributions*

We now consider the average systemic risk ranking of all financial institutions from a given sector. We derive empirical ranking distributions as follows. For each week, we sort all firms in the sample according to their level of risk. Depending on its rank, we assign each firm to one of five risk buckets so that each bucket holds the same number of firms. For each sector, we then compute what share of firms from the sector has been assigned to each bucket. Figure 2.9 reports the mean, lower 5 percent quantile, and upper 5 percent quantile of the ranking distributions for each sector. We organize our analysis of the sample insurers' ranking by risk measure.

Considering marginal DIP first, P/C insurers, bond and mortgage insurers, and reinsurers mostly populate risk buckets in the lower tail of the ranking distribution. Insurers from these sectors therefore appear to individually contribute only a relatively small share to the aggregate level of systemic risk in the financial system. Multi-line insurers and life insurers, on the contrary, have a considerable share of their probability mass in the upper tail of the ranking distribution. Insurers from these sectors therefore appear to individually contribute a relatively large share to aggregate systemic risk.

Under the CoPD measure, the ranking distribution of P/C insurers is again skewed to the right. The default risk of P/C insurers therefore tends to be low during turmoil in the broader financial system. The ranking distribution of bond and mortgage insurers, however, is now skewed to the left. This indicates that bond and mortgage insurers tend to rank among the most distressed financial institutions in times of adverse market conditions. Multi-line insurers have about half of their probability mass allocated to the two highest risk buckets, and therefore, also tend to have a high level of distress risk if a financial crisis occurs. Life insurers have a relatively symmetric ranking distribution spanning all risk buckets. Reinsurers also populate all risk buckets, but appear to be less exposed than life insurers.

Turning to CoPSD, the ranking distributions of P/C insurers and bond and mortgage insurers are skewed to the right. Distress at the level of individual P/C insurers and bond and mortgage insurers therefore tends to be only marginally associated with financial crises. The ranking distributions of multi-line insurers and reinsurers are skewed to the left, indicating that distress at the individual level of one of these institutions tends to be associated with a financial crisis. Life insurers again have a rather symmetric ranking distribution and are also represented in the in the highest risk bucket.

2.5.2.3 *Individual Institution Rankings*

The ranking distributions considered in the previous section reflect the average ranking of all firms in a given sector over time. We can apply the same methodology to identify the individual financial institutions that show the greatest levels of risk. For the purpose of empirical illustration, we focus below on those

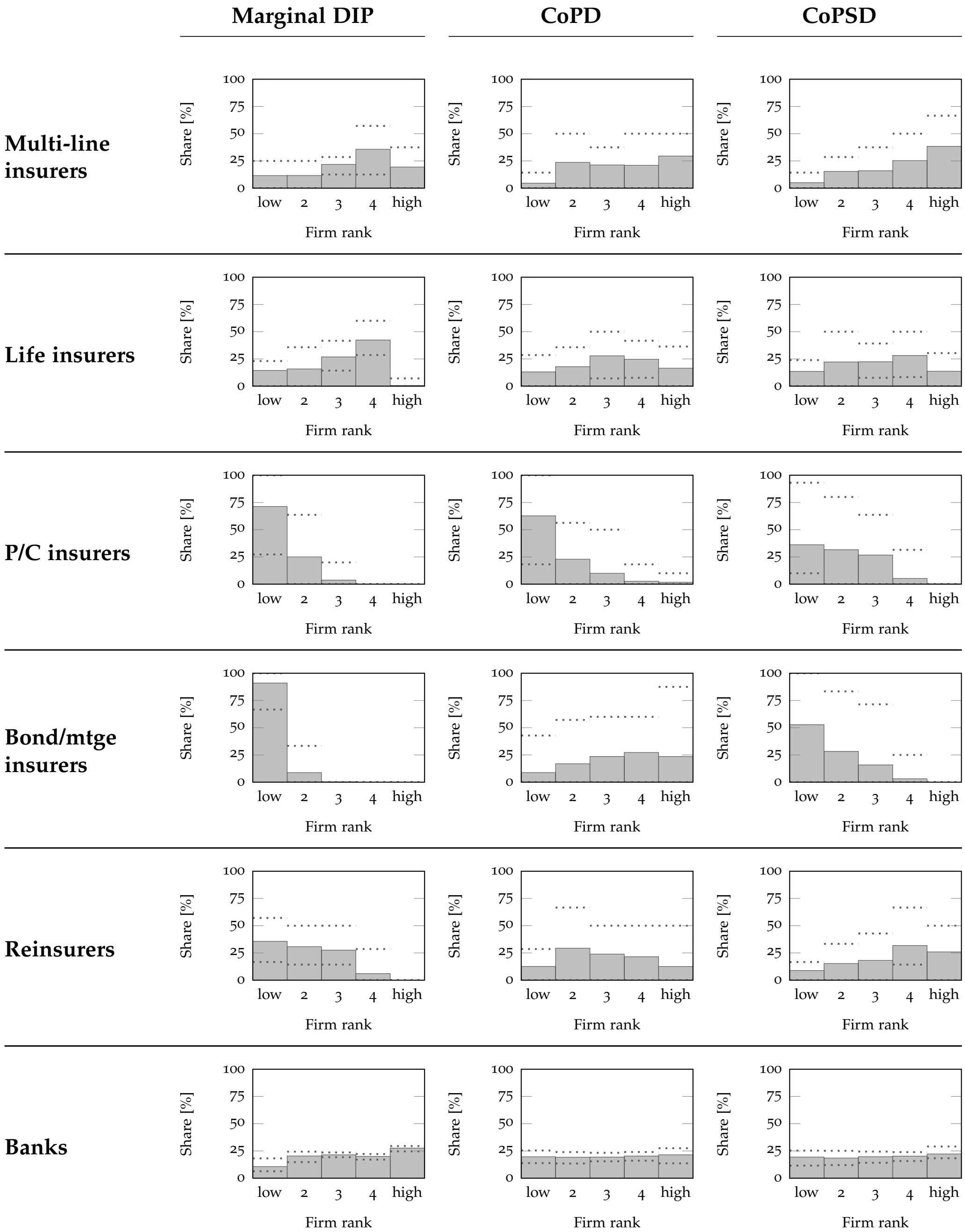


FIGURE 2.9: Firm ranking distributions by sector
This figure shows firm ranking distributions by sector. For each sector, the distributions report the share of firms that rank in one of five risk buckets. The distributions are derived as follows: for each week, we sort all firms in the sample according to their level of risk. Depending on its rank, we assign each firm to one of five risk buckets so that each bucket holds the same number of firms. For each sector, we then compute what share of firms from the sector has been assigned to each bucket. The figure reports distributions for three risk measures: the marginal DIP, the risk-neutral CoPD, and the risk-neutral CoPSD. The bars refer to the average share of firms, and the dotted lines mark the lower and upper 5 percent quantiles.

TABLE 2.2: Firms ranking among riskiest financial institutions

	Marginal DIP			CoPD			CoPSD		
Sector	Total	G-SIFIs	Nonp.	Total	G-SIFIs	Nonp.	Total	G-SIFIs	Nonp.
Consistently – 100 percent of respective sample period									
Banks	25	19	3	3	1	–	7	4	1
Insurers	2	2	–	–	–	–	1	1	–
Multi-line ins.	2	2	–	–	–	–	1	1	–
Life insurers	–	–	–	–	–	–	–	–	–
P/C insurers	–	–	–	–	–	–	–	–	–
Bond/mtge ins.	–	–	–	–	–	–	–	–	–
Reinsurers	–	–	–	–	–	–	–	–	–
Very frequently – at least 75 percent but less than 100 percent of respective sample period									
Banks	20	6	4	27	15	4	22	16	3
Insurers	7	6	–	6	4	–	9	5	1
Multi-line ins.	2	2	–	2	2	–	3	2	1
Life insurers	5	4	–	2	2	–	3	3	–
P/C insurers	–	–	–	–	–	–	–	–	–
Bond/mtge ins.	–	–	–	1	–	–	–	–	–
Reinsurers	–	–	–	1	–	–	3	–	–
Frequently – at least 50 percent but less than 75 percent of respective sample period									
Banks	11	3	5	19	3	2	11	1	–
Insurers	1	1	–	9	2	1	3	1	–
Multi-line ins.	–	–	–	3	2	1	1	1	–
Life insurers	1	1	–	1	–	–	1	–	–
P/C insurers	–	–	–	–	–	–	–	–	–
Bond/mtge ins.	–	–	–	4	–	–	–	–	–
Reinsurers	–	–	–	1	–	–	1	–	–

This table shows the number of firms ranking among the riskiest financial institutions in the global financial system. For each week, all firms in the sample are assigned to one of five equally sized risk buckets depending on their level of risk. *Total* reports the total number of institutions ranking in the two highest risk buckets, grouped by the share of their individual sample period spent in these buckets. *G-SIFIs* reports the number of such firms that have been designated either as G-SIBs or as G-SIIs in the period from 2011 through 2015. *Nonpublic* reports the number of such firms that are nonpublic for the majority of their sample period. We consider three risk measures: the marginal DIP, the risk-neutral CoPD, and the risk-neutral CoPSD.

financial institutions that are represented in the two risk buckets in the upper tail of the ranking distribution.

Table 2.2 shows the number of firms included in the two highest risk buckets, grouped by the share of their respective sample period spent in the upper tail of the ranking distribution. We report the number of firms which consistently rank among the riskiest financial institutions (100 percent of their respective sample period), very frequently rank among the riskiest financial institutions (at least 75 percent but less than 100 percent of their respective sample period), and frequently rank among the riskiest financial institutions (at least 50 percent but less than 75 percent of their respective sample period). We further report the number of G-SIFIs among these institutions, as well as the number of nonpublic institutions appearing in the rankings.

The left panel refers to the ranking by marginal DIP. We identify 10 insurers that are represented in the upper tail of the ranking distribution for at least half of their sample period. Nine of these insurers have been designated as G-SIIs, representing all of the G-SIIs included in our sample. Our methodology, therefore, replicates the official list of G-SIIs very closely using only publicly available market and financial statements data. All identified insurers belong to the multi-line and life insurance sectors. Two multi-line insurers consistently rank among the riskiest financial institutions.[31]

The mid panel refers to the ranking by CoPD. We identify 15 insurers that are represented in the upper tail of the ranking distribution for at least half of their sample period. The list includes insurers from every sector except P/C insurance, providing further evidence that insurers from this sector are resilient in times of market turmoil. Six of the identified insurers have been designated as G-SIIs. Two of the identified insurers are reinsurers, which regulators deliberately excluded when compiling the relevant G-SII lists. The remaining difference between the list of insurers we identify and the official list of G-SIIs is mostly explained by five bond and mortgage insurers appearing in our ranking. Overall, the ranking by CoPD appears to be more volatile than the ranking by marginal DIP. No insurer consistently ranks among the riskiest financial institutions, and only three banks consistently rank among the riskiest financial institutions.

The right panel refers to the ranking by CoPSD. We identify 13 insurers that are represented in the upper tail of the ranking distribution for at least half of their sample period. Four of these are reinsurers, and the remaining nine insurers are from the multi-line and life insurance sectors. Seven of the nine multi-line and life insurers we identify have received G-SII status, again yielding a considerable overlap between our model-based assessment approach and the official indicator-based assessment approach.

A final observation is on nonpublic financial institutions. In total, the ranking by marginal DIP includes 12 nonpublic banks and insurers, the ranking by CoPD includes 7 nonpublic financial institutions, and the ranking by CoPSD includes 5 such firms. The risk rankings represent privately held firms, state-owned firms, and subsidiaries of publicly traded firms. This further highlights nonpublic financial institutions as a source of systemic risk, which may be monitored empirically using indicators derived from debt markets.

2.5.2.4 *Discussion of Findings*

Based on the results reported above, we can draw the following conclusions about the systemic importance of insurers. We do not find evidence that P/C or bond and mortgage insurers are systemically important. The marginal contribution of

31 We also determine the number of banks ranking among the riskiest financial institutions. The ranking by marginal DIP identifies 56 banks that are represented in the upper tail of the ranking distribution for at least half of their sample period, 28 of which have been designated as G-SIBs. We should note, however, that the list of banks we identify and the official list of G-SIBs are drawn from different populations, as our list includes a number of banks that were acquired or failed before the first list of G-SIBs was published.

individual insurers from these sectors to systemic losses is limited. Moreover, distress at the institution level is not associated with financial crises, as these insurers are probably too small individually to severely impair the broader financial system upon their default. However, P/C insurers' and bond and mortgage insurers' resilience to systemic shocks differs. Although financial crises do not seem to affect P/C insurers, financial turmoil appears to impair bond and mortgage insurers. This is most likely explained by different kinds of risk underwritten by these types of insurers. Traditional P/C insurers focus on underwriting idiosyncratic risks, which are not linked to financial markets. The bond and mortgage insurers in our sample fall into two groups: financial guarantee insurers, which underwrite municipal bonds, and private mortgage insurers, which underwrite mortgage loans. The performance of bonds and mortgages is highly correlated with the overall state of financial markets, which exposes these insurers to financial crises.

Several multi-line and life insurers, on the contrary, are associated with levels of systemic risk resembling those of the riskiest sample banks. The highest-ranking multi-line and life insurers individually contribute significantly to aggregate systemic risk in the financial system. Moreover, the distress of some multi-line and life insurers is associated with financial crises. Several factors may contribute to this finding. Multi-line and life insurers are on average an order of magnitude larger than P/C insurers and bond and mortgage insurers. Moreover, the multi-line and life insurers in our sample include internationally active financial institutions with global business activities and exposures. Finally, the nature of these insurers' investment and funding strategies as well as their underwriting of nontraditional or noninsurance risks may strengthen their interconnectedness with financial markets. The last point may also serve as a potential explanation for the high default risk of some multi-line and life insurers in times of turmoil in the broader financial system.

Reinsurers fall somewhere in between. Individually, they do not contribute a significant share to the financial system's aggregate systemic risk, yet the distress of some reinsurers is associated with financial crises. This may be interpreted as evidence that the default of these reinsurers poses a large negative externality, potentially due to a high degree of interconnectedness within the insurance sector and the wider financial system.[32]

32 Indeed, reinsurance contracts may contribute to reinsurers' interconnectedness within the insurance sector. Primary insurers ceding part of their underwriting risk to reinsurers expose themselves to the assuming reinsurers' credit risk. Cummins and Weiss (2014) thus argue that primary insurers might be prone to reinsurance crises. In analyses of reinsurance exposures, van Lelyveld et al. (2011) and Park and Xie (2014), however, find that the risk of insurance sector crises caused by reinsurance failures is relatively limited.

TABLE 2.3: Input factor determinants of aggregate systemic risk

Model	(1)	(2)	(3)
Panel A: DIP			
Constant	−6.6816***	−35.6738***	−14.1218***
	(0.4626)	(1.7742)	(0.9742)
PD	14.1440***		12.8646***
	(0.2846)		(0.3936)
Corr		1.5506***	0.2550***
		(0.0517)	(0.0373)
Adjusted R^2	0.87	0.52	0.88
Observations	521	521	521
Panel B: PSD			
Constant	−0.3386***	−1.9610***	−0.7000***
	(0.0284)	(0.1052)	(0.0566)
PD	0.8148***		0.7527***
	(0.0175)		(0.0256)
Corr		0.0882***	0.0124***
		(0.0031)	(0.0024)
Adjusted R^2	0.88	0.51	0.88
Observations	521	521	521
Panel C: ETL			
Constant	13.4365***	8.6431***	9.1290***
	(0.1070)	(0.0586)	(0.0825)
PD	1.0308***		0.2900***
	(0.0353)		(0.0248)
Corr		0.1769***	0.1477***
		(0.0016)	(0.0034)
Adjusted R^2	0.63	0.92	0.95
Observations	521	521	521

This table reports input factor regressions for measures of aggregate systemic risk. The dependent variables are the DIP (in basis points), the risk-neutral PSD (in percentage points), and the ETL (in percentage points). The independent variables are the cross-sectional averages of the risk-neutral probabilities of default (PD; in percentage points) and the asset return correlations (corr; in percentage points). The variance inflation factor in the third regression is 2.05. Heteroscedasticity-consistent standard errors are given in parentheses. Significance is indicated by: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

2.5.3 *Input Factor Determinants of Systemic Risk*

In this section, we analyze the role of the input factors for our systemic risk measures.[33] Table 2.3 examines the input factor determinants of the measures of aggregate systemic risk. We consider the aggregate DIP in unit price, the risk-neutral PSD, and the ETL in unit price as the dependent variables, and focus on the explanatory power of the cross-sectional average of risk-neutral probabilities of default and asset return correlations.

33 Huang et al. (2012a,b) and Black et al. (2016) report similar results for the DIP indicators in the context of banking sector distress. Going beyond the analyses reported therein, our analysis also sheds light on the determinants of the other measures of aggregate systemic risk and individual systemic importance that we consider.

The average risk-neutral probability of default is the prime determinant of the aggregate DIP and the risk-neutral PSD, on its own explaining 87 percent and 88 percent of these measures' time-series variation, respectively. Asset return correlations individually explain 52 percent of the time-series variation of the aggregate DIP and 51 percent of the time-series variation of the risk-neutral PSD, but their impact diminishes once the default probabilities are included in the regressions.

The level of asset return correlations is the dominant factor for the ETL, on its own explaining 92 percent of the time-series variation. Risk-neutral probabilities of default individually explain 63 percent of the time-series variation of the ETL, but have limited additional explanatory power once the asset return correlations are taken into account.

Table 2.4 examines the input factor determinants of our measures of individual systemic importance. We consider the marginal DIP in unit price, the risk-neutral CoPD, and the risk-neutral CoPSD as the dependent variables, and include firm-level risk-neutral probabilities of default, asset return correlations, and liability weights as explanatory variables. For each firm, we compute the asset return correlation as the average correlation between the firm and all other firms in the sample, and the liability weight as the liability size of the firm relative to the aggregate liabilities of the financial system. We use ordinary least squares regressions on the panel data, clustering standard errors at the firm level to control for potential bias.

The liability weight is the most important determinant of the marginal DIP, explaining 45 percent of the observed variation. Correlations are the prime determinant of the other two risk measures, explaining 46 percent of the variation in the CoPD, and 68 percent of the variation in the CoPSD. Apparently, this empirical result reflects the mathematical definitions of the firm-level risk measures. Financial institutions' size directly enters the computation of the marginal DIP as a liability weight, whereas it only indirectly enters the CoPD and CoPSD formulae via the systemic event definition. Thus, by construction, size and correlation—relating to the common *too-big-to-fail* notion and the related *too-interconnected-to-fail* concern—explain these metrics to varying degree.

Risk-neutral probabilities of default do not explain the variation in any of the firm-level risk measures well, and are only weakly statistically significant for marginal DIP. This contrasts with the role of the average risk-neutral probability of default for aggregate systemic risk. Whereas the average risk-neutral probability of default in a financial system appears to be an important determinant of aggregate systemic risk, firm-level risk-neutral probabilities of default are not a good indicator of individual contributions and exposures to systemic risk.

We additionally interact the liability weight with the risk-neutral probability of default and the asset return correlation to capture nonlinear effects. To alleviate concerns on multicollinearity, we calculate the interaction terms from the centered variables. The interaction terms have considerable additional explanatory power for the marginal DIP, and some additional explanatory power for the

TABLE 2.4: Input factor determinants of individual systemic importance

Model	(1)	(2)	(3)	(4)	(5)
Panel A: Marginal DIP					
Constant	0.2008***	−0.2441***	−0.0412***	−0.3623***	−0.5095***
	(0.0283)	(0.0382)	(0.0119)	(0.0452)	(0.0222)
PD	0.0077*			0.0248***	0.1109***
	(0.0044)			(0.0050)	(0.0146)
Corr		0.0111***		0.0063***	0.0040***
		(0.0015)		(0.0008)	(0.0008)
Weight			0.3491***	0.3415***	0.4580***
			(0.0252)	(0.0247)	(0.0400)
PD × Weight					0.1616***
					(0.0208)
Corr × Weight					0.0082***
					(0.0011)
Adjusted R^2	0.00	0.13	0.45	0.53	0.87
Observations	69,467	69,467	69,467	69,467	69,467
Panel B: CoPD					
Constant	27.3430***	−0.9395	28.3419***	−6.0059***	−5.9163***
	(1.2908)	(0.8757)	(1.1506)	(0.6882)	(0.8226)
PD	2.0961***			2.0976***	2.1751***
	(0.2320)			(0.1167)	(0.2271)
Corr		0.8064***		0.7171***	0.7091***
		(0.0218)		(0.0224)	(0.0265)
Weight			5.8712***	4.5240***	4.8508***
			(0.9802)	(0.7651)	(1.0741)
PD × Weight					0.1152
					(0.3293)
Corr × Weight					−0.0404
					(0.0407)
Adjusted R^2	0.12	0.46	0.08	0.59	0.59
Observations	69,467	69,467	69,467	69,467	69,467
Panel C: CoPSD					
Constant	29.3807***	−26.3801***	26.8757***	−29.3728***	−32.8221***
	(1.2596)	(1.6863)	(1.0820)	(1.8322)	(1.5750)
PD	1.4031***			1.1318***	3.4038***
	(0.4181)			(0.1775)	(0.4166)
Corr		1.4215***		1.3565***	1.2850***
		(0.0410)		(0.0398)	(0.0405)
Weight			8.1615***	3.7210***	7.2299***
			(0.9130)	(0.5096)	(1.2041)
PD × Weight					4.2055***
					(0.5789)
Corr × Weight					0.1230**
					(0.0475)
Adjusted R^2	0.03	0.68	0.08	0.70	0.76
Observations	69,467	69,467	69,467	69,467	69,467

This table reports input factor regressions for measures of individual systemic importance. The dependent variables are the marginal DIP (in basis points), the risk-neutral CoPD (in percentage points), and the risk-neutral CoPSD (in percentage points). The independent variables are risk-neutral probabilities of default (PD; in percentage points), asset return correlations (corr; in percentage points), and liability weights (weight; in percentage points). The independent variables are centered when computing the interaction terms. The maximum variance inflation factor in the regressions is 2.84. Heteroscedasticity-consistent standard errors clustered at the firm level are given in parentheses. Significance is indicated by: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

risk-neutral CoPSD. Large firms with high levels of distress risk and large firms that are highly coupled with the wider financial system thus appear to be most systemically risky. The interaction terms have no additional explanatory power for the risk-neutral CoPD. This is to be expected, as a ceteris paribus increase in the unconditional risk-neutral probability of default or the asset return correlation should have the same impact on an institution's distress risk in a financial crisis irrespective of the institution's size.

Overall, the share of explained variation remains lower for the risk-neutral CoPD and the risk-neutral CoPSD than for the marginal DIP. This may well be due to a higher sensitivity of the CoPD and the CoPSD to nonlinear tail interdependencies of the financial system.

2.5.4 *Robustness Tests*

In this section, we analyze the robustness of the previous results along two important dimensions: using alternative recovery rates and varying the systemic loss threshold. Our findings on systemic risk in insurance remain qualitatively unchanged relative to the baseline analysis reported in the previous sections.

2.5.4.1 *Alternative Recovery Rate Assumption*

For the default scenarios in the baseline analysis, we modeled sector-specific recovery rates with a time-series average of 57 percent for banks and 72 percent for insurers. These recovery rates are based on recovery assumptions for different types of financial institutions' liabilities. To explore the sensitivity of our results to changes in the recovery rate assumption, we repeat our analysis using the same recovery rate of 40 percent for all financial institutions. This alternative assumption corresponds to the market practice for senior unsecured debt.

The change in the recovery rates affects the level of systemic risk in the financial system, but not its dynamics. In response to the generally lower recovery rates, the systemic risk indicator peaks on the same occasions, but with greater values than in the baseline analysis. The systemic risk contribution of the insurance sector averages 14 percent during the crisis episodes, up from 9 percent in the baseline analysis. This reflects the greater reduction in the insurers' recovery rate relative to the banks' recovery rate. Importantly, even under this adverse recovery rate scenario, systemic risk in the insurance sector is relatively small compared to that in the banking sector. This finding is therefore not induced by a specific recovery rate assumption, but is linked to fundamental characteristics reflected in our systemic risk measure.

Regarding individual financial institutions, the results on the firm level are also robust to the change in the recovery rate. In particular, ranking banks and insurers according to their systemic importance yields the same qualitative results as it does in the baseline analysis.

2.5.4.2 *Variation of the Systemic Loss Threshold*

The systemic loss threshold defines at what level financial institutions' losses are so severe as to turn systemic. In the baseline analysis, we chose a loss in aggregate liabilities of more than 10 percent over a 1-year horizon. To rule out the possibility that our results are driven by that particular choice, we also consider thresholds of 5 percent and 15 percent.

Decreasing the systemic loss threshold assumes that the financial system will be impaired already at lower levels of distress; increasing the systemic loss threshold assumes that the financial system can absorb larger losses before a financial crisis ensues. We have no hypothesis on the effect on the aggregate systemic risk indicator: decreasing the systemic loss threshold increases the propensity for a systemic event, but lowers the average loss in a systemic event, and vice versa when increasing the systemic loss threshold.

Although changing the systemic loss threshold affects the level of systemic risk, it does not affect its time-series variation. A systemic loss threshold of 5 percent increases the level of aggregate systemic risk relative to the baseline analysis, whereas a threshold of 15 percent results in a decrease. This indicates that, within a sensible range, changes in the probability of a systemic event outweigh opposing changes in expected systemic losses.

The findings on systemic risk in insurance are highly robust to variations in the systemic loss threshold. In both alternative scenarios, the insurance sector's systemic risk share remains at 9 percent during the crisis episodes, and the ranking of individual financial institutions by their level of systemic risk yields the same implications as before. We can therefore safely conclude that our results are not driven by the particular definition of a financial crisis within our modeling framework.

2.6 policy and analysis implications

The results presented in the previous section have a number of important implications for the effective regulation of systemic risk in financial markets. Regulators targeting systemic risk aim to limit the costs of financial crises to the economy as a whole. Such costs arise from negative externalities of financial institutions. Whereas negative externalities in banking are widely acknowledged, those in insurance require further explanation.

Acharya et al. (2016) distinguish two types of negative externalities of distressed financial institutions: (i) a *going-concern externality*, in which solvency problems diminish future intermediation capacity; and (ii) a *fire-sale externality*, which impairs the value of existing assets in a downward spiral of liquidity problems and asset liquidations. The authors argue that different types of financial institutions probably engender different externalities. Banks likely exhibit both externalities. Insurers operating within the traditional insurance business model, if they engender externalities at all, should pose only a going-concern externality, as they rely less on short-term liabilities and are unlikely to experience runs. Insurers that have expanded into banking-like activities, however, may also generate a fire-sale externality.[34]

Recognizing that both banks and insurers may pose externalities in a state of distress, our results prompt the following policy recommendations. Throughout the sample period, the banking sector contributes most of the systemic risk in the global financial system, whereas the insurance sector contributes only a minor share. This finding does not support generally stricter regulation of the insurance industry with respect to systemic risk. Rather, we advocate that most of the regulatory effort to enhance the stability of the global financial system should be directed toward the banking sector. Systemic risk in the insurance sector should still be closely monitored to provide an early warning should the sector's systemic risk increase in the future.[35]

Although the systemic risk contribution of the insurance sector as a whole is relatively contained, some individual insurers show levels of systemic risk comparable to the riskiest banks. Our results, therefore, provide a preliminary affirmation that some insurers are indeed systemically important financial institutions, which lends support to selectively stricter regulation. The analysis of insurers' systemic importance by principal line of business further reveals a significant difference in the level of systemic risk associated with different types of business activities. In particular, nontraditional activities, such as securities lending (Harrington, 2009), funding-agreement backed securities (Foley-Fisher et al., 2015), and shadow insurance (Koijen and Yogo, 2016) appear to warrant regulatory scrutiny. We therefore endorse targeting systemic risk in insurance by a combination of entity- and activity-based regulation. If we envision financial markets as a network, where the nodes represent the market participants and the edges represent the business activities linking those participants, entity-based regulation will target the nodes of this network, and activity-based regulation will target the edges.

At the entity level, regulators may impose higher capital requirements for systemically important insurers to induce these institutions to consider the costs of their negative externalities, and to enhance these institutions' resilience in times of crisis. Capital surcharges for systemic risk should directly reflect an institution's degree of systemic importance and may be derived using alternative methods. Following a potential future model-based designation of systemically

34 Acharya et al. (2016) cite the role of life insurers in U.S. capital markets as an example of how insurers may give rise to a going-concern externality. As estimated by the American Council of Life Insurers, at the end of 2013, life insurers held one-fifth of all outstanding U.S. commercial bonds and one-eighth of all U.S. commercial mortgages. The disruption of this financing activity due to solvency problems in the insurance sector could cause potentially severe stress for the real economy. Further, rapidly unwinding such positions to free up liquidity might result in a fire-sale externality.

35 We should note that this implication is based on an analysis of systemic risk on the global stage, and thus extends to the global financial system. The relative importance and systemic risk contributions of the banking and insurance sectors may well vary across countries. Regulators aiming to enhance financial stability at the domestic levels thus need to be aware that the insurance sector could play an outsized role in the respective financial systems.

important insurers, such capital surcharges could be derived from the respective empirical measures of systemic risk, as suggested by Huang et al. (2012a,b).

Alternatively, capital surcharges could be determined using risk weights for different business activities. This approach should cover both sides of the insurance balance sheet, including underwriting activity as well as investment and financing. The additional capital requirement per business activity should be in proportion to the activity's systemic risk contribution. Activities related to providing insurance for idiosyncratic risks should not entail capital surcharges, whereas activities interconnecting insurers with financial market movements may justify elevated capital surcharges. Importantly, whereas deriving macroprudential capital surcharges from empirical measures of systemic importance will capture mitigating or exacerbating effects on systemic risk stemming from the combination of different lines of business in a single institution, basing capital surcharges on risk weights will only reflect the systemic risk posed by different business activities in isolation.

Activity-based regulation designed to support such efforts to foster financial stability should be based on a careful evaluation of the entire regulatory toolkit, and may include measures such as enhanced transparency requirements, taxes on transactions engendering systemic risk, and limitations on the extent of certain activities. We expect that an effective combination of entity- and activity-based regulation will provide systemically important insurers with clear incentives to curtail those business activities that contribute most to systemic risk. In this respect, we expect such an approach to mark a clear route for these firms to ultimately shed their systemic risk label by reducing their engagement in systemically risky business activities.

Our results further have important implications for the design of a potential future model-based assessment methodology for monitoring the systemic risk posed by individual financial institutions.[36] First, we find that market-based risk measures differed only marginally between systemically important and non-systemically important financial institutions during the pre-crisis period. With the onset of the financial crisis, the level of systemic risk associated with systemically important financial institutions increased considerably. To avoid pro-cyclicality when identifying G-SIFIs, we therefore recommend ranking financial institutions relative to one another, rather than applying fixed thresholds when determining systemic risk. Moreover, we find that different firm-level risk measures tend to be explained to varying degrees by different aspects of systemic importance, such as size and interconnectedness. To mitigate model risk in the assessment of financial institutions' systemic importance, a model-based assessment methodology should therefore be based on a diverse set of indicators. Finally, our analysis highlights nonpublic financial institutions as an economi-

36 Indeed, the Basel Committee on Banking Supervision has considered a model-based approach as an alternative to the current indicator-based approach for identifying G-SIBs. However, in BCBS (2011, p. 3), model-based approaches were still seen as being "at a very early stage of development." More recently, the IAIS stated that it might consider systemic risk metrics for setting a threshold for systemic importance when identifying G-SIIs (IAIS, 2016, p. 25).

cally relevant source of systemic risk. Model-based assessment methodologies should therefore include systemic risk measures derived from debt markets to capture the systemic risk of nonpublic firms.

Finally, our analysis of the input factor determinants of aggregate systemic risk and individual systemic importance has a number of general implications for measuring and managing systemic risk.[37] In the analysis of the determinants of aggregate systemic risk, we find that financial institutions' average risk-neutral probability of default explains most of the variation in the aggregate DIP and the risk-neutral PSD, whereas average asset return correlations explain most of the variation in the ETL. This supports the following three conclusions. First, indicators reflecting financial institutions' average risk-neutral probabilities of default and asset return correlations may be used to monitor the buildup of systemic risk in financial markets. In particular, the level and comovement of financial institutions' CDS spreads may be used as ad hoc approximations of the aggregate risk measures we consider. Second, none of the aggregate risk measures is fully explained by a linear relationship with its input factors. The level of systemic risk in financial markets additionally depends on nonlinear dependencies within the financial system. Third, there are two main levers for policy measures aiming at financial stability. A broad array of measures that both reduce financial institutions' average default risk and de-correlate their assets is regulators' best toolkit for diminishing the propensity for and severity of systemic distress.

In the analysis of the determinants of individual systemic importance, we find that financial institutions' unconditional probability of default does not explain their systemic importance as measured by the marginal DIP and the risk-neutral CoPSD. This underscores the importance of carefully distinguishing between microprudential and macroprudential approaches when assessing systemic importance: firms in good financial condition may nevertheless be systemically risky; likewise, firms in bad shape may not be systemically important.

2.7 CONCLUSION

How systemically important are insurers? Our analysis suggests that overall, the insurance sector accounts for a relatively small share of the systemic risk in the global financial system. However, several individual insurers exhibit elevated levels of systemic risk and may, therefore, be considered systemically important financial institutions. The marginal contribution of these insurers to total systemic risk is comparable to the riskiest banks, and these firms' distress tends to be associated with systemic events.

Our results indicate a difference in the level of systemic risk associated with different types of insurance. Overall, multi-line and life insurers tend to show

37 Huang et al. (2012a,b) and Black et al. (2016) discuss similar implications for the aggregate and marginal DIP in the context of banking sector distress.

the highest levels of systemic risk. Bond and mortgage insurers are vulnerable to turmoil in the broader financial system, but do not appear to contribute to financial instability. P/C insurers consistently rank lowest and do not appear to be systemically important. The ranking of reinsurers depends on the risk metric. The marginal contributions of individual reinsurers to aggregate systemic risk are rather small; however, the distress of some reinsurers is associated with a systemic crisis in the broader financial system.

We derived these stylized facts by grouping insurers into sectors reflecting their principal line of business. In practice, insurers will often engage in a range of activities beyond their core businesses. Our results, therefore, indicate the relative level of systemic risk entailed by different types of insurance, and they support complementing entity-based regulation of such risk by activity-based measures. We did not attempt, however, to allocate insurers' systemic risk to specific business activities. Decomposing the systemic risk posed by insurers at the entity level into the marginal contributions of individual business activities, and separating such activity effects from size effects, is an important area for further research. In particular, an interesting issue is whether the high levels of systemic risk we observed for some multi-line insurers are driven by their life insurance businesses. Such research will inform activity-based regulation of systemic risk, which, if applied more broadly across financial markets, could be an effective disincentive to regulatory arbitrage.

We conclude with a remark on the dynamic nature of the insurance industry. Although P/C insurance shows the lowest overall distress risk during our sample period, future developments in this line of business need to be closely monitored. In recent years, the industry has seen increasing demand to insure against cyber risk, which may be systemic by its very nature. Security breaches affecting information technology systems can occur simultaneously across the globe, potentially producing multi-billion dollar claims by the affected corporations, institutions, or governments. This and other new risks, as well as changes in the insurance business model, will have to be taken into account when designing future methodologies for identifying and regulating G-SIIs.

APPENDIX

2.A DATA SOURCES AND DEFINITIONS

This appendix describes the data sources and definitions used in the analysis.

CREDIT DEFAULT SWAP DATA CDS spreads are available from Thomson Reuters Datastream. This database offers two data sets with end-of-day pricing information for single-name CDS contracts. The first data set is provided by CMA DataVision and covers the period running from January 1, 2003 through September 30, 2010.[38] The second data set is compiled by Thomson Reuters and initiates coverage on December 14, 2007.[39] We merge both data sets at the reference entity level to obtain a longer time series as well as a broader cross section. Reference entity coverage of the merged data set increases considerably in January 2004, which marks the beginning of the sample period.

CDS contracts are quoted for a range of standardized tenors, tiers, currencies, and restructuring clauses.[40] We require 5-year senior unsecured CDS contracts, because these represent the most liquid tenor and tier. For each reference entity, we retrieve daily spreads for the full set of matching contracts. Following a screening procedure, we then calculate weekly spreads adopting the methodology underlying Moody's Analytics' CDS-implied expected default frequency measures described in Dwyer et al. (2010). This approach comprises two steps: (i) converting spreads to a common restructuring clause, namely complete restructuring, and (ii) aggregating spreads across currencies and unified restructuring clauses.

According to CMA DataVision and Thomson Reuters, spreads are disseminated only if they pass a set of quality assurance procedures for identifying and removing outliers and otherwise doubtful data. As a further control of data quality, we exclude stale observations, setting spreads to missing if they remain constant over more than 20 trading days. We then convert all remaining spreads to complete restructuring equivalents using adjustment factors provided

38 CMA DataVision reports observed and derived spreads. Observed spreads are calculated by aggregating spread contributions received from a consortium of buy-side firms, including investment banks, hedge funds, and asset managers. When there are insufficient spread contributions to produce an entire term structure, derived spreads are calculated for the rest of the curve fitting a proprietary term structure model.

39 Thomson Reuters reports composite spreads. These spreads are calculated as the arithmetic average of spread contributions received from a consortium of sell-side banks. Composite spreads are only disseminated if contributor prices have been received.

40 The restructuring clause determines whether restructuring constitutes a credit event, and if so, which obligations are deliverable in a restructuring event. Sorted from most restrictive (restructuring does not constitute a credit event) to least restrictive (restructuring is treated like other credit events), the following restructuring clauses are available: *no restructuring*, *modified restructuring*, *modified-modified restructuring*, and *complete restructuring*.

by Markit.[41] Following this conversion, spreads are first aggregated at the restructuring clause level, taking the arithmetic average across currencies, and then aggregated at the reference entity level, taking the arithmetic average across the unified restructuring clauses. Finally, we compute the arithmetic average of the aggregated daily spreads to obtain weekly spreads.

We choose to unify restructuring clauses and to aggregate spreads over two alternatives. The first alternative is to use only contracts with a given currency and restructuring clause. However, this would considerably reduce the size of the cross section and would potentially introduce a selection bias, because currency and restructuring clause preferences differ across regions. The second alternative is to use the most liquid currency and restructuring clause for each region. This approach, however, would introduce a bias in a global setting, because spreads differ systematically between restructuring clauses. Further, restructuring clause preferences have changed over time. Unifying restructuring clauses and aggregating spreads alleviates these concerns and results in more robustness as well as wider coverage.[42]

FINANCIAL STATEMENTS DATA Financial statements data are available from Bloomberg. We retrieve data on total liabilities from the consolidated annual balance sheets. Some firms have missing or incomplete data on the Bloomberg record. Where possible, we fill gaps in the total liabilities data by collecting additional financial information from investor relations Web sites, regulatory authorities, and exchanges. All liabilities are converted into U.S. dollars using historical exchange rates. We compute weekly portfolio weights from the annual liability data using linear interpolation within the firms' fiscal years.

RISK-FREE RATE As a proxy for the risk-free rate, we rely on Bloomberg-supplied interest rate curves derived from interbank rates and instruments linked to interbank rates. We use 5-year rates to match the tenor of the CDS contracts used in the analysis. We retrieve historical daily rates for 12 major currencies, including the U.S. dollar, Canadian dollar, Euro, pound sterling, Swiss franc, Danish krone, Norwegian krone, Swedish krona, Singapore dollar, Japanese yen, Korean won, and Australian dollar. Firms are matched to their domestic currency where possible. For the remaining markets, we use the U.S. dollar rates.

41 The adjustment factors are taken from Markit (2012, p. 85). The procedure of unifying restructuring clauses using adjustment factors follows Chen et al. (2014) and Schläfer and Uhrig-Homburg (2014).

42 See also the related discussion in Dwyer et al. (2010).

2.B ADDITIONAL DESCRIPTIVE STATISTICS

This appendix supplements the descriptive statistics on our sample. Section 2.B.1 lists all firms in the sample. Section 2.B.2 provides descriptive statistics on the nonpublic firms.

2.B.1 *List of Sample Firms*

See Table 2.5.

2.B.2 *Statistics on Nonpublic Firms*

In our sample of 183 financial institutions, 51 firms are nonpublic for the majority of their sample period.[43] We define a firm as nonpublic if we cannot identify a publicly traded equity issue. This definition includes privately held firms, state-owned firms, and subsidiaries of publicly traded firms. With the exception of ING Groep's two principal subsidiaries, banking firm ING Bank and insurance company NN Group, subsidiaries of publicly traded firms are represented in our sample only if there is insufficient CDS spread data at the holding company level. Although there is sufficient data for ING Groep, we opt to model this firm at the subsidiary level for a more precise allocation of systemic risk to the banking and insurance sectors. Table 2.6 lists the individual nonpublic firms in the sample along with their liability sizes and sample periods.

Based on financial statements for 2009, the average nonpublic firm has total liabilities of USD 294 billion, less than those of the average public firm, which has USD 458 billion in liabilities. Although the nonpublic firms are on average notably smaller than the public firms, they have relatively similar sample periods. The average nonpublic firm is represented in the sample for 6.7 years, which is comparable to the average of 7.5 years for the public firms.

Figure 2.10 shows the median CDS spreads of the nonpublic and the public firms, along with the individual CDS spreads of selected nonpublic firms: Cooperative Rabobank and China Development Bank, the largest privately held and state-owned firms, and ING Bank and NN Group, ING Groep's two principal subsidiaries. Importantly, the nonpublic firms' median CDS spreads exhibit a trajectory similar to that of the public firms' median CDS spreads, which underlines their value as timely indicators of distress in financial markets. Moreover, comparing the CDS spreads of ING Bank and NN Group illustrates that CDS spreads do in fact capture the distinct credit risk dynamics at the subsidiary level of diversified financial holding companies.

43 We manually exclude two large nonpublic firms, Barclays Bank PLC and Standard Chartered Bank, from this statistic. Whereas both banks are technically a nonpublic subsidiary of a publicly traded firm, both firms reported almost identical total liabilities as their respective public parents did during the sample period.

TABLE 2.5: List of sample firms

Firm name	Region	Country	G-SIFI
Banks			
AMP Bank Ltd	Asia-Pacific	Australia	no
ANZ Group Ltd	Asia-Pacific	Australia	no
Commonwealth Bank of Australia	Asia-Pacific	Australia	no
Macquarie Bank Ltd	Asia-Pacific	Australia	no
National Australia Bank Ltd	Asia-Pacific	Australia	no
St George Bank Ltd	Asia-Pacific	Australia	no
Suncorp-Metway Ltd	Asia-Pacific	Australia	no
Westpac Banking Corp	Asia-Pacific	Australia	no
Bank of China Ltd	Asia-Pacific	China	yes
China Development Bank Corp	Asia-Pacific	China	no
Export-Import Bank of China	Asia-Pacific	China	no
Industrial & Commercial Bank of China Ltd	Asia-Pacific	China	yes
Bank of India	Asia-Pacific	India	no
Export-Import Bank of India	Asia-Pacific	India	no
ICICI Bank Ltd	Asia-Pacific	India	no
IDBI Bank Ltd	Asia-Pacific	India	no
State Bank of India	Asia-Pacific	India	no
Bank of Tokyo-Mitsubishi UFJ Ltd	Asia-Pacific	Japan	yes
Daiwa Securities Group Inc	Asia-Pacific	Japan	no
Development Bank of Japan Inc	Asia-Pacific	Japan	no
Mizuho Bank Ltd	Asia-Pacific	Japan	no
Nomura Holdings Inc	Asia-Pacific	Japan	no
Sumitomo Mitsui Banking Corp	Asia-Pacific	Japan	yes
BTA Bank JSC	Asia-Pacific	Kazakhstan	no
Halyk Bank JSC	Asia-Pacific	Kazakhstan	no
Kazkommertsbank JSC	Asia-Pacific	Kazakhstan	no
CIMB Bank Bhd	Asia-Pacific	Malaysia	no
Malayan Banking Bhd	Asia-Pacific	Malaysia	no
DBS Bank Ltd	Asia-Pacific	Singapore	no
OCBC Bank Corp Ltd	Asia-Pacific	Singapore	no
Export-Import Bank of Korea	Asia-Pacific	South Korea	no
Hana Bank	Asia-Pacific	South Korea	no
Industrial Bank of Korea	Asia-Pacific	South Korea	no
Kookmin Bank	Asia-Pacific	South Korea	no
Korea Development Bank	Asia-Pacific	South Korea	no
Korea Exchange Bank	Asia-Pacific	South Korea	no
Shinhan Bank	Asia-Pacific	South Korea	no
Woori Finance Holdings Co Ltd	Asia-Pacific	South Korea	no
CTBC Financial Holding Co	Asia-Pacific	Taiwan	no
TMB Bank PCL	Asia-Pacific	Thailand	no
BAWAG PSK AG	Europe	Austria	no
Erste Group AG	Europe	Austria	no
Raiffeisen Zentralbank Oesterreich AG	Europe	Austria	no
Fortis[a]	Europe	Belgium	no
KBC Groep NV	Europe	Belgium	no
Danske Bank AS	Europe	Denmark	no
Banque Federative du Credit Mutuel SA	Europe	France	no
BNP Paribas SA	Europe	France	yes
Credit Agricole SA	Europe	France	yes
Dexia Credit Local SA	Europe	France	yes
Natixis SA	Europe	France	no
Societe Generale SA	Europe	France	yes
Bayerische Landesbank	Europe	Germany	no
Commerzbank AG	Europe	Germany	yes
Deutsche Bank AG	Europe	Germany	yes
HSH Nordbank AG	Europe	Germany	no
IKB Deutsche Industriebank AG	Europe	Germany	no
Landesbank Baden-Wuerttemberg	Europe	Germany	no
Landesbank Hessen-Thueringen	Europe	Germany	no
Landwirtschaftliche Rentenbank	Europe	Germany	no
Norddeutsche Landesbank	Europe	Germany	no
WestLB AG	Europe	Germany	no
Alpha Bank AE	Europe	Greece	no
National Bank of Greece SA	Europe	Greece	no
Kaupthing Bank hf	Europe	Iceland	no
Landsbanki Islands	Europe	Iceland	no
Allied Irish Banks PLC	Europe	Ireland	no
Anglo Irish Bank Corp PLC	Europe	Ireland	no
Bank of Ireland	Europe	Ireland	no
Banca Monte dei Paschi di Siena SpA	Europe	Italy	no
Banca Popolare di Lodi SpA	Europe	Italy	no
Banca Popolare di Milano Scarl	Europe	Italy	no
Banco Popolare SC	Europe	Italy	no
Capitalia SpA	Europe	Italy	no
Intesa Sanpaolo SpA	Europe	Italy	no
Mediobanca SpA	Europe	Italy	no
SanPaolo IMI SpA	Europe	Italy	no
UniCredit SpA	Europe	Italy	yes
Unione di Banche Italiane SpA	Europe	Italy	no
ABN AMRO Bank NV	Europe	Netherlands	no
Cooperatieve Rabobank UA	Europe	Netherlands	no
F van Lanschot Bankiers NV	Europe	Netherlands	no
ING Bank NV	Europe	Netherlands	yes
SNS Bank NV	Europe	Netherlands	no
DNB Bank ASA	Europe	Norway	no
Banco Comercial Portugues SA	Europe	Portugal	no
Banco Espirito Santo SA	Europe	Portugal	no

Continued on next page

table 2.5 – *continued from previous page*

Firm name	Region	Country	G-SIFI
Caixa Geral de Depositos SA	Europe	Portugal	no
Banco Bilbao Vizcaya Argentaria SA	Europe	Spain	yes
Banco de Sabadell SA	Europe	Spain	no
Banco Pastor SA	Europe	Spain	no
Banco Popular Espanol SA	Europe	Spain	no
Banco Santander SA	Europe	Spain	yes
Bankinter SA	Europe	Spain	no
Caja de Ahorros del Mediterraneo	Europe	Spain	no
Caja de Ahorros y Monte de Piedad de Madrid	Europe	Spain	no
La Caixa	Europe	Spain	no
Nordea Bank AB	Europe	Sweden	yes
Skandinaviska Enskilda Banken AB	Europe	Sweden	no
Svenska Handelsbanken AB	Europe	Sweden	no
Swedbank AB	Europe	Sweden	no
Credit Suisse Group AG	Europe	Switzerland	yes
UBS AG	Europe	Switzerland	yes
Akbank TAS	Europe	Turkey	no
Turkiye Is Bankasi	Europe	Turkey	no
Barclays Bank PLC	Europe	United Kingdom	yes
HBOS PLC	Europe	United Kingdom	no
HSBC Holdings PLC	Europe	United Kingdom	yes
Lloyds Bank PLC	Europe	United Kingdom	yes
Northern Rock PLC	Europe	United Kingdom	no
Royal Bank of Scotland Group PLC	Europe	United Kingdom	yes
Standard Chartered Bank	Europe	United Kingdom	yes
Yorkshire Building Society	Europe	United Kingdom	no
Abu Dhabi Commercial Bank PJSC	Middle East	United Arab Emirates	no
National Bank of Abu Dhabi PJSC	Middle East	United Arab Emirates	no
Bank of America Corp	North America	United States	yes
Bear Stearns Cos Inc	North America	United States	no
Citigroup Inc	North America	United States	yes
Goldman Sachs Group Inc	North America	United States	yes
JPMorgan Chase & Co	North America	United States	yes
Lehman Brothers Holdings Inc	North America	United States	no
Merrill Lynch & Co Inc	North America	United States	no
Morgan Stanley	North America	United States	yes
SLM Corp	North America	United States	no
Wachovia Corp	North America	United States	no
Washington Mutual Inc	North America	United States	no
Wells Fargo & Co	North America	United States	yes
Gazprombank JSC	Russia	Russia	no
Rosselkhozbank OJSC	Russia	Russia	no
Sberbank of Russia	Russia	Russia	no
VTB Bank OJSC	Russia	Russia	no
Brazilian Development Bank	South America	Brazil	no
Corp Andina de Fomento	South America	Venezuela	no

Continued on next page

TABLE 2.5 – *continued from previous page*

Firm name	Region	Country	G-SIFI
Multi-line insurers			
AXA SA	Europe	France	yes
Allianz SE	Europe	Germany	yes
Assicurazioni Generali SpA	Europe	Italy	yes
Zurich Insurance Co Ltd	Europe	Switzerland	no
RSA Insurance Group PLC	Europe	United Kingdom	no
American International Group Inc	North America	United States	yes
Hartford Financial Services Group Inc	North America	United States	no
Liberty Mutual Group Inc	North America	United States	no
Life insurers			
Cathay Financial Holding Co Ltd	Asia-Pacific	Taiwan	no
Fubon Financial Holding Co Ltd	Asia-Pacific	Taiwan	no
Ageas[b]	Europe	Belgium	no
Aegon NV	Europe	Netherlands	yes
NN Group NV	Europe	Netherlands	no
Aviva PLC	Europe	United Kingdom	yes
Legal & General Group PLC	Europe	United Kingdom	no
Old Mutual PLC	Europe	United Kingdom	no
Prudential Inc	Europe	United Kingdom	yes
Assurant Inc	North America	United States	no
Genworth Holdings Inc	North America	United States	no
Lincoln National Corp	North America	United States	no
MetLife Inc	North America	United States	yes
Prudential Financial Inc	North America	United States	yes
Unum Group	North America	United States	no
P/C insurers			
Mitsui Sumitomo Insurance Co Ltd	Asia-Pacific	Japan	no
Sompo Japan Insurance Inc	Asia-Pacific	Japan	no
Tokio Marine & Nichido Fire Insurance Co Ltd	Asia-Pacific	Japan	no
XLIT Ltd	Europe	Ireland	no
ACE Ltd	Europe	Switzerland	no
Fairfax Financial Holdings Ltd	North America	Canada	no
Allstate Corp	North America	United States	no
American Financial Group Inc	North America	United States	no
Chubb Corp	North America	United States	no
Loews Corp	North America	United States	no
Safeco Corp	North America	United States	no
Travelers Cos Inc	North America	United States	no
Bond and mortgage insurers			
Ambac Financial Group Inc	North America	United States	no
Assured Guaranty Corp	North America	United States	no
Assured Guaranty Municipal Corp	North America	United States	no
Financial Guaranty Insurance Co	North America	United States	no
MBIA Inc	North America	United States	no
MGIC Investment Corp	North America	United States	no
PMI Group Inc	North America	United States	no
Radian Group Inc	North America	United States	no
Reinsurers			
QBE Insurance Group Ltd	Asia-Pacific	Australia	no
SCOR SE	Europe	France	no
Hannover Re SE	Europe	Germany	no
Munich Re AG	Europe	Germany	no
Swiss Reinsurance Co Ltd	Europe	Switzerland	no
Everest Re Group Ltd	North America	Bermuda	no
Berkshire Hathaway Inc	North America	United States	no

This table lists the banking and insurance firms covered in the sample. Within each sector, firms are sorted alphabetically first by *region*, then by *country*, and finally by *firm name*. *G-SIFI* indicates whether firms (i) have been included on one of the lists of G-SIBs published by the FSB from 2011 through 2015, (ii) have been included on one of the lists of G-SIIs published by the FSB from 2013 through 2015, or (iii) operate as a principal subsidiary of one of these firms.
[a] Included in the sample up to December 2008; included as insurance company Ageas from January 2009 following the sale of Fortis' banking operations.
[b] Included in the sample from January 2009; former banking firm Fortis.

TABLE 2.6: Descriptive statistics on nonpublic firms

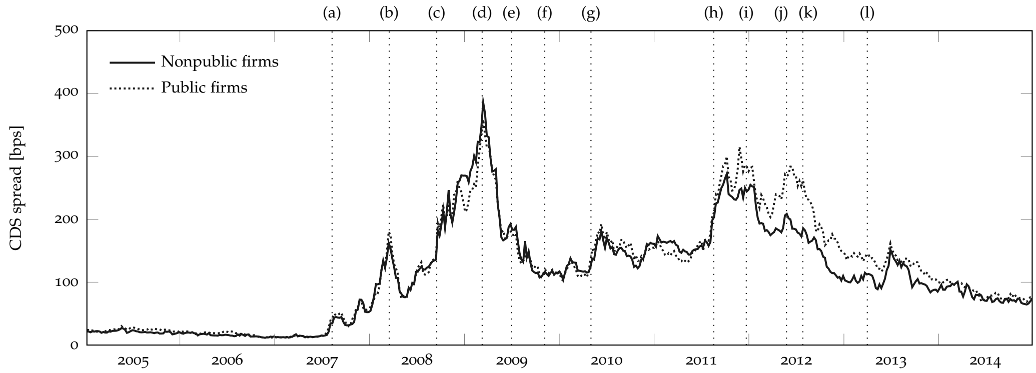
Firm *(publicly traded parent)*	Sector	Liabilities	Period
Panel A: Privately held and state-owned firms			
Banque Federative du Credit Mutuel SA	Banking	585	3.9
BAWAG PSK AG	Banking	56	6.6
Bayerische Landesbank	Banking	465	7.8
Brazilian Development Bank	Banking	218	3.4
Caixa Geral de Depositos SA	Banking	163	7.3
Caja de Ahorros y Monte de Piedad de Madrid	Banking	258	2.2
China Development Bank Corp	Banking	610	9.2
Cooperatieve Rabobank UA	Banking	816	10.0
Corp Andina de Fomento	Banking	11	3.2
Development Bank of Japan Inc	Banking	120	3.5
Export-Import Bank of China	Banking	115	8.1
Export-Import Bank of India	Banking	8	9.4
Export-Import Bank of Korea	Banking	31	8.9
Financial Guaranty Insurance Co	Insurance	5	3.1
Gazprombank JSC	Banking	51	5.2
HSH Nordbank AG	Banking	244	6.7
Korea Development Bank	Banking	105	10.0
La Caixa	Banking	352	5.8
Landesbank Baden-Wuerttemberg	Banking	575	5.3
Landesbank Hessen-Thueringen	Banking	236	5.4
Landwirtschaftliche Rentenbank	Banking	108	2.2
Liberty Mutual Group Inc	Insurance	95	9.0
Norddeutsche Landesbank	Banking	334	5.0
Raiffeisen Zentralbank Oesterreich AG	Banking	197	6.7
Rosselkhozbank OJSC	Banking	24	6.6
WestLB AG	Banking	342	7.5
Yorkshire Building Society	Banking	35	3.0
Panel B: Subsidiaries of publicly traded firms			
ABN AMRO Bank NV *(ABN AMRO Holding NV)*	Banking	646	2.8
AMP Bank Ltd *(AMP Ltd)*	Banking	10	4.7
Assured Guaranty Corp *(Assured Guaranty Ltd)*	Insurance	3	9.1
Assured Guaranty Municipal Corp *(Assured Guaranty Ltd)*	Insurance	9	8.9
CIMB Bank Bhd *(CIMB Group Holdings Bhd)*	Banking	52	2.0
DBS Bank Ltd *(DBS Group Holdings Ltd)*	Banking	138	5.2
Dexia Credit Local SA *(Dexia SA)*	Banking	514	6.8
DNB Bank ASA *(DNB ASA)*	Banking	242	4.7
Hana Bank *(Hana Financial Group Inc)*	Banking	111	9.9
ING Bank NV *(ING Groep NV)*	Banking	1,219	10.0
NN Group NV *(ING Groep NV)*[a]	Insurance	393	8.2
Kookmin Bank *(KB Financial Group Inc)*	Banking	207	10.0
Lloyds Bank PLC *(Lloyds Banking Group PLC)*	Banking	903	10.0
Macquarie Bank Ltd *(Macquarie Group Ltd)*[b]	Banking	86	10.0
Bank of Tokyo-Mitsubishi UFJ Ltd *(Mitsubishi UFJ Financial Group Inc)*	Banking	1,550	10.0
Mizuho Bank Ltd *(Mizuho Financial Group Inc)*	Banking	856	7.9
Mitsui Sumitomo Insurance Co Ltd *(MS&AD Insurance Group Holdings Inc)*[c]	Insurance	54	9.4
Shinhan Bank *(Shinhan Financial Group Co Ltd)*	Banking	169	10.0
SNS Bank NV *(SNS Reaal NV)*	Banking	112	6.7
Sumitomo Mitsui Banking Corp *(Sumitomo Mitsui Financial Group Inc)*	Banking	1,121	5.8
Suncorp-Metway Ltd *(Suncorp Group Ltd)*	Banking	68	3.9
Tokio Marine & Nichido Fire Insurance Co Ltd *(Tokio Marine Holdings Inc)*	Insurance	82	6.7
F van Lanschot Bankiers NV *(Van Lanschot NV)*	Banking	27	2.2
Zurich Insurance Co Ltd *(Zurich Insurance Group AG)*	Insurance	340	10.0

This table lists firms that are nonpublic for the majority of their sample period. We define a firm as nonpublic if we cannot identify a publicly traded equity issue. The upper panel shows privately held and state-owned firms, including subsidiaries of such firms. The lower panel shows subsidiaries of publicly traded firms. *Firm* names the firm and, where applicable, its publicly traded parent; *sector* lists the sector to which the firm belongs; *liabilities* refers to the total liabilities for 2009 in USD billion; and *period* is the sample period in years. Unless noted otherwise, firms are nonpublic for their entire sample period.

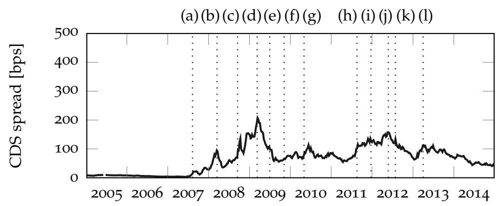
[a] NN Group NV completed an initial public offering in July 2014.

[b] Macquarie Bank Ltd stopped trading in November 2007.

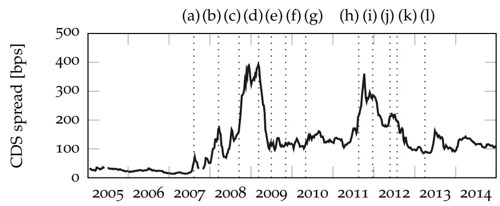
[c] Mitsui Sumitomo Insurance Co Ltd stopped trading in March 2008.



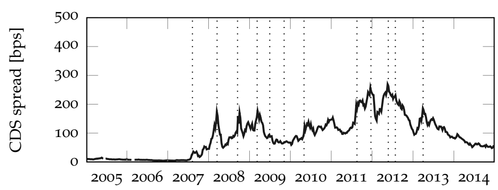
(A) Nonpublic and public firms



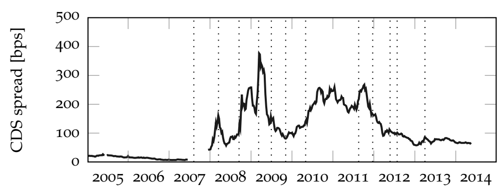
(B) Cooperative Rabobank UA



(C) China Development Bank Corp



(D) ING Bank NV



(E) NN Group NV

FIGURE 2.10: CDS spreads of nonpublic and public firms
This figure shows nonpublic and public firms' CDS spreads. The upper panel shows median spreads for all nonpublic and public firms in the sample. The lower panels show spreads for the largest privately held and state-owned firms in the sample, Cooperative Rabobank and China Development Bank, and for ING Groep's two principal subsidiaries, ING Bank and NN Group. All spreads are for 5-year senior unsecured CDS contracts and in weekly frequency. The vertical lines represent the same events as those in Figure 2.1.

3

CONTAGION IN FINANCIAL MARKETS: HOW INTERCONNECTED ARE INSURERS?

ABSTRACT

This study investigates the interconnectedness of insurers in systemic risk networks with banks and sovereigns. Systemic risk in the banking and insurance industries is measured using market-based indicators for a global sample of 183 major financial institutions. Granger causality tests reveal a multitude of systemic risk spillovers during the financial crisis and the European sovereign debt crisis. As an important finding, I document a feedback loop between the banking and life insurance sectors, which persists when controlling for sovereign risk. In contrast, I do not find evidence of systemic risk spillovers within the insurance sector when common exposures are taken into account. These findings contribute to a better understanding of contagion in financial markets and hence to an effective regulation of systemic risk.

KEYWORDS: Systemic risk, sovereign risk, interconnectedness, financial contagion, spillover effect

JEL CLASSIFICATION: G01, G17, G21, G22, G28

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3.1 introduction

Over the last few decades, financial integration has increased significantly (see, e.g., Kose et al., 2009), introducing close interconnections among financial institutions and markets around the world. Linkages in the financial system tend to amplify in times of crisis. Shocks that initially affect only part of the financial system may then spread contagiously to other institutions and markets, eventually impairing the financial system as a whole. These mechanisms were at the heart of the financial crisis of 2007–2009, which started in a limited segment of the U.S. subprime mortgage market and unfolded into a global crisis leading to the demise or state-aided rescue of major banks and insurers (see, e.g., Longstaff, 2010; Gorton and Metrick, 2012; Covitz et al., 2013).

A precise understanding of how distress spreads among financial institutions enables regulators to design, implement, and enforce effective policies that act as circuit breakers in times of crisis, with the goal of limiting the high economic costs of cascading failures. In the aftermath of the financial crisis, much of the regulatory effort to enhance financial stability has focused on identifying financial institutions whose failure may cause significant disruption for the wider economy. These endeavors have resulted in the designation of global systemically important banks (G-SIBs) and global systemically important insurers (G-SIIs), which are subject to tighter regulation. Indicators relating to the interconnectedness of banks and insurers with the broader financial system are an integral part of the underlying assessment approaches.[1]

Despite the pivotal role of financial institutions' interconnectedness in the regulation of systemic risk in financial markets, surprisingly few studies have analyzed the role of insurers, and the existing empirical evidence is at least partly inconclusive. Billio et al. (2012), for example, find that insurers are an integral part of a highly interconnected financial system and may indeed propagate shocks to banks and other financial institutions. Chen et al. (2014), on the contrary, point out that the insurance sector is vulnerable to distress in the banking sector, but that distress in the insurance sector is unlikely to impair the broader financial system.

In a recent companion paper, Kaserer and Klein (2018) show that insurance as an industry poses a much lower systemic risk than banking, but that individual insurers may still be systemically important financial institutions. Importantly, the companion paper takes a contemporaneous perspective on systemic risk and does not take a stand on how systemic shocks may spread through the financial system. The present paper sets out to complement this research by shedding further light on the interconnectedness of insurers in systemic risk networks with banks and sovereigns. In particular, I address the following questions. First,

1 Global systemically important financial institutions (G-SIFIs) are defined as "institutions of such size, market importance, and global interconnectedness that their distress or failure would cause significant dislocation in the global financial system and adverse economic consequences across a range of countries" (FSB, 2010, p. 2). The initial assessment methodology for G-SIBs is described in BCBS (2011), and the initial assessment methodology for G-SIIs is described in IAIS (2013).

which insurance segments are interconnected most closely with the banking sector? Second, how interconnected are the individual insurance segments with one another? Third, what is the role of sovereign risk in contagion between the banking and insurance sectors?

The empirical analysis follows the approach of Chen et al. (2014). In the first part of the analysis, I employ the distress insurance premium (DIP) framework of Huang et al. (2009) to derive market-based indicators of systemic risk in the banking and insurance industries. In the second part of the analysis, I exploit the lead–lag relationships among these indicators to test for contagion by means of Granger causality tests. The sample is the set of large financial institutions from around the world analyzed by Kaserer and Klein (2018).

Overall, the empirical analysis confirms that systemic risk is higher in the banking sector than it is in the insurance sector, but it also indicates considerable distress potential in insurance segments that underwrite risks correlated with financial market variables. During the financial crisis and the European sovereign debt crisis, contagion appears to have spread in the financial system via several linkages. As an important result, in contrast to Chen et al. (2014), I document a bidirectional dependency between the banking and insurance sectors. I provide novel evidence that this feedback loop can be attributed to the life insurance segment. Robustness tests confirm that the feedback loop is not mediated by sovereign risk. By contrast, interconnections within the insurance sector appear to be weak once common exposures of different lines of business have been taken into account. In particular, I do not find evidence of feedback loops within the insurance sector.

In summary, I contribute to the literature on systemic risk and contagion along several important dimensions. First, I provide a comprehensive analysis of systemic risk in the global and regional banking and insurance sectors and of risk transmission among these sectors. Moreover, as I also analyze the impact of sovereign risk during the financial crisis and the European sovereign debt crisis, my work further informs the literature on sovereign contagion. My results have important implications for financial institutions and regulatory authorities. Financial institutions' risk managers need to be aware of potential sources of distress beyond the counterparty risk of direct exposures. Regulators require transparency concerning the full set of linkages in the financial system in order to be able to devise effective measures to enhance financial stability. I therefore inform both internal risk management procedures in financial institutions and macroprudential measures to mitigate systemic risk.

The remainder of this paper proceeds as follows. Section 3.2 reviews the prior literature and discusses the hypotheses tested in the empirical analysis. Section 3.3 presents the modeling framework, and Section 3.4 describes the sample. Section 3.5 analyzes indicators of systemic risk in the banking and insurance industries, and Section 3.6 investigates the industries' interconnectedness. Section 3.7 offers concluding remarks.

3.2 RELATED LITERATURE AND HYPOTHESES

Systemic risk and contagion are closely related concepts and may indeed entail and reinforce each other. Systemic risk may be defined as the risk of financial crises likely to severely impair the real economy (Group of Ten, 2001; FSB, 2010). Contagion is commonly referred to as a state of increased interconnectedness after a shock to a financial institution or market (Forbes and Rigobon, 2002; Longstaff, 2010). In this sense, it describes a mechanism by which distress initially limited to a small part of the financial system may turn systemic.

Contagion may spread through direct and indirect channels. Direct channels of contagion include financial institutions' mutual exposures via contractual obligations, such as those in the interbank and reinsurance markets (Allen and Gale, 2000; Park and Xie, 2014). Indirect channels of contagion are mediated by financial markets through, for example, investors acting on information from other parts of the financial system, downward spirals of liquidity shortages and fire sales, or the reassessment of risk premiums (Longstaff, 2010). From an empirical perspective, the interconnectedness of financial institutions may be analyzed based on either accounting data or market data. Measures based on accounting data will capture only direct channels of contagion. To the extent that financial markets are informationally efficient, measures based on market data should reflect both direct and indirect channels of contagion.

In this section, I first review the literature on contagion between the banking and insurance industries. I then outline the specific hypotheses on the industries' interconnectedness tested in the main part of the paper.

3.2.1 *Related Literature*

The banking sector is widely recognized as a source of systemic risk. The insurance sector, however, has traditionally not been considered a threat to financial stability. Arguing against systemic risk in insurance, Kessler (2014) suggests that insurers' traditional business model enhances financial stability rather than instigates financial turmoil. Acharya et al. (2010) and Cummins and Weiss (2014), on the contrary, challenge the view that the insurance industry is not systemically risky. These authors agree that traditional insurance focused on underwriting idiosyncratic risks is unlikely to pose a systemic risk. However, they note that insurers are now also engaged in nontraditional activities such as providing financial guarantees, writing derivatives, and investing in structured products. Such activities arguably increase both insurers' interconnectedness in financial markets and their contribution to systemic risk.

Few prior studies have analyzed contagion between the banking and insurance industries empirically, and they have come to different conclusions regarding insurers' interconnectedness. Billio et al. (2012) investigate the network structure of the financial system by testing for pairwise Granger causality among financial institutions' returns. Insurers appear to be highly interrelated with banks and other financial institutions and to be potential propagators of shocks. Hautsch et al. (2015) analyze the interconnectedness of U.S. financial institutions in terms of tail interdependence among their return distributions. Although insurers do not appear to be as interconnected as banks and some insurers act primarily as shock absorbers, a subset of insurers also appears to propagate shocks to the broader financial system.

In partial contrast to these firm-level studies, Chen et al. (2014) find that the insurance sector is a sink rather than a source of systemic risk. These authors measure systemic risk in the banking and insurance sectors using the DIP indicator of Huang et al. (2009), which they infer from debt and equity market data on U.S.-listed financial institutions. Interconnectedness is again measured using bivariate Granger causality tests, this time at the sector level. Although there is some evidence of a feedback loop between the banking and insurance sectors, the link from insurers to banks loses its significance once conditional heteroscedasticity has been accounted for. Stress test scenarios confirm that banks' impact on insurers is more powerful and lasts longer than vice versa. Using a similar approach, Bégin et al. (2019) also document a unilateral dependence of the insurance sector on the banking sector.

Banks' balance sheets are closely linked via bilateral exposures in the interbank market. Equivalently, the reinsurance market introduces links between insurers' balance sheets. Primary insurers that cede underwriting risks to reinsurers expose themselves to credit risk, as the assuming reinsurer may default on the reinsurance contract. Both life and nonlife insurers may therefore be prone to reinsurance failures (Cummins and Weiss, 2014). Importantly, however, the topology of interbank and reinsurance networks differs: in contrast to the interbank market, the reinsurance market has a mostly hierarchical network structure. Primary insurers are exposed to reinsurers, but there are few contractual interconnections among primary insurers. This hierarchical structure of the reinsurance market is expected to attenuate contagion and systemic risk in the insurance sector (IAIS, 2011; Kessler, 2014).

Indeed, empirical studies have found only limited evidence that the default of reinsurers may trigger insurance crises. Van Lelyveld et al. (2011) consider the impact of reinsurance failures on life and nonlife insurers using confidential data on reinsurance exposures. Even under extreme scenarios for the loss of reinsurance cover, only a small number of primary insurers fail. Park and Xie (2014) provide evidence that market participants recognize the contractual relationships between reinsurers and property–casualty (P/C) insurers, as rating downgrades of reinsurers adversely affect counterparty P/C insurers' ratings and stock prices. However, scenario analyses again confirm that the failure even of a major reinsurer should have only limited knock-on effects. Chen et al. (2018) analyze the reinsurance network of the U.S. P/C insurance sector and arrive at similar conclusions.

An important additional factor in the spillover of distress in the financial system is sovereign risk. As sovereigns' credit risk increases, the value of sovereign bonds held by financial institutions deteriorates while financial institutions' funding costs increase. In turn, as financial institutions come under stress, they may pose an increasing contingent liability to sovereigns and thus increase sovereigns' credit risk (IMF, 2010).

The feedback mechanisms between financial institutions and sovereigns have been documented in a number of empirical studies. Analyzing the credit risk of European sovereigns and banks, Alter and Schüler (2012) show that, in the period before government interventions took place during the financial crisis, contagion dispersed mostly from banks to sovereigns. After government interventions were implemented, the relationship reversed, and sovereign credit risk strongly determined banks' credit risk. Acharya et al. (2014) obtain similar findings regarding the relationship between sovereigns' and banks' credit risk in the post-bailout era. Further empirical evidence of the nexus between the financial system and sovereigns is provided by Lahmann (2012), who documents a multitude of interconnections between sovereigns and regional banking sectors, and Billio et al. (2014), who find evidence of credit risk spillovers between sovereigns and individual banks and insurers.

Relative to this literature, my study provides novel empirical evidence of systemic risk spillovers during the financial crisis and the European sovereign debt crisis. Like Chen et al. (2014), I provide an empirical assessment of contagion in the banking and insurance industries by exploiting lead–lag relationships in DIP indicators. The analysis in this paper, however, goes beyond theirs in several important respects, which collectively also distinguish my work from other contributions.

First, I examine the role of individual insurance segments. Chen et al. (2014) analyze the interconnectedness between banks and insurers at the industry level. I additionally examine the interconnectedness between the banking industry and individual insurance segments as well as contagion among individual insurance segments. As observed by Chen et al. (2014), their sample is dominated by P/C insurers. Analyzing the interconnectedness of individual insurance segments may thus uncover important additional risk spillovers, including feedback mechanisms between the banking and insurance sectors.

Second, I examine interregional linkages. Chen et al. (2014) analyze contagion between U.S.-listed banks and insurers in a sample spanning the pre-crisis period and the early stages of the financial crisis. In my empirical analysis, I examine contagion between North American and European banks and insurers over the entirety of the financial crisis and the ensuing European sovereign debt crisis. Analyzing interregional contagion sheds further light on how regional crises may spread across the globe and on what role insurers may play in transmitting regional shocks to the global financial system.

Moreover, I account for common exposures. Chen et al. (2014) base their analysis on unconditional Granger causality tests without additional control variables, leaving open the possibility that contagion between the banking and insurance industries is mediated by sovereign risk. Distinguishing between genuine and spurious contagion is important to formulate appropriate policy responses. To rule out spurious contagion, I therefore run additional conditional Granger causality tests that control for common exposures.

3.2.2 *Interconnectedness Hypotheses*

The modeling framework implemented in the next section enables me to address important research questions relating to systemic risk and contagion in financial markets. In the first part of the analysis, I investigate the contemporaneous level of systemic risk in the global, North American, and European banking and insurance sectors using market-based distress indicators. In the second part of the analysis, I exploit the lead–lag relationships among these indicators to trace channels of contagion. In the following, I outline the specific interconnectedness hypotheses tested in the main part of the paper. These refer to contagion (i) between the banking and insurance industries, (ii) within the insurance industry, and (iii) between financial sectors and sovereigns.

Although previous empirical studies have come to different conclusions concerning the interconnectedness of the banking and insurance industries, overall, banks appear to be more contagious for insurers than vice versa. As for contagion between the banking and insurance industries, I therefore expect to find:

HYPOTHESIS I.A:
Systemic risk spillovers from the banking industry to the insurance industry are more significant than in the other direction.

This hypothesis should hold for the global financial system as well as for the North American and European financial systems. While the insurance sector is expected to be mostly a sink of systemic risk rather than a source, some insurance segments may be more contagious than others and may propagate shocks to the banking sector. I expect that contagion is most likely to emanate from lines of business that compete with banks to some extent or invest heavily in capital markets, such as life insurance:

HYPOTHESIS I.B:
Feedback loops between banks and insurers involve insurance segments that offer banking-like products or are closely interlinked with capital market movements.

Interconnections among primary insurers and reinsurers via contractual relationships in the reinsurance market have been argued to be mostly hierarchical. Moreover, as different types of primary insurers operate in distinct markets and underwrite different types of risks, the potential for indirect contagion between primary insurance segments is expected to be limited. As for contagion within the insurance industry, I therefore test:

HYPOTHESIS II:
The network structure of the insurance industry is mostly hierarchical. There are vertical interconnections from the reinsurance sector to primary insurance sectors but limited horizontal interconnections among primary insurance sectors.

As for interregional contagion, I expect the lead–lag relationships between the North American and European banking sectors to reflect the general dynamics of the financial crisis and the European sovereign debt crisis. In line with the hypothesized generally lower interconnectedness of the insurance sector, however, I expect at most weak interregional contagion among insurers:

HYPOTHESIS III.A:
There is interregional contagion in banking, with North American banks leading European banks during the financial crisis and vice versa during the European sovereign debt crisis. Interregional contagion in insurance is weak in comparison.

The existing literature on sovereign contagion highlights a two-way interaction between banks' distress and sovereign risk. As illustrated by the state-aided rescue of American International Group (AIG), however, insurers may also trigger government interventions in a state of distress and thus pose a contingent liability to sovereigns. Moreover, insurers often hold sizable inventories of sovereign bonds. I therefore expect a bidirectional dependency between banks and sovereigns as well as between insurers and sovereigns:

HYPOTHESIS III.B:
There is a feedback loop between the financial system and sovereigns that involves both the banking sector and the insurance sector.

3.3 MODELING FRAMEWORK

In this section, I introduce the modeling framework. I first describe the empirical systemic risk measure. I then discuss Granger causality tests as a means of analyzing systemic risk spillovers.

3.3.1 *Distress Insurance Premium*

I define systemic crises in the banking and insurance industries as a situation where a substantial portion of the industries' liabilities is in default. I measure systemic risk using the DIP indicator of Huang et al. (2009). This indicator corresponds to the premium of a hypothetical insurance policy that protects financial institutions' creditors against distressed losses in a systemic crisis.[2]

DIP indicators have been widely employed to assess the systemic risk of banks (Huang et al., 2009, 2012a,b; Lahmann and Kaserer, 2011; Black et al., 2016) and

2 Beyond DIP, a broad array of alternative risk metrics has been proposed (see, e.g., Adrian and Brunnermeier, 2016; Acharya et al., 2017; Brownlees and Engle, 2017). For a comprehensive review of systemic risk measures, see Bisias et al. (2012).

have recently been used to analyze contagion between banks and insurers (Chen et al., 2014). In this section, I describe my implementation.[3]

3.3.1.1 *Implementing the Systemic Risk Measure*

For a formal representation of the DIP indicator, consider a portfolio of liabilities of firms $i \in \{1, \ldots, N\}$. Let $L_{i,t}$ denote the marginal loss of firm i at time t, and let L_t denote the aggregate loss across all firms. Following Huang et al. (2009), the portfolio's level of systemic risk is measured as the expected present value of portfolio losses in excess of a systemic loss threshold, SLT:

$$\mathrm{DIP}_t\left(h\right) = E^{Q}\left(L_{t+h} \cdot \mathcal{I}\left(L_{t+h} > SLT\right)\right) \cdot e^{-r_t h}. \tag{3.1}$$

Q denotes the risk-neutral measure, r_t is the risk-free rate, and h is the risk horizon. I define $\mathcal{I}\left(x\right) = 1$ if condition x is true and 0 otherwise.

As in the Merton (1974) model, I assume that individual firms default if their asset values fall short of a minimum solvency requirement. In the case of default, creditors recover a fraction of their claims as determined by the firms' recovery rates, and the unrecoverable liabilities contribute to the portfolio's aggregate loss. I introduce dependence among the default of individual firms by modeling their standardized asset returns over the period between time t and $t+h$ by the usual multi-factor model:

$$R_{i,t:t+h} = F_i\, Y_{t:t+h} + \sqrt{1 - F_i F_i^{\top}}\, Z_{i,t:t+h}, \tag{3.2}$$

where $Y_{t:t+h} = \left[Y_{1,t:t+h}, \ldots, Y_{M,t:t+h}\right]^{\top}$ are M systematic risk factors common to all firms, $Z_{i,t:t+h}$ is an idiosyncratic risk factor specific to firm i, and $F_i = [F_{i,1}, \ldots, F_{i,M}]$, $F_i F_i^{\top} \leqslant 1$, are the common factor loadings. All risk factors are assumed to be standard normally distributed and mutually independent.

I implement the DIP indicator using Monte Carlo methods. For each time t, I simulate 500,000 default scenarios of failing and surviving firms. Naturally, systemic events are rarely observed. To enhance the efficiency of the estimators in the rare-event simulation of systemic losses, I employ the mean-shifting importance sampling procedure of Glasserman and Li (2005).

3.3.1.2 *Estimating the Credit Risk Parameters*

I base my analysis on probabilities of default and asset return correlations estimated from credit default swap (CDS) spreads. CDSs offer protection against credit events, that is, the risk that a firm or sovereign will default on its debt. CDS spreads have been found to provide clearer and more timely signals of credit risk than other debt market indicators (see, e.g., Hull et al., 2004; Longstaff et al., 2005; Zhu, 2006; Norden and Wagner, 2008). I expect this informational advantage to benefit the systemic risk measure.

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3 The exposition in this section closely follows the companion paper by Kaserer and Klein (2018).

PROBABILITIES OF DEFAULT I estimate *risk-neutral* probabilities of default from CDS spreads using the reduced-form valuation framework described in the literature (see, e.g., Hull and White, 2000; Tarashev and Zhu, 2008). Under no-arbitrage, the expected present value of the protection buyer's spread payments (the left-hand side of Equation (3.3)) initially equals the expected present value of the protection seller's default loss payment (the right-hand side of the equation):

$$\int_t^{t+T} s_{i,t} e^{-r_\tau(\tau-t)} \bar{q}_{i,\tau} d\tau = \int_t^{t+T} \left(1 - RR_{i,t}^{CDS}\right) e^{-r_\tau(\tau-t)} q_{i,\tau} d\tau. \tag{3.3}$$

$RR_{i,t}^{CDS} \in [0,1]$ is the time-t expectation of the recovery rate on the debt referenced in the CDS, $s_{i,t}$ is the annual spread, $q_{i,\tau}$ is the risk-neutral default intensity, $\bar{q}_{i,\tau} = 1 - \int_t^\tau q_{i,\nu} d\nu$ is the associated risk-neutral probability of survival up to time τ, and T is the tenor of the contract. As in Tarashev and Zhu (2008, p. 8), I solve for the 1-year risk-neutral probability of default under the common simplifying assumptions that the term structures of the risk-free rate and the default intensity are flat, $r_\tau = r_t$ and $q_{i,\tau} = q_{i,t}$ for all $\tau \in [t, t+T]$:

$$q_{i,t} = \frac{a s_{i,t}}{a(1 - RR_{i,t}^{CDS}) + b s_{i,t}}, \tag{3.4}$$

where $a = \int_t^{t+T} e^{-r_t(\tau-t)} d\tau$ and $b = \int_t^{t+T} (\tau - t) e^{-r_t(\tau-t)} d\tau$.

ASSET RETURN CORRELATIONS Following Tarashev and Zhu (2008, p. 8), I infer *physical* asset return correlations from the risk-neutral probabilities of default estimated in Equation (3.4):

$$\begin{aligned} \rho_{ij} &= \text{corr}\left(R_{i,t:t+h}, R_{j,t:t+h}\right) \\ &\approx \text{corr}\left(\Delta\Phi^{-1}\left(q_{i,t}\right), \Delta\Phi^{-1}\left(q_{j,t}\right)\right). \end{aligned} \tag{3.5}$$

Δ is the first difference in discrete time, and Φ denotes the cumulative standard normal distribution function. The second line serves as an approximation due to the assumption of a flat term structure of default intensities used in Equation (3.4). Based on Equation (3.5), I first estimate nonparametric pairwise correlations. These are then fitted to the factor model of Equation (3.2) using the principal factors method of Andersen et al. (2003).

3.3.2 *Granger Causality Analysis*

In my empirical analysis, I will investigate whether distress in one financial sector can have contagious effects on other parts of the financial system. Importantly, financial contagion refers to a causal dependence between financial market variables rather than only to their comovement.

Granger causality is a statistical approach to causality that builds on predictability in time series data. Following Granger (1969), a time series Granger-causes another time series if its history helps to predict the future of the other time series above and beyond *any* other relevant information. In practice, the information set is usually restricted to the histories of the time series of interest. Testing for Granger causality then amounts to testing parameter restrictions in a model for the time series' conditional mean.[4]

The linear dependencies between two time series can be modeled in the following way. Let Y_t, Z_t be two time series. The k-lag vector autoregressive (VAR(k)) model for these time series is:

$$\begin{aligned} Y_t &= a_0 + \sum_{i=1}^{k} a_i Y_{t-i} + \sum_{i=1}^{k} b_i Z_{t-i} + \epsilon_t, \\ Z_t &= c_0 + \sum_{i=1}^{k} c_i Z_{t-i} + \sum_{i=1}^{k} d_i Y_{t-i} + \eta_t, \end{aligned} \tag{3.6}$$

where a_i, b_i, c_i, d_i are the coefficients of the model, and ϵ_t, η_t are two uncorrelated white noise processes. Then, Z_t Granger-causes Y_t if and only if $b_i \neq 0$ for some $i = 1, \ldots, k$. Similarly, Y_t Granger-causes Z_t if and only if $d_i \neq 0$ for some $i = 1, \ldots, k$. If both time series Granger-cause each other, a feedback loop exists. If Y_t, Z_t are stationary, Wald tests of the corresponding null hypotheses $H_0 : b_i = 0$ for all $i = 1, \ldots, k$ and $H_0 : d_i = 0$ for all $i = 1, \ldots, k$ have the usual chi-square limiting distribution.

INTEGRATED AND COINTEGRATED TIME SERIES Testing for Granger causality is straightforward if the time series are stationary. However, if the variables under research are integrated or cointegrated, standard asymptotic theory does not apply to their levels representation in the general case. The Wald test statistic will then generally have a nonstandard limiting distribution that may involve nuisance parameters (Toda and Phillips, 1993).

If the integration and cointegration properties of the time series were known, statistical inference using standard asymptotic theory could be applied based on a suitable model representation. If the time series were known to be integrated of order one but not cointegrated, the model could be estimated in the first differences of the variables; similarly, if the variables were known to be cointegrated, an error correction model could be estimated.[5]

In empirical work, the integration and cointegration properties of the time series are rarely known to the researcher in advance. These properties therefore have to be determined in a pretesting procedure, and the outcome of the respective tests is naturally not certain. Consequently, conditioning the Granger causality tests on the outcome of preliminary tests may introduce a pretest bias

4 I will consider tests for linear Granger causality in the mean. Hiemstra and Jones (1994) and Diks and Panchenko (2006) propose complementary tests for nonlinear Granger causality.

5 For Wald tests of Granger causality, standard asymptotic theory always applies to the differenced model but may still be inapplicable to the error correction model. Standard asymptotics will apply to the error correction model if an additional rank condition holds (Toda and Phillips, 1993, Theorem 3). This condition is always fulfilled in the bivariate case (Lütkepohl and Reimers, 1992).

(Toda and Yamamoto, 1995; Dolado and Lütkepohl, 1996), possibly resulting in a severe size distortion (Clarke and Mirza, 2006).

I therefore follow the surplus-lag approach proposed by Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996). The surplus-lag approach is appealing in that it opens up the analysis to standard asymptotic theory while modeling the time series in the levels of the variables, irrespective of whether they are stationary, integrated, or cointegrated. It proceeds as follows. The lag order of the conditional mean model may be chosen using one of the usual model selection criteria. Let $\hat{k}$ be the lag order, and let d be the maximum order of integration. Then $\hat{k}+d$ lags will be included in the conditional mean model. When testing for Granger causality, only the first $\hat{k}$ coefficients of the causal variable are restricted under the null hypothesis of no causality. The corresponding Wald test statistic can then be shown to have the standard limiting distribution.

The surplus-lag approach depends much less on pretesting, as only the maximum order of integration d needs to be determined.[6] Simulation studies have shown that the surplus-lag approach is preferable to pretesting procedures in terms of test size and that it often results in only little loss of power (Clarke and Mirza, 2006). To limit the number of additional lags and hence a potential reduction in power, I implement this approach by treating the causal variable as the unmodeled component in a VAR with exogenous variables (VARX; see Bauer and Maynard, 2012). The VARX(k,k + d) model for Y_t has the form:

$$Y_t = a_0 + \sum_{i=1}^{k} a_i Y_{t-i} + \sum_{i=1}^{k+d} b_i Z_{t-i} + \epsilon_t. \tag{3.7}$$

In addition to accommodating integration and cointegration, Granger causality tests in this framework are robust to long-memory and unmodeled structural breaks of the causal variable (Bauer and Maynard, 2012).

Conditional heteroscedasticity Granger causality tests may yield spurious results in the presence of conditional heteroscedasticity (Vilasuso, 2001). To control for conditional heteroscedasticity in the market-based systemic risk measures, I augment the conditional mean model by a generalized autoregressive conditional heteroscedasticity (GARCH) model for the conditional variance. The combined VARX–GARCH model for Y_t can be summarized as follows:

$$Y_t = a_0 + \sum_{i=1}^{k} a_i Y_{t-i} + \sum_{i=1}^{k+d} b_i Z_{t-i} + \sigma_{Y,t} u_t, \qquad u_t \sim WN(0,1), \tag{3.8}$$

$$\sigma_{Y,t}^2 = \alpha_0 + \sum_{i=1}^{r} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{s} \beta_i \sigma_{Y,t-i}^2, \qquad \epsilon_t = \sigma_{Y,t} u_t, \tag{3.9}$$

where r, s are the lag orders and α_i, β_i are the coefficients of the GARCH(r,s) model, and where u_t is a white noise process.

6 In practice, d can reasonably be assumed to be at most 2 (Toda and Yamamoto, 1995).

IDENTIFICATION, ESTIMATION, AND DIAGNOSTIC CHECKING I apply the VARX–GARCH model introduced above to test for Granger causality among the systemic risk measures implemented in the previous section. All variables are transformed to natural logarithms before analysis. I use the Bayesian information criterion (BIC) as the model selection criterion for determining the number $\hat{k}$ of lags to be included in the conditional mean model,[7] and assume a GARCH(1,1) model for the conditional variance. As a means of diagnostic checking, I examine the model for residual autocorrelation and residual conditional heteroscedasticity by inspecting the autocorrelation functions of the standardized residuals and the squared standardized residuals, respectively. If necessary, I increment the lag orders of the conditional mean model and the conditional variance model to achieve whiteness of the residuals.

To account for the possibility of integration and cointegration, I include an additional lag of the causal variable in the conditional mean model, which remains untested in the Granger causality tests.[8] I estimate the model using a quasi-maximum-likelihood procedure, and report p-values based on robust standard errors to account for potential nonnormality of the residuals.

3.4 EMPIRICAL DATA

The sample analyzed in this study is a panel of banks and insurers from around the world that has also been analyzed in the companion paper by Kaserer and Klein (2018). I here briefly introduce the sample. For a detailed description of the sample and data sources, see Kaserer and Klein (2018).

The analysis spans the period from January 2005 through December 2014. Firms are selected into the sample based on data availability criteria so as to ensure an individual sample period of at least 2 years. CDS spreads are available from Thomson Reuters Datastream, and data on firms' liabilities are collected from Bloomberg. I aggregate daily CDS spreads for 5-year senior unsecured contracts to weekly frequency and compute weekly portfolio weights from annual total liabilities using linear interpolation within firms' fiscal years. Finally, as a proxy for the risk-free rate, I use Bloomberg-supplied interest rate curves based on interbank rates and instruments linked to interbank rates. I use the 5-year rate to match the tenor of the CDS contracts used in the analysis.

3.4.1 *Data Set*

In the sample, there are 133 banks and 50 insurers. There are 38 financial firms from North America, 91 from Europe, and 54 from other regions. The insurance sample is split into five lines of business that represent insurers' principal business activity: *multi-line insurance* (8 firms, e.g., AIG), *life insurance* (15 firms,

7 I search 20 lags in the VAR model of Equation (3.6).
8 Augmented Dickey–Fuller (ADF) tests confirm that the integration order of the variables used in my analysis is at most one. I report the test results in Appendix 3.B.1.

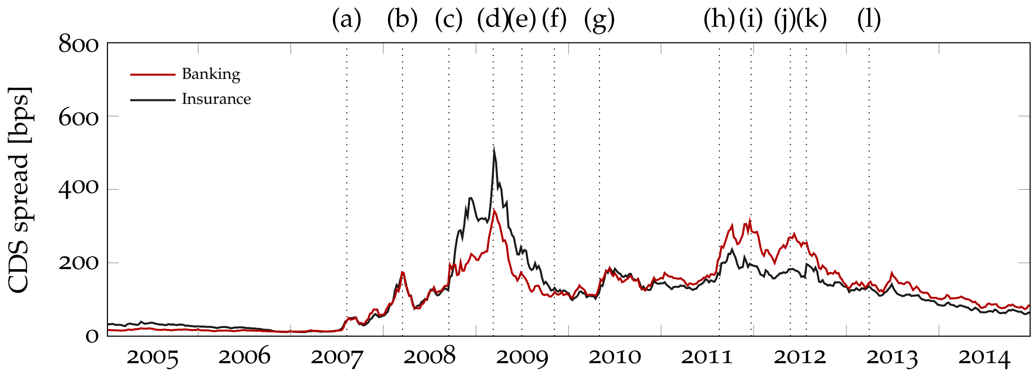


FIGURE 3.1: CDS spreads by sector
This figure shows median CDS spreads by sector. All spreads are for 5-year senior unsecured contracts. The vertical lines represent the following events: (a) BNP Paribas funds freeze, (b) Bear Stearns takeover, (c) Lehman Brothers failure, (d) U.S. stock market low, (e) U.S. leaves recession, (f) Greek government revises budget deficit, (g) first support package for Greece agreed upon, (h) global stock markets fall on uncertain world economic outlook, (i) European Central Bank conducts first round of 3-year longer-term refinancing operations, (j) Mario Draghi's "courageous leap" speech, (k) Mario Draghi's "whatever it takes" speech, and (l) euro area leaves recession.

e.g., MetLife), *P/C insurance* (12 firms, e.g., Allstate), *bond and mortgage insurance* (8 firms, e.g., MBIA), and *reinsurance* (7 firms, e.g., Munich Re).

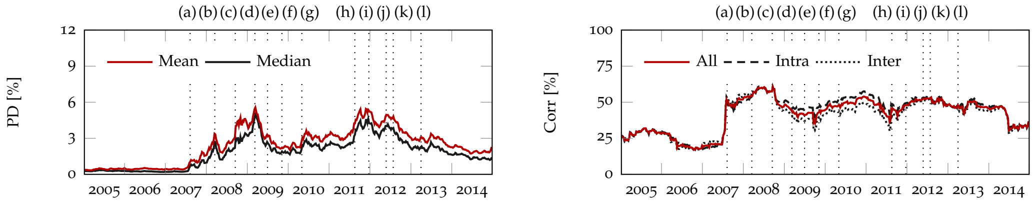
At the end of 2009, the banking sample's liabilities totaled USD 59,148 billion, and the insurance sample's liabilities totaled USD 9,318 billion. Overall, the sample represents many of the banking and insurance industries' largest firms, including most G-SIFIs, and accounts for about half of the global banking and insurance assets (Kaserer and Klein, 2018).

Figure 3.1 illustrates banks' and insurers' CDS spreads. As is evident from the figure, the banking and insurance sectors' credit risk showed distinct dynamics during the crisis episodes. At the height of the financial crisis, the insurance sector evinced higher levels of credit risk than the banking sector, and vice versa during the height of the European sovereign debt crisis. In light of these dynamics, an interesting objective of the empirical analysis will be to trace the sources and sinks of distress in the financial system.

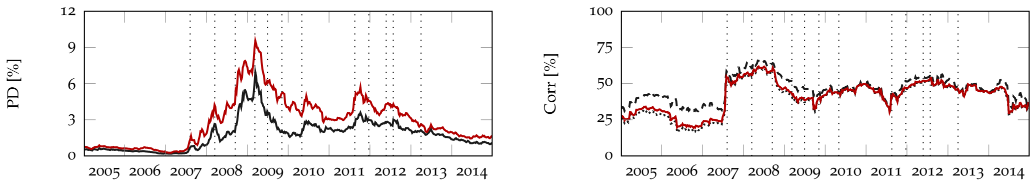
3.4.2 *Model Estimation*

The set of credit risk parameters includes risk-neutral probabilities of default, asset return correlations, and recovery rates for default scenarios. I estimate weekly time series of risk-neutral probabilities of default and asset return correlations from the CDS spreads as follows. I calculate the risk-neutral probabilities of default for a 1-year horizon, adopting the market convention of a 40 percent recovery rate on senior unsecured debt. Further, I calculate the asset return correlations using a rolling window of 1 year. Figure 3.2 shows plots of the resulting time series of credit risk parameters.[9]

9 For descriptive statistics on the risk-neutral probabilities of default and the asset return correlations for insurers' lines of business and the regional subsamples, see Appendix 3.A.

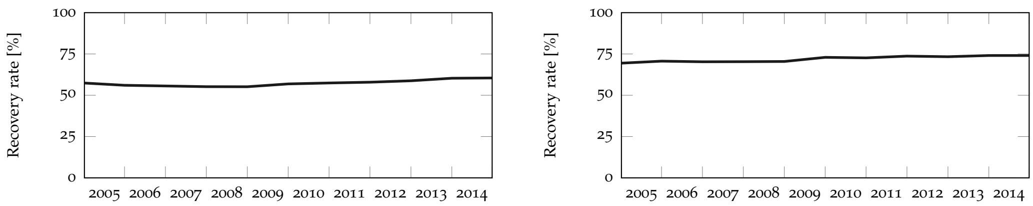


(A) Banking



(B) Insurance

FIGURE 3.2: Probabilities of default and asset return correlations by sector
This figure shows 1-year risk-neutral probabilities of default and average asset return correlations by sector. Both parameters are calculated at weekly frequency from 5-year senior unsecured CDS spreads. Correlations are calculated using a rolling window of 1 year. For each financial institution, pairwise correlations are calculated between the firm and all other firms in the sample (*all correlations*), between the firm and all other firms from the same sector (banking and insurance, *intra-sector correlations*), and between the firm and all firms from the respective other sector (*inter-sector correlations*). The vertical lines represent the same events as those in Figure 3.1.

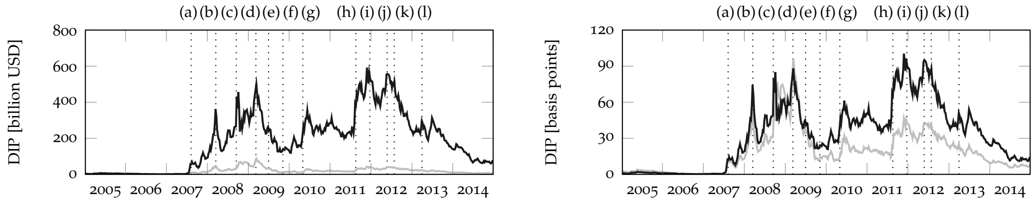


(A) Banking

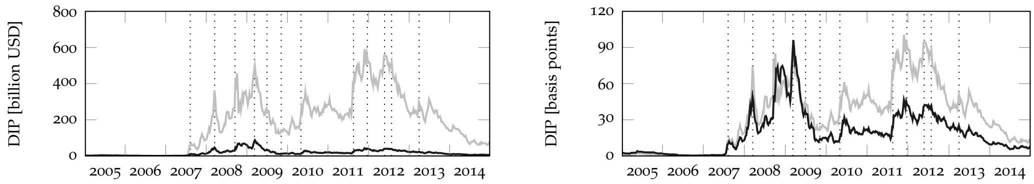
(B) Insurance

FIGURE 3.3: Recovery rate by sector
This figure shows the recovery rate for the banking and insurance sectors. The recovery rates are liability-weighted average rates calculated as in Kaserer and Klein (2018).

Finally, for default scenarios in the systemic event simulation, I use sector-specific recovery rates. I calculate these recovery rates as in the companion paper by Kaserer and Klein (2018), as follows. For insurers, I assume a recovery rate of 80 percent on technical provisions and of 40 percent on all other liabilities. For banks, I assume a recovery rate of 80 percent on customer deposits and of 40 percent on all other liabilities. The recovery rates on technical provisions and customer deposits are derived from empirical evidence presented in Kaserer and Klein (2018), and the recovery rate on other liabilities follows market practice for senior unsecured debt. Using these recovery rates, I then calculate liability-weighted recovery rates for the banking and insurance sectors. Figure 3.3 shows plots of the corresponding time series of recovery rates.



(A) Banking



(B) Insurance

FIGURE 3.4: Systemic risk in global financial sectors
This figure shows the level of systemic risk in the global banking and insurance sectors. Systemic risk is measured using the DIP indicator. This indicator is reported in nominal price in the left-hand panels and in unit price relative to aggregate sector liabilities in the right-hand panels. The dark lines represent the respective sector, and for comparison, the light lines show the time series for the other sector. The vertical lines represent the same events as those in Figure 3.1.

3.5 SYSTEMIC RISK IN THE BANKING AND INSURANCE INDUSTRIES

In this section, I analyze systemic risk in the banking and insurance industries. For the purpose of empirical illustration, I define systemic events as a loss in aggregate sector liabilities of more than 10 percent over a 1-year horizon. All risk measures are reported at weekly frequency to closely monitor systemic risk during the sample period.

To facilitate the discussion, I will sometimes report average values for the level of systemic risk during the pre-crisis and crisis periods. I define the pre-crisis period as the period from January 2005 through July 2007, the financial crisis and intermittent recovery as the period from August 2007 through April 2010, and the European sovereign debt crisis and ensuing recovery as the period from May 2010 through December 2014.

3.5.1 *Global Financial System*

This section analyzes systemic risk on the global stage. As a first step, I examine the time series of systemic risk in the global banking and insurance sectors; then, I assess the level of systemic risk in the individual primary insurance and reinsurance segments.

3.5.1.1 *Banking and Insurance Sector*

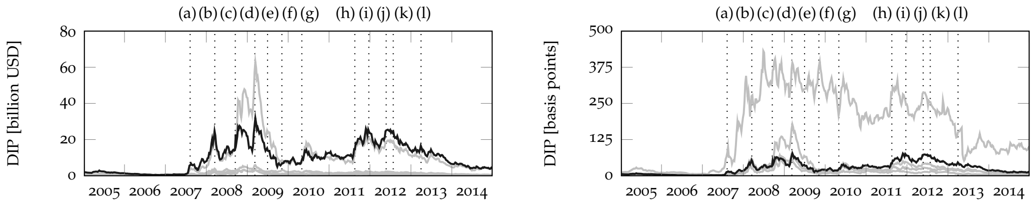
Figure 3.4 shows plots of the time series of systemic risk in the global banking and insurance sectors. Figure 3.4a illustrates the banking sector, and Figure 3.4b illustrates the insurance sector. The left-hand panels show the level of systemic risk in nominal price expressed in U.S. dollars, and the right-hand panels show the level of systemic risk in unit price relative to aggregate sector liabilities. To account for the different liability sizes of the banking and insurance sectors, I focus on unit prices and report nominal prices in parentheses.

The level of systemic risk in the global banking and insurance sectors exhibits considerable variation over the sample period, and it reflects major events occurring during the financial crisis and the European sovereign debt crisis. During the pre-crisis period, systemic risk is very low in both sectors, averaging about 1 basis point (USD 3 billion) for the banking sector and about 2 basis points (USD 1 billion) for the insurance sector. Following the spillover of the subprime mortgage crisis to the broader financial system, both industries experience significantly increased levels of distress. During the financial crisis, the banking sector's systemic risk averages 38 basis points (USD 208 billion), and the insurance sector's systemic risk averages 32 basis points (USD 29 billion). During the European sovereign debt crisis, the banking sector experiences a further increase in systemic risk, averaging 47 basis points (USD 271 billion), whereas the insurance sector evinces reduced levels of systemic risk, averaging 22 basis points (USD 20 billion). Systemic risk in the banking sector peaks at 100 basis points (USD 591 billion) for the week of November 25, 2011, at the height of the European sovereign debt crisis. Systemic risk in the insurance sector reaches its highest level at 96 basis points (USD 87 billion) for the week of March 13, 2009, the time of the financial crisis U.S. stock market low.

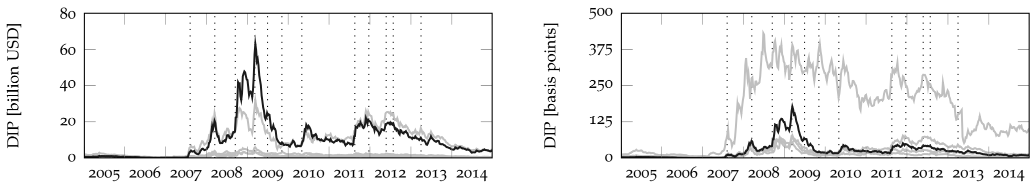
Throughout the sample period, the banking sector's nominal systemic risk exceeds the insurance sector's nominal systemic risk. Nominal systemic risk in the banking sector is typically much higher than it is in the insurance sector, in particular during the crisis episodes. Interestingly, however, the sectors' ranking by relative systemic risk changes over time. During the pre-crisis period, the unit prices of systemic risk in the banking and insurance sectors are very similar, though the insurance sector is slightly more risky on average. Throughout the early stage of the financial crisis, from August 2007 through September 2008, the banking and insurance sector closely track each other, with the insurance sector's systemic risk peaking below that of the banking sector. For several weeks during the period from October 2008 through May 2009, however, the insurance sector has a higher relative systemic risk than the banking sector. Finally, during the intermittent recovery period and throughout the European sovereign debt crisis, the banking sector again evinces a higher level of relative systemic risk than the insurance sector.

3.5.1.2 *Individual Insurance Segments*

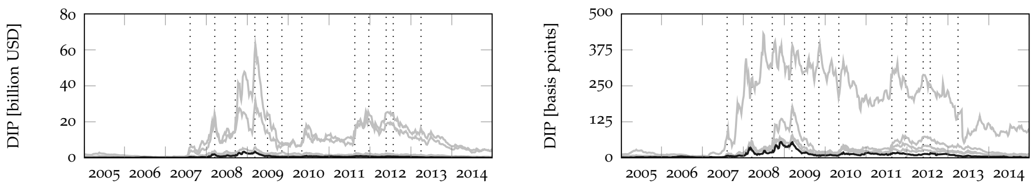
Insurers engage in a wide range of different business activities and underwrite different types of risks. An interesting objective, therefore, is to analyze the level of systemic risk associated with different insurance segments. To further analyze



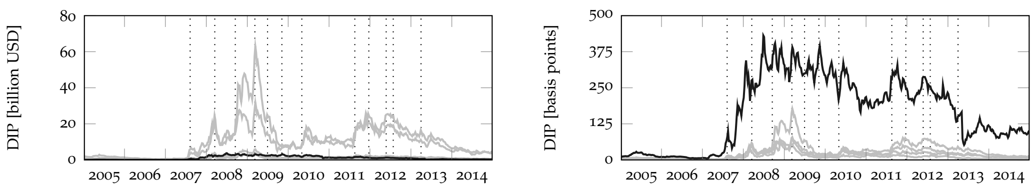
(A) Multi-line insurance



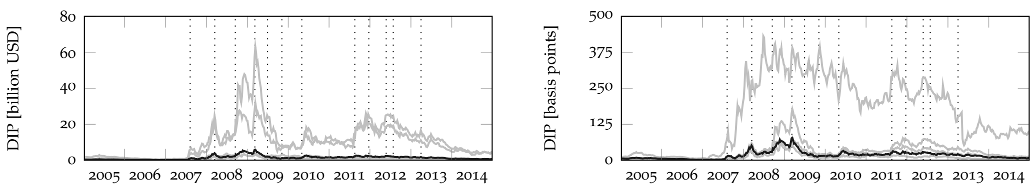
(B) Life insurance



(C) P/C insurance



(D) Bond and mortgage insurance



(E) Reinsurance

FIGURE 3.5: Systemic risk in global insurance segments
This figure shows the level of systemic risk in the individual segments of the global insurance sector. Systemic risk is measured using the DIP indicator. This indicator is reported in nominal price in the left-hand panels and in unit price relative to aggregate segment liabilities in the right-hand panels. The dark lines represent the respective segment, and for comparison, the light lines show the time series for the other segments. The vertical lines represent the same events as those in Figure 3.1.

systemic risk in the global insurance sector, I repeat the systemic risk analysis for each insurance segment: multi-line insurance, life insurance, P/C insurance, bond and mortgage insurance, and reinsurance. Figure 3.5 shows plots of the systemic risk in each of these lines of business. As above, the left-hand panels report systemic risk in nominal price in U.S. dollars, and the right-hand panels report systemic risk in unit price relative to aggregate segment liabilities.

Across segments, nominal systemic risk is low during the pre-crisis period and begins to hike upward at the onset of the financial crisis. During the financial crisis and the European sovereign debt crisis, nominal systemic risk is highest for the multi-line and life insurance sectors, each averaging about USD 13 billion. The life insurance sector reaches its highest level of nominal systemic risk at USD 63 billion for the week of March 13, 2009, the time of the financial crisis U.S. stock market low. The multi-line insurance sector reaches its highest level of nominal systemic risk at about half this value, USD 32 billion, for the same week. Nominal systemic risk in P/C insurance, bond and mortgage insurance, and reinsurance is small in comparison, averaging USD 1 billion, USD 1 billion, and USD 2 billion during the crisis episodes, respectively.

The dynamics of the relative risk measure differ substantially from those of the absolute risk measure. Throughout the crisis episodes, the bond and mortgage insurance sector has the highest level of relative systemic risk, averaging 221 basis points. The multi-line and life insurance sectors follow at significantly lower levels, each averaging 34 basis points. Interestingly, though, the relative riskiness of the multi-line and life insurance sectors differs between the financial crisis and the European sovereign debt crisis: during the financial crisis, the life insurance sector is on average riskier; during the European sovereign debt crisis, the multi-line insurance sector is on average riskier. Systemic risk in reinsurance averages 22 basis points. P/C insurance exhibits the lowest level of relative systemic risk during the crisis period, averaging 13 basis points.

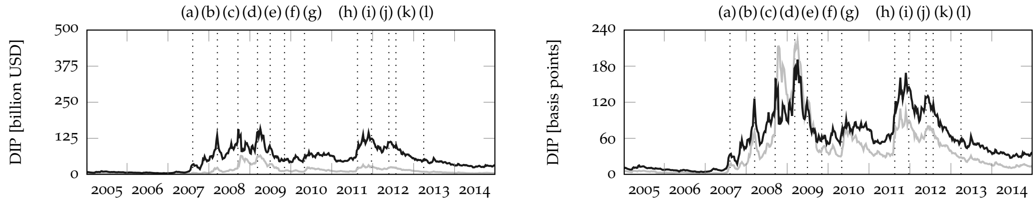
3.5.2 *Regional Financial Systems*

I now analyze systemic risk on the regional level. I first describe the time series of systemic risk in the North American banking and insurance sectors; then, I turn to the European banking and insurance sectors.[10]

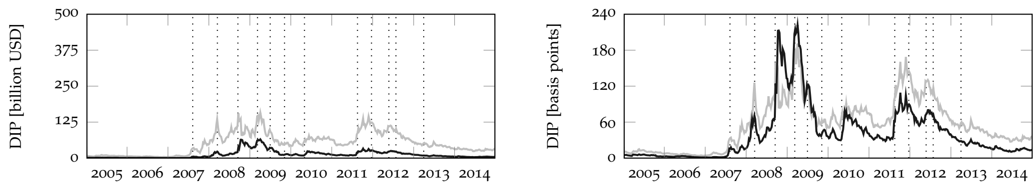
3.5.2.1 *North America*

Figure 3.6 shows plots of the time series of systemic risk in the North American banking and insurance sectors. Systemic risk in the North American financial system is relatively low before the financial crisis, averaging 8 basis points (USD 7 billion) for the banking sector and 3 basis points (USD 1 billion) for the insurance sector. During the financial crisis, both sectors experience significantly increased levels of systemic risk, averaging 80 basis points (USD 74 billion) for

10 Data availability for the other regions is not sufficient to enable regional analyses.



(A) Banking



(B) Insurance

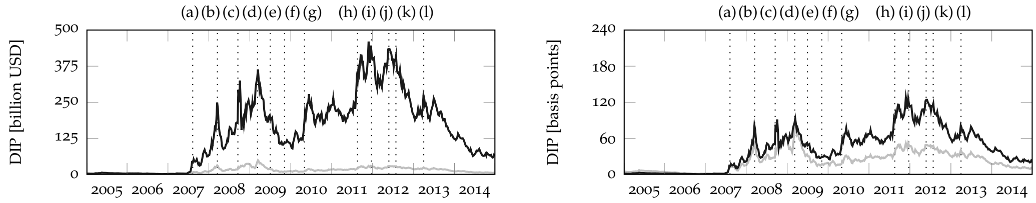
FIGURE 3.6: Systemic risk in North American financial sectors
This figure shows the level of systemic risk in the North American banking and insurance sectors. Systemic risk is measured using the DIP indicator. This indicator is reported in nominal price in the left-hand panels and in unit price relative to aggregate sector liabilities in the right-hand panels. The dark lines represent the respective sector, and for comparison, the light lines show the time series for the other sector. The vertical lines represent the same events as those in Figure 3.1.

the banking sector and 75 basis points (USD 22 billion) for the insurance sector. The ensuing European sovereign debt crisis sees slightly reduced systemic risk in the banking sector, where it averages 70 basis points (USD 60 billion), and a more pronounced reduction of systemic risk in the insurance sector, where it averages 41 basis points (USD 13 billion). The banking sector reaches its highest level of systemic risk at 191 basis points (USD 158 billion) for the week of April 3, 2009, in the aftermath of the financial crisis U.S. stock market low. The insurance sector reaches its highest level of systemic risk at 222 basis points (USD 65 billion) in the same week.

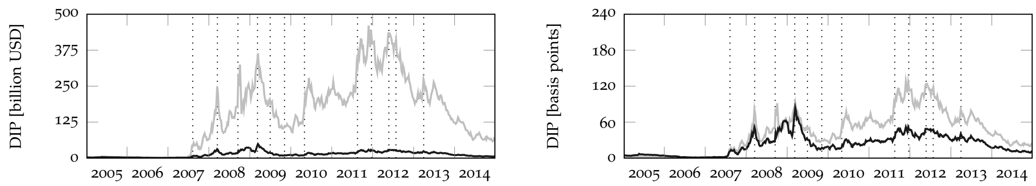
Throughout the sample period, the banking sector's nominal systemic risk is higher than that of the insurance sector. The ranking of the banking and insurance sectors by relative systemic risk, however, varies over time. The banking sector exhibits a higher relative systemic risk during the pre-crisis period, the beginning of the financial crisis, and the European sovereign debt crisis. During the year following the bankruptcy of Lehman Brothers and the near-bankruptcy of AIG in September 2008, however, the relative systemic risk of the insurance sector typically exceeds that of the banking sector.

3.5.2.2 *Europe*

Figure 3.7 shows plots of the time series of systemic risk in the European banking and insurance sectors. Systemic risk in the European financial system is very low in the years leading up to the financial crisis, averaging only 1 basis point (USD 3 billion) for the banking sector and 3 basis points (USD 2 billion) for the insurance sector. During the financial crisis, both sectors experience significantly increased levels of systemic risk, averaging 42 basis points (USD 152 billion) for



(A) Banking



(B) Insurance

FIGURE 3.7: Systemic risk in European financial sectors
This figure shows the level of systemic risk in the European banking and insurance sectors. Systemic risk is measured using the DIP indicator. This indicator is reported in nominal price in the left-hand panels and in unit price relative to aggregate sector liabilities in the right-hand panels. The dark lines represent the respective sector, and for comparison, the light lines show the time series for the other sector. The vertical lines represent the same events as those in Figure 3.1.

the banking sector and 30 basis points (USD 17 billion) for the insurance sector. During the European sovereign debt crisis, systemic risk in the banking sector increases further, averaging 65 basis points (USD 226 billion), whereas systemic risk in the insurance sector remains at a similar level, averaging 29 basis points (USD 17 billion). The banking sector reaches its highest level of systemic risk at 128 basis points (USD 460 billion) for the week of November 25, 2011, at the height of the European sovereign debt crisis. The insurance sector reaches its highest level of systemic risk at 84 basis points (USD 49 billion) for the week of March 13, 2009, at the time of the financial crisis U.S. stock market low.

As in North America, the banking sector's nominal systemic risk is higher than the insurance sector's nominal systemic risk throughout the sample period. The ranking of the banking and insurance sectors by relative systemic risk, however, again varies over time. Whereas the insurance sector exhibits a slightly higher level of relative systemic risk during most of the pre-crisis period, the banking sector typically exhibits a notably higher level of relative systemic risk during the financial crisis and European sovereign debt crisis. In the immediate aftermath of the bankruptcy of Lehman Brothers and the near-bankruptcy of AIG in September 2008, however, the insurance sector evinces a level of relative systemic risk similar to and occasionally even higher than that of the banking sector.

3.5.3 *Comparative Analysis and Discussion*

During the sample period, systemic risk in the banking and insurance industries exhibits a high degree of commonality but also important regional and sectoral differences, which I summarize and discuss below. Across regions and sectors, financial markets enjoy a period of tranquility during the early sample years, and experience varying degrees of distress throughout the crisis periods. Comparing the level of systemic risk across regions, I find that the North American and European banking sectors reflect the distinct dynamics of the crisis episodes: systemic risk in the North American banking sector peaks during the financial crisis, and systemic risk in the European banking sector peaks at the height of the European sovereign debt crisis. Interestingly, though, systemic risk in the insurance sector peaks during the financial crisis in both regions.

Comparing the level of systemic risk across sectors, I find that the nominal systemic risk of the insurance sector is typically low relative to that of the banking sector. This indicates that the insurance sector is not a major source of systemic risk, either for the global financial system or for the North American and European financial systems. I note, however, that the contribution of the insurance sector to the aggregate systemic risk in the financial system appears to vary across regions. In North America, the insurance sector's systemic importance, as measured by the nominal price of systemic risk, is significantly higher vis-à-vis the banking sector than is the case in Europe.

Although the banking sector is more systemically risky than the insurance sector on a nominal scale, the ranking of the sectors by relative systemic risk varies over the crisis period. During the first stage of the financial crisis, up to September 2008, when Lehman Brothers filed for bankruptcy and AIG received government support, the relative systemic risk of the banking sector exceeds that of the insurance sector both in North America and in Europe. During the second stage of the financial crisis, the relative systemic risk of the insurance sectors exceeds that of the banking sectors on several occasions, most notably in North America. Finally, throughout the European sovereign debt crisis, the relative systemic risk of the banking sector again dominates that of the insurance sector across regions.

The higher relative systemic risk of the insurance sector during the height of the financial crisis is surprising, given that insurers are typically less associated with systemic risk than banks. Asymmetric market perception of government guarantees for banks and insurers may at least partially explain the difference in the sectors' systemic risk. In the aftermath of the bankruptcy of Lehman Brothers, governments around the world announced support packages for financial institutions to mitigate the consequences of the financial crisis.[11] In essence, these interventions transferred risks from financial institutions onto the sovereign balance sheet. Market participants may have expected banks to benefit more from support packages than insurers, hence pricing systemic risk in the banking sector net of a higher government guarantee than systemic risk in the insurance sector. In fact, Schweikhard and Tsesmelidakis (2013) present evidence suggesting that government interventions significantly attenuated banks' credit

11 For a discussion of government interventions during the financial crisis, see IMF (2009).

risk but notably less so insurers' credit risk.

With respect to insurers' different lines of business, the analysis of relative systemic risk points to a significant difference in the riskiness of insurers' individual business activities. During the crisis periods, the bond and mortgage insurance sector consistently exhibits the highest level of relative systemic risk. This insurance sector includes two distinct types of insurers: financial guarantee insurers, which underwrite municipal bonds, and private mortgage insurers, which underwrite mortgages. Both risks are highly correlated with financial market variables, which exposes bond and mortgage insurers to financial turmoil. At the other end of the spectrum, P/C insurers exhibit the lowest level of relative systemic risk during the crisis periods. P/C insurers traditionally underwrite idiosyncratic risks, such as fire, theft, or accident, which are not correlated with the overall state of financial markets. They are therefore less prone to come under stress during episodes of financial turmoil. The nature of the business activities of the other insurance sectors falls in between, and these insurers also exhibit intermediate levels of relative systemic risk.

3.6 Contagion in the Banking and Insurance Industries

The analysis in the previous section has illustrated the surge in the financial systems' systemic risk following the onset of the financial crisis. Although reflecting different levels of concern, systemic risk indicators were found to exhibit a high degree of commonality and to closely track one another across sectors and regions. Importantly, however, no inference has yet been made regarding which parts of the financial system were instigators of systemic risk and which parts were victims of financial turmoil during the crisis episodes.

To shed light on the dynamic interactions that took place during the crisis periods, this section analyzes linkages in the financial system and the role of sovereign risk by means of Granger causality tests. Distress in the banking and insurance industries is measured by the DIP indicator discussed in the previous section. I use the unit price series to consider all sectors on a common and uniform scale. Sovereign risk is measured by sovereign CDS spreads. The analysis focuses on the period of the financial crisis and the European sovereign debt crisis, when the risk of systemic defaults was highest and when contagion effects can thus be expected to be strongest.

3.6.1 *Unconditional Systemic Risk Networks*

I first investigate the interconnectedness of the global and regional banking and insurance sectors using pairwise Granger causality tests. On the global stage, I analyze contagion between and within the banking and insurance industries. On the regional level, I analyze intraregional and interregional contagion for the North American and European banking and insurance sectors and sovereigns.

TABLE 3.1: Granger causality tests for the global banking and insurance sectors

Variables		VARX–GARCH model				Granger causality test	
Y	Z	k	d	r	s	$\chi^2(k)$	p-value
Insurance	Banking	3	1	2	1	12.23***	0.0066
Banking	Insurance	2	1	4	1	6.18**	0.0456

This table summarizes tests of Granger causality between the systemic risk of the global banking and insurance sectors. Systemic risk is measured by the DIP indicator. The sample period is from August 2007 through December 2014. I examine the null hypothesis that variable Z does not Granger-cause variable Y. Wald tests of no Granger causality are set in a VARX$(k, k+d)$–GARCH(r, s) model, where the d surplus lags of variable Z remain unrestricted under the null hypothesis. I report $\chi^2(k)$ statistics and p-values adjusting standard errors for nonnormality. Significance is indicated by: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

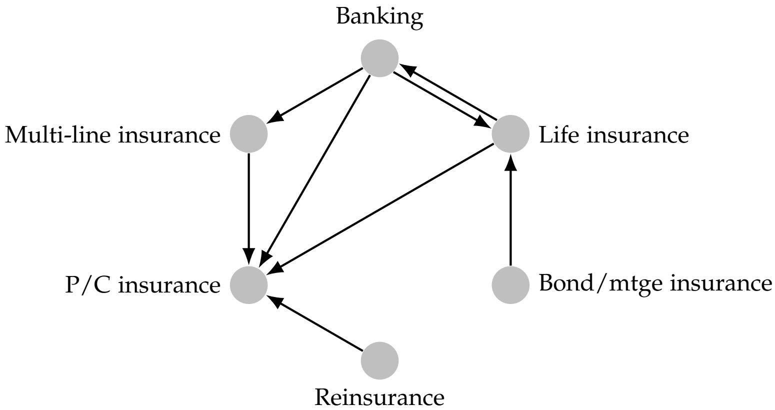
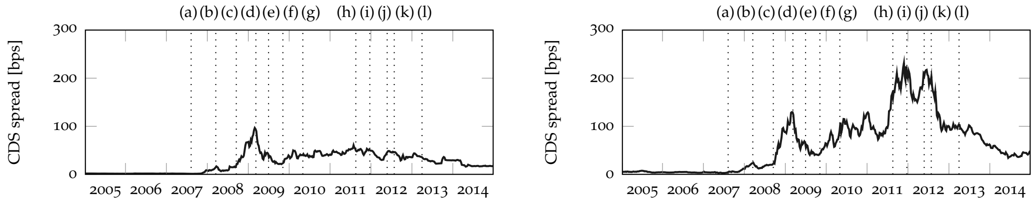


FIGURE 3.8: Network graph of the global financial system
This network graph shows pairwise Granger-causal relationships among the systemic risk of different sectors of the global financial system. Systemic risk in the banking and insurance sectors is measured by the DIP indicator. The sample period is from August 2007 through December 2014. Relationships that are statistically significant at the 5 percent level are represented by arrows.

3.6.1.1 *Global Financial System*

Table 3.1 presents the results of tests of Granger causality between the systemic risk of the global banking and insurance sectors during the financial crisis and the European sovereign debt crisis. I observe a feedback loop: the banking sector Granger-causes the insurance sector at the 1 percent level of statistical significance. Conversely, the insurance sector Granger-causes the banking sector at the 5 percent level of statistical significance.

This finding is consistent with the results of Billio et al. (2012), who show that individual insurers may propagate shocks to the broader financial system, but it contrasts at least partially with the results of Chen et al. (2014), who do not find a statistically significant impact of the insurance sector on the banking sector once conditional heteroscedasticity has been taken into account. Two interesting questions emerge. First, are some parts of the insurance sector connected more tightly with the banking sector than others? Second, are there significant interconnections within the global insurance sector?



(A) United States (B) European countries

FIGURE 3.9: Sovereign CDS spreads
This figure shows sovereign CDS spreads for the United States and large European countries. The spreads for Europe are the average spread of France, Germany, Italy, Spain, and the United Kingdom, weighted by GDP. All spreads are for 5-year senior unsecured contracts. The vertical lines represent the same events as those in Figure 3.1.

To fully appreciate the interconnectedness of the global banking and insurance sectors, I run pairwise Granger causality tests for the banking sector and the individual insurance segments in the sample: multi-line insurance, life insurance, P/C insurance, bond and mortgage insurance, and reinsurance. Figure 3.8 shows the network graph of Granger-causal relationships among these sectors. Interconnections that are statistically significant at the 5 percent level are represented by arrows. Appendix 3.B.2 provides detailed results of the underlying Granger causality tests.

The network graph reveals a multitude of links between the banking and insurance sectors, and it offers insights into the connectedness of the individual insurance segments. The banking sector Granger-causes the multi-line insurance, life insurance, and P/C insurance sectors. The life insurance sector Granger-causes the banking sector, giving rise to a feedback loop between these sectors. Within the insurance sector, the multi-line insurance, life insurance, and reinsurance sectors all lead the P/C insurance sector, and the bond and mortgage insurance sector leads the life insurance sector.

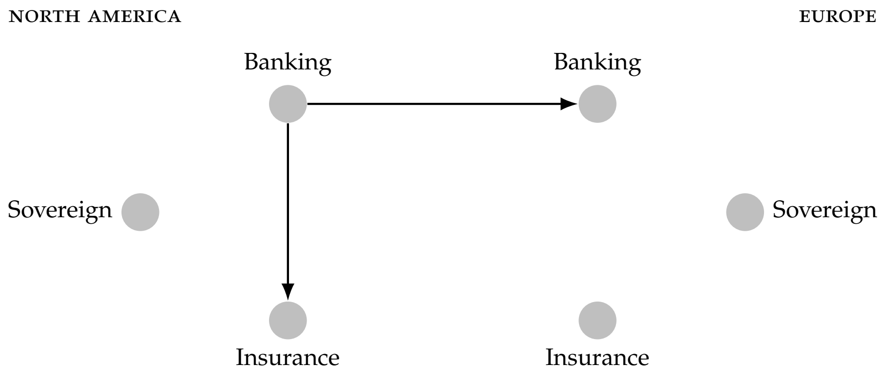
3.6.1.2 *Regional Financial Systems*

In addition to the analyses on the global stage, I test for pairwise Granger causality among the North American and European banking and insurance sectors and sovereigns. To proxy sovereign risk in North America, I use the sovereign CDS spread for the United States.[12] To proxy sovereign risk in Europe, I use the average sovereign CDS spread of the five largest European economies represented in the sample, weighted by gross domestic product (GDP): France, Germany, Italy, Spain, and the United Kingdom.[13] Figure 3.9 shows plots of the sovereign risk in North America and Europe.

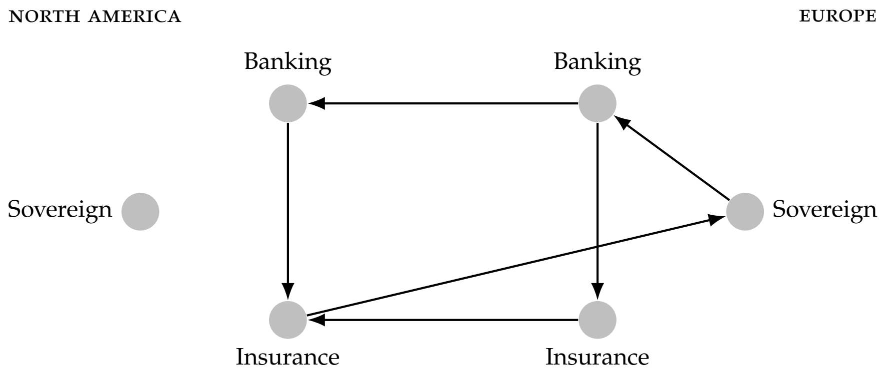
Figure 3.10 shows the network graph of Granger-causal relationships at the regional level for two periods: the financial crisis and the European sovereign

12 Out of the 38 financial firms from North America in the sample, 36 are from the United States. Datastream provides 5-year senior unsecured CDS spreads for the United States from mid-December 2007 onward. I fill the gap in coverage using additional CDS data from Markit.

13 To ensure consistency with the data underlying the DIP indicators, I collect all sovereign spreads for 5-year senior unsecured CDS contracts.



(A) Financial crisis



(B) European sovereign debt crisis

FIGURE 3.10: Network graphs of regional financial systems
The network graphs show pairwise Granger-causal relationships among systemic risk and sovereign risk in regional financial systems for two periods: (a) the financial crisis and intermittent recovery from August 2007 through April 2010, and (b) the European sovereign debt crisis and ensuing recovery from May 2010 through December 2014. Systemic risk is measured by the DIP indicator. Sovereign risk is measured by sovereign CDS spreads. Relationships that are statistically significant at the 5 percent level are represented by arrows.

debt crisis. Granger-causal relationships that are statistically significant at the 5 percent level are represented by arrows. Appendix 3.B.2 provides detailed results of the underlying Granger causality tests.

The two network graphs reflect the distinct dynamics of the financial crisis and the European sovereign debt crisis. During the financial crisis, the North American banking sector Granger-causes the North American insurance sector and the European banking sector. In this period, there are no links between sovereigns and the financial system.

During the European sovereign debt crisis, financial sectors' interconnectedness increases, and additionally, interconnections between sovereigns and the financial system emerge. Most notably, the European banking sector leads the European insurance sector and the North American banking sector. Moreover, the North American banking sector and the European insurance sector both Granger-cause the North American insurance sector. Finally, European sovereigns lead the European banking sector, and there is a link from the North American insurance sector to European sovereigns.

TABLE 3.2: Conditional Granger causality tests for the global banking and insurance sectors

Variables		VARX–GARCH model				Granger causality test	
Y	Z	k	d	r	s	$\chi^2(k)$	p-value
Insurance	Banking	3	1	2	1	13.12***	0.0044
Banking	Insurance	2	1	4	1	5.54*	0.0627

This table summarizes conditional tests of Granger causality between the systemic risk of the global banking and insurance sectors. The model includes controls for sovereign risk in North America and Europe as measured by sovereign CDS spreads. Systemic risk is measured by the DIP indicator. The sample period is from August 2007 through December 2014. I examine the null hypothesis that variable Z does not Granger-cause variable Y. Wald tests of no Granger causality are set in a VARX$(k, k+d)$–GARCH(r, s) model, where the d surplus lags of variable Z remain unrestricted under the null hypothesis. I report $\chi^2(k)$ statistics and p-values adjusting standard errors for nonnormality. Significance is indicated by: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

3.6.2 *Conditional Systemic Risk Networks*

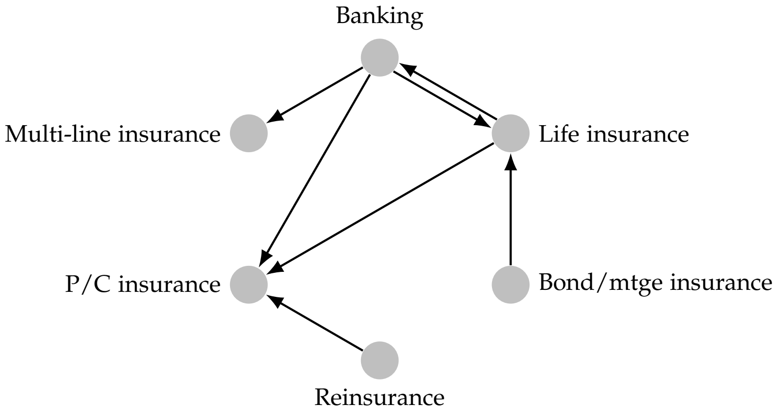
A limitation of pairwise Granger causality tests is that they may identify spurious relationships if two variables are influenced by a common factor: in a bivariate setting, Granger causality tests cannot distinguish whether one variable leads another one or whether a third variable leads both. In the context of my analyses, the interconnectedness of the banking and insurance sectors could thus be driven by sovereign risk, and the interconnectedness of different insurance segments could additionally arise due to a common exposure to the banking sector.

To address a potential confounding influence of common exposures, I repeat the analysis of contagion in the global financial system with suitable control variables. I reestimate each model with controls for North American and European sovereign risk, and I further consider controls for systemic risk in the banking sector in a separate robustness test.[14]

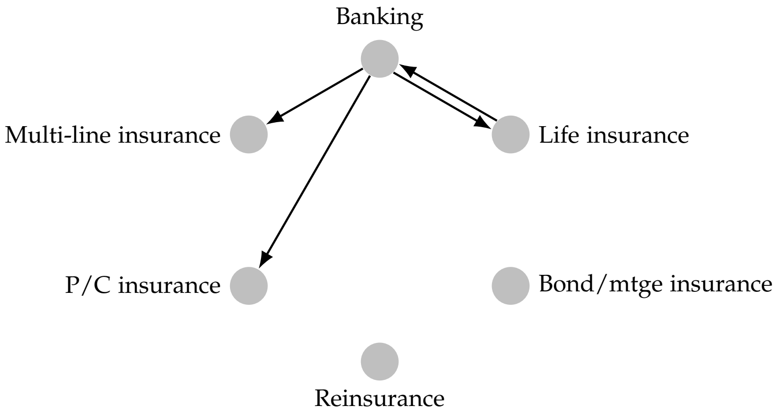
Table 3.2 presents the results of conditional tests of Granger causality between the banking and insurance sectors, where the model includes control variables for sovereign risk. As for the role of the banking sector, controlling for sovereign risk gives rise to results similar to those of the unconditional model, whereas the insurance sector's impact is now less significant. The banking sector again Granger-causes the insurance sector at the 1 percent level of statistical significance, and the insurance sector Granger-causes the banking sector at the 10 percent level of statistical significance.

Figure 3.11 shows conditional network graphs of pairwise Granger-causal relationships among the banking sector and the individual insurance segments. Figure 3.11a shows the network graph conditional on sovereign risk, and Figure 3.11b shows the network graph conditional on systemic risk in the banking sector. Relationships that are statistically significant at the 5 percent level are represented by arrows. Appendix 3.B.2 provides detailed results of the underlying Granger causality tests.

14 To determine the lag order of the augmented conditional mean models, I use the BIC. I search 20 lags in multivariate VAR models of the original variables and the control variables.



(A) Network graph conditional on sovereign risk



(B) Network graph conditional on systemic risk in the banking sector

FIGURE 3.11: Conditional network graphs of the global financial system
The network graphs show conditional pairwise Granger-causal relationships among the systemic risk of different sectors of the global financial system. The network graph shown in the upper panel is conditional on sovereign risk in North America and Europe. The network graph shown in the lower panel is conditional on systemic risk in the banking sector. Systemic risk is measured by the DIP indicator. Sovereign risk is measured by sovereign CDS spreads. The sample period is from August 2007 through December 2014. Relationships that are statistically significant at the 5 percent level are represented by arrows.

When controlling for sovereign risk, the results are mostly similar to those of the unconditional network graph. The banking sector still unilaterally Granger-causes the multi-line insurance sector and the P/C insurance sector, and the feedback loop between the banking sector and the life insurance sector persists. Within the insurance sector, the life and reinsurance sectors Granger-cause the P/C insurance sector, and the bond and mortgage insurance sector leads the life insurance sector, as before. These relationships are therefore not explained by common exposures to sovereign risk. Only the link from the multi-line insurance sector to the P/C insurance sector loses its significance. Distress in the multi-line insurance sector thus does not help to predict distress in the P/C insurance sector once sovereign risk has been accounted for.

When controlling for systemic risk in the banking sector, however, the Granger-causal links within the insurance sector all lose their significance. Once systemic risk in the banking sector is taken into account, distress in individual insurance segments does not appear to convey additional information about distress in other lines of business.

3.6.3 *Evaluation of Hypotheses and Discussion*

The analyses in the previous sections have uncovered numerous linkages by which contagion spread in the financial system during the financial crisis and the European sovereign debt crisis. In this section, I summarize my findings and evaluate them against the initial hypotheses.

Overall, the empirical results are consistent with the hypothesis that the insurance sector is, for the most part, a sink rather than a source of systemic risk. In the global analysis, the impact of the banking sector on the insurance sector is found to be more significant than vice versa. The relationships between the regional banking and insurance sectors reinforce this result: in North America and Europe, I find highly significant links from the regional banking sector to the regional insurance sector, but not in the other direction.

There is, however, also evidence of a bidirectional dependency between the global banking and insurance sectors, which I trace to a feedback loop between the banking sector and the life insurance sector. No other segment of the insurance sector Granger-causes the banking sector. The special role of the life insurance sector may be effected by both sides of life insurers' balance sheets: on the liability side, life insurers offer products that share many of the same characteristics and indeed compete with savings and investment products offered by banks (see, e.g., Trichet, 2005). Market participants may therefore perceive life insurance and banking as related markets, potentially giving rise to contagion effected by correlated information. On the asset side, life insurers are major investors in financial markets, in particular in the bond market (see, e.g., Acharya et al., 2010). Since banks invest in the same financial markets, this introduces the possibility of contagion induced by liquidity spirals or risk premium reassessments following life insurers' distress.

Systemic risk spillovers within the insurance sector are weaker than expected. In the unconditional Granger causality tests, multi-line insurance, life insurance, and reinsurance all lead the P/C insurance sector, and there is an additional link from bond and mortgage insurance to life insurance. When the Granger causality tests are conditioned on systemic risk in the banking sector, however, the interconnectedness of the insurance sector breaks down. This may be interpreted as evidence that ties between individual insurance segments, such as those introduced by reinsurance contracts, are too loose to transmit contagion in times of crisis. In this respect, the insurance sector appears to have sufficient shock-absorbing capacity to prevent self-reinforcing insurance crises.[15]

15 Indeed, only the link from bond and mortgage insurers to life insurers remains weakly significant when conditioned on systemic risk in the banking sector, indicating that this may be the most significant interconnection within the insurance sector. Following Acharya et al. (2010, p. 262), a potential explanation of a causal link between bond and mortgage insurers and life insurers is as

The findings regarding the regional dynamics of the crisis episodes corroborate the notion that the financial crisis was mostly a banking crisis, whereas the European sovereign debt crisis can be characterized as a joint sovereign and banking crisis. The interregional relationships in banking are as hypothesized: during the financial crisis, North American banks lead European banks, and vice versa during the European sovereign debt crisis. Interestingly, however, there is also interregional contagion in insurance, as the European insurance sector leads the North American insurance sector during the European sovereign debt crisis. During this period, distress also spills over from European sovereigns to European banks. Overall, however, the link between sovereigns and individual financial sectors is weaker than expected, as no feedback loops can be observed during either crisis period.

3.7 Conclusion

This paper analyzes the level of systemic risk in different banking and insurance sectors and spillover effects among these sectors using a market-based risk measure. I find that systemic risk in the insurance sector is relatively contained compared to that in the banking sector when measured in absolute terms. When measuring systemic risk in relative terms, per unit of exposure, the banking sector is again riskier for most of the crisis episodes, though the insurance sector occasionally exhibits higher levels of relative systemic risk at the height of the financial crisis. Within the insurance sector, systemic risk varies widely by line of business, indicating that different business activities contribute to insurers' systemic risk by varying degrees. Bond and mortgage insurance experiences by far the highest relative systemic risk. Multi-line and life insurance exhibit intermediate levels, whereas P/C insurance and reinsurance consistently exhibit low levels of relative systemic risk.

The interconnectedness analysis indicates that overall, the banking sector has a more significant impact on the insurance sector than vice versa. There is, however, also evidence of a bidirectional dependency between the banking and insurance sectors. I provide novel evidence that this interdependency can be traced to a feedback loop between the banking sector and the life insurance sector. This relationship is robust when controlling for banks' and life insurers' common exposure to sovereign risk. In contrast, interconnectedness within the insurance sector is weak when controlling for individual insurance segments' common exposure to the banking sector. In particular, the reinsurance market does not appear to introduce interconnections among insurers that may act as direct channels of contagion in a fashion similar to the interbank market.

follows. In the course of the financial crisis, bond and mortgage insurers came under pressure and experienced rating downgrades. In turn, the ratings of municipal bonds underwritten by the downgraded insurers experienced downgrades as well. These bonds thus depreciated, which exerted stress on financial institutions with inventories of such bonds. Life insurers are a major investor in capital markets, in particular in the bond market. Therefore, life insurers' distress could have been effected by bond and mortgage insurers through this market price channel.

The insurance sector thus seems to have sufficient shock-absorbing capacity to prevent cascading failures should a shock impair individual insurers or a limited segment of the broader insurance industry.

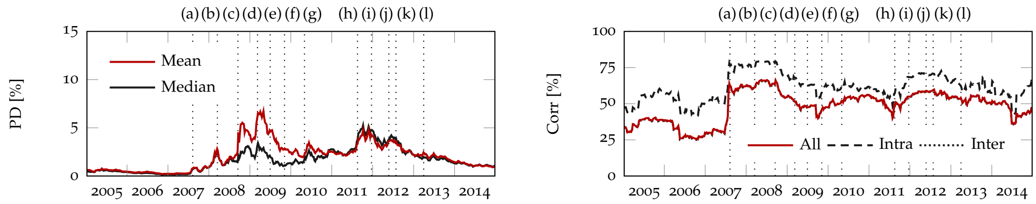
In summary, based on the results of the interconnectedness analysis, financial sectors can be classified as either shock propagators or shock absorbers. Policymakers, regulators, and supervisors need to be aware of this distinction in order to design, implement, and enforce effective measures to contain distress in the financial system. Financial sectors that may propagate shocks to a substantial part of the broader financial system, such as the banking and life insurance sectors, arguably provide an occasion for macroprudential measures to enhance financial stability. By contrast, financial sectors that act as shock absorbers, such as the P/C insurance sector, are best addressed by microprudential measures to safeguard their resilience in times of crisis.

Importantly, the interconnectedness analysis has focused on the existence of systemic risk spillovers but has not investigated which specific channels of contagion effect these spillovers. To the extent that the CDS market is informationally efficient, both direct and indirect channels of contagion are reflected in the empirical analysis. An interesting objective for future research will thus be to identify the distinct mechanisms by which contagion spread between the banking and life insurance industries, such as correlated information, liquidity spirals, and risk premium reassessments.

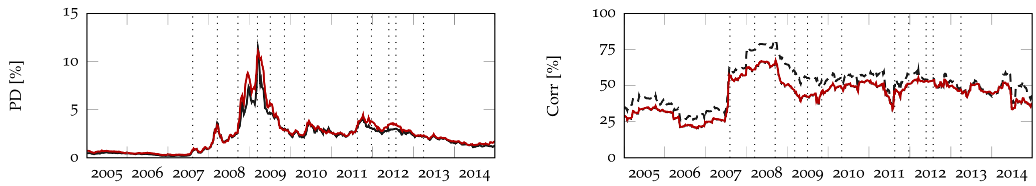
APPENDIX

3.A ADDITIONAL DESCRIPTIVE STATISTICS

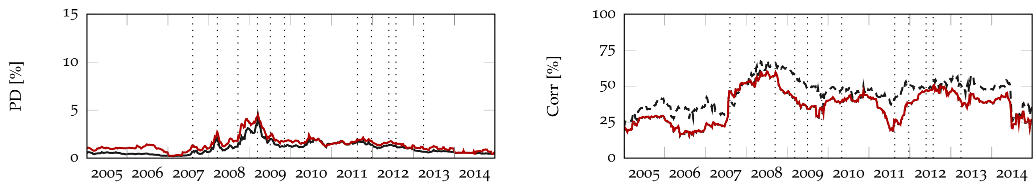
In this appendix, I provide additional descriptive statistics on the banking and insurance sectors examined in the Granger causality tests. Figure 3.12 shows plots of the time series of probabilities of default and asset return correlations for the global insurance segments. Figure 3.13 shows these time series for the North American banking and insurance sectors, and Figure 3.14 shows them for the European banking and insurance sectors.



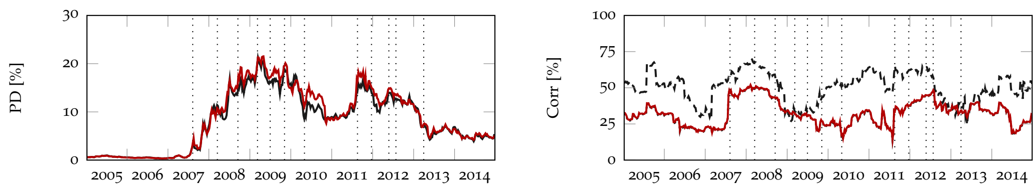
(A) Multi-line insurance



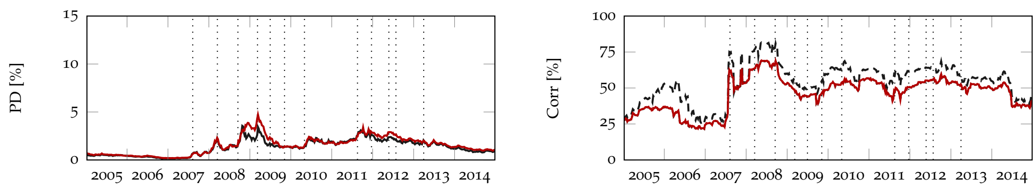
(B) Life insurance



(C) P/C insurance

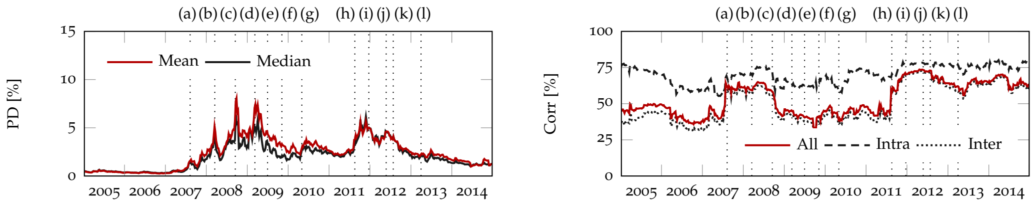


(D) Bond and mortgage insurance

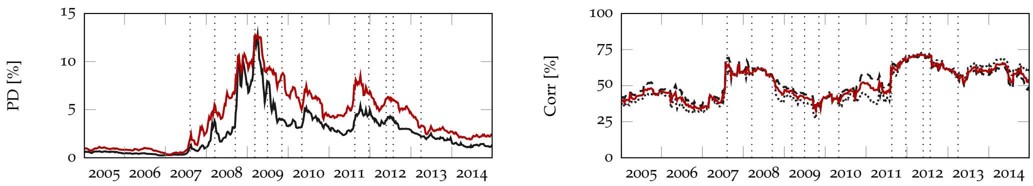


(E) Reinsurance

FIGURE 3.12: Credit risk parameters for global insurance segments
This figure shows 1-year risk-neutral probabilities of default and average asset return correlations for the individual segments of the global insurance sector. Both parameters are calculated at weekly frequency from 5-year senior unsecured CDS spreads. Correlations are calculated using a rolling window of 1 year. For each insurer, pairwise correlations are calculated between the firm and all other firms in the global sample (*all correlations*), between the firm and all other firms from the same insurance segment (*intra-segment correlations*), and between the firm and all firms from a different insurance segment (*inter-segment correlations*). The vertical lines represent the same events as those in Figure 3.1.

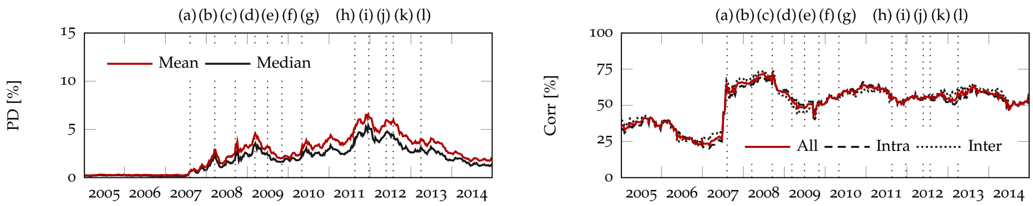


(A) Banking

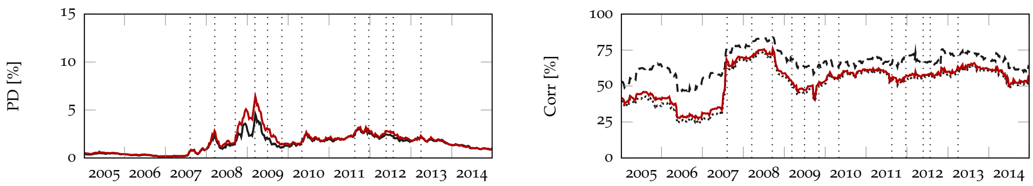


(B) Insurance

FIGURE 3.13: Credit risk parameters for North America
This figure shows 1-year risk-neutral probabilities of default and average asset return correlations in North American financial sectors. Both parameters are calculated at weekly frequency from 5-year senior unsecured CDS spreads. Correlations are calculated using a rolling window of 1 year. For each financial institution, pairwise correlations are calculated between the firm and all other firms in the North American sample (*all correlations*), between the firm and all other firms from the same sector (banking and insurance, *intra-sector correlations*), and between the firm and all firms from the respective other sector (*inter-sector correlations*). The vertical lines represent the same events as those in Figure 3.1.



(A) Banking



(B) Insurance

FIGURE 3.14: Credit risk parameters for Europe
This figure shows 1-year risk-neutral probabilities of default and average asset return correlations in European financial sectors. Both parameters are calculated at weekly frequency from 5-year senior unsecured CDS spreads. Correlations are calculated using a rolling window of 1 year. For each financial institution, pairwise correlations are calculated between the firm and all other firms in the European sample (*all correlations*), between the firm and all other firms from the same sector (banking and insurance, *intra-sector correlations*), and between the firm and all firms from the respective other sector (*inter-sector correlations*). The vertical lines represent the same events as those in Figure 3.1.

3.B STATISTICAL APPENDIX

3.B.1 *Augmented Dickey–Fuller Tests*

TABLE 3.3: ADF unit root tests for systemic risk and sovereign risk

	Log levels		Log differences	
Variable	l	τ_{ADF}	l	τ_{ADF}
Panel A: August 2007 through December 2014				
BNK	1	−2.359	0	−18.423***
INS	1	−2.050	0	−16.480***
INS_ML	3	−2.578*	2	−10.550***
INS_LI	1	−1.946	0	−15.317***
INS_PC	0	−0.483	0	−19.041***
INS_BM	1	−2.617*	0	−15.475***
INS_RE	1	−2.219	0	−15.290***
Panel B: August 2007 through April 2010				
NAM_BNK	0	−2.246	0	−10.793***
NAM_INS	1	−1.826	0	−9.322***
NAM_SOV	1	−2.225	0	−8.106***
EUR_BNK	1	−3.118**	0	−10.508***
EUR_INS	1	−2.210	0	−9.296***
EUR_SOV	1	−2.068	0	−9.148***
Panel C: May 2010 through December 2014				
NAM_BNK	0	−0.714	0	−14.429***
NAM_INS	1	−0.692	0	−12.750***
NAM_SOV	2	−0.864	1	−11.416***
EUR_BNK	0	−0.221	0	−14.314***
EUR_INS	0	−0.477	0	−14.170***
EUR_SOV	0	−0.445	0	−13.505***

This table presents the results of ADF tests for a unit root in time series of systemic risk and sovereign risk. Systemic risk is measured by the DIP indicator. Sovereign risk is measured by sovereign CDS spreads. The testing procedure examines the null hypothesis of a unit root in the time series. l specifies the number of lagged difference terms included in the test regression, and τ_{ADF} denotes the test statistic assuming a random walk without drift under the null hypothesis. Global variables are banking (BNK), insurance (INS), multi-line insurance (INS_ML), life insurance (INS_LI), P/C insurance (INS_PC), bond and mortgage insurance (INS_BM), and reinsurance (INS_RE); North American variables are banking (NAM_BNK), insurance (NAM_INS), and sovereign (NAM_SOV); European variables are banking (EUR_BNK), insurance (EUR_INS), and sovereign (EUR_SOV). Significance is indicated by: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

3.B.2 *Granger Causality Tests*

In this appendix, I provide detailed results of the Granger causality tests discussed in Section 3.6. Table 3.4 presents the results underlying the network graph shown in Figure 3.8. Table 3.5 presents the results underlying the network graph shown in Figure 3.10, and Table 3.6 presents the results underlying the network graph shown in Figure 3.11.

TABLE 3.4: Granger causality tests for the global financial system

Variables		VARX–GARCH model				Granger causality test	
Y	Z	k	d	r	s	$\chi^2(k)$	p-value
INS_ML	BNK	3	1	2	1	12.83***	0.0050
INS_LI	BNK	2	1	1	1	8.08**	0.0176
INS_PC	BNK	2	1	1	1	23.74***	0.0000
INS_BM	BNK	2	1	1	1	0.30	0.8611
INS_RE	BNK	2	1	3	1	1.26	0.5328
BNK	INS_ML	2	1	4	1	2.06	0.3576
INS_LI	INS_ML	3	1	1	1	5.56	0.1352
INS_PC	INS_ML	2	1	1	1	11.39***	0.0034
INS_BM	INS_ML	2	1	1	1	0.17	0.9170
INS_RE	INS_ML	2	1	3	1	3.77	0.1518
BNK	INS_LI	2	1	4	1	8.89**	0.0117
INS_ML	INS_LI	3	1	2	1	5.81	0.1211
INS_PC	INS_LI	2	1	1	1	19.39***	0.0001
INS_BM	INS_LI	2	1	1	1	0.32	0.8536
INS_RE	INS_LI	2	1	3	1	0.08	0.9631
BNK	INS_PC	2	1	4	1	5.62*	0.0603
INS_ML	INS_PC	4	1	2	1	2.81	0.5898
INS_LI	INS_PC	2	1	1	1	1.24	0.5373
INS_BM	INS_PC	2	1	1	1	2.34	0.3096
INS_RE	INS_PC	2	1	3	1	0.03	0.9838
BNK	INS_BM	2	1	4	1	1.15	0.5634
INS_ML	INS_BM	4	1	2	1	2.12	0.7144
INS_LI	INS_BM	2	1	1	1	8.98**	0.0112
INS_PC	INS_BM	2	1	1	1	2.82	0.2440
INS_RE	INS_BM	2	1	3	1	4.33	0.1149
BNK	INS_RE	2	1	4	1	1.75	0.4160
INS_ML	INS_RE	3	1	2	1	6.46*	0.0912
INS_LI	INS_RE	2	1	1	1	4.15	0.1252
INS_PC	INS_RE	2	1	1	1	19.29***	0.0001
INS_BM	INS_RE	2	1	1	1	0.30	0.8612

This table summarizes tests of Granger causality among the systemic risk of different sectors of the global financial system. Systemic risk is measured by the DIP indicator. The sample period is from August 2007 through December 2014. I examine the null hypothesis that variable Z does not Granger-cause variable Y. Wald tests of no Granger causality are set in a VARX$(k, k+d)$–GARCH(r, s) model, where the d surplus lags of variable Z remain unrestricted under the null hypothesis. The variables are banking (BNK), multi-line insurance (INS_ML), life insurance (INS_LI), P/C insurance (INS_PC), bond and mortgage insurance (INS_BM), and reinsurance (INS_RE). I report $\chi^2(k)$ statistics and p-values adjusting standard errors for nonnormality. Significance is indicated by: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

table 3.5: Granger causality tests for regional financial systems

Variables		VARX–GARCH model				Granger causality test	
Y	Z	k	d	r	s	$\chi^2(k)$	p-value
Panel A: Financial crisis							
NAM_INS	NAM_BNK	2	1	1	1	6.97**	0.0307
NAM_SOV	NAM_BNK	2	1	1	1	0.82	0.6626
EUR_BNK	NAM_BNK	1	1	1	1	9.05***	0.0026
EUR_INS	NAM_BNK	2	1	1	1	5.75*	0.0563
EUR_SOV	NAM_BNK	2	1	1	1	0.26	0.8783
NAM_BNK	NAM_INS	2	1	4	1	3.22	0.1995
NAM_SOV	NAM_INS	2	1	1	1	0.63	0.7288
EUR_BNK	NAM_INS	2	1	1	1	1.54	0.4631
EUR_INS	NAM_INS	2	1	1	1	4.02	0.1340
EUR_SOV	NAM_INS	2	1	1	1	4.06	0.1315
NAM_BNK	NAM_SOV	2	1	4	1	0.39	0.8211
NAM_INS	NAM_SOV	2	1	1	1	0.78	0.6762
EUR_BNK	NAM_SOV	2	1	1	1	0.07	0.9650
EUR_INS	NAM_SOV	2	1	1	1	0.06	0.9701
EUR_SOV	NAM_SOV	2	1	1	1	1.01	0.6030
NAM_BNK	EUR_BNK	1	1	4	1	3.55*	0.0596
NAM_INS	EUR_BNK	2	1	1	1	0.51	0.7748
NAM_SOV	EUR_BNK	2	1	1	1	0.10	0.9521
EUR_INS	EUR_BNK	2	1	1	1	0.36	0.8369
EUR_SOV	EUR_BNK	2	1	1	1	0.90	0.6378
NAM_BNK	EUR_INS	2	1	4	1	1.05	0.5910
NAM_INS	EUR_INS	2	1	1	1	2.30	0.3161
NAM_SOV	EUR_INS	2	1	1	1	0.18	0.9150
EUR_BNK	EUR_INS	2	1	1	1	0.24	0.8873
EUR_SOV	EUR_INS	2	1	1	1	3.06	0.2169
NAM_BNK	EUR_SOV	2	1	4	1	0.17	0.9169
NAM_INS	EUR_SOV	2	1	1	1	3.63	0.1632
NAM_SOV	EUR_SOV	2	1	1	1	0.87	0.6474
EUR_BNK	EUR_SOV	2	1	1	1	0.26	0.8768
EUR_INS	EUR_SOV	2	1	1	1	0.08	0.9585

Continued on next page

TABLE 3.5 – *continued from previous page*

Variables		VARX–GARCH model				Granger causality test	
Y	Z	k	d	r	s	$\chi^2(k)$	p-value
Panel B: European sovereign debt crisis							
NAM_INS	NAM_BNK	1	1	1	1	8.81***	0.0030
NAM_SOV	NAM_BNK	3	1	1	1	2.04	0.5649
EUR_BNK	NAM_BNK	1	1	3	1	0.45	0.5040
EUR_INS	NAM_BNK	1	1	1	1	2.64	0.1043
EUR_SOV	NAM_BNK	1	1	1	1	2.02	0.1550
NAM_BNK	NAM_INS	1	1	1	1	1.17	0.2801
NAM_SOV	NAM_INS	3	1	1	1	0.49	0.9203
EUR_BNK	NAM_INS	2	1	4	1	2.00	0.3682
EUR_INS	NAM_INS	1	1	1	1	1.62	0.2034
EUR_SOV	NAM_INS	2	1	1	1	8.55**	0.0139
NAM_BNK	NAM_SOV	2	1	1	1	1.82	0.4033
NAM_INS	NAM_SOV	2	1	1	1	0.19	0.9109
EUR_BNK	NAM_SOV	2	1	3	1	0.40	0.8169
EUR_INS	NAM_SOV	2	1	1	1	1.15	0.5635
EUR_SOV	NAM_SOV	2	1	1	1	0.18	0.9142
NAM_BNK	EUR_BNK	1	1	4	1	7.53***	0.0061
NAM_INS	EUR_BNK	2	1	1	1	5.16*	0.0757
NAM_SOV	EUR_BNK	3	1	1	1	0.88	0.8298
EUR_INS	EUR_BNK	1	1	1	1	11.27***	0.0008
EUR_SOV	EUR_BNK	1	1	1	1	0.78	0.3775
NAM_BNK	EUR_INS	1	1	4	1	2.69	0.1007
NAM_INS	EUR_INS	1	1	1	1	10.34***	0.0013
NAM_SOV	EUR_INS	3	1	1	1	0.54	0.9110
EUR_BNK	EUR_INS	1	1	3	1	0.46	0.4957
EUR_SOV	EUR_INS	1	1	1	1	0.31	0.5806
NAM_BNK	EUR_SOV	1	1	1	1	2.77*	0.0959
NAM_INS	EUR_SOV	2	1	1	1	3.63	0.1628
NAM_SOV	EUR_SOV	3	1	1	1	1.32	0.7243
EUR_BNK	EUR_SOV	1	1	3	1	5.92**	0.0150
EUR_INS	EUR_SOV	1	1	1	1	3.48*	0.0621

This table summarizes tests of Granger causality among systemic risk and sovereign risk in regional financial systems. Systemic risk is measured by the DIP indicator. Sovereign risk is measured by sovereign CDS spreads. The sample period in Panel A is the financial crisis and intermittent recovery from August 2007 through April 2010, and the sample period in Panel B is the European sovereign debt crisis and ensuing recovery from May 2010 through December 2014. I examine the null hypothesis that variable Z does not Granger-cause variable Y. Wald tests of no Granger causality are set in a VARX$(k, k+d)$–GARCH(r, s) model, where the d surplus lags of variable Z remain unrestricted under the null hypothesis. North American variables are banking (NAM_BNK), insurance (NAM_INS), and sovereign (NAM_SOV); European variables are banking (EUR_BNK), insurance (EUR_INS), and sovereign (EUR_SOV). I report $\chi^2(k)$ statistics and p-values adjusting standard errors for nonnormality. Significance is indicated by: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

TABLE 3.6: Conditional Granger causality tests for the global financial system

Variables		VARX–GARCH model				Granger causality test	
Y	Z	k	d	r	s	$\chi^2(k)$	p-value
Panel A: Controls for sovereign risk							
INS_ML	BNK	3	1	2	1	12.45***	0.0060
INS_LI	BNK	2	1	1	1	11.41***	0.0033
INS_PC	BNK	2	1	1	1	9.74***	0.0077
INS_BM	BNK	2	1	1	1	0.70	0.7053
INS_RE	BNK	2	1	3	1	0.96	0.6201
BNK	INS_ML	2	1	4	1	2.46	0.2926
INS_LI	INS_ML	2	1	1	1	2.22	0.3293
INS_PC	INS_ML	2	1	1	1	1.84	0.3984
INS_BM	INS_ML	2	1	1	1	0.31	0.8577
INS_RE	INS_ML	3	1	3	1	6.40*	0.0937
BNK	INS_LI	2	1	4	1	8.56**	0.0139
INS_ML	INS_LI	3	1	3	1	4.92	0.1775
INS_PC	INS_LI	2	1	1	1	9.64***	0.0081
INS_BM	INS_LI	2	1	1	1	0.48	0.7885
INS_RE	INS_LI	2	1	3	1	0.09	0.9559
BNK	INS_PC	2	1	4	1	2.32	0.3137
INS_ML	INS_PC	4	1	3	1	2.09	0.7197
INS_LI	INS_PC	2	1	1	1	1.17	0.5557
INS_BM	INS_PC	2	1	1	1	2.97	0.2264
INS_RE	INS_PC	3	1	3	1	2.07	0.5589
BNK	INS_BM	2	1	4	1	1.37	0.5033
INS_ML	INS_BM	4	1	3	1	2.20	0.6990
INS_LI	INS_BM	2	1	1	1	8.92**	0.0116
INS_PC	INS_BM	2	1	1	1	1.97	0.3726
INS_RE	INS_BM	2	1	2	1	3.94	0.1391
BNK	INS_RE	2	1	4	1	1.19	0.5505
INS_ML	INS_RE	3	1	3	1	5.73	0.1253
INS_LI	INS_RE	2	1	1	1	4.39	0.1116
INS_PC	INS_RE	2	1	1	1	10.58***	0.0050
INS_BM	INS_RE	2	1	1	1	0.46	0.7926

Continued on next page

TABLE 3.6 – *continued from previous page*

Variables		VARX–GARCH model				Granger causality test	
Y	Z	k	d	r	s	$\chi^2(k)$	p-value
Panel B: Controls for systemic risk in the banking sector							
INS_ML	BNK	3	1	2	1	12.83***	0.0050
INS_LI	BNK	2	1	1	1	8.08**	0.0176
INS_PC	BNK	2	1	1	1	23.74***	0.0000
INS_BM	BNK	2	1	1	1	0.30	0.8611
INS_RE	BNK	2	1	3	1	1.26	0.5328
BNK	INS_ML	2	1	4	1	2.06	0.3576
INS_LI	INS_ML	2	1	1	1	0.84	0.6563
INS_PC	INS_ML	2	1	1	1	3.34	0.1878
INS_BM	INS_ML	2	1	1	1	0.37	0.8316
INS_RE	INS_ML	2	1	3	1	4.30	0.1165
BNK	INS_LI	2	1	4	1	8.89**	0.0117
INS_ML	INS_LI	3	1	2	1	6.63*	0.0846
INS_PC	INS_LI	2	1	1	1	1.39	0.5001
INS_BM	INS_LI	2	1	1	1	2.03	0.3619
INS_RE	INS_LI	2	1	3	1	0.34	0.8432
BNK	INS_PC	2	1	4	1	5.62*	0.0603
INS_ML	INS_PC	4	1	2	1	4.10	0.3928
INS_LI	INS_PC	2	1	1	1	0.59	0.7462
INS_BM	INS_PC	2	1	1	1	1.26	0.5328
INS_RE	INS_PC	2	1	3	1	0.02	0.9902
BNK	INS_BM	2	1	4	1	1.15	0.5634
INS_ML	INS_BM	4	1	2	1	1.18	0.8816
INS_LI	INS_BM	2	1	1	1	5.84*	0.0539
INS_PC	INS_BM	2	1	1	1	0.23	0.8895
INS_RE	INS_BM	2	1	3	1	3.85	0.1457
BNK	INS_RE	2	1	4	1	1.75	0.4160
INS_ML	INS_RE	3	1	2	1	4.83	0.1847
INS_LI	INS_RE	2	1	1	1	1.36	0.5058
INS_PC	INS_RE	2	1	1	1	1.37	0.5034
INS_BM	INS_RE	2	1	1	1	0.50	0.7798

This table summarizes conditional tests of Granger causality among the systemic risk of different sectors of the global financial system. Panel A shows the results for model specifications including controls for sovereign risk in North America and Europe. Panel B shows the results for model specifications including controls for systemic risk in the banking sector. Systemic risk is measured by the DIP indicator. Sovereign risk is measured by sovereign CDS spreads. The sample period is from August 2007 through December 2014. I examine the null hypothesis that variable Z does not Granger-cause variable Y. Wald tests of no Granger causality are set in a VARX$(k, k+d)$–GARCH(r, s) model, where the d surplus lags of variable Z remain unrestricted under the null hypothesis. The variables are banking (BNK), multi-line insurance (INS_ML), life insurance (INS_LI), P/C insurance (INS_PC), bond and mortgage insurance (INS_BM), and reinsurance (INS_RE). I report $\chi^2(k)$ statistics and p-values adjusting standard errors for nonnormality. Significance is indicated by: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

4

IS THE FINANCIAL SYSTEM SPECIAL? SYSTEMIC RISK IN FINANCIAL AND NONFINANCIAL FIRMS

ABSTRACT

This study analyzes whether systemic risk is a phenomenon unique to financial institutions or whether real sector firms may also engender a more broadly defined type of industry-wide distress risk. The sample is a set of 260 major U.S. financial and nonfinancial firms over the period from April 2002 through September 2016. Based on an empirical measure of systemic risk, the analysis confirms that systemic risk is generally much higher in the financial sector than in the nonfinancial sector. Over the full sample period, the expected present value of annual systemic losses averages USD 63 billion in the financial sample and USD 9 billion in the nonfinancial sample. Where systemic risk emerges in the nonfinancial sector, it appears to be driven by nonfinancial firms' engagement in financial services. These findings warrant close monitoring of nonfinancial firms' shadow-banking activities. Importantly, the results indicate that empirical measures appear to reflect systemic risk as defined in the traditional sense rather than a generic type of distress risk.

KEYWORDS:	Financial system, real economy, systemic risk, systemically important nonbank financial institution, shadow banking
JEL CLASSIFICATION:	G01, G17, G21, G23
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> *Systemic financial risk* is the risk that an event will trigger a loss of economic value or confidence in [...] a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy.
>
> —Group of Ten, 2001, emphasis in original

4.1 introduction

Systemic risk, although recognized long before the financial crisis of 2007–2009, has seen a tremendous increase in interest sparked by the events and adverse consequences of the crisis. Regulators, in an effort to strengthen financial stability, have since identified systemically important financial institutions. Researchers, in a quest to provide the toolkit for monitoring the buildup of systemic risk in financial markets, have devised empirical methodologies to measure such risk. Although there is no universally accepted definition of systemic risk, these efforts are typically guided by working definitions that require an impairment of the financial system. Such a definition is restrictive in the sense that it excludes the possibility of systemic risk beyond the financial system. Indeed, empirical measures of systemic risk have almost exclusively been applied to financial institutions, and little is known about the performance of these measures for real sector firms. This lack of knowledge leaves open the important question of whether empirical measures reflect systemic risk in the intended sense or whether they reflect a generic type of distress for any industry or set of firms they are applied to. Research on this issue is closely linked to the fundamental question of whether systemic risk is indeed limited to financial firms or whether it may also be caused by nonfinancial firms.

Systemic risk in financial institutions can be illustrated through the example of banks. These may be systemically risky for at least three reasons (see, e.g., Trichet, 2005). First, banks are likely to fail in times of crisis due to high degrees of leverage. To the extent that they engage in maturity transformation, liquidity risks, possibly exacerbated by runs, add to their vulnerability (see, e.g., Diamond and Dybvig, 1983). Second, turmoil in part of the banking sector may spill over to other, healthy firms through various channels of contagion. These channels may be direct, for example, through the interbank market, or indirect, for example, through similar portfolio exposures (see, e.g., Allen and Gale, 2000; Brunnermeier and Pedersen, 2009). Third, and most importantly, the distress or failure of banks is likely to exert negative externalities on the real economy. Such externalities may materialize when banks ration the supply of credit or engage in fire sales (see, e.g., Acharya et al., 2016).

These characteristics are arguably much less likely to be found in nonfinancial firms' core business (see, e.g., Brownlees and Engle, 2017). Nonfinancial firms are typically less leveraged, and they do not engage in maturity transformation as a central and inevitable part of their business models. Further, interconnectedness among nonfinancial firms is considerably less pronounced, as direct links should generally be limited to supplier–vendor relationships and cross-shareholdings. As nonfinancial firms' inventory of financial assets is usually small, the risk of fire-sale externalities should be minimal. Nevertheless, the bankruptcy of a large nonfinancial firm could still have repercussions for the wider economy through a rise in unemployment and a loss in consumer confidence.

Naturally, the argument changes when nonfinancial firms expand beyond the boundaries of their traditional businesses and engage in financial intermediation. Manufacturing firms, for example, often complement their product offerings with financing solutions, such as auto finance or equipment finance. The arguments for financial institutions also apply to financial subsidiaries of nonfinancial firms, which thus may be systemically risky. In the United States, the Financial Stability Oversight Council (FSOC) has recognized the potential systemic risk of such businesses as part of its efforts to identify systemically important nonbank financial institutions. To date, the council has designated a single nonbank, noninsurer financial firm, GE Capital, the financial services division of General Electric, as systemically important.[1] Three years after the firm was identified as a potential threat to U.S. financial stability in July 2013, however, its designation was rescinded in June 2016.

In summary, the informational content of empirical measures of systemic risk and the potential for such risks in real sector firms are not immediately obvious. In particular, two important interrelated questions require further research. First, do empirical measures of systemic risk pick up characteristics unique to financial institutions? Second, if these measures indicate economically relevant systemic risk in the nonfinancial sector, what causes such risk?

In this paper, I set out to shed light on these issues via an empirical analysis of systemic risk in the U.S. financial and nonfinancial industries. These industries are represented by a sample of 53 financial firms and 207 nonfinancial firms. Systemic risk is defined as the risk of catastrophic industry losses. To measure such risk, I employ the distress insurance premium (DIP) indicator proposed by Huang et al. (2009, 2012a,b). The analysis spans the period from April 2002 through September 2016, allowing to track systemic risk through three distinct crisis episodes: the aftermath of the bursting of the dot-com bubble in the early 2000s, the global financial crisis of 2007–2009, and the repercussions of the European sovereign debt crisis that peaked in 2011–2012.

An extensive literature has analyzed the systemic risk of U.S. financial firms using market data. Huang et al. (2009, 2012b), Adrian and Brunnermeier (2016), Acharya et al. (2017), Brownlees and Engle (2017), and many others have analyzed contemporaneous systemic risk in the U.S. financial system. Billio et al. (2012) and Chen et al. (2014) have analyzed the lead–lag relationships between U.S.-listed financial institutions. Although the financial sector is included in the sample analyzed in the present paper, it is not the primary focus of the analysis.

1 Apart from GE Capital, the FSOC has designated three insurers as systemically important nonbank financial institutions: American International Group, MetLife, and Prudential Financial.

Instead, financial firms serve as a point of reference against which the level of systemic risk in nonfinancial firms is evaluated.

Compared to the vast literature on systemic risk in financial institutions, little research has been conducted on potential systemic risks in real sector firms. Of the very few analyses available, Brownlees and Engle (2017) provide evidence that the nonfinancial sector suffered much less from increasing capital shortfalls during the financial crisis than the financial sector did. Moreover, financial firms' distress is found to provide an early warning of future declines in macroeconomic activity, whereas nonfinancial firms' distress is much less predictive of future macroeconomic downturns. Similarly, Allen et al. (2012) find that financial firms' systemic risk predicts macroeconomic distress about half a year into the future, whereas nonfinancial firms' systemic risk has no marginal predictive power.

Another branch of the literature is concerned with the interdependency of the financial system and the real sector. Distress in the financial system may lead to recessions, and vice versa, distress in the real sector may engender financial crises (Kaserer and Lahmann, 2012; Trapp and Wewel, 2013). On the one hand, as financial institutions come under stress, they may ration the amount of credit available to nonfinancial firms and thus constrain operating and capital expenditures. On the other hand, as nonfinancial firms experience economic difficulties, the credit quality of lending financial institutions deteriorates. Kaserer and Lahmann (2012) analyze the interconnectedness of regional banking and nonbanking sectors using credit default swap (CDS) spreads and equity returns. For the period of the financial crisis, the authors find that variations in the banking sector's CDS spreads tend to cause variations in the nonbanking sectors' CDS spreads rather than vice versa. The opposite relationship is observed for the sectors' equity returns. Trapp and Wewel (2013), however, find that the upper tail dependence of financial and nonfinancial firms' CDS spreads is limited. In fact, these authors argue that economic downturns are caused by the default of a large nonfinancial firm rather than by the failure of a major bank.

Relative to this literature, I contribute to a better understanding of the distress potential in the overall economy by analyzing systemic risk in the nonfinancial sector. I explore the time series of aggregate systemic risk at the sector level and the cross section of individual systemic importance at the firm level. To the best of my knowledge, the present paper provides the first analysis of nonfinancial firms' actual systemic risk contributions. Importantly, my analysis enables me to disentangle the interdependent issues regarding whether empirical indicators measure systemic risk as it is traditionally defined and whether there is systemic risk in the nonfinancial sector.

The empirical analysis confirms that overall, the financial sector is much more vulnerable to widespread losses than the nonfinancial sector. At the height of the financial crisis, however, both sectors experience similar levels of relative distress. Furthermore, on the firm level, a small set of nonfinancial firms exhibits similar systemic risk contributions as the riskiest financial firms. Importantly, whereas these results are seemingly only partially consistent with the earlier argument on financial and nonfinancial firms, systemic risk in the nonfinancial sector can largely be traced to nonfinancial firms' engagement in financial services. In summary, the key findings are twofold. First, well-designed empirical measures of systemic risk are indeed indicators of true systemic risk rather than of generic distress risk. Second, large nonfinancial firms' engagement in financial services may engender sizable systemic risk contributions. These findings have important policy implications for the measurement and regulation of systemic risk. To complement the present assessment methodologies, regulators should include empirical measures in systemic risk assessments. Furthermore, to capture all potential sources of financial instability, regulators should continue to scrutinize the shadow-banking activities of nonfinancial firms.[2]

The remainder of this paper proceeds as follows. Section 4.2 implements the modeling framework, and Section 4.3 introduces the data. Section 4.4 analyzes systemic risk in the financial and nonfinancial sectors. Section 4.5 elaborates on the policy and analysis implications and offers concluding remarks.

4.2 MODELING FRAMEWORK

I define and measure systemic risk in the financial and nonfinancial sectors using the DIP framework of Huang et al. (2009, 2012a,b). In this framework, systemic crises are triggered by the simultaneous default of a sizable portion of a given sector's liabilities. The aggregate level of systemic risk in the sector is represented by the premium of a hypothetical insurance policy that protects individual firms' creditors against distressed losses during a systemic crisis. The systemic importance of an individual firm then corresponds to its marginal contribution to this insurance premium.[3]

DIP indicators have been employed in a number of recent studies on systemic risk and contagion in the financial system (see, e.g., Huang et al., 2009, 2012a,b; Lahmann and Kaserer, 2011; Chen et al., 2014; Black et al., 2016). In this section, I describe my implementation.[4]

4.2.1 *Implementing the Systemic Risk Measure*

For a formal representation of the aggregate and marginal DIP indicators, consider a portfolio of liabilities of firms $i \in \{1, \dots, N\}$. Let $L_{i,t}$ denote the

2 The FSB (2017, p. 6) defines shadow banking as "credit intermediation involving entities and activities (fully or partially) outside the regular banking system." Note that shadow banking may be undertaken by nonbank financial firms and by nonfinancial firms.

3 Alternative systemic risk measures include CoVaR by Adrian and Brunnermeier (2016), marginal expected shortfall by Acharya et al. (2017), and SRISK by Brownlees and Engle (2017). For a comprehensive review of systemic risk measures, see Bisias et al. (2012).

4 The exposition closely follows Kaserer and Klein (2018). The main difference between the modeling framework implemented in their study and the implementation used in my study is that Kaserer and Klein (2018) estimate the asset return correlations from CDS spreads, whereas I follow Huang et al. (2009, 2012a,b) and estimate the correlations from equity returns.

marginal loss of firm i at time t, and let L_t denote the aggregate loss across all firms. Following Huang et al. (2009), the portfolio's aggregate level of systemic risk is measured as the expected present value of portfolio losses in excess of a systemic loss threshold, SLT:

$$DIP_t(h) = E^Q\left(L_{t+h} \cdot \mathcal{I}\left(L_{t+h} > SLT\right)\right) \cdot e^{-r_t h}. \tag{4.1}$$

Q denotes the risk-neutral measure, r_t is the risk-free rate, and h is the risk horizon. I define $\mathcal{I}(x) = 1$ if condition x is true and 0 otherwise.

The aggregate level of systemic risk can be allocated to the individual firms in the portfolio in an additive fashion. Following Huang et al. (2012a,b), the marginal contribution of firm i to the total level of systemic risk amounts to:

$$DIP_{i,t}(h) = E^Q\left(L_{i,t+h} \cdot \mathcal{I}\left(L_{t+h} > SLT\right)\right) \cdot e^{-r_t h}. \tag{4.2}$$

As in the Merton (1974) model, I assume that individual firms default if their asset values fall short of a minimum solvency requirement. In the case of default, creditors recover a fraction of their claims as determined by the firms' recovery rates, and the unrecoverable liabilities contribute to the portfolio's aggregate loss. I introduce dependence among the default of individual firms by modeling their standardized asset returns over the period between time t and $t + h$ by the usual multi-factor model:

$$R_{i,t:t+h} = F_i\, Y_{t:t+h} + \sqrt{1 - F_i F_i^{\top}}\, Z_{i,t:t+h}, \tag{4.3}$$

where $Y_{t:t+h} = \left[Y_{1,t:t+h}, \ldots, Y_{M,t:t+h}\right]^{\top}$ are M systematic risk factors common to all firms, $Z_{i,t:t+h}$ is an idiosyncratic risk factor specific to firm i, and $F_i = [F_{i,1}, \ldots, F_{i,M}]$, $F_i F_i^{\top} \leqslant 1$, are the common factor loadings. All risk factors are assumed to be standard normally distributed and mutually independent.

I implement the DIP indicators using Monte Carlo methods. First, in an outer loop of the simulation, I determine default scenarios, that is, which firms default and survive. Then, in an inner loop of the simulation, I determine recovery rate scenarios for defaulted firms by sampling recovery rates from beta distributions.[5] The outer simulation loop generates 500,000 default scenarios, and the inner simulation loop draws 100 recovery rate realizations. Naturally, systemic events are rarely observed. To enhance the efficiency of the estimators in the rare-event simulation of systemic losses, I employ the mean-shifting importance sampling procedure of Glasserman and Li (2005) and Glasserman (2005).

4.2.2 *Estimating the Credit Risk Parameters*

I base my analysis on market-implied credit risk parameters. Following Huang et al. (2009, 2012a,b), I estimate the probabilities of default from CDS spreads

5 For a defaulted firm i, the realized recovery rates are drawn from a $\text{Beta}\left(\alpha_{i,t}, \beta_{i,t}\right)$ distribution with a mean matching the expected recovery rate and $\alpha_{i,t} > 0$, $\beta_{i,t} > 0$ such that $\alpha_{i,t} + \beta_{i,t} = 10$.

and the asset return correlations from equity returns.

PROBABILITIES OF DEFAULT CDSs offer protection against credit events, that is, the risk that a firm will default on its debt. This protection is extended in exchange for periodic spread payments. CDS spreads have been found to provide clearer and more timely signals of credit risk than other debt market indicators (see, e.g., Hull et al., 2004; Longstaff et al., 2005; Zhu, 2006; Norden and Wagner, 2008). I expect this informational advantage to benefit the empirical risk measures.

I estimate *risk-neutral* probabilities of default from CDS spreads using the reduced-form valuation framework described in the literature (see, e.g., Hull and White, 2000; Tarashev and Zhu, 2008). Under no-arbitrage, the expected present value of the protection buyer's spread payments (the left-hand side of Equation (4.4)) initially equals the expected present value of the protection seller's default loss payment (the right-hand side of the equation):

$$\int_t^{t+T} s_{i,t} e^{-r_\tau(\tau-t)} \bar{q}_{i,\tau} d\tau = \int_t^{t+T} \left(1 - RR_{i,t}^{CDS}\right) e^{-r_\tau(\tau-t)} q_{i,\tau} d\tau. \tag{4.4}$$

$RR_{i,t}^{CDS} \in [0,1]$ is the time-t expectation of the recovery rate on the debt referenced in the CDS, $s_{i,t}$ is the annual spread, $q_{i,\tau}$ is the risk-neutral default intensity, $\bar{q}_{i,\tau} = 1 - \int_t^\tau q_{i,\nu} d\nu$ is the associated risk-neutral probability of survival up to time τ, and T is the tenor of the contract. As in Tarashev and Zhu (2008, p. 8), I solve for the 1-year risk-neutral probability of default under the common simplifying assumptions that the term structures of the risk-free rate and the default intensity are flat, $r_\tau = r_t$ and $q_{i,\tau} = q_{i,t}$ for all $\tau \in [t, t+T]$:

$$q_{i,t} = \frac{a s_{i,t}}{a(1 - RR_{i,t}^{CDS}) + b s_{i,t}}, \tag{4.5}$$

where $a = \int_t^{t+T} e^{-r_t(\tau-t)} d\tau$ and $b = \int_t^{t+T} (\tau - t) e^{-r_t(\tau-t)} d\tau$.

ASSET RETURN CORRELATIONS Following Huang et al. (2009), I estimate *physical* asset return correlations from equity return correlations:

$$\begin{aligned} \rho_{ij} &= \operatorname{corr}\left(R_{i,t:t+h}, R_{j,t:t+h}\right) \\ &\approx \operatorname{corr}\left(\Delta \ln E_{i,t}, \Delta \ln E_{j,t}\right). \end{aligned} \tag{4.6}$$

Δ is the first difference in discrete time, and $E_{i,t}$ denotes firm i's equity value at time t. Note that, under the assumption of constant leverage, the approximation in the second line is exact in a Merton (1974) setting; see Huang et al. (2009, Appendix A) for a proof. Based on Equation (4.6), I first estimate nonparametric pairwise correlations. These are then fitted to the factor model of Equation (4.3) using the principal factors method of Andersen et al. (2003).

4.3 EMPIRICAL DATA

The sample is a set of large U.S.-listed firms. I select all firms with a market capitalization of at least USD 10 billion at the end of June 2007 and sufficient data availability for an individual sample period of at least 2 years during the period from April 2002 through September 2016.

I obtain daily equity return and market capitalization data from the Center for Research in Security Prices (CRSP) database and quarterly financial statements data from Compustat. CDS data for 5-year senior unsecured contracts are available from Markit at daily frequency. I aggregate the daily CDS spreads to weekly frequency and use linear interpolation within fiscal quarters to compute weekly portfolio weights from the firms' quarterly total liabilities. The resulting sample is an unbalanced panel as data availability differs across firms. Firms naturally exit the sample once they experience a credit event. Appendix 4.A gives a complete account of the data sources and definitions.

I split the sample into a set of financial firms and a set of nonfinancial firms. The financial sample covers the industries *banking*, *financial services*, *insurance*, and *others*. The nonfinancial sample covers the industries *oil and gas*, *manufacturing*, *retail*, *service and leisure*, *media and communications*, *transportation*, and *utilities*.[6] For ease of reference, Appendix 4.B lists the names and tickers of all firms.

4.3.1 *Data Set*

Table 4.1 shows summary statistics on the samples' size, market capitalization, and liabilities. There are 53 firms in the financial sample and 207 firms in the nonfinancial sample. At the end of June 2007, the financial firms' market capitalization totals USD 2,900 billion, and the nonfinancial firms' market capitalization totals USD 9,084 billion. Collectively, the financial and nonfinancial samples account for 69 percent of the U.S. market capitalization covered by CRSP.[7]

Based on financial statements data current as of June 2007, the average financial firm has total liabilities with a book value of USD 323 billion. Nonfinancial firms are substantially smaller, averaging USD 23 billion. The largest financial firms

6 Mergent's Fixed Income Securities Database industry codes are used to assign firms to sectors. To align the definition of financial and nonfinancial firms with the Standard Industry Classification scheme frequently used in other empirical studies of systemic risk in U.S. financial firms (see, e.g., Adrian and Brunnermeier, 2016; Acharya et al., 2017; Brownlees and Engle, 2017), I make a limited number of adjustments to the original classification. First, Automatic Data Processing, originally classified under financial services, and First Data, originally classified under credit and financing, are reassigned to service and leisure. Second, Western Union, classified under media and communications, is reassigned to financial services, and UnitedHealth, classified under service and leisure, is reassigned to insurance. Some of the resulting financial and nonfinancial industries include very few firms, and therefore, I consolidate such industries as follows. In the financial sample, CIT Group, the only firm remaining in the industry credit and financing, and Fannie Mae and Freddie Mac, classified under U.S. agencies, are allocated to others. In the nonfinancial sample, telephone is merged into media and communications, and railroad is merged into transportation.

7 CRSP covers securities whose primary listing is on NYSE, NYSE MKT, NASDAQ, and Arca.

TABLE 4.1: Sample size, market capitalization, and liabilities

		Market cap.[a]		Liabilities[b]			
Sample	N	Mean	Sum	Min	Mean	Max	Sum
Financial firms	53	55	2,900	2	323	2,093	17,115
Banking	15	61	912	38	352	1,399	5,285
Financial services	15	53	795	2	460	2,093	6,897
Insurance	20	54	1,079	10	162	920	3,241
Others	3	38	114	78	564	818	1,691
Nonfinancial firms	207	44	9,084	1	23	614	4,681
Oil & gas	16	69	1,109	1	27	112	433
Manufacturing	106	47	4,953	1	24	614	2,495
Retail	20	37	748	3	16	93	310
Service & leisure	22	32	711	2	16	66	358
Media & communications	14	67	941	2	34	156	480
Transportation	7	28	197	8	16	22	114
Utilities	22	19	424	6	22	36	490

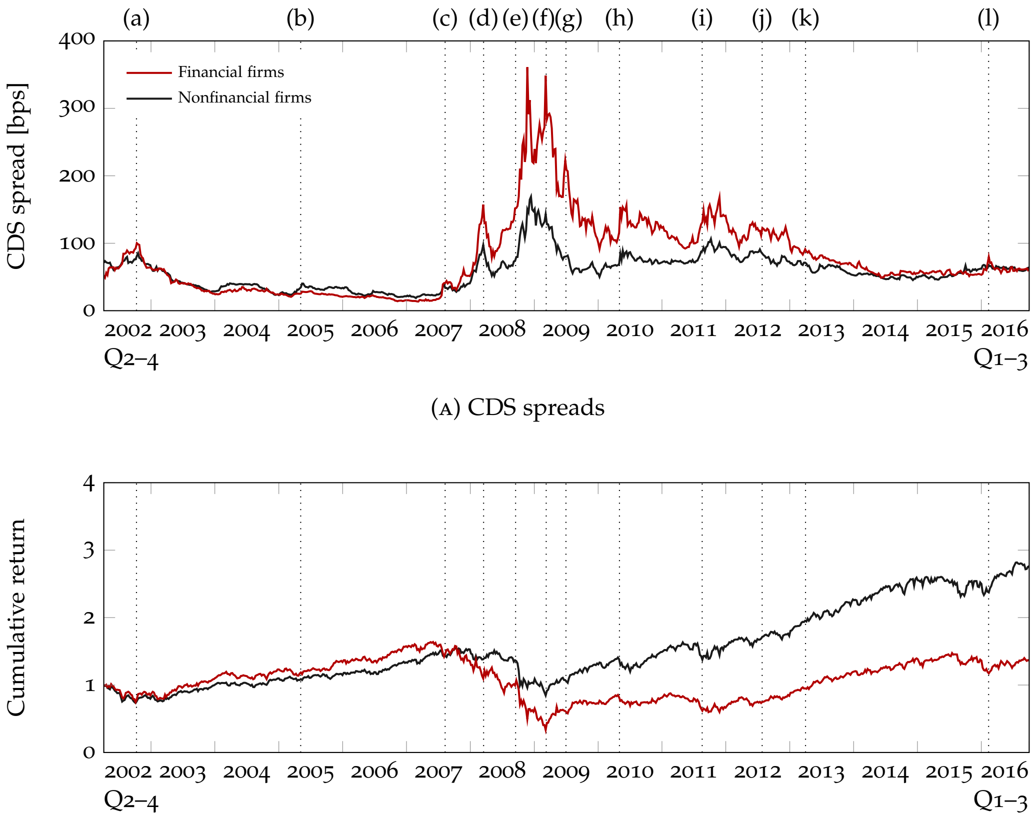
[a] Market capitalization at the end of June 2007 in USD billion.
[b] Book value of total liabilities at the end of June 2007 in USD billion.

by total liabilities are Citigroup (USD 2,093 billion), Bank of America (USD 1,399 billion), and JPMorgan Chase (USD 1,339 billion). The largest nonfinancial firms are General Electric (USD 614 billion), Ford (USD 280 billion), and General Motors (USD 189 billion). Financial firms owe a total of USD 17,115 billion, and nonfinancial firms owe a total of USD 4,681 billion.

Figure 4.1 illustrates the dynamics of the CDS spreads and the equity returns of the firms in the sample. Figure 4.1a shows the median CDS spread for the financial and nonfinancial samples, and Figure 4.1b shows the samples' cumulative total return over the sample period, indexed to the beginning of the sample period. Both samples experience relatively similar levels of credit risk in the early and late stages of the sample period, although the nonfinancial firms' CDS spreads tend to be slightly higher than the financial firms' CDS spreads in the years immediately preceding the financial crisis. During the financial crisis, however, the financial and nonfinancial firms' credit risk diverges. Financial firms' CDS spreads peak substantially higher than nonfinancial firms' CDS spreads. This wedge in the samples' credit risk persists throughout the ensuing European sovereign debt crisis.

The samples' cumulative total returns tell a similar story. Over the years preceding the financial crisis, the financial sample slightly outperforms the nonfinancial sample, only to drop more severely during the financial crisis. After the crisis period, the nonfinancial sample recovers more quickly than the financial sample. At the end of the sample period, the financial return index still has not recovered to its pre-crisis level, whereas the nonfinancial return index has appreciated markedly relative to its pre-crisis high.

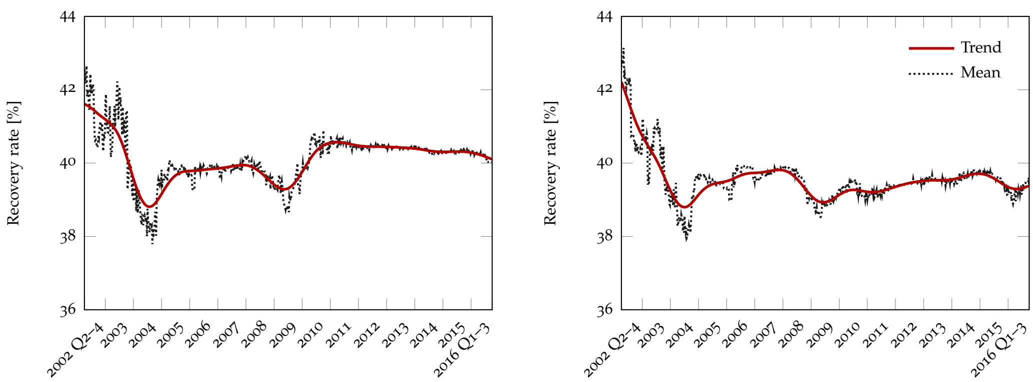
Whereas there is significant variation in the sample firms' CDS spreads over the sample period, market participants' *ex ante* expectation of the corresponding recovery rates exhibits relatively limited variation in the long run; see Figure 4.2.



(A) CDS spreads

(B) Equity returns

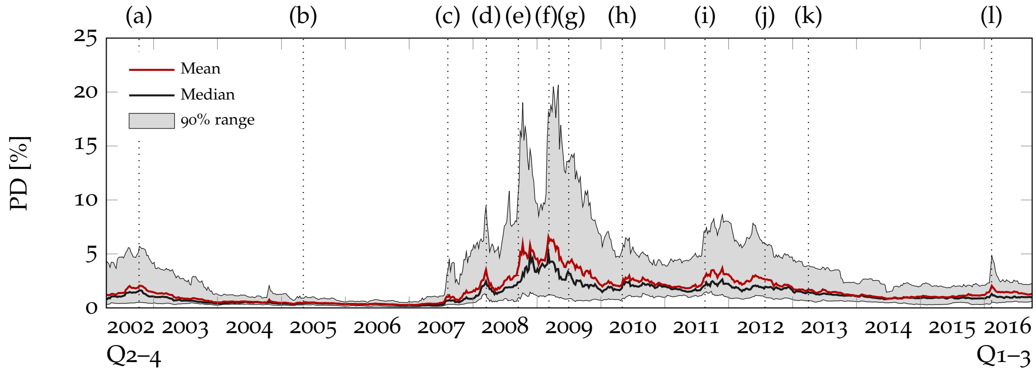
FIGURE 4.1: CDS spread and equity return dynamics
This figure shows the sample firms' CDS spread and equity return dynamics. The upper panel shows median spreads for 5-year senior unsecured CDS contracts. The lower panel shows cumulative total returns over the sample period, weighted by the firms' market capitalization and indexed to the beginning of the sample period. The vertical lines represent the following events: (a) U.S. stock market dot-com crisis low, (b) General Motors and Ford downgrade, (c) BNP Paribas funds freeze, (d) Bear Stearns takeover, (e) Lehman Brothers failure, (f) U.S. stock market financial crisis low, (g) U.S. leaves recession, (h) first support package for Greece agreed upon, (i) global stock markets fall on uncertainty over world economic outlook, (j) Mario Draghi's "whatever it takes" speech, (k) euro area leaves recession, and (l) global stock markets fall and concerns over European banks rise.



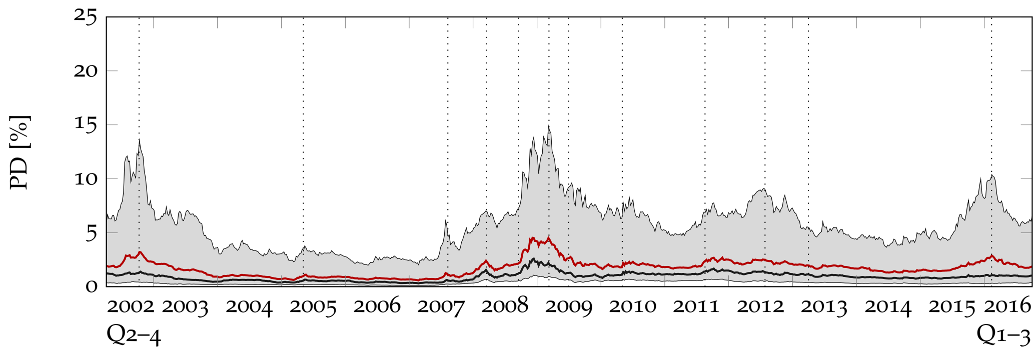
(A) Financial firms

(B) Nonfinancial firms

FIGURE 4.2: Recovery rates on senior unsecured debt
This figure shows the expected recovery rate used by market participants when pricing senior unsecured CDS contracts. The trend components are extracted using a Hodrick–Prescott filter.



(A) Financial sample



(B) Nonfinancial sample

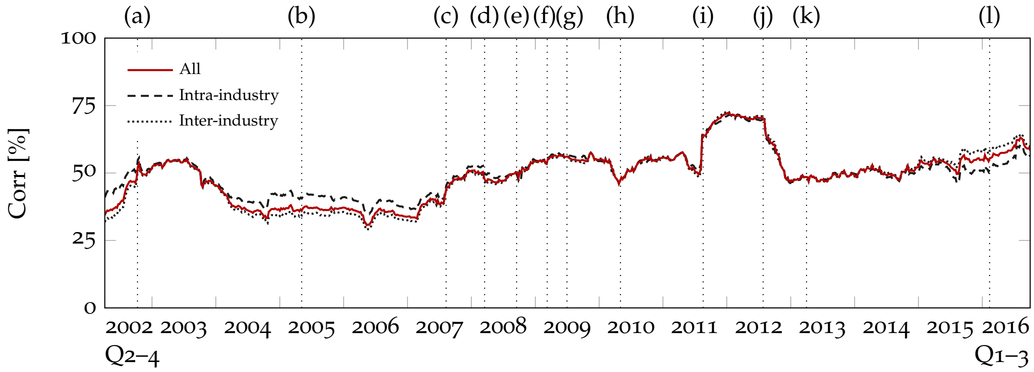
FIGURE 4.3: Probabilities of default by sample
This figure shows 1-year risk-neutral probabilities of default for the financial and nonfinancial samples. The risk-neutral probabilities of default are calculated at weekly frequency from 5-year senior unsecured CDS spreads. The vertical lines represent the same events as those in Figure 4.1.

To eliminate noisy movements in the data, I extract the trend components using a Hodrick–Prescott filter. Overall, the recovery rates average 40.1 percent for the financial firms and 39.6 percent for the nonfinancial firms.[8]

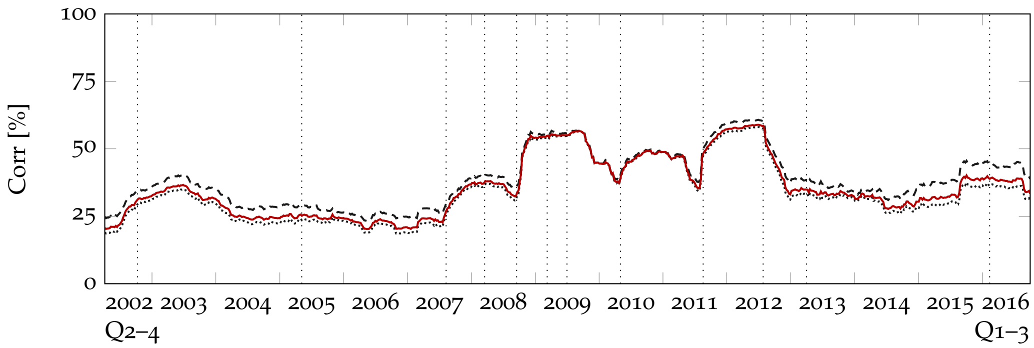
4.3.2 *Model Estimation*

The set of credit risk parameters for the individual firms in the sample includes risk-neutral probabilities of default, asset return correlations, and recovery rates for default scenarios. I estimate weekly time series of 1-year risk-neutral probabilities of default from the CDS spreads and the corresponding recovery rates described in the previous section. Figure 4.3 shows plots of the resulting default probabilities. I report the mean, median, lower 5 percent quantile, and upper 5 percent quantile for the financial and nonfinancial samples. The median default probabilities reflect the time-series and cross-sectional variation of the

8 Whereas the actual recovery rates for individual defaults may deviate significantly from the expected recovery rates, the average *ex ante* expected recovery rates used in this study are in line with average *ex post* observed recovery rates reported in the literature. Averaging recovery rates across bond seniorities, Jankowitsch et al. (2014) report realized recovery rates of 38.8 percent for U.S. financial firms and 38.5 percent for U.S. nonfinancial firms.



(A) Financial sample



(B) Nonfinancial sample

FIGURE 4.4: Asset return correlations by sample
This figure shows the average of pairwise asset return correlations for the financial and nonfinancial samples. For each firm, pairwise correlations are calculated between the firm and all other firms in the respective sample (*all correlations*), between the firm and all other firms from the same industry (*intra-industry correlations*), and between the firm and all firms from a different industry in the same sample (*inter-industry correlations*). The correlations are calculated at weekly frequency from daily equity returns using a rolling window of 1 year. The vertical lines represent the same events as those in Figure 4.1.

median CDS spreads. The financial sample accounts for the most severely distressed firms during the financial crisis, and the nonfinancial sample accounts for the most severely distressed firms during the early and late stages of the sample period. Indeed, in the aftermath of the bursting of the dot-com bubble in the early 2000s and around the global stock market decline in early 2016, the most distressed nonfinancial firms exhibited levels of default risk resembling those observed during the financial crisis.

I further estimate weekly asset return correlations using a rolling window of 1 year of daily equity returns. Figure 4.4 shows plots of the resulting asset return correlations. For each firm, I compute the average asset return correlation between the firm and all other firms in the respective sample (*all correlations*), between the firm and all other firms from the same industry (*intra-industry correlations*), and between the firm and all firms from different industries in the same sample (*inter-industry correlations*). The figure shows the mean of these pairwise correlations for the financial and nonfinancial samples. For both samples, crisis periods are marked by bumps in the correlation time series, whereas the correlations decline in periods of relative tranquility. Financial firms exhibit higher correlations than nonfinancial firms for most of the sample period. Overall, the financial firms' correlations average 49 percent, and the nonfinancial firms' correlations average 36 percent. Almost throughout the sample period for the nonfinancial firms, and for most of the sample period for the financial firms, intra-industry correlations are higher than inter-industry correlations.

The third parameter estimate is the expected recovery rate on defaulted firms' debts. To proxy for this recovery rate, I use the sector-specific expected recovery rates on senior unsecured debt reported in Figure 4.2.

4.4 findings on systemic risk

This section analyzes systemic risk in the U.S. financial and nonfinancial sectors. The analysis is divided into three parts. In the first part, I analyze the aggregate level of systemic risk in the financial system and the real sector. In the second part, I analyze the individual systemic importance of financial and nonfinancial firms. Finally, I evaluate alternative model specifications.

For the purpose of empirical illustration, I define systemic events as a loss in aggregate sector liabilities of more than 15 percent over a 1-year horizon. All risk measures are reported at weekly frequency to closely track systemic risk over the sample period.

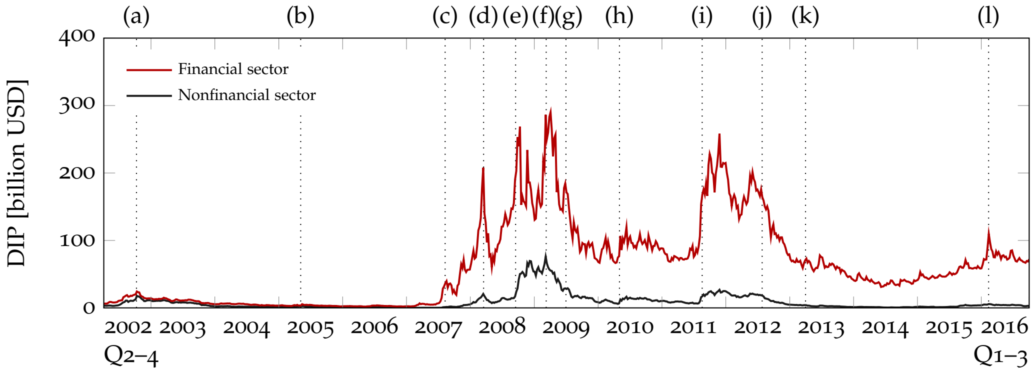
4.4.1 *Aggregate Systemic Risk*

In this section, I consider the aggregate systemic risk in the financial and nonfinancial sectors. I first study the time series of systemic risk over the sample period. I then analyze the marginal contribution of individual industries to aggregate financial and nonfinancial systemic risk.

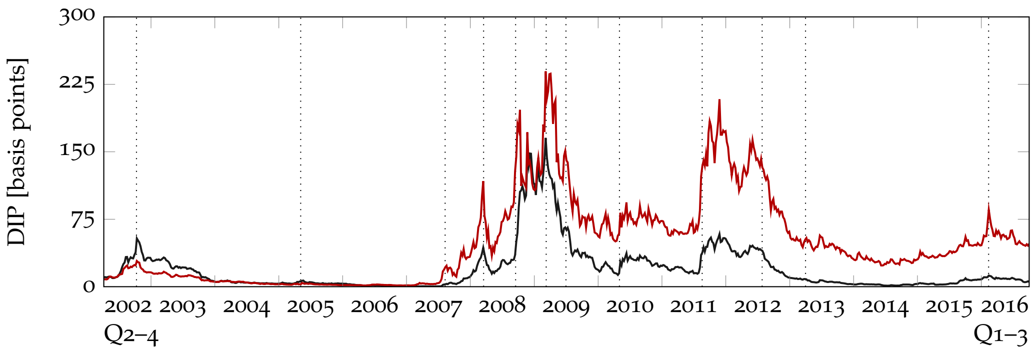
4.4.1.1 *Time Series of Systemic Risk*

Figure 4.5 shows plots of the time series of systemic risk in the financial and nonfinancial sectors. Systemic risk in both sectors is measured by the DIP indicator, defined as the premium of a hypothetical insurance contract protecting creditors against systemic losses. This premium is reported in nominal price expressed in U.S. dollars in Figure 4.5a and in unit price relative to aggregate total liabilities in Figure 4.5b. The nominal price of systemic risk reflects the difference in the sectors' liability sizes, whereas the unit price refers to the systemic risk per unit of exposure. Therefore, the unit price measure compares the sectors' level of distress on a common and uniform scale.

As a first impression, industry-wide distress risk is apparently not confined to the financial sector but is also present in the nonfinancial sector, although to a lesser degree. Financial and nonfinancial systemic risk follows a similar trajectory



(A) DIP indicator in nominal price



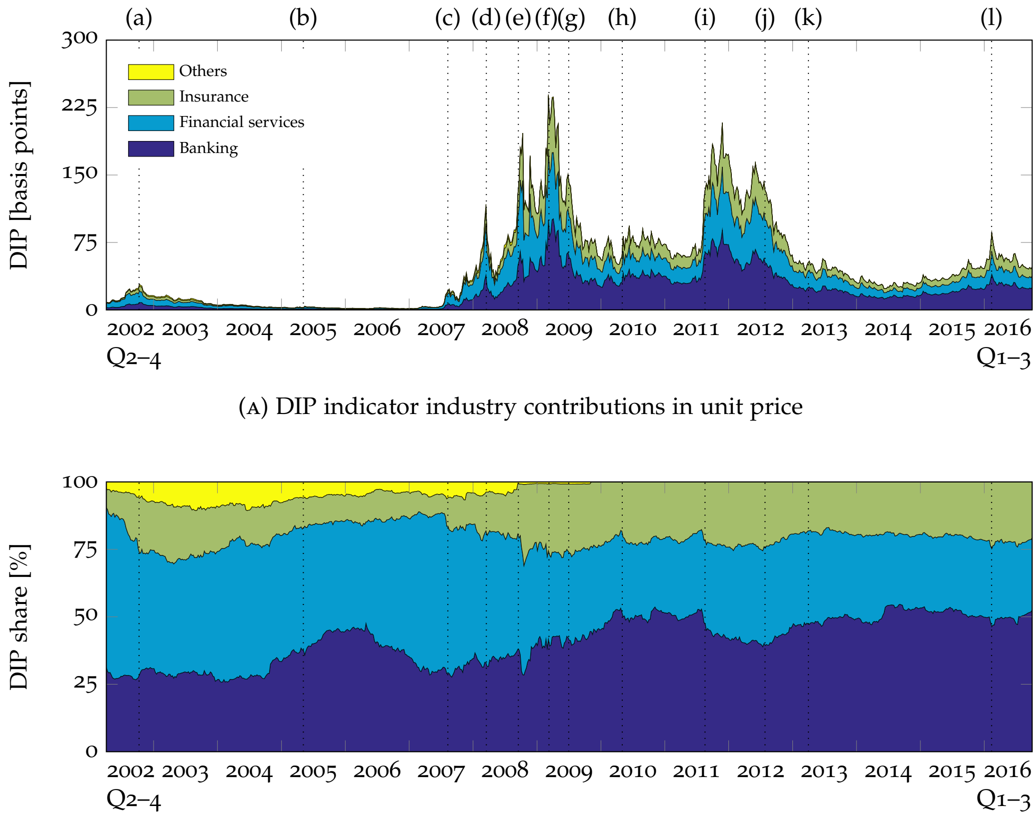
(B) DIP indicator in unit price

FIGURE 4.5: Systemic risk in the financial and nonfinancial sectors
This figure shows the level of systemic risk in the financial and nonfinancial sectors. Systemic risk is measured using the DIP indicator. This indicator is reported in nominal price in the upper panel and in unit price relative to aggregate total liabilities in the lower panel. The vertical lines represent the same events as those in Figure 4.1.

and peaks around the same events. Whereas the systemic risk indicators for the financial and nonfinancial sectors exhibit important commonalities, overall, they reflect different levels of concern. Nonfinancial systemic risk, on average, is much lower than financial systemic risk under both measures. Over the full sample period, financial systemic risk averages USD 63 billion, or 49 basis points, and nonfinancial systemic risk averages USD 9 billion, or 19 basis points.

The absolute systemic risk in the financial sector consistently dominates the absolute systemic risk in the nonfinancial sector. The sectors' ranking by relative systemic risk, however, varies over the different crisis episodes during the sample period. During the repercussions of the dot-com crisis, the nonfinancial sector mostly appears more distressed per unit of exposure than the financial sector. Both sectors' relative systemic risk peaks for the week of October 11, 2002, just as U.S. stock markets reached their lowest point in the early 2000s. For this week, nonfinancial systemic risk stands at 54 basis points (USD 18 billion), higher than financial systemic risk, which reaches 29 basis points (USD 24 billion).

The financial crisis mostly sees higher relative systemic risk in the financial sector than in the nonfinancial sector, although both sectors exhibit similar levels



(A) DIP indicator industry contributions in unit price

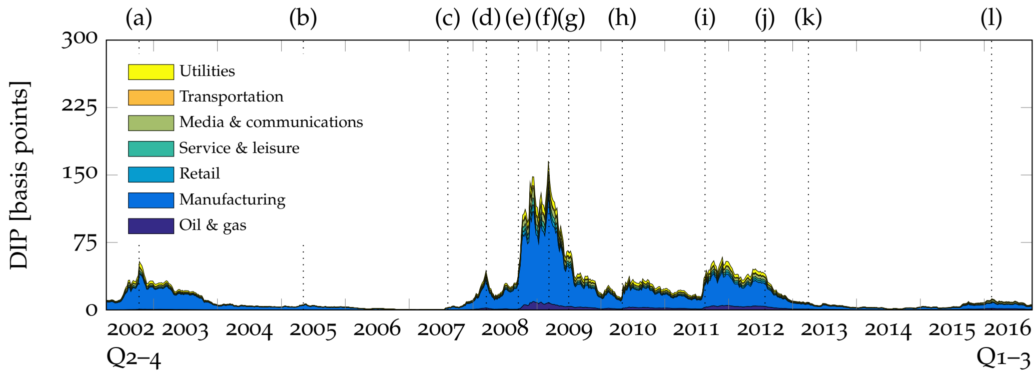
(B) DIP indicator industry contributions as share of total

FIGURE 4.6: Financial sector systemic risk by industry
This figure shows the level of systemic risk in the financial sector by industry. Systemic risk is measured using the DIP indicator. The industry contributions to this indicator are shown in unit price in the upper panel and as shares of total systemic risk in the lower panel. The vertical lines represent the same events as those in Figure 4.1.

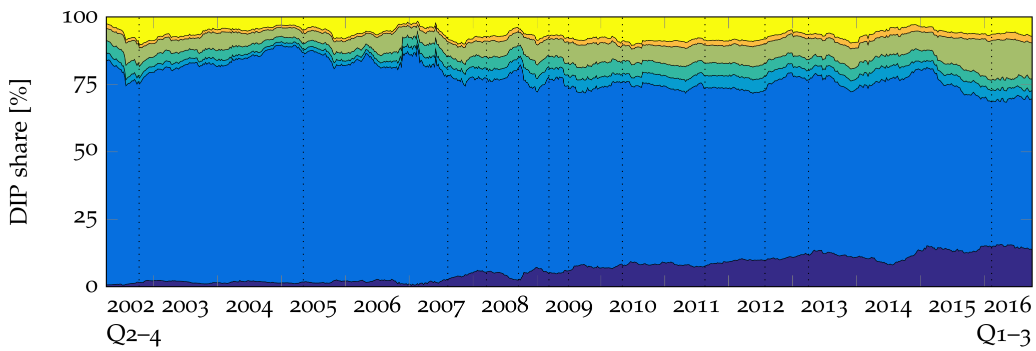
of relative systemic risk in the aftermath of the demise of Lehman Brothers in mid-September 2008. Relative systemic risk reaches its highest levels in both sectors around the time of the U.S. financial crisis stock market low. The financial sector's systemic risk peaks at 239 basis points (USD 286 billion) for the week of March 6, 2009, immediately before the stock market low. The nonfinancial sector's systemic risk peaks at 165 basis points (USD 76 billion) for the same week. During the European sovereign debt crisis, and throughout the remaining sample period, relative systemic risk continues to be higher in the financial sector than in the nonfinancial sector.

4.4.1.2 *Sector Contributions*

For a given level of systemic risk in the financial and nonfinancial sectors, an interesting objective is to trace the origins of distress, that is, to identify the industries and firms that contribute most to systemic risk. I explore the industry contributions to financial and nonfinancial systemic risk below and investigate the systemic importance of individual firms in Section 4.4.2.



(A) DIP indicator industry contributions in unit price



(B) DIP indicator industry contributions as share of total

FIGURE 4.7: Nonfinancial sector systemic risk by industry
This figure shows the level of systemic risk in the nonfinancial sector by industry. Systemic risk is measured using the DIP indicator. The industry contributions to this indicator are shown in unit price in the upper panel and as shares of total systemic risk in the lower panel. The vertical lines represent the same events as those in Figure 4.1.

Figure 4.6 shows the contributions of the different financial industries to systemic risk in the financial sector. Over the full sample period, banking, on average, accounts for 41 percent of systemic risk in the financial sector, financial services for 38 percent, insurance for 18 percent, and others for 3 percent. Interestingly, the relative importance of these industries changes over time. Whereas financial services tends to be the largest contributor to systemic risk in the first half of the sample period, banking consistently contributes the most in the second half. Furthermore, the relative importance of the insurance industry appears to increase during the financial crisis.

Figure 4.7 shows the contributions of the different nonfinancial industries to systemic risk in the nonfinancial sector. Manufacturing is, by far, the largest contributor to systemic risk in the nonfinancial sector, on average accounting for 71 percent of total systemic risk. Media and communications, on average, accounts for 7 percent, oil and gas for another 7 percent, and utilities for 6 percent. The other industries—service and leisure, retail, and transportation—collectively account for 9 percent. As in the financial sector, the industry shares change over time. The relative importance of the manufacturing industry gradually declines over the sample period, whereas, in particular, the contribution of the oil and gas industry increases. Toward the end of the sample period, the contribution of the media and communications industry also increases; however, this development takes place when the aggregate level of systemic risk in the nonfinancial sector is very low.

4.4.2 *Individual Systemic Importance*

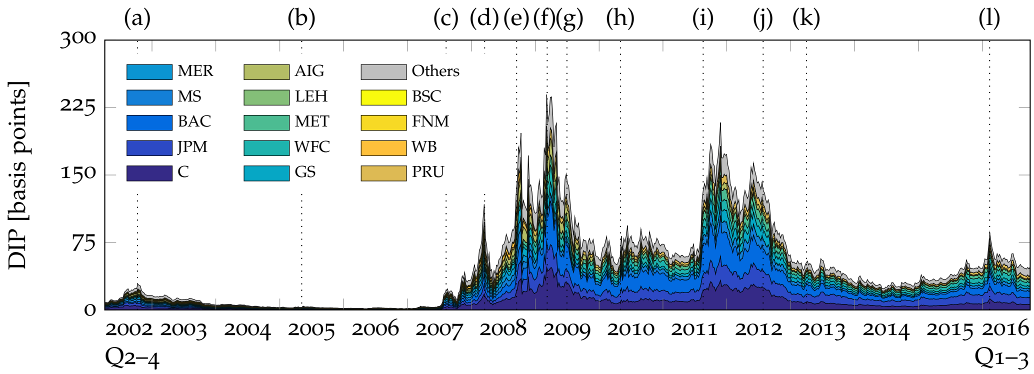
In this section, I analyze the systemic importance of individual firms in the financial and nonfinancial sectors. I first provide a descriptive analysis of the firms' systemic risk rankings and investigate their systemic importance over the sample period. Next, I explore which firm characteristics predict individual firms' systemic risk contributions.

4.4.2.1 *Systemic Risk Rankings*

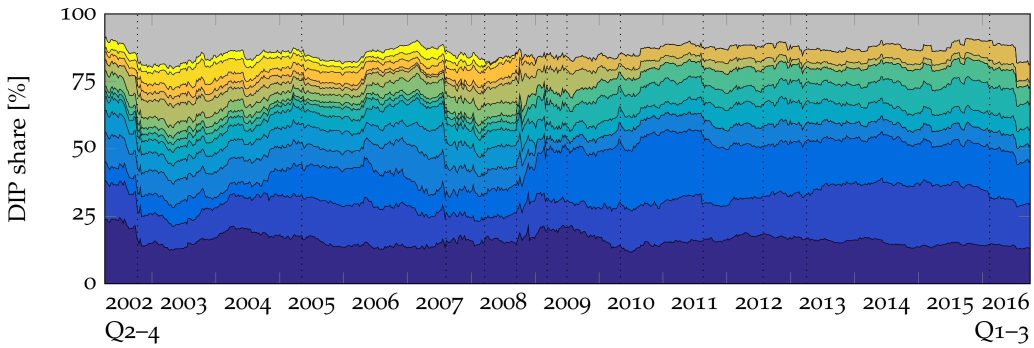
Individual firms' systemic importance can be analyzed in a similar fashion as individual industries' contributions to systemic risk. Figure 4.8 shows the financial firms' marginal contributions to systemic risk in the financial sector, and Figure 4.9 shows the nonfinancial firms' marginal contributions to systemic risk in the nonfinancial sector.

Ranking firms by their marginal contributions over their respective sample periods, Citigroup, JPMorgan Chase, and Bank of America emerge as the most systemically risky firms in the financial sample. General Electric, General Motors, and Ford rank as the most systemically risky firms in the nonfinancial sample. Interestingly, the level of risk concentration in the two samples follows opposite trends. In the period preceding the failure of Lehman Brothers, systemic risk in the nonfinancial sector is highly concentrated in the three riskiest firms. During that period, General Electric, General Motors, and Ford account for 69 percent of the nonfinancial sector's systemic risk, whereas the three riskiest financial firms account for a notably smaller fraction, 38 percent, of the systemic risk in the financial sector. In the aftermath of the failure of Lehman Brothers, marginal risk contributions in the nonfinancial sector become more fragmented, whereas the concentration of systemic risk tends to increase in the financial sector.

The outsized contribution of General Electric, General Motors, and Ford to systemic risk in the nonfinancial sector points to an important commonality in these firms' business models. During the sample period, each firm engaged not only in manufacturing activities but also in financial services: General Electric through its subsidiary GE Capital, General Motors through GMAC, and Ford through Ford Credit. Each subsidiary accounted for a sizable share of the respective parent firm's consolidated balance sheet. Indeed, the systemic risk contributions of the parent firms are likely driven by the financial services subsidiaries, rather than by the firms' core manufacturing activities, as I discuss below.



(A) DIP indicator firm contributions in unit price



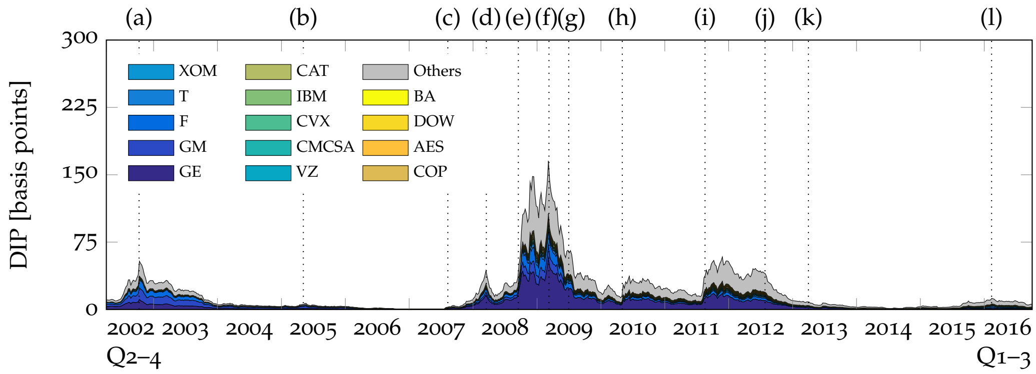
(B) DIP indicator firm contributions as share of total

FIGURE 4.8: Financial sector systemic risk by firm
This figure shows the level of systemic risk in the financial sector by firm. Systemic risk is measured using the DIP indicator. The firm contributions to this indicator are shown in unit price in the upper panel and as shares of total systemic risk in the lower panel. The firms with the highest individual contributions are identified by their ticker symbols as listed in Table 4.4. The vertical lines represent the same events as those in Figure 4.1.

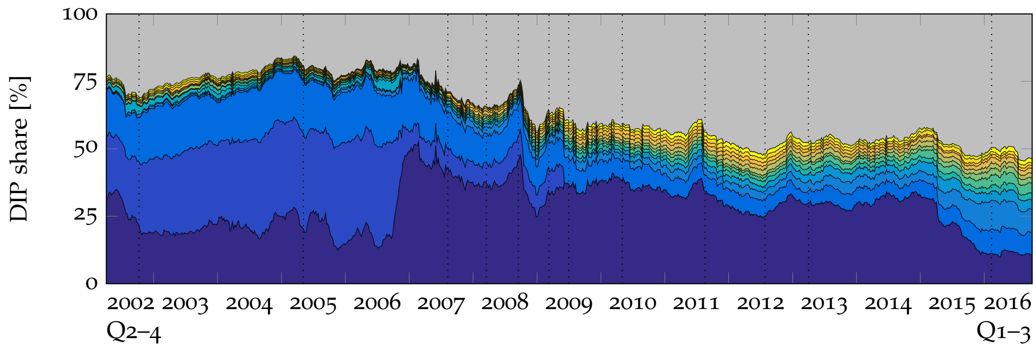
When traced over time, financial and nonfinancial firms' systemic risk appears to closely track corporate events, such as mergers and acquisitions and restructurings. In the financial sample, JPMorgan Chase's systemic importance increased as the firm took over Bear Stearns in May 2008 and the banking operations of Washington Mutual in September 2008. Wells Fargo's systemic importance increased as it merged with Wachovia in December 2008, and Bank of America's risk share increased as it acquired Merrill Lynch in January 2009.

In the nonfinancial sample, General Motors' systemic importance declined when it sold a majority interest in GMAC in November 2006. General Electric's systemic importance diminished over the year 2015, coinciding with a transformation of GE Capital's business, which included the sale of major assets, a reduction in the reliance on short-term funding, and a reorganization of the firm's corporate structure. Following these measures, in June 2016, the FSOC rescinded its July 2013 designation of GE Capital as a systemically important nonbank financial institution.[9]

9 For a detailed account of the transformation of GE Capital's business and the rescission of its designation as a systemically important nonbank financial institution, see FSOC (2016).



(A) DIP indicator firm contributions in unit price



(B) DIP indicator firm contributions as share of total

FIGURE 4.9: Nonfinancial sector systemic risk by firm
This figure shows the level of systemic risk in the nonfinancial sector by firm. Systemic risk is measured using the DIP indicator. The firm contributions to this indicator are shown in unit price in the upper panel and as shares of total systemic risk in the lower panel. The firms with the highest individual contributions are identified by their ticker symbols as listed in Table 4.4. The vertical lines represent the same events as those in Figure 4.1.

To fully appreciate individual firms' systemic importance, I rank financial and nonfinancial firms' marginal systemic risk contributions on three pivotal dates: the week of October 11, 2002, when U.S. stock markets reached their dot-com crisis low; the week of March 13, 2009, when U.S. stock markets reached their financial crisis low; and the week of September 30, 2016, the end of the sample period. Table 4.2 reports the ranking. At the height of the dot-com crisis and the financial crisis, General Electric, General Motors, and Ford are the only nonfinancial firms of similar systemic importance as high-ranking financial firms. At the end of the sample period, systemic risk in the nonfinancial sector is generally low, and no firm from the sector has an absolute systemic risk contribution comparable to high-ranking financial institutions.

The ranking further illustrates the dynamic nature of financial firms' relative systemic importance. In particular, the composition of the financial sector's ranking changes over the sample period, as insurers appear to become more systemically important. Three of the insurers listed in the empirical ranking—AIG, MetLife, and Prudential Financial—were also designated as systemically important nonbank financial institutions by the FSOC.

TABLE 4.2: Systemic risk rankings of individual firms

Financial firms			DIP		Nonfinancial firms			DIP	
Rk	Firm	Industry	Nom.	Shr.	Rk	Firm	Industry	Nom.	Shr.
Panel A: October 11, 2002									
1	C	Fin. services	3.9	16.1	1	GM	Manufacturing	4.3	23.9
2	JPM	Banking	2.6	10.6	2	GE	Manufacturing	3.7	20.9
3	MS	Fin. services	2.1	8.8	3	F	Manufacturing	3.0	17.1
4	BAC	Banking	1.8	7.2	4	VZ	Media & comm.	0.5	3.0
5	MER	Fin. services	1.7	7.1	5	TWX	Service & leis.	0.3	1.7
6	AIG	Insurance	1.6	6.4	6	AEP	Utilities	0.3	1.5
7	GS	Fin. services	1.2	5.0	7	WMB	Utilities	0.3	1.5
8	LEH	Fin. services	1.0	4.0	8	TXU	Utilities	0.3	1.4
9	FNM	Other	0.9	3.7	9	EP	Utilities	0.3	1.4
10	WB	Banking	0.8	3.2	10	Q	Media & comm.	0.2	1.3
Memo: Total systemic risk			*24.3*	*100.0*	*Memo: Total systemic risk*			*17.8*	*100.0*
Panel B: March 13, 2009									
1	C	Fin. services	52.3	20.9	1	GE	Manufacturing	21.7	32.9
2	BAC	Banking	44.6	17.8	2	F	Manufacturing	7.0	10.6
3	JPM	Banking	27.3	10.9	3	GM	Manufacturing	5.6	8.5
4	AIG	Insurance	19.7	7.9	4	T	Media & comm.	1.5	2.2
5	WFC	Banking	18.7	7.5	5	CAT	Manufacturing	0.9	1.4
6	GS	Fin. services	14.0	5.6	6	CMCSA	Media & comm.	0.8	1.1
7	PRU	Insurance	12.9	5.1	7	S	Media & comm.	0.7	1.1
8	MET	Insurance	12.8	5.1	8	COP	Oil & gas	0.6	0.9
9	MS	Fin. services	10.3	4.1	9	BA	Manufacturing	0.6	0.9
10	HIG	Insurance	5.6	2.2	10	IBM	Manufacturing	0.6	0.8
Memo: Total systemic risk			*250.6*	*100.0*	*Memo: Total systemic risk*			*65.8*	*100.0*
Panel C: September 30, 2016									
1	JPM	Banking	12.1	16.9	1	GE	Manufacturing	0.3	10.9
2	BAC	Banking	11.4	15.8	2	T	Media & comm.	0.2	8.6
3	C	Fin. services	9.6	13.3	3	F	Manufacturing	0.2	8.0
4	WFC	Banking	7.0	9.7	4	CVX	Oil & gas	0.1	3.7
5	PRU	Insurance	4.5	6.3	5	XOM	Oil & gas	0.1	3.5
6	GS	Fin. services	4.3	6.0	6	CMCSA	Media & comm.	0.1	2.5
7	MET	Insurance	4.2	5.9	7	MSFT	Manufacturing	0.1	2.1
8	MS	Fin. services	4.2	5.8	8	IBM	Manufacturing	0.1	2.0
9	AIG	Insurance	1.5	2.1	9	ORCL	Manufacturing	0.1	1.9
10	LNC	Insurance	1.5	2.0	10	CAT	Manufacturing	<0.1	1.7
Memo: Total systemic risk			*72.0*	*100.0*	*Memo: Total systemic risk*			*2.7*	*100.0*

This table shows the firms with the largest marginal contributions to systemic risk in the financial and nonfinancial sectors on three dates. *Rk* is individual firms' rank. Systemic risk is measured using the DIP indicator. This indicator is reported in nominal price in USD billion (*nom.*), and as a share of total systemic risk in percentages (*shr.*). Firms are identified by their ticker symbols as listed in Table 4.4.

4.4.2.2 *Firm Characteristics*

The evidence presented in the previous section supports the hypothesis that nonfinancial firms may contribute to systemic risk via engagement in financial services at the subsidiary level. To further examine the determinants of firms' individual systemic importance, I explore the role of firm characteristics in regression analyses. The dependent variable is the firms' marginal systemic risk share. The independent variables are various accounting- and market-based measures of firm characteristics that may be associated with systemic risk, such as size, capital structure, and engagement in financial services. I run quarterly regressions, where the dependent variable is averaged over 3 months, and yearly regressions, where the dependent variable is averaged over 1 year. To alleviate concerns on reverse causality, which might ensue if firms' contemporaneous systemic importance induced them to adjust their strategy or otherwise had an impact on their financial statements or market performance, I lag all explanatory variables by 1 year. I run pooled ordinary least squares regressions. To address potential bias, I include industry and time fixed effects and use heteroscedasticity-consistent standard errors clustered at the firm level (see, e.g., Petersen, 2009). The regression results are reported in Table 4.3. Summary statistics on the independent variables are provided in Appendix 4.C.1.

Size, measured as the natural logarithm of total assets, is a predictor of firms' relative systemic importance in all regressions. Firm size directly enters the systemic risk measure as a portfolio weight and thus drives firms' systemic risk contributions by construction. More interestingly, the relative systemic importance of financial and nonfinancial firms also depends on their balance sheet structure, as well as on additional firm characteristics.

Firms' balance sheet structure enters the regressions as the degree of equity financing and as the dependency on short-term funding. Equity financing, computed as the ratio of book equity to total assets, is a predictor of nonfinancial firms' systemic risk in the first two regressions, which do not control for engagement in financial business activities. A low share of equity financing, that is, a high degree of leverage, appears to amplify nonfinancial firms' systemic importance. Conversely, a high share of equity financing appears to serve as a buffer, preventing firms from contributing to aggregate systemic losses.[10]

Firms' dependency on short-term funding is approximated by the ratio of short-term debt to total debt. I find significant coefficients for this variable in the regressions for the financial firms. The positive sign corroborates the view that financial firms with a strong dependency on short-term funding contribute more to industry-wide distress than those with a high share of long-term debt, as they are more prone to liquidity shortages during crises.

10 Interestingly, whereas equity financing is not a statistically significant predictor of systemic risk in the regressions for U.S. financial firms reported here, Black et al. (2016) find that the systemic risk of European banks *increases* in the share of equity financing. For a potential explanation, these authors cite the argument of Perotti et al. (2011), who show that well-capitalized banks might be incentivized to take on additional tail risks.

Additionally, I explore the explanatory power of profitability and the book-to-market ratio. Profitability, calculated as the return on average assets, is at least weakly statistically significant in all regressions for the nonfinancial firms. The negative coefficient indicates that nonfinancial firms that are more profitable might be less likely to contribute to systemic losses, potentially because these firms are more resilient in times of crisis. In the yearly regression for the financial firms, however, profitability is weakly significant with a positive coefficient. As the profitability measure is not adjusted for the riskiness of a firm's strategy, financial firms that generate above-average profits by taking on higher risks might exhibit an outsized systemic risk contribution. Overall, the role of profitability for the sample firms' systemic importance remains ambiguous. The book-to-market ratio relates the firms' book value of equity to their market capitalization. This variable is significant with a negative coefficient in one of the regressions for the nonfinancial firms.

Finally, in the last two regressions, I include measures of nonfinancial firms' engagement in financial services. These measures are derived from the segment reporting in the firms' annual financial statements as follows. First, I classify business segments as financial services segments if the business activities undertaken in the segments are primarily in the area of financing, insurance, or payments. Next, as measures of nonfinancial firms' degree of engagement in such activities, I compute the share of firms' assets tied up in such segments and the share of firms' revenues generated in such segments.

Both measures are statistically and economically significant predictors of nonfinancial firms' relative systemic importance. A higher degree of engagement in financial services is associated with a higher contribution to systemic risk, even when factors that are typically associated with financial business activities, such as larger balance sheet size and higher degrees of leverage, are included in the regression. Overall, these results support the observations of the previous section, suggesting that systemic risk in the nonfinancial sector is largely driven by nonfinancial firms' engagement in financial services.

To examine the robustness of the regression results, I consider two alternative regressions. First, as some of the independent variables show extreme values, I winsorize all independent variables at the 1st and 99th percentiles. Second, recognizing that the dependent variable is the share of total systemic risk attributable to an individual firm, and thus bound to be between zero and one, I estimate Tobit models. The findings on the engagement of nonfinancial firms in financial business activities remain unchanged in both robustness tests. Detailed results for the robustness tests are reported in Appendix 4.C.2.

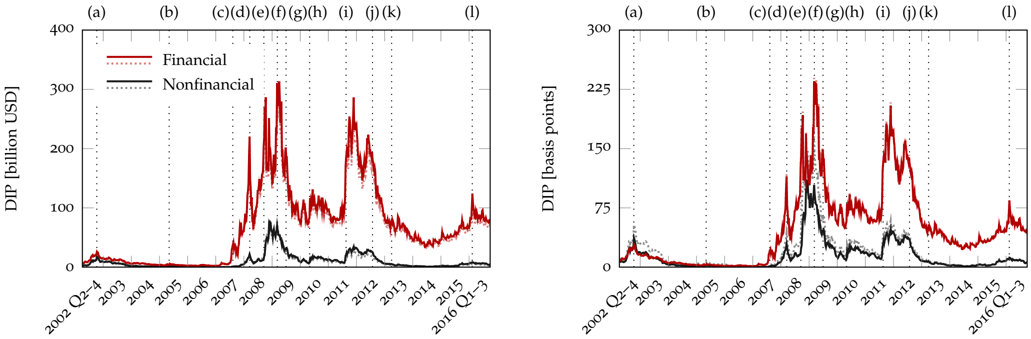
4.4.3 *Alternative Model Specifications*

In this section, I investigate the level of systemic risk in the financial and nonfinancial sectors under alternative model specifications. I analyze three

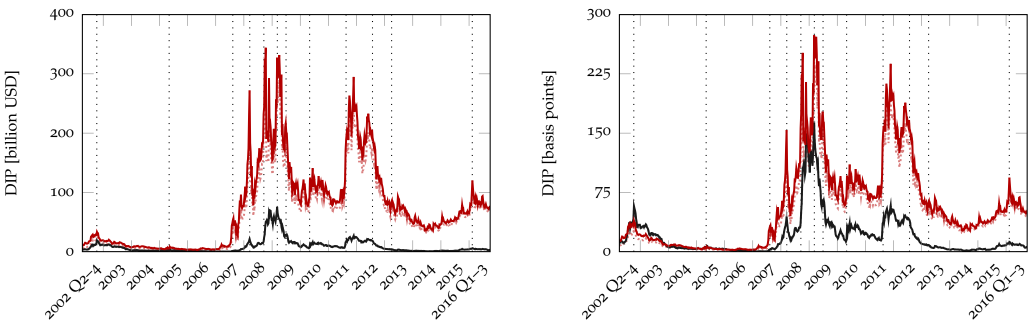
TABLE 4.3: Determinants of individual systemic importance

	Financial firms		Nonfinancial firms			
Model	(1)	(2)	(3)	(4)	(5)	(6)
Log total assets	0.0209***	0.0225***	0.0107*	0.0125**	0.0075***	0.0074***
	(0.0045)	(0.0051)	(0.0057)	(0.0053)	(0.0022)	(0.0023)
Equity/total assets	0.0424	0.0347	−0.0282*	−0.0347**	−0.0050	−0.0127
	(0.0301)	(0.0311)	(0.0159)	(0.0151)	(0.0050)	(0.0094)
Short-term debt/total debt	0.0319**	0.0239*	0.0068	0.0109	−0.0022	0.0020
	(0.0125)	(0.0125)	(0.0054)	(0.0070)	(0.0029)	(0.0040)
Return on average assets	0.3787	0.1840*	−0.0244*	−0.0174*	−0.0121*	−0.0148**
	(0.2613)	(0.1084)	(0.0128)	(0.0091)	(0.0062)	(0.0064)
Book-to-market ratio	0.0023	0.0043	0.0010	0.0003	−0.0007***	−0.0005
	(0.0027)	(0.0028)	(0.0019)	(0.0008)	(0.0002)	(0.0003)
Financial services assets/total assets					0.1317**	
					(0.0606)	
Financial services revenues/total revenues						0.4291**
						(0.1915)
Constant	−0.0909***	−0.0942***	−0.0137*	−0.0138*	−0.0155**	−0.0118***
	(0.0233)	(0.0246)	(0.0078)	(0.0083)	(0.0067)	(0.0041)
Industry fixed effects	yes	yes	yes	yes	yes	yes
Time fixed effects	yes	yes	yes	yes	yes	yes
Maximum VIF	2.72	2.74	2.60	2.26	2.25	2.25
Adjusted R^2	0.61	0.60	0.20	0.24	0.45	0.51
Firms	53	53	207	207	207	207
Observations	2,154	638	9,884	2,649	2,641	2,643
Frequency	quarterly	yearly	quarterly	yearly	yearly	yearly

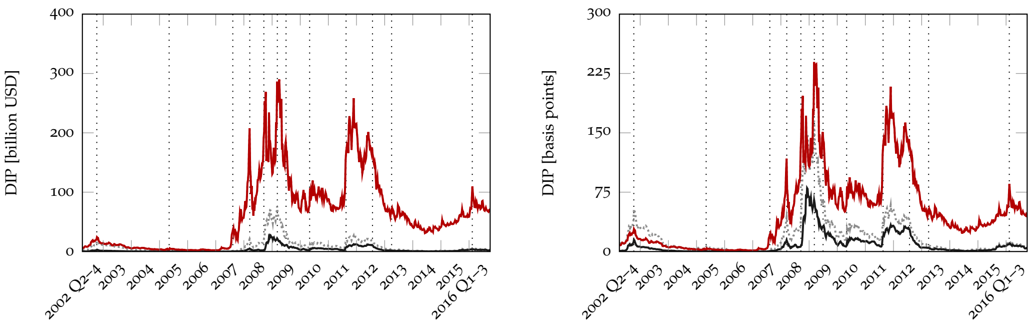
This table reports regressions of firms' systemic importance on accounting- and market-based measures. The dependent variable is individual firms' marginal DIP, normalized by the sectors' aggregate DIP. In models (1) and (3), the dependent variable is averaged over 3 months; in models (2), (4), (5), and (6), the dependent variable is averaged over 1 year. VIF is the variance inflation factor. Heteroscedasticity-consistent standard errors clustered at the firm level are given in parentheses. Significance is indicated by: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.



(A) Total assets as portfolio weights



(B) Observed recovery rates for default scenarios



(C) Exclusion of nonfinancial firms with substantial financial operations

FIGURE 4.10: Systemic risk for alternative model specifications
This figure shows the level of systemic risk in the financial and nonfinancial sectors for three alternative model specifications. Systemic risk is measured using the DIP indicator. This indicator is reported in nominal price in the left-hand panels and in unit price relative to aggregate total liabilities in the right-hand panels. The dark lines refer to the alternative model specifications, and the light lines show the results for the baseline scenario for means of comparison. The vertical lines represent the same events as those in Figure 4.1.

variations of the baseline model: (i) using firms' assets instead of the firms' liabilities as portfolio weights, (ii) basing default scenarios on observed recovery rates rather than on expected recovery rates, and (iii) excluding nonfinancial firms with an exceptionally high share of financial business activities from the sample. Figure 4.10 shows the results for these three scenarios, which are discussed in detail below. Appendix 4.C.3 provides supplemental descriptive statistics for the first two scenarios.

PORTFOLIO WEIGHTS The baseline model uses the book value of the firms' total liabilities as exposure weights. Total liabilities are a natural choice, as the systemic risk measure considered in the analysis is based on a credit risk model, where firms' individual default probabilities are derived from CDS spreads. However, using liabilities might distort the comparison between industries with substantially different degrees of leverage. Nonfinancial firms are typically much less leveraged than financial firms, and a nonfinancial firm's exposure weight, therefore, tends to be smaller than that of a financial firm with a similar-sized balance sheet. To exclude variations in firms' sources of financing, I use the book value of firms' total assets as an alternative exposure weight.

Generally, the effect of using assets instead of liabilities on the level of systemic risk is ambiguous. Consider, for example, an industry where all firms have the same leverage. When the portfolio weights are switched from liabilities to assets, the nominal price of systemic risk will increase, whereas the unit price of systemic risk will remain constant. If, however, firms in the industry have varying degrees of leverage, and systemic events are mostly driven by highly leveraged firms, using total assets instead of total liabilities might decrease the unit price of systemic risk. Conversely, the unit price of systemic risk might increase if systemic events were mostly due to firms with low leverage.

Figure 4.10a shows the results for the alternative portfolio weights. In the financial sector, the average nominal systemic risk is moderately higher than in the baseline model, whereas the unit price of systemic risk is virtually unchanged. In the nonfinancial sector, systemic risk is also moderately higher under the nominal measure, but it is notably lower under the unit price measure. Overall, these results are consistent with a small subset of highly leveraged firms driving the nonfinancial sector's systemic risk.

RECOVERY RATES In the baseline model, the losses in default scenarios are modeled based on sector-specific, ex ante expected recovery rates. Whereas these recovery rates reflect market participants' aggregate expectation on future defaults, ex post observed recovery rates might differ substantially. Jankowitsch et al. (2014) analyze the recovery rates on U.S. bond defaults during the period from July 2002 through October 2010. The defaulted bonds' recovery rates are measured as the bonds' trading prices, averaged over the day of default and the following 30 days. To explore whether the specific choice of the recovery rate has an impact on the results, I repeat the analysis using these observed recovery rates in the default scenarios. Note that this approach effectively introduces a look-ahead bias, as the procedure makes use of information unavailable to market participants during a substantial part of the sample period.

Figure 4.10b shows the results for the alternative recovery rate specification. Systemic risk increases in the financial sector under the nominal and unit price measures but remains virtually identical in the nonfinancial sector under both measures. Therefore, the main conclusions are robust to this change in the modeling assumption.

firm exclusions The analysis of individual nonfinancial firms' systemic importance has revealed that a large share of the nonfinancial sector's systemic risk can be allocated to three firms: General Electric, General Motors, and Ford. These firms are distinct in that they own, fully or partially, large financial businesses throughout their respective sample periods. The nonfinancial sector's systemic risk thus appears to be driven by a relatively small number of nonfinancial firms that engage in financial business activities. To get a better understanding of pure nonfinancial systemic risk, special consideration must be given to firms that operate large financial businesses.

Ideally, I would like to model only the nonfinancial businesses of such firms, excluding their financial subsidiaries. Whereas there are often separate CDS contracts written on nonfinancial firms' financial subsidiaries, there are, however, no separate CDS contracts written on the firms' nonfinancial businesses. Therefore, to give a more precise account of pure nonfinancial systemic risk, I repeat the analysis excluding nonfinancial firms heavily engaged in financial business activities from the nonfinancial sample altogether. In particular, I exclude seven nonfinancial firms that report more than half of their assets in financial business segments at some stage of the sample period. Beyond General Electric, General Motors, and Ford, this applies to manufacturers Caterpillar, Deere, and Textron, and to services firm First Data.

Figure 4.10c shows the resulting level of nonfinancial systemic risk. As expected, the level of systemic risk in the nonfinancial sector decreases in absolute and relative terms. The pronounced decrease in absolute risk likely reflects a combination of the reduced exposure size and the exclusion of financial business activities. The also significantly reduced relative risk, however, further supports the hypothesis that a substantial share of industry-wide distress risk in the nonfinancial sector is driven by nonfinancial firms' engagement in financial activities, rather than by the firms' core businesses.

4.5 conclusion

Is the financial system special, or can real sector firms also be systemically risky? This paper analyzes distress in the U.S. financial and nonfinancial industries using a market-based systemic risk measure. On an absolute scale, measured in U.S. dollars, systemic risk in the financial sector is generally much higher than systemic risk in the nonfinancial sector. On a relative scale, measured per unit of exposure, however, the nonfinancial sector sometimes exhibits elevated levels of systemic risk, in particular during the financial crisis of 2007–2009. In line with the common definition of systemic risk that associates such risk with financial undertakings but not with nonfinancial activities, this result appears to be driven by a small set of nonfinancial firms that have expanded beyond their nonfinancial businesses and also engage in financial services, such as financing, insurance, and payments.

These findings have important implications for regulatory policies for financial stability and empirical approaches to measuring systemic risk. Whereas nonfinancial firms' financial businesses do not appear to be an imminent threat to the U.S. economy toward the end of the sample period, regulators around the world should closely monitor nonfinancial firms' engagement in financial services. In particular, regulators may want to scrutinize how well nonfinancial firms' financial activities are aligned with the firms' core businesses. Nonfinancial firms that offer financial services purely to support their core activities are not expected to provide an occasion for tighter regulation. On the contrary, nonfinancial firms whose financial undertakings are detached from their core activities, such that the firms engage in financial services in addition to, rather than in support of, their core businesses, arguably warrant regulatory action.

As for empirical measures of systemic risk, two important implications can be drawn from the analysis. First, the findings reassure that suitable market-based measures indeed pick up systemic risk as caused by financial activities, as opposed to a generic type of distress risk. The analysis, therefore, reinforces the argument for using such metrics for monitoring aggregate systemic risk and determining individual systemic importance. Second, the findings point to the need to refine existing empirical approaches to capture all sources of systemic risk. Rather than measuring systemic risk exclusively at the holding company level, systemic risk should also be measured at finer granularity at the subsidiary level. As nonfinancial firms' financial subsidiaries are an important part of the financial system, these subsidiaries should be included in analyses of systemic risk. However, this poses an empirical challenge, as equity returns for nonfinancial firms' financial subsidiaries are usually not available. Kaserer and Klein (2018) adapt the modeling framework used in this paper so that only CDS spreads are required. I expect such an approach would be useful for monitoring the exact contribution of nonfinancial firms' financial subsidiaries to systemic risk in the financial system.

APPENDIX

4.A DATA SOURCES AND DEFINITIONS

This appendix describes the data sources and definitions used in the analysis.

CREDIT DEFAULT SWAP DATA CDS data are available from Markit. This database provides end-of-day composite spreads and expected recovery rates contributed by sell-side institutions. Coverage of the firms in the sample increases considerably in the first quarter of 2002, which marks the beginning of the systemic risk analysis.

CDS contracts are quoted for a range of standardized tenors, tiers, currencies, and restructuring clauses.[11] I require 5-year, senior unsecured, no restructuring contracts denominated in U.S. dollars. These represent the most liquid tenor and tier. I use end-of-week spreads to aggregate the daily spread observations to weekly frequency.[12]

According to Markit, composite spreads are disseminated only if they pass a set of quality assurance procedures to identify and remove outliers and otherwise doubtful data. Markit classifies all passing spreads based on the number of quote contributions and the level of aggregation. To ensure that only spreads of actively quoted contracts reflecting timely information are used in the analysis, I discard spreads of contracts with a low level of quote activity.[13] As a further control of data quality, I exclude stale observations, setting spreads to missing if they remain constant over more than 20 trading days. Finally, I discard all spreads recorded after a credit event.

EQUITY DATA Equity return and market capitalization data are available from the CRSP database. I use daily total returns for firms' common stock issues. Firms' market capitalization is calculated from the number of common stock outstanding and the respective daily closing price.

11 The restructuring clause determines whether restructuring constitutes a credit event, and if so, which obligations are deliverable in a restructuring event. Sorted from most restrictive (restructuring does not constitute a credit event) to least restrictive (restructuring is treated like other credit events), the following restructuring clauses are available: *no restructuring*, *modified restructuring*, *modified-modified restructuring*, and *complete restructuring*.

12 Following Chen et al. (2014), I use Friday spreads to construct the weekly time series. If there is no spread with the specified restructuring clause for a given Friday, I check whether a spread for a different restructuring clause exists for that day. If such a spread exists, I convert this spread to no restructuring using a Markit-supplied adjustment factor. If no spread is available for a given Friday, I use the no restructuring spread for Thursday, and if that spread is missing, the converted spread for another restructuring clause. If necessary, I repeat the process by checking the availability of spreads on Wednesday, Tuesday, and Monday.

13 Markit assigns each passing spread a *CompositeLevel*, which, in order of increasing aggregation, can take the values *CcyGrp*, *DocAdj*, *EntityTier*, and *Thin*. I retain only the spreads marked CcyGrp or DocAdj for the analysis. See Markit (2012) for details on Markit's methodology.

FINANCIAL STATEMENTS DATA Financial statements data are available from Compustat. I retrieve data on total liabilities from the consolidated quarterly balance sheets. All liabilities are collected in U.S. dollars. I compute weekly portfolio weights from the quarterly liability data using linear interpolation within the firms' fiscal quarters.

RISK-FREE RATE As a proxy for the risk-free rate, I rely on Bloomberg-supplied interest rate curves derived from interbank rates and instruments linked to interbank rates. I use 5-year rates to match the tenor of the CDS contracts. I retrieve historical daily rates denominated in U.S. dollars.

4.B LIST OF SAMPLE FIRMS

TABLE 4.4: List of sample firms

Financial firms

AET	Aetna Inc	CFC	Countrywide Financial Corp	MS	Morgan Stanley
AFL	Aflac Inc	FRE	Federal Home Loan Mtge Corp	NCC	National City Corp
ALL	Allstate Corp	FNM	Federal National Mtge Assn	PNC	PNC Financial Svcs Grp Inc
AXP	American Express Co	BEN	Franklin Resources Inc	PFG	Principal Financial Grp Inc
AIG	American Internat Grp Inc	GNW	Genworth Financial Inc	PGR	Progressive Corp
AOC	Aon Corp	GS	Goldman Sachs Grp Inc	PRU	Prudential Financial Inc
BAC	Bank of America Corp	HIG	Hartford Financial Svcs Grp Inc	SLM	SLM Corp
BK	Bank of New York Co Inc	HUM	Humana Inc	STT	State Street Corp
BBT	BB&T Corp	JPM	JPMorgan Chase & Co	STI	SunTrust Banks Inc
BSC	Bear Stearns Cos Inc	KEY	KeyCorp	TRV	Travelers Cos Inc
BRK	Berkshire Hathaway Inc	LM	Legg Mason Inc	UNH	UnitedHealth Grp Inc
COF	Capital One Financial Corp	LEH	Lehman Brothers Holdings Inc	USB	US Bancorp
SCHW	Charles Schwab Corp	LNC	Lincoln National Corp	WB	Wachovia Corp
CB	Chubb Corp	LTR	Loews Corp	WM	Washington Mutual Inc
CI	CIGNA Corp	MMC	Marsh & McLennan Cos Inc	WLP	WellPoint Inc
CIT	CIT Grp Inc	MEL	Mellon Financial Corp	WFC	Wells Fargo & Co
C	Citigroup Inc	MER	Merrill Lynch & Co Inc	WU	Western Union Co
CNA	CNA Financial Corp	MET	MetLife Inc		

Continued on next page

TABLE 4.4 – *continued from previous page*

Nonfinancial firms

MMM	3M Co	EMC	EMC Corp	NEM	Newmont Mining Corp
ABT	Abbott Laboratories	EMR	Emerson Electric Co	NWS	News Corp
AES	AES Corp	ETR	Entergy Corp	NKE	Nike Inc
A	Agilent Technologies Inc	EOG	EOG Resources Inc	NBL	Noble Energy Inc
APD	Air Products & Chemicals Inc	EXC	Exelon Corp	JWN	Nordstrom Inc
AA	Alcoa Inc	XOM	Exxon Mobil Corp	NSC	Norfolk Southern Corp
ATI	Allegheny Technologies	FDX	FedEx Corp	NOC	Northrop Grumman Corp
AGN	Allergan Inc	FDC	First Data Corp	NRG	NRG Energy Inc
AT	Alltel Corp	FE	FirstEnergy Corp	NUE	Nucor Corp
MO	Altria Grp Inc	F	Ford Motor Co	OXY	Occidental Petroleum Corp
AEE	Ameren Corp	FO	Fortune Brands Inc	OMC	Omnicom Grp Inc
AEP	American Electric Power Co Inc	FPL	FPL Grp Inc	ORCL	Oracle Corp
ASD	American Standard Cos Inc	FCX	Freeport-McMoRan Cpr & Gld	PH	Parker Hannifin Corp
AMT	American Tower Corp	GCI	Gannett Co Inc	BTU	Peabody Energy Corp
AMGN	Amgen Inc	GPS	Gap Inc	PEP	PepsiCo Inc
APC	Anadarko Petroleum Corp	DNA	Genentech Inc	PFE	Pfizer Inc
ADI	Analog Devices Inc	GD	General Dynamics Corp	PCG	PG&E Corp
BUD	Anheuser-Busch Cos Inc	GE	General Electric Co	PBI	Pitney Bowes Inc
APA	Apache Corp	GIS	General Mills Inc	PPG	PPG Industries Inc
AMAT	Applied Materials Inc	GM	General Motors Corp	PPL	PPL Corp
ADM	Archer-Daniels-Midland Co	GENZ	Genzyme Corp	PX	Praxair Inc
T	AT&T Inc	HAL	Halliburton Co	PCP	Precision Castparts Corp
ADP	Automatic Data Processing Inc	HET	Harrah's Entertainment Inc	PG	Procter & Gamble Co
AVP	Avon Products Inc	HES	Hess Corp	PGN	Progress Energy Inc
BHI	Baker Hughes Inc	HPQ	Hewlett-Packard Co	PEG	Public Svc Enterprise Grp Inc
BAX	Baxter Internat Inc	HLT	Hilton Htls Corp	Q	Qwest Comms Intl Inc
BDX	Becton Dickinson & Co	HNZ	HJ Heinz Co	RTN	Raytheon Co
BBY	Best Buy Co Inc	HD	Home Depot Inc	RAI	Reynolds American Inc
BA	Boeing Co	HON	Honeywell Internat Inc	ROK	Rockwell Automation Inc
BSX	Boston Scientific Corp	ITW	Illinois Tool Works Inc	COL	Rockwell Collins Inc
BMY	Bristol-Myers Squibb Co	INTC	Intel Corp	ROH	Rohm & Haas Co
BNI	Burlington N Santa Fe Corp	IBM	Internat Business Machs Corp	SWY	Safeway Inc
CA	CA Inc	IGT	Internat Game Technology	SLE	Sara Lee Corp
CPB	Campbell Soup Co	IP	Internat Paper Co	SGP	Schering-Plough Corp
CAH	Cardinal Health Inc	INTU	Intuit Inc	SRE	Sempra Energy
CAT	Caterpillar Inc	ITT	ITT Corp	SO	Southern Co
CBS	CBS Corp	JCP	JC Penney Co Inc	PCU	Southern Copper Corp
CHK	Chesapeake Energy Corp	JNJ	Johnson & Johnson	LUV	Southwest Airlines Co
CVX	Chevron Corp	JCI	Johnson Controls Inc	S	Sprint Nextel Corp
CSCO	Cisco Systems Inc	JNPR	Juniper Networks Inc	SPLS	Staples Inc
CCU	Clear Channel Comms Inc	K	Kellogg Co	HOT	Starwood Htls & Rsrts Wldwd Inc
KO	Coca-Cola Co	KMB	Kimberly-Clark Corp	SUNW	Sun Microsystems Inc
CCE	Coca-Cola Enterprises Inc	KSS	Kohl's Corp	SYY	Sysco Corp
CL	Colgate-Palmolive Co	KFT	Kraft Foods Inc	TGT	Target Corp
CMCSA	Comcast Corp	KR	Kroger Co	TXN	Texas Instruments Inc
CSC	Computer Sciences Corp	LLL	L-3 Comms Hldgs Inc	TXT	Textron Inc
CAG	ConAgra Inc	LVS	Las Vegas Sands Corp	TWC	Time Warner Cable Inc
COP	ConocoPhillips	LCAPA	Liberty Media Corp	TWX	Time Warner Inc
ED	Consolidated Edison Inc	LLY	Lilly Eli & Co	TJX	TJX Cos Inc
CEG	Constellation Energy Grp Inc	LTD	Limited Brands Inc	TXU	TXU Corp
GLW	Corning Inc	LMT	Lockheed Martin Corp	UNP	Union Pacific Corp
COST	Costco Wholesale Corp	LOW	Lowe's Cos Inc	UPS	United Parcel Svc Inc
CCI	Crown Castle Internat Corp	M	Macy's Inc	X	United States Steel Corp
CSX	CSX Corp	MRO	Marathon Oil Corp	UTX	United Technologies Corp
CMI	Cummins Inc	MAR	Marriott Internat Inc	VLO	Valero Energy Corp
CVS	CVS Caremark Corp	MAS	Masco Corp	VZ	Verizon Comms Inc
DHR	Danaher Corp	MCD	McDonald's Corp	VFC	VF Corp
DE	Deere & Co	MHP	McGraw-Hill Cos Inc	VIA	Viacom Inc
DELL	Dell Inc	MHS	Medco Health Solutions Inc	VMC	Vulcan Materials Co
DVN	Devon Energy Corp	MDT	Medtronic Inc	WMT	Wal-Mart Stores Inc
DO	Diamond Offshore Drilling Inc	MRK	Merck & Co Inc	DIS	Walt Disney Co
D	Dominion Resources Inc	MGM	MGM Mirage	WMI	Waste Management Inc
DOV	Dover Corp	MSFT	Microsoft Corp	WY	Weyerhaeuser Co
DOW	Dow Chemical Co	MIR	Mirant Corp	WMB	Williams Cos
ETN	Eaton Corp	MON	Monsanto Co	WYE	Wyeth
EIX	Edison Internat	MOS	Mosaic Co	XRX	Xerox Corp
DD	EI du Pont de Nemours & Co	MOT	Motorola Inc	XTO	XTO Energy Inc
EP	El Paso Corp	MUR	Murphy Oil Corp	YHOO	Yahoo Inc
EDS	Electronic Data Sys Corp	NOV	National Oilwell Varco Inc	YUM	Yum Brands Inc

This table lists the tickers and names of the firms covered in the financial and nonfinancial samples. Firms are sorted alphabetically by name within each sample.

4.C STATISTICAL APPENDIX

4.C.1 *Firm Characteristics*

This appendix provides descriptive statistics for the regression analysis in Section 4.4.2.2. Table 4.5 shows summary statistics on the different firm characteristics considered in the regressions.

4.C.2 *Robustness Tests*

This appendix provides robustness tests for the regression analysis in Section 4.4.2.2. Table 4.6 reports the results for the regressions with winsorized input variables, and Table 4.7 reports the results for the Tobit models.

4.C.3 *Alternative Model Specifications*

This appendix provides descriptive statistics for the alternative portfolio weight and recovery rate specifications discussed in Section 4.4.3. Table 4.8 shows summary statistics on the book value of firms' assets at the end of June 2007, as well as on observed recovery rates.

When the asset sizes are contrasted with the liability sizes reported in Table 4.1, the data corroborate that, on average, financial firms are much more leveraged than nonfinancial firms. The financial firms in the sample have a book leverage ratio of 11.9, self-financing each dollar of assets by 15 cents of book equity, and the nonfinancial firms have a book leverage ratio of 2.9, holding 42 cents of book equity against each dollar of assets.[14]

The observed recovery rates are taken from Jankowitsch et al. (2014). These authors analyze U.S. bond defaults from July 2002 through October 2010, and define recovery rates as the average of defaulted bonds' trading price on the day of default and the following 30 days. Whereas the average observed recovery rates of 38.8 percent for financial firms and 38.5 percent for nonfinancial firms are very similar to the average of the expected recovery rates reported in Figure 4.2,[15] there is considerable cross-sectional variation among industries. In the utilities industry, an industry with a high share of tangible assets, the observed recovery rates average 48.0 percent. In the financial services industry, the observed recovery rates average only 10.6 percent, driven by the very low recovery rates on Lehman Brothers' debt (Jankowitsch et al., 2014).

14 I define the leverage ratio as total assets divided by book equity, where book equity is calculated as total assets less total liabilities.

15 Note that the expected recovery rates reported in Figure 4.2 are for senior unsecured debt, whereas the observed recovery rates reported in Table 4.8 are averaged across different bond seniorities.

TABLE 4.5: Descriptive statistics on firm characteristics

	Min	$Q_{0.25}$	Mean	Median	$Q_{0.75}$	Max	SD	N
Panel A: Financial firms								
Total assets	3.9558	50.3550	325.1474	120.6511	355.9470	2,577.1480	480.2709	2,580
Equity/total assets	−0.1140	0.0736	0.1706	0.1087	0.2226	0.8132	0.1521	2,580
Short-term debt/total debt	0.0000	0.0689	0.2772	0.1987	0.4502	1.0000	0.2492	2,371
Return on average assets	−0.1322	0.0017	0.0058	0.0034	0.0077	0.1120	0.0098	2,533
Book-to-market ratio	−0.0183	0.4238	0.7875	0.6127	0.9161	18.5674	0.8538	2,565
Panel B: Nonfinancial firms								
Total assets	1.3943	10.6981	37.8102	21.0756	36.9370	846.9880	66.3416	10,804
Equity/total assets	−0.9373	0.2763	0.3849	0.3857	0.4972	0.8618	0.1638	10,804
Short-term debt/total debt	0.0000	0.0237	0.1430	0.0945	0.2024	1.0000	0.1616	10,524
Return on average assets	−0.4516	0.0078	0.0155	0.0152	0.0248	0.3811	0.0253	10,627
Book-to-market ratio	−44.1028	0.2261	0.4118	0.3580	0.5392	9.0850	0.5665	10,747
Fin. serv. assets/total assets	0.0000	0.0000	0.0242	0.0000	0.0000	0.9173	0.1083	2,701
Fin. serv. revenues/total revenues	0.0000	0.0000	0.0058	0.0000	0.0000	0.4812	0.0356	2,703

This table reports descriptive statistics on different accounting- and market-based firm characteristics. For each characteristic, the table reports the lowest value (min), 25 percent quantile ($Q_{0.25}$), mean, median, 75 percent quantile ($Q_{0.75}$), highest value (max), standard deviation (SD), and number of observations (N) for the pooled sample. The ratio of financial services assets to total assets and the ratio of financial services revenues to total revenues are observed yearly, all other variables are based on quarterly financial statements. Total assets are in USD billion.

TABLE 4.6: Systemic risk determinants with winsorized variables

	Financial firms		Nonfinancial firms			
Model	(1)	(2)	(3)	(4)	(5)	(6)
Log total assets	0.0212***	0.0229***	0.0092**	0.0108**	0.0066***	0.0056***
	(0.0043)	(0.0050)	(0.0047)	(0.0044)	(0.0019)	(0.0014)
Equity/total assets	0.0341	0.0265	−0.0303*	−0.0414**	−0.0108*	−0.0087
	(0.0283)	(0.0303)	(0.0174)	(0.0185)	(0.0065)	(0.0082)
Short-term debt/total debt	0.0318**	0.0244**	0.0101	0.0153	0.0008	0.0013
	(0.0121)	(0.0121)	(0.0079)	(0.0095)	(0.0028)	(0.0047)
Return on average assets	0.8915**	0.3005**	−0.0478	−0.0120	−0.0049	−0.0021
	(0.3946)	(0.1300)	(0.0322)	(0.0121)	(0.0070)	(0.0065)
Book-to-market ratio	0.0094	0.0096	0.0040	0.0096	0.0073	0.0079*
	(0.0062)	(0.0060)	(0.0032)	(0.0065)	(0.0044)	(0.0047)
Financial services assets/total assets					0.1322**	
					(0.0661)	
Financial services revenues/total revenues						0.8656**
						(0.3847)
Constant	−0.0962***	−0.0995***	−0.0101**	−0.0114*	−0.0145**	−0.0135***
	(0.0233)	(0.0249)	(0.0050)	(0.0060)	(0.0058)	(0.0049)
Sector fixed effects	yes	yes	yes	yes	yes	yes
Time fixed effects	yes	yes	yes	yes	yes	yes
Maximum VIF	2.91	2.87	2.60	2.26	2.26	2.26
Adjusted R^2	0.62	0.61	0.17	0.21	0.40	0.47
Firms	53	53	207	207	207	207
Observations	2,154	638	9,884	2,649	2,641	2,643
Frequency	quarterly	yearly	quarterly	yearly	yearly	yearly

This table reports regressions of firms' systemic importance on accounting- and market-based measures. The dependent variable is individual firms' marginal DIP, normalized by the sectors' aggregate DIP. In models (1) and (3), the dependent variable is averaged over 3 months; in models (2), (4), (5), and (6), the dependent variable is averaged over 1 year. The independent variables are winsorized at the 1st and 99th percentiles. VIF is the variance inflation factor. Heteroscedasticity-consistent standard errors clustered at the firm level are given in parentheses. Significance is indicated by: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

TABLE 4.7: Systemic risk determinants in Tobit models

	Financial firms		Nonfinancial firms			
Model	(1)	(2)	(3)	(4)	(5)	(6)
Log total assets	0.0209***	0.0225***	0.0107*	0.0125**	0.0075***	0.0074***
	(0.0044)	(0.0050)	(0.0057)	(0.0053)	(0.0022)	(0.0023)
Equity/total assets	0.0424	0.0347	−0.0282*	−0.0347**	−0.0050	−0.0127
	(0.0296)	(0.0305)	(0.0159)	(0.0151)	(0.0050)	(0.0094)
Short-term debt/total debt	0.0319***	0.0239*	0.0068	0.0109	−0.0022	0.0020
	(0.0123)	(0.0123)	(0.0054)	(0.0070)	(0.0029)	(0.0039)
Return on average assets	0.3787	0.1840*	−0.0244*	−0.0174*	−0.0121**	−0.0148**
	(0.2573)	(0.1065)	(0.0127)	(0.0090)	(0.0061)	(0.0064)
Book-to-market ratio	0.0023	0.0043	0.0010	0.0003	−0.0007***	−0.0005
	(0.0027)	(0.0027)	(0.0019)	(0.0008)	(0.0002)	(0.0003)
Financial services assets/total assets					0.1317**	
					(0.0603)	
Financial services revenues/total revenues						0.4291**
						(0.1906)
Constant	−0.0909***	−0.0942***	−0.0137*	−0.0138*	−0.0155**	−0.0118***
	(0.0230)	(0.0242)	(0.0078)	(0.0082)	(0.0067)	(0.0041)
Industry fixed effects	yes	yes	yes	yes	yes	yes
Time fixed effects	yes	yes	yes	yes	yes	yes
Firms	53	53	207	207	207	207
Observations	2,154	638	9,884	2,649	2,641	2,643
Frequency	quarterly	yearly	quarterly	yearly	yearly	yearly

This table reports Tobit models of firms' systemic importance. The dependent variable is individual firms' marginal DIP, normalized by the sectors' aggregate DIP. In models (1) and (3), the dependent variable is averaged over 3 months; in models (2), (4), (5), and (6), the dependent variable is averaged over 1 year. Heteroscedasticity-consistent standard errors clustered at the firm level are given in parentheses. Significance is indicated by: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

TABLE 4.8: Assets and observed recovery rates

	Assets[a]				Recovery rates[b]			
Sample	Min	Mean	Max	Sum	Min	Average	Max	Defaults
Financial firms	5	351	2,221	18,591	0.01	38.76	98.63	1,145
Banking	43	388	1,534	5,820	14.32	49.26	69.50	62
Financial services	5	484	2,221	7,258	0.01	10.64	98.63	363
Insurance	13	187	1,034	3,748	7.96	43.37	96.14	17
Others	85	588	858	1,765	0.01	52.24	98.01	703
Nonfinancial firms	4	36	739	7,419	0.01	38.46	116.50	1,089
Oil & gas	4	54	228	861	9.85	44.37	92.79	21
Manufacturing	4	35	739	3,700	0.01	38.93	110.80	573
Retail	6	27	155	542	1.41	33.40	100.50	33
Service & leisure	4	28	130	613	0.03	38.65	116.50	190
Media & comm.	4	60	267	846	0.01	34.70	101.00	163
Transportation	15	28	37	194	16.78	38.17	78.38	70
Utilities	12	30	48	663	23.81	48.03	102.80	39

[a] Book value of total assets at the end of June 2007 in USD billion.

[b] Recovery rates for U.S. bonds that defaulted during the period from July 2002 through October 2010, defined as the bonds' average trading price on the day of default and the following 30 days. *Defaults* lists the number of bond defaults underlying the *minimum*, *average*, and *maximum* recovery rate statistics. *Source:* Jankowitsch et al. (2014, Table 2), own calculations.

5 CONCLUSION

In the aftermath of the financial crisis of 2007–2009, a considerable body of research has examined systemic risk in the banking sector. There is, however, limited research on systemic risks in other parts of the economy that have also attracted regulatory scrutiny, including the insurance sector and real sector firms' financing arms. The three empirical studies in this thesis contribute to a better understanding of systemic risk beyond the banking sector. Based on a set of indicators derived from market and financial statements data, each study sheds light on a specific threat to financial stability. The first study investigates systemic risk in insurance. The second study focuses on contagion among the banking and insurance sectors. The third study analyzes systemic risk in real sector firms.

5.1 MAIN RESULTS AND IMPLICATIONS

5.1.1 *Systemic Risk in the Insurance Industry*

Insurance has been identified as a source of systemic risk by global regulators, and several insurance companies have been designated systemically important. There is, however, considerable controversy over the existence of systemic risk in insurance and the appropriate policy response to such risk (see, e.g., Harrington, 2009; Kessler, 2014; Bierth et al., 2015). The first study takes an empirical perspective on systemic risk in insurance. In this study, I examine the insurance sector's contribution to systemic risk in the global financial system and the level of systemic risk associated with individual insurers.

As my main result, I point out an important ambiguity between the insurance sector's aggregate systemic risk and individual insurers' systemic importance. As an industry, insurance accounts for a relatively small share of the systemic risk in the financial system. During the financial crisis and the European sovereign debt crisis, the banking sector accounts for 91 percent of systemic losses on average, whereas the insurance sector accounts for 9 percent. Systemic risk in the insurance sector is mostly driven by multi-line insurance and life insurance, which each account for about 4 percent of aggregate systemic losses during the crisis episodes. The other lines of business—property–casualty (P/C) insurance, bond and mortgage insurance, and reinsurance—collectively contribute only about 1 percent of the total systemic risk in the financial system.

A number of individual insurers, however, exhibit elevated levels of systemic risk and may, therefore, be considered systemically important financial institutions. In particular, several multi-line and life insurers contribute as much to total systemic risk as the riskiest banks in the sample. Furthermore, distress in some multi-line insurers, life insurers, and reinsurers is associated with turmoil in the broader financial system. On the contrary, P/C insurers and bond and mortgage insurers do not appear to be systemically important. These findings are robust to changes in key model parameters, including the systemic event definition.

My findings have important policy implications for the effective regulation of systemic risk in financial markets. As the insurance industry is responsible for only a minor share of systemic risk, most of the regulatory effort to enhance financial stability should be directed toward the banking sector. The empirical evidence does not support regulating the insurance sector as such more tightly. Regulators should still monitor the insurance sector closely to have an early warning should the industry become more systemically risky in the future.

However, as individual insurers may be systemically important, there is arguably an occasion for selective policy measures. Effective regulation targeting systemically important insurers should combine entity- and activity-based measures. Such an approach would strongly incentivize systemically risky insurers to curtail those business activities that contribute most to systemic risk, and it is expected to mark a clear route to shedding a systemic risk designation.

Beyond shedding light on systemic risk in insurance, the first study also investigates the systemic importance of nonpublic financial institutions. In the aggregate, the nonpublic firms in the sample account for 14 percent of systemic losses during the crisis episodes. Moreover, several nonpublic firms are represented among the most systemically risky firms in the sample. Nonpublic financial institutions thus appear to be an economically relevant source of systemic risk that is not captured by measures estimated from equity data.

5.1.2 *Interconnectedness of Banks and Insurers*

Systemic risk may materialize through a broad shock that impairs a substantial portion of the financial system simultaneously or through a narrow shock to a limited part of the financial system that then contagiously spreads to other institutions and markets (see, e.g., de Bandt and Hartmann, 2000; Group of Ten, 2001). The second study examines such systemic risk spillovers between and within the banking and insurance industries during the financial crisis and the European sovereign debt crisis.

To this end, I exploit the lead–lag relationships among market-based indicators of systemic risk. In the first part of the analysis, I examine different financial sectors' distress over the financial crisis and the European sovereign debt crisis. The banking sector is found to pose significantly higher levels of systemic risk than the insurance sector in nominal terms, but the difference in the sectors' riskiness diminishes when the difference in their liability sizes is taken into account. Within the insurance sector, the relative level of distress varies significantly by line of business. Bond and mortgage insurance exhibit the highest level of distress. P/C insurance, in contrast, is relatively resilient to financial turmoil and experiences the lowest level of distress. The other insurance segments—multi-line insurance, life insurance, and reinsurance—experience intermediate to low levels of distress.

In the second part of the analysis, I investigate the interconnectedness of the banking and insurance industries by testing for Granger causality among the different sectors' distress. I find that overall, the impact of distress in the banking sector on the insurance sector is more significant than in the other direction. However, at the level of individual insurance segments, I provide novel evidence of a feedback loop between the banking sector and the life insurance sector. The banking sector additionally affects the multi-line insurance and the P/C insurance sectors, but neither of these insurance segments appears to impair the banking sector. The interconnections between the banking sector and the insurance sector's different lines of business are robust when controlling for a common exposure to sovereign risk.

By contrast, the interconnectedness within the insurance sector is relatively weak, and there are no feedback loops between the different lines of business. Multi-line insurers, life insurers, and reinsurers all lead P/C insurers, but not vice versa. Additionally, bond and mortgage insurers lead life insurers. These interconnections, however, appear to be mediated by a common exposure of insurers to systemic risk in the banking sector, as the links between different insurance sectors mainly lose their statistical significance once the insurance sectors' exposure to distress in the banking sector is taken into account.

In summary, the analysis identifies two broad types of financial sectors that call for different regulatory treatment: shock propagators and shock absorbers. Shock propagators, such as the banking and life insurance sectors, act as sources of systemic risk in the financial system. They should thus be targeted by macroprudential policies to reduce their potential to impair the broader financial system in times of crisis. Shock absorbers, such as the P/C insurance sector, act as sinks of systemic risk in the financial system. They should thus be targeted by microprudential policies to safeguard their resilience during financial turmoil. Interestingly, whereas some insurers may propagate shocks to the broader financial system, the insurance industry appears to be unlikely to experience self-reinforcing insurance crises.

5.1.3 *Systemic Risk in the Real Sector*

Working definitions of systemic risk typically refer to an impairment of the financial system that potentially has severe repercussions for the real economy. The third study explores whether empirical measures of systemic risk indeed pick up a unique characteristic of financial institutions or whether real sector firms may also exhibit a more broadly defined type of systemic risk.

The analysis investigates systemic risk in the U.S. financial and nonfinancial industries over the period from April 2002 through September 2016. Overall, the level of distress is found to be much higher in the financial sector than in the nonfinancial sector. Relative to nonfinancial systemic risk, financial systemic risk is on average more than 7 times as high when measured on a nominal basis and 2.5 times as high when measured per dollar of sector liabilities. During the financial crisis and the ensuing European sovereign debt crisis, however, the nonfinancial sector experiences economically meaningful levels of distress. A sizable share of this distress risk can be attributed to a small set of nonfinancial firms mostly from the manufacturing industry. These firms individually contribute similarly to aggregate industry losses as systemically important financial institutions do.

The contribution of nonfinancial firms to sector-wide distress is found to be largely due to their engagement in financial services. Beyond their core industrial businesses, the nonfinancial firms with the highest contributions to systemic risk operate large financing arms. These firms' contributions to systemic risk closely track corporate reorganizations targeting their financial subsidiaries. The share of assets tied up in and the share of revenues generated from nonfinancial firms' financial services businesses are statistically and economically significant predictors of systemic risk in nonfinancial firms. These results hold when controlling for other firm characteristics that are typically associated with systemic risk in financial institutions, such as size, leverage, and short-term funding.

The findings regarding the nonfinancial sector have important implications for measuring and managing systemic risk. Suitable empirical measures appear to reflect systemic risk as a risk inherent in financial services rather than a generic type of distress. In contrast to measures derived from accounting data, measures derived from market data offer timely and transparent information on the buildup of systemic risks in the financial system. Rather than relying only on backward-looking measures derived from accounting data, regulators should thus additionally use forward-looking measures derived from market data as complementary indicators of systemic risk in their financial stability assessments. To encompass all sources of systemic risk, such assessments should include not only financial institutions but also relevant operations of nonfinancial firms. In particular, shadow-banking activities undertaken by nonfinancial firms appear to warrant regulatory scrutiny.

5.2 AVENUES FOR FUTURE RESEARCH

This thesis provides an empirical assessment of distress in financial institutions and real sector firms. The empirical evidence points to a significant difference in the riskiness of the different business activities that firms undertake. It would be interesting to further investigate the contribution of specific business activities to systemic risk. Although previous research has analyzed the systemic risk of individual business activities to some extent (see, e.g., Harrington, 2009; Foley-Fisher et al., 2015; Koijen and Yogo, 2016), several important questions warrant further research. For example, do financial conglomerates that operate both banking and insurance businesses dampen or exacerbate systemic risk? Further, how may asset management contribute to systemic risk and contagion in financial markets? Moreover, what are the implications of newly emerging risks and business models, such as those related to cyber risk, climate change, and fintech firms, for financial stability?

The empirical assessment of systemic risk in this thesis is based on indicators derived from market data. By their very nature, such metrics reflect the amount of systemic risk retained in financial markets and borne by market participants, that is, equity and debt investors. In times of crisis, governments may intervene and support distressed firms to prevent their ultimate failure. These explicit and implicit guarantees effectively transfer systemic risks from financial markets onto the sovereign balance sheet. An additional interesting area warranting further research is the role of government guarantees in systemic risk. To the extent that government guarantees affect equity and debt instruments in distinct ways, the value of government guarantees can be inferred from pricing differentials in equity and debt markets (see, e.g., Jobst and Gray, 2013). Future research on the valuation of government guarantees may, for example, address the empirical challenge that such guarantees have been shown to depress the spreads on debt instruments below their fair value levels as implied by equity returns (see, e.g., Li et al., 2011; Schweikhard and Tsesmelidakis, 2013), while financial institutions' equity returns themselves appear to be affected by government guarantees (see, e.g., Gandhi and Lustig, 2015; Dewenter and Riddick, 2018).

Finally, future research could further enhance the empirical toolkit for measuring systemic risk. Existing measures of systemic risk could be extended both along the input and output dimensions. As for the input dimension, empirical measures would benefit from a more detailed modeling of financial institutions' balance sheet structure. In particular, incorporating the distinct dynamics of financial institutions' different types of assets and liabilities in times of crisis would allow for more precise estimates of systemic losses for different types of financial institutions and shocks.

As for the output dimension, next-generation measures of systemic risk could attempt to model the real consequences of financial crises. Regulators' ultimate objective of managing systemic risk is to limit the cost of financial crises to the economy as a whole. Existing empirical measures, however, focus mostly on financial sector losses. Future measures of systemic risk that directly assess financial institutions' negative externalities would help regulators distinguish between crises limited to the financial system, which are not systemic under the regulatory definition, and crises affecting the wider economy, which arguably provide an occasion for macroprudential policy.

APPENDIX: CONTRIBUTION TO WORKING PAPERS

WORKING PAPER 1 (CHAPTER 2):
Systemic Risk in Financial Markets: How Systemically Important Are Insurers?

Christian Klein developed the research design, collected the data, and conducted the analyses. The interpretation of the results was an iterative, cooperative process involving both authors. Christian Klein prepared and revised the manuscript in accordance with comments and suggestions provided by the coauthor.

Christoph Kaserer	Christian Klein
(Coauthor)	(First author)

WORKING PAPER 2 (CHAPTER 3):
Contagion in Financial Markets: How Interconnected Are Insurers?

I developed the research design, collected the data, conducted the analyses, interpreted the results, and prepared and revised the manuscript.

Christian Klein
(First author)

WORKING PAPER 3 (CHAPTER 4):
Is the Financial System Special? Systemic Risk in Financial and Nonfinancial Firms

I developed the research design, collected the data, conducted the analyses, interpreted the results, and prepared and revised the manuscript.

Christian Klein
(First author)

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