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CDS spreads and systemic risk – a spatial econometric approach

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Non-technical summary

In the current crisis, credit risk not only evolved from a financial institution's fundamentals but also from a system-inherent mechanism of risk propagation. Therefore, the credit event of a single entity spread risk across the whole network of institutions. This contagion effect has been demonstrated dramatically in the ongoing economic and financial crisis. We apply to the field of finance a – to our knowledge – novel way of measuring, quantifying and modelling the degree of systemic risk and the magnitude of risk spill over effects by introducing a specific weighting scheme in a regression that relates observations to each other. We measure contagion effects in CDS levels as well as CDS changes. This approach originally stems from spatial econometrics. The methodology allows for a decomposition of the total risk charge (i.e. the credit spread) into a systemic, systematic and idiosyncratic risk charge. While the systemic component measures the degree of risk spillovers due to the interconnectedness of the financial institutions, the systematic part accounts for the risk stemming from institutions fundamentals and macro-economic fundamentals. The idiosyncratic risk compontent reflects an instition's specfic and diversifiable risk. We apply this methodology to a sample of 15 banks and insurance companies over the period from 2004 to 2009. This research uses equity correlations as a measure of economic distance and CDS spreads as a measure of a financial entity's credit risk. We find considerable risk spill overs due to the interconnectedness of the fifteen systemically important banks and insurance companies. Depending on the state of the economy, up to a fifth of the total predicted CDS spread changes are due to financial infection, highlighting the need for macro-prudential supervision and serving as an alternative explanation for the nonlinear relationship between a debtor's theoretical probability of default and observed credit spreads – known as the "credit spread puzzle". However, we find that this systemic risk charge spreads heterogeneously across geographical regions and financial institutions due to varying integration into the financial system.

Nicht-technische Zusammenfassung

Die globale Banken- und Finanzkrise der Jahre 2007/08 zeigte eindrucksvoll, dass das Kreditrisiko nicht nur von den Fundamentaldaten eines Instituts und dem makroökonomischen Umfeld beeinflusst wird, sondern dass das Risiko auch zwischen den Institutionen weitergegeben wird. In einem solchen Umfeld beeinflusst die mögliche Insolvenz eines einzelnen Instituts beinahe alle anderen Finanzunternehmen im Finanzsystem. Dieser sogenannte Ansteckungseffekt (englisch: contagion) wurde in der immer noch andauernden europäischen Finanzkrise eindrucksvoll dargelegt. Zur Analyse, Messung und Modellierung dieser Ansteckungseffekte und somit zur Quantifizierung dieses Risikos verwendet diese Studie ein für die Analyse von Finanzintermediären neuartiges Gewichtungsschema, das die Einbeziehung von Netzwerkstrukturen erlaubt. Dieser Ansatz entstammt ursprünglich der räumlichen Ökonometrie. Herausragend ist dabei die Möglichkeit, den Kreditrisikoaufschlag in eine systemische, eine systematische und eine idiosynkratische Komponente aufzuteilen. Die drei Komponenten ermöglichen also eine Aufteilung des Risikos in einen Teil, der durch die Einbindung der Bank ins Finanzsystem entsteht, dem Risiko, das durch Markt- und Fundamentaldaten entsteht, und einen individuellen Teil des Risikos, der auf Spezifika des Finanzinstituts zurückgeht und diversifizierbar ist. Die Studie untersucht eine Stichprobe von 15 systemrelevanten Banken und Versicherungen und verwendet die oben dargestellte Methode zur Untersuchung von Kreditrisikoaufschlägen über den Zeitraum zwischen 2004 und 2009. Zur Messung der systemischen Vernetzung der Finanzinstitute werden Korrelationen der Aktienrenditen der Finanzintermediäre verwendet. Als Maß für das Kreditrisiko eines Finanzinstituts dienen Credit Default Swap (CDS) Spreads. Die Studie zeigt erhebliche Ausbreitungseffekte (spill overs) von örtlich beschränkten Finanzmarktschocks aufgrund der Vernetzung der untersuchten Banken und Versicherungsgesellschaften. Bis zu einem Fünftel des CDS-Aufschlags geht auf systemische Verflechtungen zurück. Gleichwohl ist die Höhe des Aufschlags abhängig von den wirtschaftlichen Rahmenbedingungen, der geographischen Region und dem Grad der Integration in das Finanzsystem. Diese Ergebnisse betonen die Notwendigkeit einer makroprudenziellen Überwachung. Gleichzeitig bieten die gemessenen systemischen Risikoaufschläge eine Erklärung für den nichtlinearen Zusammenhang zwischen der theoretischen Insolvenzwahrscheinlichkeit und dem empirisch beobachteten Kreditrisikoaufschlag (das sogenannte Credit Spread Puzzle).

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CDS spreads and systemic risk – a spatial econometric approach*

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Abstract

This study applies a novel way of measuring, quantifying and modelling the systemic risk within the financial system. The magnitude of risk spill over effects is gauged by introducing a specific weighting scheme. This approach originally stems from spatial econometrics. The methodology allows for a decomposition of the credit spread into a systemic, systematic and idiosyncratic risk premium. We identify considerable risk spill overs due to the interconnectedness of the financial institutes in the sample. In stress tests, up to one fifth of the CDS spread changes are owing to financial contagion. These results also give an alternative explanation for the nonlinear relationship between a debtor's theoretical probability of default and the observed credit spreads – known as the "credit spread puzzle".

Keywords: systemic risk, financial contagion, spatial econometrics, CDS spreads, government policy and regulation.

JEL classification: C21, G12, G18, G21.

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1 Motivation

Banks and insurance companies (henceforth financial institutions, FIs, or banks) play a crucial role in an economy by exercising a liquidity transformation, risk transformation and monitoring function. However, the crisis in 2007/2008 illustrated once again that the malfunctioning of the financial system can be disastrous. Being aware of the costly consequences of financial turmoil, regulators and supervisors focused on guaranteeing the soundness of each individual FI by setting minimum capital requirements (e.g. Basel I and II, Solvency I, Swiss Solvency Test) known as micro-prudential regulation and supervision. With the onset of the global liquidity, credit and confidence crisis it became obvious that micro-prudential regulation should be amplified by another dimension, the macro perspective. The need for a macro perspective was underscored by the origins of the financial crisis, where problems in a corner market – the subprime mortgage market, which only accounted for three percent of U.S. financial assets (Eichengreen and Sarno, 2009) – had infected the entire banking system. Eventually this jeopardised the stability of the global financial system. The fact that shocks were transmitted between seemingly independent entities and markets, denoted as contagion or spill over effects, revealed a high degree of financial interconnectedness. And the presence of spill overs across markets and banks indicates a system-inherent mechanism of shock transmission that affects all entities. This contradicts the hypothesis of a system of independent FIs. In the no contagion case, one would expect an institution's stability to relate solely to its key economic data (the fundamentals). Yet instabilities were quickly transmitted across banks in the recent crisis; we may therefore conclude that it is not only banks' fundamentals that determine their stability but also the financial system as a whole. It is vital to understand the risks and risk dynamics of a banking system in order to prevent crises.

To model systemic risk, we propose a regression approach which uniquely integrates the micro and macro perspectives of financial supervision. This approach enables systemically important financial institutions to be identified and delivers a convenient stress testing tool which combines and interacts macro and micro stress situations. More precisely, our approach demonstrates how an idiosyncratic shock to an FI is transmitted across the financial market and will influence the solvency of each entity in the system. Furthermore, we show that such a shock does not affect all institutions to the same extent and that the magnitude of the spill over effect strongly depends on the interconnectedness of the financial institutions.

A bank's health can be measured by its probability of default, which we measure by its CDS spread. We decompose movements in CDS spreads into a systemic, a systematic and an idiosyncratic risk component by applying a regression approach which originally stems from spatial econometrics. The systematic and idiosyncratic risk factors have a similar interpretation to those used in the capital asset pricing model or the arbitrage pricing model. However, the systemic risk component in our regression is novel to the literature. We set up a parsimonious regression model in which each FI is linked with all the other entities through the financial market. The (single) parameter which indicates the degree of the systemic risk then has to be estimated. By this it is possible to test for and quantify the relevance and presence of financial spill overs. Systemic proximity (i.e. the financial system) is modelled using stock return correlations and observations are weighted by this measure of economic distance.[1] High equity return correlations imply a market perception that FIs will suffer simultaneously as a result of a shock, qualifying return correlations as an adequate measure of economic distance.[2] Contemporaneous equity market movements could either result from common exposures or from financial contagion. We explicitly do not characterise movements in CDS markets due to common exposures as contagion and will distinguish between direct effects owing to common exposures and indirect effects which constitute pure contagion. We find the systemic risk charge stemming from financial contagion to be a considerable driver of CDS spreads.

To summarise, our main line of argument is as follows: First, given the probability of default (PD, expressed as CDS premiums) of the firms, we are able to separate the FI's specific contribution to its CDS premium (e. g. via the fundamentals) and the system-inherent contribution due to financial contagion. Understanding the determinants of FIs' CDS premiums therefore helps with assessing the solvency of each individual firm in a stand-alone optic as well as evaluating the resilience of the whole financial system. Second, our approach adds a further dimension to stress testing by providing the opportunity to analyse how an idiosyncratic shock experienced by one FI is transmitted across the entire financial system. Finally, we highlight that an appropriate way of specifying, quantifying and testing for the impact of systemic risk arises from the field of spatial econometrics.

The next section introduces the relevant literature for our study and seeks to discuss our contributions to the current debate. We then introduce the methodological underpinnings for CDS and the econometric approach, before analysing the data used. In the subsequent Subsection on results, we analyse the findings of our study. The final section summarises and briefly discusses the findings.

[1] The terminology in this study is borrowed from spatial econometrics. Economic distance, contiguity and proximity are used interchangeably and refer to the explained measure of return correlations.

[2] Note that in the framework of Merton (1974) the firm's equity value is under the condition of a constant interest rate, volatility and asset to book value of debt ratio proportional to its asset value, and asset and equity return correlations are thus equal.

2 Literature

This section discusses the theoretical foundations and relevant studies for our analysis. It points out where this study contributes to the current debate. There are numerous studies on financial contagion in theoretical and empirical publications. Allen and Gale (2000) and Freixas, Parigi, and Rochet (2000), for example, explore contagion via the interbank market. Both studies argue that the architecture of the interbank market is of crucial importance and a system where each bank borrows from only one bank is more fragile than a system where the sources of funds are more diversified. In our study we take up the idea of the importance of inter-institutional linkages as a source of risk propagation. However, we do not concentrate solely on bilateral interbank market exposures. In contrast, we analyse contagion stemming from general financial markets. Our model uses common exposures, inferred from equity return correlations, to replicate the financial system.

Another branch of literature makes use of counterfactual simulation methods to analyse the soundness of the interbank market (e.g. Upper, 2011; Mistrulli, 2011). These studies aim to assess the vulnerability of different interbank market structures to contagious defaults by applying a simulation approach. In general, these models are not well suited to stress testing due to their lack of behavioural foundations. In contrast to counterfactual simulation, the approach applied in this paper uses regression analysis to explore the effect of financial contagion on market prices in a financial crisis. The advantage of such a model is that it relies on market data being observations of humans' actions in times of financial turmoil. Therefore, these models are better suited to stress testing and policy analysis.

A further area of theoretical literature argues that financial markets in general may also serve as channels which transmit shocks. In particular, the interaction between funding liquidity and asset liquidity may create systemic risk (e.g. Fecht, 2004). The theoretical literature on the transmission of shocks via the asset market has been accompanied by empirical investigations measuring the resilience of the financial system based on market data. That branch of literature defines systemic risk as the *nth*-to-default probability of a portfolio of credit default swaps or an equity portfolio (e.g. Chan-Lau and Gravelle, 2005; Lehar, 2005).[3] Similarly, Huang, Zhou, and Zhu (2009) propose an indicator – the price of insurance against large default losses in the banking sector in the coming 12 weeks – to assess the systemic risk of the banking sector. All these empirical studies propose risk indicators which do not shed much light on the mechanism which transmits financial shocks. Moreover, macro-prudential analysis is entirely detached from the micro perspective in these analyses. In contrast, this paper directly models the interconnectedness of financial

[3] *nth*-to-default probability refers to the probability of having n credit events in a CDS portfolio.

institutions and estimates the degree to which an idiosyncratic shock experienced by one FI is propagated via the financial system. The model thus integrates the macro and micro perspectives of banking supervision.

In order to capture the phenomenon of financial contagion empirically, it has been modelled econometrically in various ways. One approach is to estimate changes in correlation coefficients of assets after having controlled for the fundamentals. A significant jump in the asset correlation is considered to be evidence of contagion (e.g. Baig and Goldfajn, 1999; Hernández and Valdés, 2001; Fratzscher, 2003). A second approach estimates spill overs in volatility using ARCH or GARCH techniques (e.g., Edwards and Susmel (2000) and Edwards and Susmel (2001)). A third method is to estimate a system of equations where a bank's probability of default is a function of the probability of default of another bank. This only works if the researcher wants to analyse the spill over effects from a few financial institutions or sectors on others due to an exploding model size (known as the curse of dimensionality). This method has, for example, been applied by Adams, Füss, and Gropp (2010). A spatial econometric model, however, is able to overcome the curse of dimensionality and is therefore perfectly applicable to financial data sets. Indeed a spatial model is a restricted version of a system of regressions.

Even though spatial econometric models deliver a straightforward way of modelling the interconnectedness of observations, they have not yet received much attention in finance. One reason for that might lie in the difficulty of finding an adequate measure of economic distance in finance applications. One interesting application of a spatial econometric model in this field has been presented by Fernandez (2011). She develops a spatial capital asset pricing model (S-CAPM) and shows the implications of spatial autocorrelation in asset return series for risk management by deriving a value at risk from the S-CAPM formulation. Spatial econometric models have also been used to model contagion in a macroeconomic context. Kelejian, Tavlas, and Hondroyiannis (2006), for example, analyse the extent to which instabilities in the foreign exchange market of one emerging market economy are transmitted to others.

Many other studies have investigated determinants of CDS premiums in the past (see, for example, Alexander and Kaeck (2008) or Ericsson, Jacobs, and Oviedo (2009) and extensive comments in Section 3.1). Our analysis differs from these studies by additionally modelling the interconnectedness of observations. This allows the degree of financial contagion in the CDS market to be measured. Moreover, the model structure allows movements in CDS spreads to be decomposed into a systemic and an FI-specific component, which – to the best of our knowledge – is novel to the literature.

3 Methodology

3.1 CDS spread dynamics

Credit default swaps offer a hedge against credit risk in which the protection seller offers to compensate the buyer if the underlying defaults before the maturity of the contract. The fee charged by the protection seller, usually on a quarterly basis, is paid up to maturity or up to a previously specified credit event (e.g. the default of the borrower). We denote this fee as the CDS spread and quote it in basis points. Most contracts include a variable upfront payment and no payment is made by the seller if there is no default. The contract design makes a CDS spread an adequate proxy for the probability of default of the borrower. The most striking argument for using CDS to assess a company's stability is the fact that market data are forward-looking, since today's price change reflects anticipated future performance changes of the underlying FI.[4]

There are two main approaches to modelling credit risk – the main driver behind CDS spreads. The so called *reduced form models* focus on modelling an exogenously determined hazard rate which describes the frequency of failure. This approach is used by Jarrow and Turnbull (1995), Jarrow, Lando, and Turnbull (1997) and Duffie and Singleton (1999) amongst others. A second approach, usually referred to as *structural models* is based on the contingent claim analysis for valuing debt developed by Black and Scholes (1973) and Merton (1974). This study builds upon the latter. Essentially, this category of models assumes that the default of a firm occurs if the value of its assets drops below a given threshold. While the asset's value is usually seen as a stochastic process following some trend (i.e. the drift rate, usually approximated using the interest rate level), firm debt is held constant (Ericsson et al., 2009). The original model by Merton (1974) prices risky debt solely as a function of the underlying firm value. Recent studies extend this approach and model credit spreads as a function of firm asset value and other state variables (Collin-Dufresne, Goldstein, and Martin, 2001).[5]

4 CDS premiums are also considered to be a superior measure of PDs because CDS spreads are found to lead bond spreads when responding to shocks. See, for example, Forte and Peña (2009) or Deutsche Bundesbank (2010a).

5 For an extensive review of relevant variables, see Allen, Boudoukh, and Saunders (2004, pp. 124–127)

3.2 Econometric approach

This section introduces the econometric approach applied in this study. Spatial econometrics, as a branch of econometrics, evolved from the need to incorporate spatial structures within econometric models (Anselin, 1988). In traditional econometric studies the researcher is interested in the functional relationship between a dependent variable (denoted as y_i) and several independent variables (denoted as $x_{i,k}$).

$$y_i = f(x_{i,1}, x_{i,2}, ., x_{i,K}) + \varepsilon_i$$

For example, in this study we analyse how the CDS spread of company i, denoted as y_i, depends on that company's fundamentals $x_{i,k}$ (i.e. financial leverage, equity volatility, etc.). In classical linear regression $f(.)$ is a linear function. Spatial econometrics advances from the traditional approach by allowing y_i to depend not only on $x_{i,k}$ but also on the dependent variable of all other entities in the system.

$$y_i = f(y_{j \neq i}; x_{i,1}, x_{i,2}, ., x_{i,K}) + \varepsilon_i$$

By applying such a model structure, we address the question of how the CDS spread of FI i depends on the CDS spreads of all other companies within the financial system. If we find that the CDS spread of company i depends significantly on the CDS spread of any other company, this constitutes evidence of financial contagion. Consequently, such a model allows us to measure and test for the presence of spill over effects.

The drawback of such a model is that it cannot be estimated in an unrestricted fashion due to the curse of dimensionality. The research branch of spatial econometrics overcomes this problem with the idea that the information of (geographical) distance between two observations can be exploited. Naturally, first applications stem from the fields of urban and regional economics as well as real estate economics, since distance has a straightforward interpretation in these contexts. In its simplest form, spatial econometric models specify the contiguity of two observations as a binary variable, i.e. being or not being a neighbour. Other studies use measures of geographic and economic distance. Spatial econometrics have quickly found their way into topics such as international economics and labour economics. With the growing attention, a set of estimators, models and tests have been developed that allow various forms of proximity between subjects to be modelled. This study takes up the idea of measuring the effect of economic distance between individuals. It concentrates on financial institutions interacting and working on common markets and reinterprets spatial spill overs as financial contagion.

Most empirical examinations of the structural approach introduced in Section 3.1 regress a measure of credit risk (in our case CDS spreads) on a set of firm-specific characteristics, obtaining a classical linear model of the form $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$.[6] In this simple model, $\mathbf{y}$ is a vector of the explained variable. The matrix of independent variables is denoted $\mathbf{X}$ and $\boldsymbol{\beta}$ is the parameter vector. In this framework, $\boldsymbol{\varepsilon}$ denotes the usual Gaussian, $\boldsymbol{\varepsilon} \sim \mathcal{N}(0, \sigma^2\mathbf{I}_N)$, error vector where $\sigma^2\mathbf{I}_N$ is the covariance matrix.

In order to capture dependencies across firms within a model framework, the spatial lag model (or spatial autoregressive model, SAR) introduces the matrix $\mathbf{W}$ by which the degree of interaction between financial institutions is captured (Anselin, 1988). Equation 1 specifies the full model and introduces the term $\rho\mathbf{W}\mathbf{y}$.[7] By the degree of economic proximity determined in $\mathbf{W}$, the CDS spread of any company y_i is now dependent on all other CDS spreads (y_j) in the system and the parameter ρ gauges the degree of dependence or, in other words, the intensity of shock transmission in the system. Note that the element i of vector $\mathbf{W}\mathbf{y}$ is given by $[\mathbf{W}\mathbf{y}]_i = \sum_{j=1,.,N} w_{i,j}y_j$, hence each element of the vector $\mathbf{W}\mathbf{y}$ represents a weighted sum of the CDS spread of the neighbouring FIs. The spatial autocorrelation coefficient is bound to $|\rho| < 1$.[8]

$$\begin{aligned} \mathbf{y} &= \underbrace{\rho\mathbf{W}\mathbf{y}}_{\text{systemic risk}} + \underbrace{\mathbf{X}\boldsymbol{\beta}}_{\text{systematic risk}} + \underbrace{\boldsymbol{\varepsilon}}_{\text{idiosyncratic risk}} \\ \boldsymbol{\varepsilon} &\sim \mathcal{N}(\mathbf{0}, \sigma^2\mathbf{I}_N) \end{aligned} \tag{1}$$

The model leads to a decomposition of the CDS premium into a systemic, a systematic and an idiosyncratic risk component. The systemic risk component reflects the mechanism which transmits shocks via the financial system. The magnitude of risk spill overs strongly depends on the FI's interconnectedness and the parameter ρ measures the degree of economic dependence. The systematic risk component reflects institutions' vulnerability to changes in general risk factors (e.g. leverage, asset volatility, interest rate, etc.). The third component, the idiosyncratic risk component (also known as residual risk), is the risk to which only the specific FI is vulnerable. In contrast to systemic and systematic risk, idiosyncratic risk can be reduced or eliminated by diversification.

[6] Where, as usual, bold letters represent matrices or vectors.

[7] SAR models are a sub-category of the general spatial model where the weighting matrix is introduced to the error term as well: $\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \mathbf{u}$ and consequently $\mathbf{u} = \lambda\mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon}$, where the ε is defined as: $\boldsymbol{\varepsilon} \sim \mathcal{N}(\mathbf{0}, \sigma^2\mathbf{I}_N)$. The SAR model is a restricted variant by setting $\lambda = 0$. (Anselin, 1988)

[8] This only holds true for standardised weighting matrices. The weighting matrix in this study has been standardised by dividing all entries by the maximum eigenvalue. See Section 3.3 for more details.

At this point it might be interesting to distinguish between shocks stemming from common exposures and financial contagion. We argue that a statistically significant systemic risk component goes beyond shocks from common exposures which contemporaneously affect institutions' balance sheets. For example, imagine two FIs have invested in the same firm. A default of that firm will cause both banks to write off parts of their investment. Ceteris paribus, this will decrease equity and increase the leverage of both FIs. Eventually, the change in fundamentals will cause the CDS spreads of both firms to increase. This, of course, is also captured in the classical linear model framework and is reflected as the systematic risk component in the spatial model. However, the existence of a systemic risk component indicates that the total effect of that default is more than just the sum of all direct effects of changing fundamentals. Finding a statistically significant and economically important systemic risk component indicates the presence of a synergy effect arising from banks working in the same financial market. This risk generation process is best summarised in the words of Aristotle, "The whole (the financial system) is more than the sum of its parts (its financial institutions)." However, the classical OLS model is not able to capture that effect.

A particularly striking feature of the spatial autoregressive model (SAR) is that it nests the standard linear model and thus offers a convenient way of testing for the presence of spill over effects. In the case of $\rho = 0$ the researcher ends up with a classical linear regression model implying no spill over effects. Therefore, testing for the significance of ρ is a test for the presence of financial contagion where

$$H_0 = \text{No spill over effects} \tag{2}$$

$$H_1 = \text{Spill over effects} \tag{3}$$

Hence, a statistically significant parameter ρ not only indicates the relevance of the FI's interconnectedness to the probability of default of a financial institution; it also implies that standard linear models misestimate the effect of a change in covariates. And, what is worse: neglecting the systemic risk component in a regression may lead to biased results (LeSage and Pace, 2009).

As several authors point out, this category of model differs in interpretation from standard linear models (Anselin, 2002). For the classical linear regression model, the effect of a marginal change in any $x_{i,k}$ is the partial derivative $\partial y_i / \partial x_{i,k} = \beta_k$.[9] Yet this is not the case for spatial models (Abreu, De Groot, and Florax, 2004).

[9] This holds for all i and all k, while the partial derivative with respect to every other observation j is zero: $\partial y_i / \partial x_{j,k} = 0 \; \forall \; i \neq j$.

$$\mathbf{y} \;=\; (\mathbf{I} - \rho\mathbf{W})^{-1}\mathbf{X}\boldsymbol{\beta} + (\mathbf{I} - \rho\mathbf{W})^{-1}\boldsymbol{\varepsilon} \tag{4}$$

Equation 4 rewrites the SAR model introduced in Equation 1. The first part is often denoted as the spatial multiplier: $\mathbf{S} = (\mathbf{I} - \rho\mathbf{W})^{-1}$ (Anselin, 2003).[10] The nature of spill over effects within the system becomes evident from an in-depth analysis of this term. Since we may rewrite the multiplier as a geometric series $(\mathbf{I} - \rho\mathbf{W})^{-1} = \mathbf{I} + \rho \cdot \mathbf{W} + \rho^2 \cdot \mathbf{W}^2 + \rho^3 \cdot \mathbf{W}^3 \ldots$ we obtain a system where a shock to any y_i gets transmitted to any other y_j. This shock is transmitted forward and backward until it finally diminishes. We interpret this as a contagion effect within a financial system.

In order to separate the contagion from the FI-specific effect, LeSage and Pace (2009) note that the total impact of a change in any $x_{i,k}$ may be broken down into a *direct effect* $\partial y_i / \partial x_{i,k}$ and the *indirect effects* $\partial y_j / \partial x_{i,k}$ representing the spill over effects from individual i on individual j. Since these impacts differ for each individual i , the authors additionally propose a set of summary measures:[11]

Average direct impact: The average direct impact measures the effect of a change in $x_{i,k}$ on y_i – the effect of an individual's attributes, so to speak. It is computed as the average along the diagonal of the spatial multiplier matrix ($\mathbf{S}$) times the parameter vector $\boldsymbol{\beta}$: $\Psi_k^{direct} = \frac{1}{N} tr\left((\mathbf{I} - \rho\mathbf{W})^{-1} \beta_k\right) = \frac{1}{N} tr\left(\mathbf{S}\beta_k\right)$

Average total impact: The total effect of a change within the system is denoted as the average total impact. It is calculated as the sum over the ith row of matrix $\mathbf{S}\beta_k$ yielding the total impact to y_i from a change in vector x_k. Averaging over all N sums gives the average total impact: $\Psi_k^{total} = \frac{1}{N}\iota'\mathbf{S}\beta_k\iota$, where ι is a column vector of ones of size N.

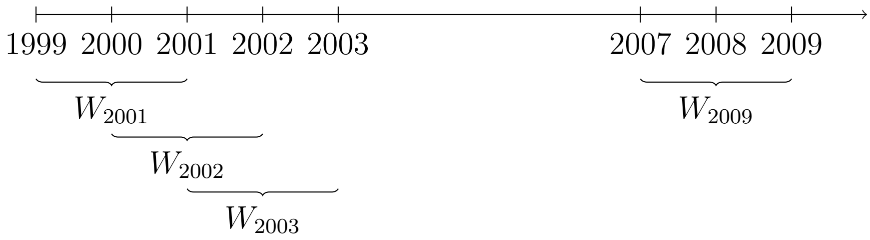
Indirect impact: The indirect impact is obtained by subtracting the direct impact from the total impact: $\Psi^{indirect} = \Psi^{total} - \Psi^{direct}$.

In this study, we determine the change in the CDS spread of an institution y_i from shocks to $x_{i,k}$ (e.g. the fundamentals). The total change in y_i is broken down into the change from the fundamental variables and from spill over effects transmitted via the connections within the financial system.

[10] The reader may be familiar with this expression from input/output analysis, where a similar representation is denoted as the Leontief inverse (Anselin, 2003).

[11] LeSage and Pace (2009) specifically distinguish between the total impact *to* an observation and *from* an observation. While these are numerically identical, they give a different interpretation. For the sake of simplicity, this is not discussed any further.

Figure 1: Rolling estimation window of the correlation matrix **W**.



3.3 Construction of the weighting matrix

The weighting matrix **W** plays a major role within our analysis of financial spill overs. This subsection looks at the construction of this measure of economic distance. The data has a panel structure with $i = 1 \dots N$ individuals and $t = 1 \dots T$ years consisting of $s = 1 \dots S$ months. Interdependence is allowed between companies within the same month (contemporal). Temporal interdependence, i.e. between years and months, is not allowed. Such a system can be obtained via a block diagonal matrix. At the most granular level, we start by constructing correlation matrices from weekly equity returns over a three-year period. Each element within the matrix **W** is a correlation coefficient γ of weekly stock returns between two financial institutions based on a three-year period $w_{i,j} \equiv \gamma_{i,j} \; \forall \; i \neq j$ in year t and month s and 0 else – this models contemporaneous economic distance only. In order to obtain endogeneity of y_i and $\gamma_{i,j}$, we lag the correlation coefficient by one year.[12]

We standardise the weighting matrix by dividing each element of the matrix by the maximum absolute eigenvalue of **W**. This guarantees that the spatial model will be stationary if ρ is bound to $(-1, 1)$. Furthermore, it retains the absolute distance.[13]

For clarification, in Equation 5 the described structure is reinterpreted in sum-notation. It builds upon Equation 1, the SAR model, for month s and year t. The focus, again, lies on the lagged weighting element $w^*_{i,j,s,t-1}$, which is the lagged correlation coefficient divided by the maximum absolute eigenvalue. This obtains a standardised weighting matrix for

[12] An extensive explanation of the construction of the weighting matrix can be obtained from the authors upon request.

[13] Spatial econometricians typically row standardise the weighting matrix (Plümper and Neumayer, 2010). This means that each matrix cell is divided by its row sum, such that the weights in each row add up to one. The absolute distance is thus altered to a relative measure of distance. Since row standardisation implies that the spill over effect on each bank in the financial system proportionally decreases with the degree of interconnectedness of the bank which initially faced the shock, this is problematic in our analysis. See Plümper and Neumayer (2010) for a detailed discussion of row standardisation.

all $i \neq j$ The main diagonal elements are zero by definition.

$$y_{i,s,t} = \rho \cdot \sum_{j=1,i\neq j}^{N} \left(y_{j,s,t} \cdot w^*_{i,j,s,t-1}\right) + \sum_{k=1}^{K} \left(\beta_k \cdot x_{i,k,s,t}\right) + \varepsilon_{i,s,t} \tag{5}$$

Element $y_{i,s,t}$ – the CDS spread of FI i in month s of year t – is modelled as a weighted average of the scaled correlation coefficients $w^*_{i,j,s,t-1}$ times the CDS spread of other companies in month s of year t ($y_{j,s,t}$) multiplied by the spatial autocorrelation parameter ρ (estimated over all periods). The exogenous determinants of the FI, the systematic risk, is added to this systemic component. While the spatial lag takes account of the systemic risk, the systematic risk is represented by including the economic situation and firm fundamentals in our regression. This is included in the second sum over all risk factors K. The unsystematic risk is included with the Gaussian error term $\varepsilon_{i,s,t}$.

However, the use of equity correlations as a measure of economic distance could be problematic if shocks influence equity correlations as well as CDS spreads. In such a case, the measure of economic distance was endogenous and statistical properties of estimators do not hold anymore (LeSage and Pace, 2009). In order to circumvent this issue, the weighting matrix is constructed by lagging the correlations by twelve months. Nevertheless, this was still insufficient if the contemporary CDS spreads $y_{i,s,t}$ contained information for explaining the correlation of equity returns $w_{i,j,s,(t-1)}$, used for constructing the weighting matrix. In our case, the correlation of the average CDS spread and the average logarithmic return in $(t - 12)$ is not present ($\gamma = -0.0001$), indicating (at least) no linear dependence of equity returns in $(t - 1)$ and CDS spreads in time t. We conclude from this that the matrix $\mathbf{W}$ can be treated as exogenous.

In general, the construction of the weighting matrix has been the subject of heated debates. Other variants have been proposed (see for example Fernandez, 2011). However, the results reported in Section 5 are invariant to changes within $\mathbf{W}$. On the other hand, LeSage and Pace (2009) advocate a concentration on the model specification rather than focusing on measures of distance:

> We do mean to imply that far too much effort has gone into "fine-tuning" spatial weight matrices that depend on highly parameterized functions of distance, lengths of common borders, and so forth. However, due to the number of common elements in these weight matrices and selection of parameters that give the best fit for each W, good fitting models using these different forms of W are not likely to produce estimates and inferences that materially differ.

Table 1 summarises the correlations in matrix $\mathbf{W_t}$. On average, moderate correlations of roughly 0.7 predominate for all years. Compared to the mean, the median is slightly shifted towards 1. The average correlation slightly decreases during 2003-2007. In the crisis years, average correlations rise again. This is a common pattern for stocks during periods of financial distress.

	Mean	Std. dev.	Median	Min	Max
2003	0.66	0.26	0.74	0.00	0.98
2004	0.70	0.23	0.79	0.00	0.96
2005	0.71	0.22	0.78	0.04	0.96
2006	0.69	0.19	0.71	0.08	0.96
2007	0.53	0.24	0.57	0.01	0.88
2008	0.71	0.28	0.87	0.08	0.98
2009	0.72	0.27	0.84	0.09	0.98

Table 1: Descriptive statistics for the CDS weighting matrix, broken down by years. Note that only the correlations between 2003 and 2008 have been used for estimation. Furthermore, the main-diagonal elements have been excluded.

However, standard deviations show that an increased heterogeneity has been observed during the crisis. High return correlations indicate economic proximity and thus a high likelihood of financial contagion. A closer inspection of patterns leads to the conclusion that European and American financial institutions in particular are highly interconnected. This observation does not hold for Japanese FIs. While US and European institutions have average correlations of 0.73 and 0.69 respectively (see Table 2), Japanese institutions' equity correlation is 0.49 (calculated over the whole sample and time span). Therefore, the Japanese financial system is not as prone to contagion spreading from other continents as the European or American one. This has also been reported by the Deutsche Bundesbank (2010b) when investigating the German financial system's susceptibility to financial shocks. This particular study showed that financial disruptions in Europe or in the U.S. will strongly affect the soundness of the German financial system, while Japanese financial shocks have no significant impacts. This is in line with the architecture of $\mathbf{W}$. From the table it is also evident that the interconnectedness, and thus the expected spill over effects, will be highest for European institutions, followed by American companies.

4 Data

This section describes the data used for analysing CDS spreads. First, we analyse the explained variable – the spreads – in detail. Second, we explore the regressors.

	Mean	Std. dev.	Median	Min	Max
EU	0.73	0.22	0.80	-0.20	0.98
JP	0.49	0.27	0.48	-0.20	0.98
USA	0.69	0.23	0.75	-0.18	0.97

Table 2: Descriptive statistics for the CDS weighting matrix, broken down by regions. Calculated as the average correlation of all entities within a region over the whole sample and time span.

As initially described, we base our analysis on five-year credit default swap spread data obtained from Bloomberg. The choice of financial institutions is based on a preliminary list of systemically important financial institutions announced by the Financial Stability Board in 2010 (www.financialstabilityboard.org). In this study we use a balanced panel of 15 out of the originally 30 institutions. This restriction has been necessary since data for the chosen period of time has not been available for all 30 entities. Given the choice between a full set but unbalanced panel of institutions and a balanced panel over a long time span the latter alternative has been chosen for statistical reasons. The choice of a balanced panel structure is governed by statistical properties of the used estimators (LeSage and Pace, 2009).

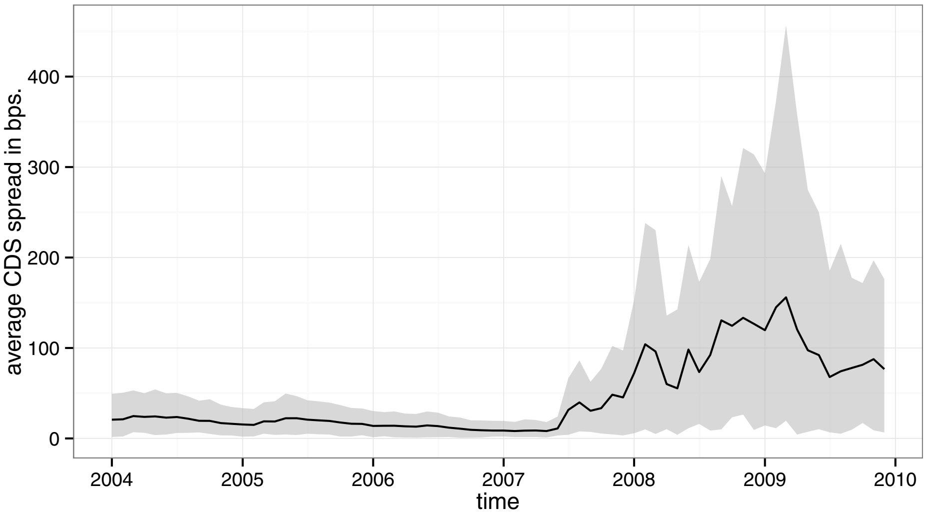
A full list of all institutions along with their abbreviations can be found in the appendix. Our data covers the 2004–2009 period at a monthly frequency. To ensure comparability, all data have been calculated as end-of-month data. Figure 2 depicts the median CDS spread over the whole sample period. The grey area indicates the .75 and the .25 percentiles. The impact of the market turmoil in 2008 and the turbulence in 2009 is evident. This is also reflected in the key figures displayed in Table 3, where the average CDS spread rises from 22.32 in 2004 to 121.35 in 2008.

	Mean	Std. dev.	Median	Min	Max
2004	22.32	7.74	20.53	9.67	47.10
2005	18.24	6.02	17.78	7.70	35.19
2006	12.63	4.19	12.51	4.69	26.42
2007	25.48	18.99	19.75	4.62	97.20
2008	121.35	96.80	101.93	42.50	1033.50
2009	136.50	98.89	105.83	43.33	631.53

Table 3: Descriptive statistics for the CDS spreads in the sample.

CDS spreads largely depend on a firm's asset value, its asset volatility and some other macro determinants (see Section 3.1 for the theoretical background. The data were obtained from Bloomberg. Since financial institutions from three different geographical

Figure 2: Plot of the median CDS spread in sample. Ribbons indicate the .75 and .25 percentiles.



regions (Asia, Europe and USA) and five currencies are covered (CHF, EUR, GBP, USD and JPY), we match FIs with their region-specific variables for the respective currency area, such as the interest rate. Variables quoted in a foreign currency are converted to USD using the appropriate exchange rate. We construct monthly time series for fundamental data by interpolating the available quarterly or semi-annual time series with a cubic spline. However, the results are neither sensitive to the method of interpolation (e.g. linear, or by carrying forward the last observation) nor to the chosen frequency. As a result, our findings remain qualitatively the same for a quarterly frequency or other interpolation methods. The following paragraphs contain an in-depth discussion of the regressors.

Leverage: The leverage describes the ratio between debt plus equity and debt. Since greater leverage leaves a higher equity cushion in the case of economic distress, greater leverage is connected with a higher probability of default (Ericsson et al., 2009; Merton, 1974). This suggests a positive relationship between this variable and the CDS spread. Moreover, the leverage is closely related to the recovery rate – the part of the loan that can be recovered in the event of a default. Higher leverage decreases the recovery rate. The recovery rate is negatively related to the CDS spread (Deutsche Bundesbank, 2010a). The interaction between leverage and the recovery rate theoretically amplifies the impact on the explained variable. In this analysis, the leverage is measured as the ratio of total liabilities over total liabilities plus market capitalisation.[14]

[14] The chosen definition differs from the Definition adapted in Basel II. For comparability it is, however,

Firm asset volatility: Higher asset volatility implies a greater probability of the firm's asset value falling below the threshold. In Merton's Model, a firm's debt is equivalent to holding a risk-free bond plus a short put on the firm's equity. From option pricing theory it is evident that a higher volatility implies a higher price for the put. Both arguments suggest a positive relationship between asset volatility and CDS spreads. Firm asset volatility is proxied by a GARCH(1,1) fit of daily stock returns, converted to end-of-month data in order to fit the frequency used in the regression.

Interest rates: Interest rates play a crucial role in the assessment of credit risk. The term structure of interest rates condenses information on the economic condition. Three common measures summarise the yield curve. The level of the yield curve describes the general interest rate level in the economy and serves as a proxy for the drift rate of the firm's assets. From the Merton model alone, we expect an inverse relationship of the interest rate level with CDS spreads since a higher drift rate implies a smaller probability of default.[15] The steepness of the yield curve summarises the relative cheapness of short-term debt compared to long-term debt. On an insurance company's balance sheet, for example, long-term liabilities are financed with shorter-term assets.[16] Contrarily, banks' assets typically exceed the duration of their liabilities. Such asset-liability-duration mismatches, combined with a change of the yield curve shape, might deteriorate FI's solvency. Finally, the curvature may indicate a hump-shaped yield curve. Hump-shaped yield curves indicate economic disruptions (Haubrich and Dombrosky, 1996). In our model, the level of the yield curve is represented by the 10-year spot rate for each geographical region. The difference between the 10-year yield and the three-month yield serves as an estimate for the slope of the curve. Finally, the curvature is estimated by $2 \cdot r_{12m} - (r_{10yr} + r_{3m})$ (Ericsson et al., 2009).[17]

Credit rating: The credit rating review process relies not only on public but also on non-public information. Thus, in addition to market data, ratings and rating events may explain the level of and changes in the CDS spread respectively. We expect an upgrade to have a significantly negative impact on the CDS spread. For downgrades we expect an inverse reaction. We use credit rating information from Standard & Poors.

consistent with the chosen definition in Ericsson et al. (2009).

15 This view, however, neglects effects from a cheaper refinancing of liabilities.

16 For Germany, such a situation is currently observable and poses pressure on insurers (Wilson, 2012).

17 While other measures for yield curve characteristics are theoretically possible (e.g. the first three components of a principal component analysis or parameter estimates of a Nelsson-Siegel model), the results are robust to variations in the construction of this measure.

Liquidity: In an imperfect market environment, liquidity is a determinant of CDS spreads. A liquidity premium has been identified by previous studies (Deutsche Bundesbank, 2004; Longstaff and Mithal, 2005). It is therefore reasonable to expect a higher CDS spread for periods of illiquidity within a market. The bid-ask spread, averaged over all FIs in period t, is included in order to account for changes in market liquidity.

Firm size: The onset of the market turmoil in 2008 highlighted the fact that some institutions are systemically important. Thus, these institutions are more likely to be saved from default (Völz and Wedow, 2009). Anticipating this behaviour, firm size might have a negative impact on the dependent variable. Furthermore, firm size may serve as a proxy for portfolio diversification and thus reduce the riskiness of big firms (Basel Committee on Banking Supervision, 2006). Another feature of firm size may be given by economies of scale (Elsas and Hackethal, 2010). All these effects suggest a negative relationship between firm size and the probability of default measured as the CDS spread. The size of a company is represented by the natural log of total assets.

Abnormal return: The residuals of a regression of the equity return adjusted for the risk-free rate on the adjusted market return should capture the FI's exceptional performance. This measure is thus simply the residual of a CAPM regression.

Economic state variables: Along with a change in fundamentals, the business climate may also affect the probability of default. Evidence on the state of the economy can be provided by the spread between the London Interbank Offered Rate (Libor) and the Overnight Indexed Swap rate (OIS), capturing the cost of credit risk as well as the health of the banking system. The Libor-OIS spread is the difference between the interest rate at which banks are willing to grant loans to other banks for a pre-specified term and the overnight funds rate expected by the markets. While the Libor market is risky, the OIS market is almost default-free because there is no exchange of principals – counterparties swap the fixed rate for the floating rate – and payments are made only at maturity. Consequently, the Libor-OIS spread reveals information on the soundness of the banking system or, as Alan Greenspan put it, "Libor-OIS remains a barometer of fears of banks insolvency".[18] Since a widening of this spread is associated with economic distress, we suggest a positive relationship.

[18] This quote has been taken from an interview given by Alan Greenspan in 2009 (Finch and McCormick, 2009).

5 Results

In this section, we report the results for the 15 examined FIs using the models introduced in Section 3.2. First, we present the estimation results for both CDS premium levels and changes in CDS premiums. Subsequently, we illustrate FIs' susceptibility to financial infection by stress testing individual institutions.

As outlined in Section 3.1, structural models, introduced by Merton (1974), identify three risk drivers for pricing risky debt: (a) the risk-free rate, (b) the firms' asset volatility and (c) the firms' capital structure. While the insight offered by this theory is fundamental, it is not feasible to accurately explain the complex credit spread dynamic with such a simple model structure. Indeed, Kim, Ramaswamy, and Sundaresan (1993) find that Merton's model fails to predict credit spreads large enough to match empirical observations. The authors argue that conventional contingent claim models are not able to predict spreads in excess of 120 basis points, but even AAA-rated corporate bonds ranged from 15 to 215 basis points in their sample. Responding to this issue, we report results for a restricted set of regressors along the lines of Merton (1974) as well as a fully specified set of explanatory variables introduced by various other authors. Moreover, both models are estimated taking into account spatial dependence (denoted as SAR), which allows for financial spill overs, and without spatial dependence, thus leading to a classic linear regression. Variants of the latter model were mainly used in literature for assessing determinants of CDS spreads in the past. All models are estimated with individual fixed effects.

5.1 Investigating CDS spreads

Table 4 compares regression results for absolute CDS spreads (levels) and first differences (changes in CDS spreads). Each has been analysed using four model specifications.[19] All models have been estimated as a pooled regression and no time lag structures have been introduced to the specifications.[20]

[19] We also examined models with further explanatory variables capturing the banks' health and profitability or the state of the economic and financial system, e.g. GDP growth, market portfolio return, inflation, return on equity, etc. However, none of these variables contributed to model performance measured by *AIC* or the *p*-value of the regressor.

[20] With such a model, the time structure is not explicitly taken into account.

Regression in levels				
Variable	ls1	sar1	ls2	sar2
Level	−10.36***	−5.86*	−5.46	−5.42
	(2.99)	(2.83)	(3.21)	(3.19)
Slope			5.91	5.33
			(3.20)	(3.17)
Curvature			14.01***	13.99***
			(3.49)	(3.43)
σ_{Equity}	14.10***	9.92***	4.48***	4.55***
	(0.66)	(0.68)	(0.76)	(0.75)
log(assets)			−33.78***	−35.20***
			(5.96)	(5.87)
Leverage	12.55***	8.10***	6.63***	6.65***
	(0.79)	(0.76)	(0.87)	(0.86)
Libor-OIS spread			52.85***	51.40***
			(5.62)	(5.73)
Bid-ask spread			6.14***	4.42***
			(0.67)	(0.82)
Rating A+			−39.17***	−36.13***
			(5.14)	(5.14)
Rating A−			24.91***	22.58***
			(6.35)	(6.27)
Rating AA			−58.85***	−56.78***
			(8.05)	(7.95)
Rating AA−			−50.08***	−46.76***
			(6.23)	(6.24)
ρ		0.40***		0.13**
		(0.03)		(0.04)
Obs	1,080	1,080	1,080	1,080
adj. R^2	0.65	0.69	0.75	0.74
AIC	11,332	11,178	10,991	10,986
BIC	11,426	11,278	11,131	11,131

Regression in differences				
Variable	dls1	dsar1	dls2	dsar2
Δ Level	−27.06***	−15.21**	−4.29	−2.39
	(6.19)	(5.64)	(6.80)	(6.67)
Δ Slope			−21.04*	−20.64*
			(8.33)	(8.18)
Δ Curvature			2.14	−1.07
			(7.35)	(7.18)
Δ σ_{Equity}	2.91***	2.30***	1.13*	1.23*
	(0.62)	(0.56)	(0.56)	(0.55)
Δ log(assets)			−15.72	−6.52
			(22.39)	(21.89)
Δ Leverage	3.89	0.43	−3.08	−3.71
	(2.84)	(2.56)	(2.54)	(2.48)
Δ Libor-OIS spread			16.44*	16.07*
			(8.18)	(8.11)
Δ Bid-ask spread			9.47***	7.25***
			(0.65)	(0.76)
Upgrade			−4.98	−5.24
			(9.86)	(9.64)
Downgrade			24.88**	20.52*
			(0.14)	(0.13)
Abnormal Return			−1.08***	−1.08***
			(9.37)	(9.16)
ρ		0.55***		0.24***
		(0.03)		(0.05)
Obs	1,065	1,065	1,065	1,065
adj. R^2	0.02	0.19	0.28	0.31
AIC	10,862	10,704	10,541	10,527
BIC	10,956	10,804	10,675	10,666

Table 4: Determinants of CDS-Premiums; standard errors in parentheses; * significant at the 5% level; ** significant at the 1% level; *** significant at the 0.1% level.

	Regression in levels					**Regression in differences**			
Variable	sar2 direct	sar2 indirect	sar2 total	ls2	Variable	dsar2 direct	dsar2 indirect	dsar2 total	dls2
Level	−5.43	−0.69	−6.12	−5.46	Δ Level	−2.41	−0.65	−3.06	−4.29
Slope	5.33	0.68	6.01	5.91	Δ Slope	−20.74	−5.63	−26.36	−21.04
Curvature	14	1.78	15.79	14.01	Δ Curvature	−1.08	−0.29	−1.37	2.14
σ_{Equity}	4.55	0.58	5.13	4.48	Δ σ_{Equity}	1.23	0.33	1.57	1.13
log(assets)	−35.24	−4.49	−39.72	−33.78	Δ log(assets)	−6.55	−1.78	−8.32	−15.72
Leverage	6.66	0.85	7.5	6.63	Δ Leverage	−3.72	−1.01	−4.73	−3.08
Libor-OIS spread	51.46	6.55	58.01	52.85	Δ Libor-OIS spread	16.15	4.38	20.53	16.44
Bid-ask spread	4.43	0.56	4.99	6.14	Δ Bid-ask spread	7.29	1.98	9.26	9.47
Rating A+	−36.17	−4.6	−40.78	−39.17	Upgrade	−5.26	−1.43	−6.69	−4.98
Rating A−	22.61	2.88	25.48	24.91	Downgrade	20.62	5.59	26.21	24.88
Rating AA	−56.85	−7.24	−64.08	−58.85	Abnormal Return	−1.09	−0.3	−1.38	−1.08
Rating AA−	−46.81	−5.96	−52.77	−50.08					

Table 5: Direct and Indirect Effects.

The table presents least squares estimation results for the Merton model (ls1 and dls1) and for a fully specified set of regressors (ls2 and dls2). The results denoted sar1 and dsar1 include the proposed methodology of introducing a spatial lag for the restricted set of regressors as well as for all regressors (sar2 and dsar2).

Obviously, the risk factors in the Merton model play a statistically significant and economically important role in CDS spreads. Yet the estimated parameters for restricted models are higher throughout. To be more precise, the restricted model versions lead to parameter estimates being twice (yield level or leverage) or even three times (equity volatility) as high as the models with the full set of explanatory variables. This result is even more pronounced for the changes in CDS spreads. Such a pattern may point to an omitted variable bias for the restricted set of regressors. In the absence of further explanatory variables, the remaining variables explain variation in y (the CDS spread in absolute terms and CDS spread changes) that pertains to omitted variables. This is reflected in a higher estimate for the coefficients.

Introducing the spatial lag strongly improves model quality measured in terms of the Akaike Information Criterion (AIC). The striking decrease in the AIC when estimating the ls1 model with a systemic risk factor (sar1) suggests that the spatial lag potentially captures the effect of omitted explanatory variables. In general, if important variables are omitted from a spatial regression, the spatial lag will capture their effects.[21] In contrast, introducing the spatial structure when a full set of regressors is present (ls2 and dls2) only moderately improves the model fit (see column sar2 as well as dsar2). However, the spatial lag remains highly significant. We interpret this as evidence for *the lack of* omitted relevant variables. In such a case, the spatial lag purely measures the importance of financial spill overs.

The estimation result provides strong evidence that it is not only an FI's individual fundamentals and the macro-economic conditions that matter when assessing its solvency; the risk of financial contagion as modelled by the spatial econometric approach is highly important as well. We argue in Section 3.2 that a test for the significance of the spatial autocorrelation coefficient (ρ) is a formal and straightforward way of testing for the presence of financial contagion. Indeed, we find the spatial lag to be highly significant; consequently, risk propagation is a statistically significant factor in the CDS market. Additionally, the test reveals that models which do not take financial spill overs into account – such as the classical linear regression – are most probably misspecified. Such models

[21] This also coincides with LeSage and Pace (2009), who reinterpret spatial models in a missing variable context along with three further motivations for applying this category of model. A similar rationale also exists for time series models.

might yield biased results (LeSage and Pace, 2009).

Despite the significance of contagion effects, the analysis of the magnitude is only made feasible by splitting the total effect of a financial shock into a direct and an indirect component. The spatial econometric approach allows for the separation of the direct effects of a change in bank A's fundamentals on bank A's solvency as well as the indirect impact due to spill over effects on the solvency of bank B – and all other banks – caused by the same change. Table 5 summarises the average total, direct and indirect effect of each risk driver in the SAR models and compares the total effect with that of ordinary least squares regressions (ls2 and dls2).

For CDS spread levels, it is particularly interesting to see that more than a tenth of the total effect of a shock is due to financial spill overs. This again highlights the economic relevance of financial spill overs in the CDS market. A note of caution should be sounded with regard to applying models that do not take account of interbank connections. The result can also be interpreted as strong evidence for the need for macro-prudential supervision and regulation. The results obtained from our regression portray the financial system's role for banks. In a model assuming N independent financial institutions (such as in an OLS regression), the effect of financial stress was reduced by 10 per cent on average. It is also important to note that it is not only the stressed FI which affects the solvency of other banks; there is also a feedback effect stemming from the fact that the reduced solvency of the sound bank causes stress to the bank which initially faced the shock. This is an inherent feature of the spatial multiplier matrix and it shows how upward and downward spirals may evolve (See Section 3.2 for an explanation of the mathematical methodology). In good times, positive contagion drives the expected default rate down to zero. In periods of financial distress, however, spill over effects lead to soaring credit spreads for all FIs in the financial system. This causes the health of the entire economic system to deteriorate. From this perspective, the results should prompt macro-prudential regulators to develop a regulatory framework which is able to prevent contagion among banks.

When comparing the total effect of the sar2 model with the parameter estimates of the ls2 model, it is striking that effects in the sar2 model exceed the linear model parameter estimates. This either stems from spill over effects being explicitly taken into account in the sar2 model or from the misspecification of the classical linear model. Furthermore, the effects in Table 5 indicate that for monthly changes in CDS spreads (dsar2) more than a fifth of the total effect is due to financial contagion. This is a substantial increase compared to the figure of 10 per cent reported for the regression in levels. The latter may perhaps be just the lower bound. Thus, financial spill overs possibly account for more than 10 per cent of the total variation in CDS premiums, stressing the conclusions we draw from analysing CDS spread levels. Regarding FIs' individual fundamentals, we review the determinants of CDS spreads in the following paragraphs.

- The first three explanatory variables in Table 4 summarise the effect of the yield curve on CDS premiums. For absolute CDS spreads, it appears that neither the yield level nor the slope of the yield curve affect FIs' CDS premiums to a statistically significant extent. Yet the curvature of the yield curve does. The result is in line with Deutsche Bundesbank (2011) who find German small and medium sized banks to be sensitive to changes of the yield curve, while big banks are hedged very well. The yield curve curvature might serve as a proxy for economic disruptions in our study; hence the significant coefficient. Another intuitively appealing explanation is that the curvature measures uncertainty in the markets. Typically, hump-shaped yield curves are associated with uncertainty. In our model specification, the yield curve level ought to serve as a proxy for the asset growth rate; hence, we expect a significant negative effect. In fact, we find an insignificant coefficient. A similar observation has also been reported by Alexander and Kaeck (2008), who find that the yield level has a significant and negative effect on credit spreads in all examined sectors but the financial.[22] A financial institution's credit spread may react to the yield level because it is not only the FI's assets which are yield sensitive but also its liabilities. Thus, depending on the FI's specific asset-liability-duration mismatch, an increase in the yield level enhances *or* deteriorates solvency. In line with this, we do not find the slope of the yield curve to be statistically significant, either. A similar mechanism may be at work here. For monthly changes in CDS spreads, we again find ambiguous results for risk factors describing the yield curve. We do not find the yield curve curvature or the yield level to be statistically significant. Only the slope of the yield curve is moderately significant.

- The estimation results provide strong evidence that a company's rating contains information about its solvency. The estimation results in Table 4 are relative to an A-rated financial institution. For example, an upgrade from A to A+ leads to a 39 basis points decrease in the CDS premium. The expected CDS premium strictly decreases with a superior rating. The results for changes in CDS spreads are in line with these findings. However, in this case only downgrades seem to have a

22 Note that the significant coefficient of the yield level in ls1 and sar1 might be explained by endogeneity. The variables might, for example, be correlated with other omitted variables. In such a case, the level would serve as a proxy variable and become significant.

significant effect. A downgrade by one notch is predicted to have an average effect of roughly 25 basis points in the concurrent month.

- According to our findings, the average health of the financial system, measured as the Libor-OIS spread, is a relevant risk factor in the CDS market. An increase in the Libor-OIS spread indicates a deteriorating financial environment. Consequently, it should be accompanied by increasing CDS premiums. This is confirmed by the estimation results.

- The results show evidence that the bid-ask spread reveals information about the smooth functioning of the CDS market. One major issue during the financial crisis was the drying up of asset liquidity. The malfunctioning of markets contributed to peaking CDS premiums. This is also reflected in the positive and significant coefficient.

- The covariates associated with the well-known Merton model turn out to be highly significant. Both the equity volatility and the financial leverage can be seen as important risk drivers.

- Empirically speaking, firm size seems to be an important determinant of CDS spreads. This may support the conclusion that (a) bigger companies are more likely to be rescued, or (b) are in a better position to diversify risk in their portfolios, or (c) are more profitable due to economies of scale. However, this pattern cannot be identified for changes in CDS spreads. This may well be due to the data structure. Since firm size changes slowly over time, a response may not be identifiable for monthly changes in CDS spreads.

- For dls1 and dsar2 specification, the regression introduces the abnormal return which captures an FI's extraordinary performance. The negative and statically significant coefficient expected in theory is confirmed by the estimation results.

In summary, we find systemic risk to be a major driver for CDS spread levels and first differences. The strong effect of systemic risk becomes evident from the results obtained in the regressions. In addition, not only the economic conditions but also the institution's fundamentals matter. The risk factors suggested from the Merton model alone turn out to be insufficient to explain credit risk. Furthermore, the market's liquidity – measured by the bid-ask spread – turns out to be a crucial factor. Credit ratings considerably condense information and therefore have explanatory power for CDS spreads.

5.2 Stress testing the financial system

In this subsection we provide an in-depth analysis of the results obtained from the regressions presented above. We demonstrate the mechanism at work as well as the implications of financial contagion based on scenario analysis. To examine the financial system, we apply a shock to certain entities and perform predictions based on estimation results. Recall that the main difference between a spatial model and the classical linear model is the assumption about the interconnectedness of FIs. Implicitly linear regressions assume independence across the system. In other words, the solvency of an entity is solely a function of its fundamentals; consequently, an FI's solvency will not be affected by a change in the fundamentals of another individual in the financial system. The second part of this subsection discusses how systemic risks shed light on the solution of the well-known credit spread puzzle.

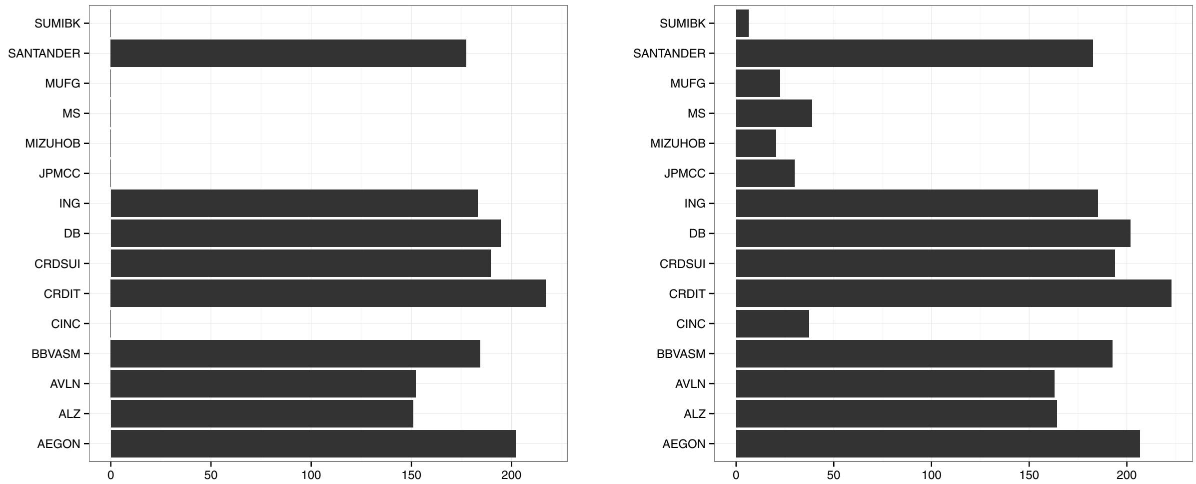
On 15 September 2008 Lehman Brothers Inc. filed for bankruptcy, causing financial turmoil around the world. In our sample, for instance, this more than doubled end-of-month daily equity volatility compared to the previous month. We use economic conditions in September 2008 as our baseline scenario for assessing the outcome of an economic shock in December 2009. For this purpose, all fundamental variables ($x_{i,k,Dec2009}$) are shocked in such a way that we end up with the institution's fundamentals in 2008 ($\Delta x_{i,k} = x_{i,k,Sep2008} - x_{i,k,Dec2009}\ \forall k = 1 \dots K$ and $i = 1 \dots N$). However, the interconnectedness is modelled using the 2009 weights. We compare predicted CDS spreads during September 2008 conditions with today's CDS markets. This approach helps us to grasp how shocks are transmitted via financial markets and it helps with identifying systemically important and less important FIs.[23]

Only European banks are stressed in our first scenario (see Figure 3). We carry out predictions ($\hat{y}_{i,k}$) for the left-hand variable in December 2009 using the in-sample values for $x_{i,k} \forall i \in$ Non-Europe as well as the altered variables $x_{i,k,Dec2009} - \Delta x_{i,k} \forall i \in$ Europe. The top left-hand panel (a) of Figure 3 depicts the predicted changes in CDS spreads for the OLS model. In contrast, the top right-hand panel (b) shows the predictions from the SAR model. Since OLS assumes N independent financial institutions, only the European banks and insurance companies are affected as depicted in panel (a). In contrast to the OLS model, the SAR model also predicts increasing spreads for all other companies (panel (b)) due to financial contagion. When comparing the magnitude of the spill over effects, it is striking that American FIs suffer more from contagion than Asian ones.

[23] For the comparative static analysis, we used the ols2 and sar2 model with the first differences of CDS premiums as the dependent variable.

This is especially true of Sumitomo Mitsui Financial Group (SUMIBK) because of its low financial interconnectedness (we already highlighted the lower connectivity between Asian and European institutions in Section 3.3.)

Figure 3: Outcomes from stress testing the financial system in scenario 1. (a) shows the expected change in the CDS premiums forecasted by the linear model due to a stress to European FIs only. (b) is a forecast of the spatial model of the same shock.[24]



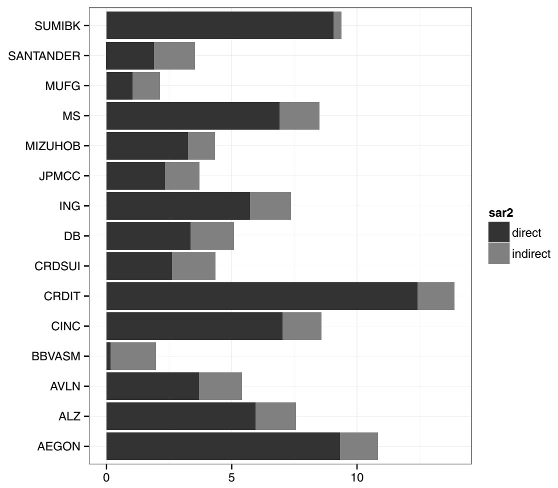
(a) (b)

Our first scenario explored the differences between a classical linear model and the proposed SAR-category models. The second scenario explores the mechanism further by shocking only the equity volatility (see Figure 4). Here, the emphasis lies on the decomposition of the total effect into direct and indirect effects. By triggering a jump in the equity volatility alone, we introduce a state of increased uncertainty (bottom left-hand panel (c)). The decomposition highlights the fact that not every FI suffers from contagion (i.e. the indirect effect) to the same extent. For example, Banco Bilbao Vizcaya Argentaria S.A. (BBVASM) faced almost no increase in their equity volatility in our scenario; hence the direct effect is almost zero. Yet many other European and American FIs suffer as a result of the shock to equity volatilities (e.g. Citi Inc., Morgan Stanley and AEGON N.V) and BBVASM is highly connected with those firms, leading to a relatively high systemic CDS charge (indicated by the grey part of the bar). The opposite is true of SUMIBK, which encountered problems due to a severe increase in its equity volatility

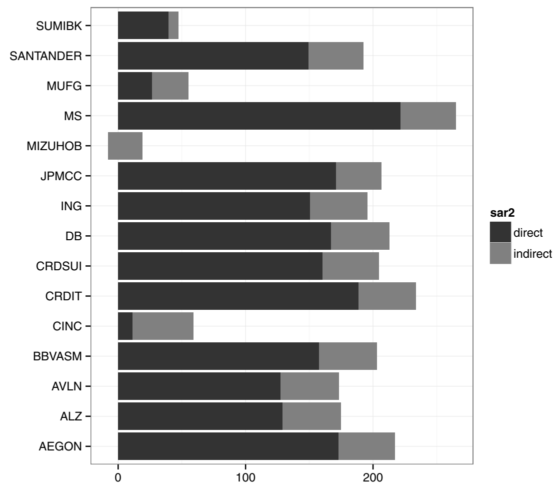
24 The x-axis plots CDS changes in basis points and the y-axis lists the financial institutions in the sample; each plot shows the impact of the reoccurrence of the September 2008 scenario on the CDS premiums observed in December 2009 ($\Delta x_{i,k} = x_{i,k,Sep2008} - x_{i,k,Dec2009}$).

but remained almost unaffected by financial contagion.

Figure 4: Outcomes from stress testing the financial system in scenario 2 and 3. (a) shows the impact of a jump in the equity volatility of each FI broken down into a direct effect (black) and an indirect effect (grey). (b) Direct and indirect effects from employing the shock to each variable to the whole financial system.[25]



(a)



(b)

The third scenario features a fully unrestricted change in variables for all entities in the sample (see Figure 4). Now the whole change in fundamental and economic variables is applied to the SAR. Interestingly, the direct effect of that shock causes the CDS spread of Mizuho Financial Group (MIZUHOB) to decrease slightly whereas all other institutions face a severe increase in their CDS spreads. Thus, the enhanced solvency of MIZHOB is accompanied by a deteriorating financial environment in this scenario. Since MIZHOB is part of the financial system and suffers from financial contagion, the indirect effect also causes MIZHOB's CDS spread to increase in total.

The proportion of the indirect effect relative to the direct impact reveals not only banks' vulnerability to financial contagion but also draws the attention to a broadly discussed phenomenon known as the credit spread puzzle (Tsuji, 2005). In a nutshell, this term describes the non-linear relationship between expected loss (EL) and observed credit spreads. For small expected losses, there is a wide gap between the observed credit spread and the EL. This is not typically true of higher ELs. Panel (d) illustrates this relationship: For entities with a smaller change in the credit spread, the systemic charge (i.e. indirect

[25] For detailed description see Figure 4.

effect) is relatively larger than for FIs with a considerable change in the CDS premium. The risk propagation mechanism offers the explanation that the credit spread puzzle may originally evolve from systemic risk. Since this kind of risk is not diversifiable (Tsuji, 2005), markets demand not only an individual credit risk charge but also a systemic risk charge.

6 Conclusion

This study explicitly models the degree of proximity between financial institutions, approximated by the equity correlation between two firms. The framework of spatial econometrics offers an efficient way of introducing banks' interconnectedness in terms of equity correlation into a regression model. Moreover, the spatial econometric approach allows for a decomposition of the variance of banks' CDS premiums into a systemic, a systematic and an idiosyncratic risk component. Our results indicate that the systemic risk component in the CDS market is important. The extent of spill over effects – measured by the spatial autoregressive parameter – and the magnitude of transmission summarised as direct as well as indirect effects are found to be significant and considerable. These effects are still present even when macroeconomic variables such as the Libor-OIS spread or proxies for risk mitigation are introduced into the model. We find that the systemic risk charge varies by geographical region as well as by time. While European and US institutions are strongly affected by financial contagion, Asian banks are found to be rather independent. Overall, we find CDS spreads to be up to a tenth higher than a model without spill over effects would predict. For first differences of CDS spreads, the degree of influence by systemic components is even higher.

The presence of indirect effects offers a new perspective on the so-called credit spread puzzle. While the systemic risk charge plays a rather substantial role for smaller credit spreads, the *relative* impact on CDS spreads decreases with the absolute level. Consequently, the answer to the credit spread puzzle might lie in the non-diversifiable risk stemming from the financial system.

Our additional findings correspond to other analyses. CDS spreads not only depend on a firm's leverage and equity volatility but also on its other characteristics and the market conditions. We find a rebate for the size of a financial institution which may be due to diversification effects, economies of scale or the fact that certain firms are simply too big to fail. Furthermore, market liquidity measured by the bid-ask spread plays an important role. Changes in spreads are largely driven by the abnormal return of companies' stock and, again, market liquidity.

The magnitude of risk propagation not only stresses the role of contagion as a determinant of CDS premiums but also highlights the need for macroprudential supervision, since the failure of a single entity may threaten the whole system. Historically, financial regulation has concentrated on ensuring the stability of each individual financial institution and neglected the risk stemming from the financial system as a whole. Recent advances in the regulatory framework (Basel III, Solvency II) already address the issue of countercyclical buffers counteracting the overdrawn market movements arising from both negative and positive financial spill overs. Our analysis shows that systemic risk is an important risk factor in today's economic and financial system, arguing for a further step towards macroprudential regulation. The findings also serve as a warning to national and regional authorities which have not yet geared their regulation towards a macro perspective. In this kind of a regulatory framework, financial institutions may possibly over-invest, which is then particularly painful in the event of a crisis.

Of course, this study focuses on the threats of connectivity patterns between financial institutions, yet neglects the potential implications of the concentration of risks stemming from massively writing CDS. Though a lively debate in the literature, this subject falls outside of the scope of this paper (Stulz, 2010).

A Appendix

A.1 List of observed financial institutions

Name	Abbreviation	Category
AEGON	AEGON N.V.	Insurer
ALZ	Allianz SE	Insurer
AVLN	AVIVA Plc.	Insurer
BBVASM	Banco Bilbao Vizcaya Argentaria S.A.	Bank
CINC	Citi Inc.	Bank
CRDIT	Unicredit S.A.	Bank
CRDSUI	Credit Suisse AG	Bank
DB	Deutsche Bank AG	Bank
ING	ING Groep N.V.	Bank
JPMCC	JP Morgan Chase Corp.	Bank
MIZUHOB	Mizuho Financial Group	Bank
MS	Morgan Stanley	Bank
MUFG	Mitsubishi UFJ Financial Group	Bank
SANTANDER	Banco Santander S.A.	Bank
SUMIBK	Sumitomo Mitsui Financial Group	Bank

Table 6: The full list of studied financial institutions.

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