

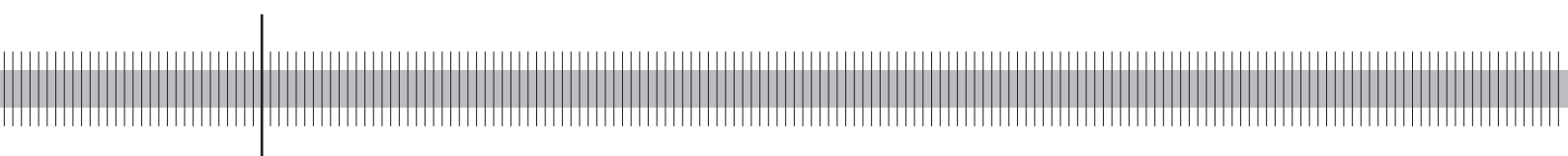
## **Contagion in the interbank market and its determinants**

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## **Abstract**

Carrying out interbank contagion simulations for the German banking sector for the period from the first quarter of 2008 to the second quarter of 2011, we obtain the following results:

(i) The system becomes less vulnerable to direct interbank contagion over time. (ii) The loss distribution for each point in time can be condensed into one indicator, the expected number of failures, without much loss of information. (iii) Important determinants of this indicator are the banks' capital, their interbank lending in the system, the loss given default and how equal banks spread their claims among other banks.

**Keywords:** Interbank market, contagion, time dimension

**JEL classification:** D53, E47, G21

## Non-technical summary

In many studies, the interbank market has been identified as a channel through which the distress of one bank is spread to other banks. In this context, direct contagion, ie contagion that emerges through losses on the exposures to other banks is investigated. Studies on this topic usually examine the vulnerability of the banking system at a certain point in time. We, however, investigate direct contagion effects over a whole time period, including fourteen quarters from the beginning of 2008 until the summer of 2011. The investigation of a whole time period instead of a certain point in time has two advantages: First, it is possible to evaluate how the danger of contagion effects evolves over time. Second, considering several points in time increases the number of observations, which makes it possible to econometrically analyze the determinants of financial stability. We model the German interbank market by considering mutual exposures of fourteen large and internationally active banks in Germany. Additionally, we include the aggregate sectors of savings and cooperative banks. The data on mutual exposures are obtained from the German credit register. The results of our paper can be summarized as follows:

1. During the time period under consideration, the German banking system has become less vulnerable to direct interbank contagion.
2. The simulation results, which comprise a whole statistical distribution of bank failures, can be condensed into one single indicator without much loss of information. For this single indicator, we choose the expected number of bank failures under the assumption that one bank fails for some exogenous reason.
3. Important determinants for this indicator are the banks' capital ratio, their interbank lending in the system, the loss given default and the degree of equality in how banks spread their claims within the system.

## Nichttechnische Zusammenfassung

Der Interbankenmarkt wird in vielen Studien als ein Kanal identifiziert, über den sich die Schieflage einer Bank auf andere Banken ausbreitet. Hierbei werden direkte Ansteckungseffekte untersucht, d.h. Ansteckungseffekte, die durch mögliche Verluste aus Krediten an andere Banken entstehen. In Studien zu diesem Thema wird dazu meist die Anfälligkeit des Bankensystems zu einem bestimmten Zeitpunkt betrachtet. In unserer Studie dagegen untersuchen wir direkte Ansteckungseffekte über einen längeren Zeitraum hinweg, der 14 Quartale von Anfang 2008 bis Sommer 2011 umfasst. Die Untersuchung eines gesamten Zeitraums anstatt eines einzelnen Zeitpunkts hat zwei Vorteile: Zum einen erlaubt der Vergleich mit anderen Zeitpunkten eine Aussage darüber, wie sich die Gefahr von Ansteckungseffekten über die Zeit entwickelt. Zum anderen erhöht die Betrachtung mehrerer Zeitpunkte die Zahl der Beobachtungen, so dass eine ökonometrische Untersuchung der Einflussfaktoren möglich wird. Wir bilden den deutschen Interbankenmarkt ab, indem wir die gegenseitigen Forderungen und Verbindlichkeiten von 14 großen, international aktiven Banken aus Deutschland untersuchen. Zusätzlich beziehen wir die Sparkassen und die Kreditgenossenschaften aggregiert als Sektoren mit ein. Die Daten zur Kreditverflechtung der Banken in Deutschland werden der Millionen-Evidenzzentrale entnommen. Die Ergebnisse unserer Studie können folgendermaßen zusammengefasst werden: 1. Im betrachteten Zeitraum nahm die Anfälligkeit des deutschen Bankensystems hinsichtlich direkter Ansteckungen ab. 2. Die Simulationsergebnisse, die als statistische Verteilungen von Verlusten vorliegen, können zu einem Indikator komprimiert werden, ohne viel Information zu verlieren. Der von uns gewählte Indikator ist die erwartete Zahl der Bankausfälle unter der Annahme, dass eine Bank aus einem exogenen Grund ausfällt. 3. Wichtige Einflussfaktoren für diesen Indikator sind die Eigenkapitalquote im Bankensystem, die durchschnittliche Höhe der Interbankforderungen, die Verlustrate bei Ausfall und das Ausmaß, wie gleichmäßig die Interbankforderungen im System verteilt sind.



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# Contagion in the Interbank Market and its Determinants<sup>1</sup>

## 1 Introduction

The ongoing financial crisis shows the importance of stress testing exercises in testing the resilience of financial systems given the occurrence of shocks. These results are important for regulatory purposes as a more unstable system has to be regulated more strictly. Furthermore, stress testing is important for bailout decisions: If there is a danger of one financial institution failing, some careful analysis has to be made on the issue of what this would mean for the rest of the financial system. To create meaningful stress testing exercises, one has to think about various channels through which financial distress could spread from one financial institution to another.

In many studies, the interbank market has been identified as one of these channels. To be more precise, the failure of one bank can trigger the failure of its creditor banks due to their direct exposures. This is the case if the write-downs on the exposures to the failed bank cannot be absorbed by the creditor banks' capital buffers. If one of these creditor banks also fails, there could be another round of bank failures. This procedure can lead to several rounds of bank failures and is therefore often denoted as "domino effects". Thus, one obvious stress testing exercise is to investigate how many subsequent bank failures occur as a consequence of direct exposures in the event that one bank fails for some exogenous reason.

Of course, there are other transmission channels of contagion, eg due to liquidity problems that result out of asset firesales, refinancing problems because of dried up interbank markets or information contagion. In this paper, however, we exclusively deal with contagion effects due to direct interbank exposures. We concentrate on this channel because we have detailed data about German banks' mutual credit exposures at our disposal. This enables us to simulate the failure of one of the large and internationally active German banks and to investigate the effects on other German banks that arise from direct interbank linkages.

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<sup>1</sup>The views expressed in this paper are those of the authors and do not necessarily reflect the opinions of the Deutsche Bundesbank. We thank Gerhard Illing and the participants of the research seminars at the Deutsche Bundesbank and at the University of Munich for their valuable comments.

This analysis can be carried out for all banks in a banking system for a certain point in time. Repeating this exercise for different points in time makes it possible to judge how the stability of the financial system (in terms of the danger of a domino effect) evolves over time. This could give regulators important information on how eg certain regulatory actions affect the stability of the financial system.

Our aim is to condense the results of the contagion exercises into one indicator for each point in time and then to investigate its determinants. Investigating the determinants of this indicator can help in two ways: First, determinants derived from theoretical considerations can be empirically validated and their importance can be assessed. Second, under the assumption that all interbank markets are similar, one can transfer the results obtained here to interbank markets for which there is no detailed data available.

Our analysis consists of three steps. First, we investigate the danger and the extent of contagion for each point in time from the first quarter of 2008 to the second quarter of 2011. Besides mutual exposures, a very important input variable for the simulations is the loss given default (LGD), ie the percentage of the interbank exposure that actually has to be written off in case of default. Thus, a LGD of 0% means that there are no write-downs (eg because of good collateral), a LGD of 100% means a complete write-down of the exposures in the event of failure. In most existing studies of contagion in the interbank market, an exogenously given and constant LGD is used. Thus, the outcome of these contagion studies crucially depends on the value of the LGD. We have, however, a unique dataset of actually realized LGD available. Thus, following Memmel et al. (2011) we use a different approach, ie we draw randomly from a beta distribution that is fitted to the empirical frequency distribution of our dataset. Hence, our simulations are based on a stochastic instead of a constant LGD. As a robustness check, we then compare these results with results under the assumption of a constant LGD that equals the mean of our dataset. It turns out that for rather stable systems, the assumption of a constant LGD systematically yields a lower number of bank failures than the assumption of a stochastic LGD (and vice versa). We use the distribution functions of bank failures for each point in time (which can be compared by using the concept of stochastic dominance) as well as the expectation of bank failures as an indicator to investigate how financial stability evolves

over time. It turns out that the system becomes less vulnerable to direct domino effects over the time span considered.

Second, we empirically check whether the information of a whole loss distribution can be sufficiently summarized in a single indicator. Our metric is by how far an indicator can predict whether or not the loss distribution of a given quarter dominates the loss distribution of another quarter, ie the comparison of a whole distribution (by using the concept of stochastic dominance) is condensed into a single indicator. In this context, we use the expected number of failures as the indicator. The discriminatory power of this indicator proves to be sufficiently high.

Third, having chosen this indicator, we investigate its determinants. Following the literature on interbank contagion, we suggest four determinants: the capital in the system, the percentage of interbank assets relative to total assets, the loss given default and – as the really systemic measure – the degree of equality in the distribution of bilateral interbank exposures (measured by the entropy of the matrix). We find that the coefficients for the four determinants have the expected sign and are all significant. More important, they can explain more than 80% of the variation of the indicator.

This paper is structured as follows: In Section 2, we provide a short overview of the literature in this field and point out our contribution. Then, in Section 3, we describe the data, explain the contagion algorithm and show our results under the assumption of a constant and a stochastic LGD. In Section 4, we construct an indicator of the stability of the interbank market and, in Section 5, we explore its determinants. Section 6 concludes.

## 2 Literature

Our paper contributes to three strands of literature. First, our method for simulating domino effects is similar to the empirical contagion analysis already applied to many countries (see eg Upper and Worms (2004) for Germany, Mistrulli (2011) for Italy or van Lelyveld and Liedorp (2006) for the Netherlands). Upper (2011) provides a comprehensive overview of this topic. Our approach, however, differs from this “standard approach” as we do not model the LGD as constant but as stochastic (see Memmel et al. (2011)). To be able to evaluate how the vulnerability of the system to interbank contagion evolves over

time, we use a time series of 14 quarters. A similar approach has been used by Degryse and Nguyen (2007). They investigate contagion in the Belgian interbank market over a ten years period ending in 2002. Another related paper in this context is Cont et al. (2010). They use a detailed dataset on exposures in the Brazilian interbank market and investigate by using a contagion exercise on how the stability of the Brazilian banking system evolves from mid 2007 to the end of 2008. Though the basic simulation mechanism of these two papers is similar to ours, there are various differences to our approach (eg the design of the shock, the way the loss given default is modeled and the way that the stability of the system is evaluated).

Second, we develop an indicator of the interbank market's resilience. Cont et al. (2010) summarize their simulation results by developing an indicator of the systemic importance of financial institutions for different points in time. Like these authors, we have detailed information on direct interbank exposures. Additionally, we use a dataset on actually realized loss given default (LGD) on the interbank market. Thus, contrary to market-based indicators that are, for example, developed by Acharya et al. (2010), Adrian and Brunnermeier (2011) and Huang et al. (2011), our stability indicator relies on detailed supervisory data.

Third, the aim of this paper is to find out which simple indicators of a financial system help to explain our (more sophisticated) stress testing results. Simple indicators would be much more convenient for regulators to calculate and interpret compared to more sophisticated ones. In this context, Drehmann and Tarashev (2011) study the effects of simple indicators (such as bank size and interbank lending / borrowing) on the systemic importance of banks. They find that these simple indicators contribute well to the explanation of the more sophisticated systemic risk measures of banks. Degryse and Nguyen (2007) find that a move from a complete structure of claims towards a multiple money center structure within the Belgian banking sector (measured by the share of domestic interbank exposures of large banks to total domestic interbank exposures) as well as its increasing internationalization (measured by the share of total domestic interbank exposures to total interbank exposures) reduced the danger of contagion in the domestic interbank market. Additionally, the banks' capitalization is identified as a crucial determinant of interbank contagion. Cont

et al. (2010) find that the size of interbank liabilities as well as some structural features of the interbank network (measured by newly created indicators) have an impact on financial stability.

The selection of the main determinants of our financial stability indicator is based on literature that focuses on theoretical simulations of interbank contagion. In this context, Nier et al. (2007) investigate, among other things, how the variation of banks' capital ratio, the size of banks' interbank exposures as well as banks' connectivity affects the stability of the system. Gai and Kapadia (2010) show, among other things, the impact of banks' connectivity and capital ratio on financial stability. Sachs (2010) examines the impact of banks' equity ratio, the amount of interbank lending, the loss given default and the degree of equality in how banks spread their claims on the stability of the network. In addition to theoretical simulations, the model of Allen and Gale (2000) also shows that it is important to consider the network structure of the banking system for the stability analysis. We test for four determinants of the vulnerability to interbank contagion: Banks' capitalization, interbank lending, the loss given default and how equally banks spread their claims among counterparties. The empirical investigations in this paper confirm, among others, the theoretical simulations of Sachs (2010), which show that a higher capital ratio, a lower share of interbank assets in relation to total assets in the system, a lower loss given default and a more equal distribution of interbank claims (given not too extreme parameter values) in a complete network yield a more stable system.

### 3 Simulation Exercise

#### 3.1 Data

Our simulation exercise starts with the exogenous failure of one bank within our sample.<sup>2</sup> Given the matrix of mutual interbank exposures and a loss given default (LGD) assigned to each of these exposures, we calculate the losses (ie the write-downs) of the creditor banks. If the Tier 1 capital ratio of one of the creditor banks falls below 6%, which is the

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<sup>2</sup>For a general discussion of the round by round algorithm applied in this paper see Upper (2011). For a detailed description of the contagion algorithm see Memmel et al. (2011)

critical threshold according to the Basel III capital requirements as well as the EBA stress tests in 2010 (and implicitly in 2009), this bank will also become distressed and fail. If at least one bank fails after the failure of the trigger bank, there will be a next round in which the losses of the creditor banks are calculated. This contagious process comes to an end if there is a round with no new bank failures.

Thus, the required data for this analysis are, first, information on banks' capital as well as their risk-weighted assets, second, data on banks' mutual exposures and third, data on the LGD. Our sample consists of 14 large and internationally active German banks as well as the aggregate sectors of the savings and cooperative banks, for which we have data from the first quarter of 2008 to the second quarter of 2011.<sup>3</sup> The banks' equity (Tier 1 capital) and their risk weighted assets (RWA) are taken from the supervisory data storage system BAKIS.<sup>4</sup> Data on the bilateral exposures are taken from the German credit register, where all bilateral exposures are collected provided that they exceed (or are equal to) a threshold of 1.5 million euro.<sup>5</sup>

To get an initial overview of the data, Figures 1 to 3 show how key characteristics of the banking system under consideration evolve over time. Figure 1 shows that the capitalization of the banking system increased substantially over time from an average of about 8.5% Tier 1 capital relative to risk weighted assets in the first quarter of 2008 to more than 12% in the second quarter of 2011. This is due to an increase in banks' Tier 1 capital on the one hand and a reduction in risk weighted assets on the other hand. Thus, banks raised their capital buffers during this time span to improve their resilience to potential shocks. Additionally, the weighted share of interbank assets (and thus the size of interbank linkages) relative to the sum of banks' balance sheet totals tends to decrease over time, as Figure 2 shows.<sup>6</sup> Following an average of more than 13.5% of interbank assets in the third quarter of 2009, the ratio decreased to 11.5% in the second quarter of 2011. The decreasing ratio of interbank assets to total assets shows a decreasing amount of interbank

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<sup>3</sup>For simplicity, these 16 entities are just called banks in the rest of the paper.

<sup>4</sup>For more information about the supervisory data in Germany see Memmel and Stein (2008).

<sup>5</sup>For more information on the German credit register see Schmieder (2006).

<sup>6</sup>One has to bear in mind that we only consider interbank assets within the system. As we consider large and internationally active banks, it is quite likely that some banks will have most of their interbank exposures abroad. However, looking at aggregate interbank lending (of domestic banks) to all banks (including foreign banks) over the time span considered yields the same result, ie a decrease in the share of interbank assets to total assets.

assets rather than an increase in banks' balance sheet totals, as banks tend to not increase their balance sheets in the time span considered due to the financial crisis. To see how the degree of equality in the distribution of interbank exposures evolves over time, we calculate the entropy of the matrix of interbank linkages. Entropy methods have been used in the literature on interbank contagion mostly to fill in missing data into the matrix of bilateral interbank exposures.<sup>7</sup> The underlying assumption of this method is that banks spread these exposures as equally as possible among their counterparties, which is equivalent to maximizing the entropy of the matrix of interbank exposures. In this paper, we use this approach the other way round. As the whole matrix of bilateral exposures is available, we calculate the entropy of the matrix as a measure of how equally/unequally exposures are distributed. Figure 3 shows that the entropy of the matrix of mutual exposures has steadily decreased over time, which means that interbank exposures tend to be distributed more unequally over time. The network we consider is almost complete, ie there are no more than two off-diagonal zero entries in the  $16 \times 16$  matrix of interbank exposures for each point in time.

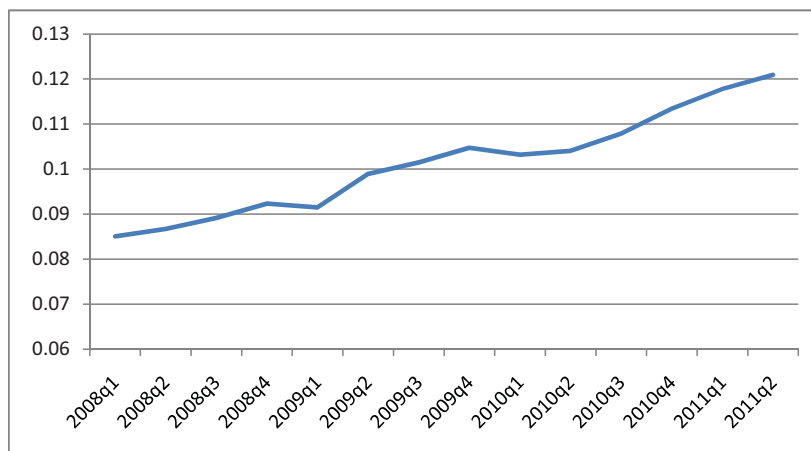


Figure 1: Development of the weighted Tier I capital ratio of all 16 entities.

Furthermore, we need data on the loss given default for our contagion exercise. In this context, we use LGD-data from the quantitative supervisory reports for banks in Germany, where once a year each bank had to report the actual provisions on interbank loans as well as the total volume of the loan for which provisions have been made. As in

<sup>7</sup>See eg Upper and Worms (2004)

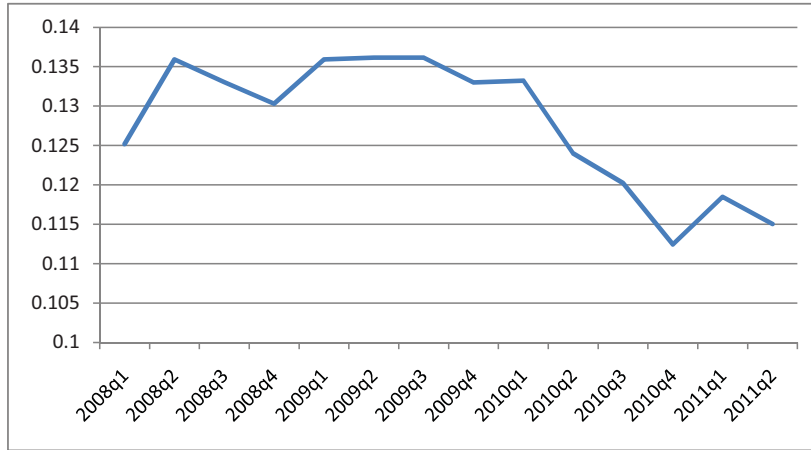


Figure 2: Development of the ratio of interbank assets within the system to total assets of all 16 entities.

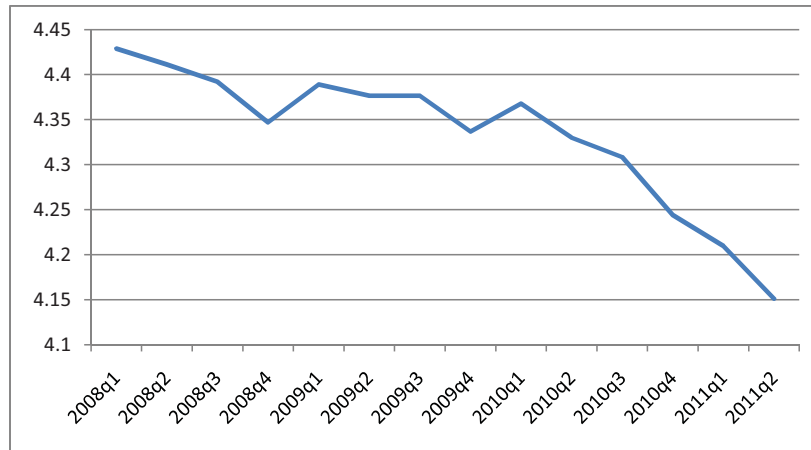


Figure 3: Development of the entropy of the matrix of interbank exposures

Memmel et al. (2011), we use the subsample of all German private commercial banks plus the central institutions of the savings and cooperative banks. This gives us an empirical frequency distribution with a mean of 0.45 and a standard deviation of about 0.39. Using this information, we can approximate the empirical frequency distribution by a (markedly u-shaped) beta distribution with parameters  $\alpha = 0.28$  and  $\beta = 0.35$ . Figure 4 shows the empirical frequency distribution of the actually observed LGD-data as well as the fitted beta distribution. To incorporate the LGD as an explanatory variable into our analysis of the main determinants of financial stability (see Section 5), we carry out the contagion exercises for different LGD distributions: We change the parameters  $\alpha$  and  $\beta$  of the beta



distribution (which can be easily calculated dependent on the mean and variance of the distribution) so as to have expected LGDs of 25%, 35%, 55% and 65%, respectively.<sup>8</sup> The different beta distributions we use for our simulations are shown in Figure 7 in the appendix.

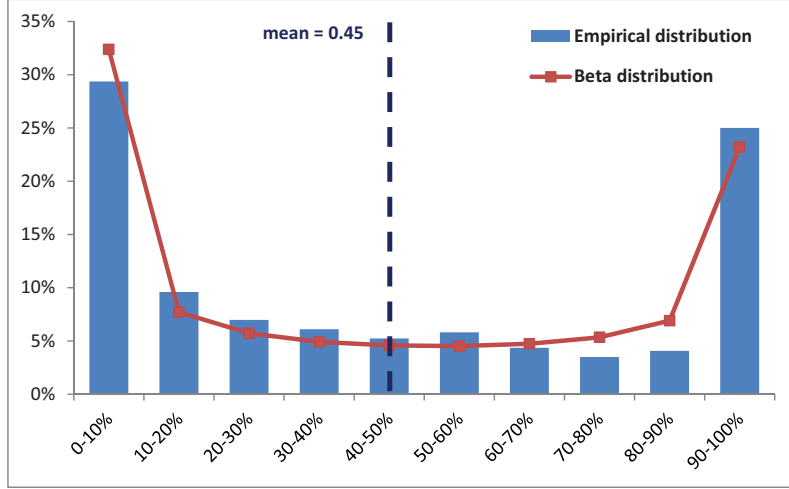


Figure 4: Empirical frequency distribution of LGD data as well as the fitted beta distribution.

### 3.2 Stochastic LGD

The simulation exercise is carried out using the round by round algorithm described in Section 3.1. At first, all simulations are run by assuming that the LGD is stochastic and follows the distribution shown in Figure 4, i.e. for each exposure to a failing bank, we randomly draw a LGD from the estimated beta distribution with parameters  $\alpha = 0.28$  and  $\beta = 0.35$ . To be more precise, we let one bank (eg bank  $i$ ) at a particular time (eg time  $t$ ) fail, assign a randomly drawn LGD to each interbank exposure and calculate how many banks fail in total due to domino effects. We repeat that exercise (ie calculating the consequences of the failure of bank  $i$  at time  $t$ ) 100 000 times in total, each time randomly

<sup>8</sup>It is straightforward to adjust the variance of the beta distribution: In order to preserve the structure of its density function, the ratio of the variance of a binomially distributed random variable and a beta distributed random variable with the same mean should be constant, ie  $\frac{\mu_1(1-\mu_1)}{\sigma_1^2} = \frac{\mu_2(1-\mu_2)}{\sigma_2^2}$  with  $\mu_i(1-\mu_i)$  being the variance of a binomially distributed variable with mean  $\mu_i$  and  $\sigma_i^2$  being the variance of a beta distributed variable with mean  $\mu_i$ . With  $\mu$  being the expected value of the LGD distribution, we can thus calculate the parameters  $\alpha = \mu \cdot 0.65$  and  $\beta = (1 - \mu) \cdot 0.65$ .

drawing a new set of LGDs from the beta distribution with estimated parameters. As a next step, we let another bank in the system fail (eg bank  $j$ ) and calculate, again 100 000 times, the number of bank failures. By repeating this exercise for each of the 16 banks in the sample, we obtain a total of 1 600 000 results of bank failures for time  $t$ . We aggregate these results in order to receive an empirical frequency distribution and the respective cumulative distribution function of bank failures. As we have data for 14 points in time, we can generate 14 cumulative distribution functions that indicate the stability of the banking system in each respective quarter. Additionally, we calculate the overall mean of bank failures for each quarter. As we also investigate the impact of the loss given default on the expected number of bank failures, we repeat this contagion exercise for each point in time four times, each time drawing from another LGD distribution shown in Figure 7. Figure 5 shows the simulation results for the first quarter of 2008 to the second quarter of

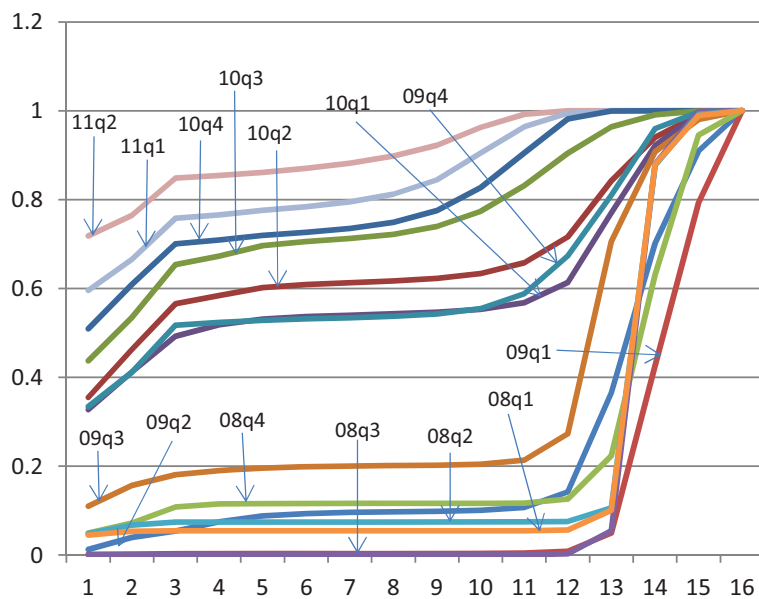


Figure 5: Distribution function of bank failures for the first quarter of 2008 to the second quarter of 2011 (stochastic LGD).

2011 under the assumption that the LGD follows the beta distribution shown in Figure 4 (ie the distribution that is derived from our LGD-dataset). The cumulative distribution function of the first quarter of 2008 (2008q1), for example, indicates that, under the assumption that each of the 16 entities fails with equal probability, the probability of observing 13 or fewer bank failures is about 10%. The probability of observing exactly

14 bank failures is around 80%. Thus, in the vast majority of cases in the first quarter of 2008, more than 13 banks fail (including the bank that fails first). This yields a rather unstable system. Looking at the cumulative distribution function of the second quarter of 2011 (2011q2), we find a different result. Here, the probability of observing just one bank failure (which is the bank that failed exogenously) is almost 72%. In only 15% of the cases more than 3 banks fail in total. Thus, in 2011q2, our results yield a considerably more stable system compared to previous quarters. One interesting result we obtain is that there is a substantial increase in system stability after the third quarter of 2009 (2009q3). In addition to the cumulative distribution function, we characterize the stability of the

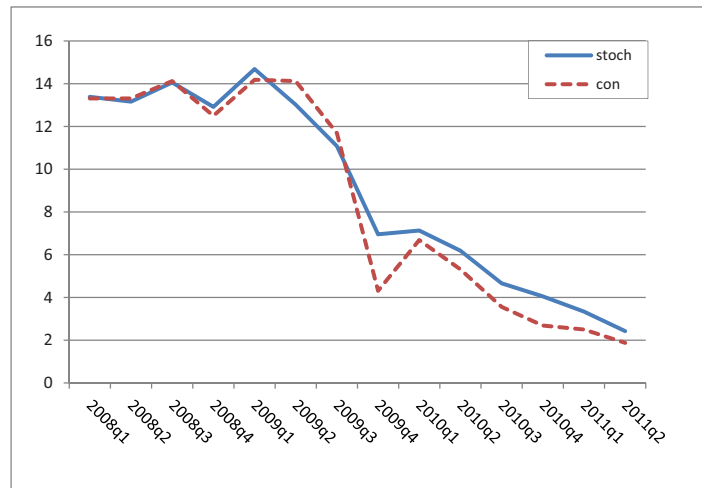


Figure 6: Overall expectation of the number of bank failures for the period from the first quarter of 2008 to the second quarter of 2011 (stochastic and constant LGD).

system for each point in time by one single figure: The expectation of the total number of bank defaults if one of the 16 entities fails. Thus, we calculate the average number of bank defaults of all 1 600 000 simulation runs (again under the assumption that the loss given default follows the beta distribution shown in Figure 4) for each point in time. Figure 6 shows the development of this expectation over time. The highest value is reached in the first quarter of 2009 with an expectation of more than 14 bank defaults. In the following quarters the expectation continuously decreases to fewer than 3 bank defaults in the second quarter of 2011. However, one has to bear in mind that our simulations only consider direct contagion via domino effects. Our simulations do not consider shocks on banks' assets other than direct interbank exposures. Thus, our simulations do not take

into account, for example, risks due to sovereign default and therefore show a very stable system in the first and second quarter of 2011.

### 3.3 Stochastic versus constant LGD

As a robustness check, we repeat the contagion exercise by assuming a constant LGD which equals the mean of our empirical distribution (= 45%). Thus, we assign the same LGD to each interbank exposure. This procedure yields, in contrast to the stochastic case, only one number of bank failures given that bank  $i$  fails at time  $t$ . Again, for each point in time we let each of the 16 entities fail and derive a number of subsequent bank failures. And similarly to the case of the stochastic LGD, we can summarize our results for each point in time by a cumulative distribution function as well as the overall average number of bank failures.<sup>9</sup>

Figure 6 shows that there is, for most points in time, not very much difference in the overall expectation of the number of bank failures between simulations with a stochastic LGD and a constant LGD. On the bank level, however, there can be a considerable variation in the results. For each of the 16 entities, we calculate the results of the 14 points in time, which yields 224 observations. In 16% of these 224 observations, there is a deviation of more than 4 bank failures, in more than 40% of the cases there is a deviation of more than one bank failure. The direction of the deviation, however, varies. In 52% of the cases, a constant LGD yields a more unstable system, in 39% of the cases, a constant LGD yields a more stable system and in the remaining 9% of the cases there is no difference (this only happens when there are no further bank failures in both cases).

A straightforward question in this context is what drives the result regarding whether a constant LGD yields a more stable or unstable system. Visual inspection suggests that the total number of bank failures, given that bank  $i$  fails at time  $t$ , is a crucial factor. Thus, let  $D_{i,t}$  be a dummy variable that takes on the value one if the failure of bank  $i$  at time  $t$  yields a less stable system under the assumption of a constant LGD and zero

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<sup>9</sup>The cumulative distribution functions (CDFs) under the assumption of a constant LGD look, in terms of the relative positions of the different CDFs, very similar to the CDFs in Figure 5.

otherwise.<sup>10</sup> In addition, let  $AV_{i,t}$  be the average of the expected number of bank failures (following the failure of bank  $i$  at time  $t$ ) under the assumption of a stochastic LGD and the respective number of bank failures under the assumption of a constant LGD. We model the probability that the assumption of a constant LGD will lead to a less stable system with a logit model, using  $AV_{i,t}$  as the explanatory variable.

$$Pr(D_{i,t} = 1) = \frac{1}{1 + \exp[-(\beta_0 + \beta_1 AV_{i,t})]} \quad (1)$$

Table 1 shows that we obtain the highly significant result that a higher average number of bank failures increases the probability that a constant LGD will yield a higher number of bank failures compared to a stochastic LGD.

As a robustness check we use a standard OLS regression to investigate the relationship between the discrepancy of the results under a constant and a stochastic LGD and the average number of bank failures. Let  $CS_{i,t}$  be the difference between the number of failures under the assumption of a constant LGD and the expected number of failures under the assumption of a stochastic LGD (following the failure of bank  $i$  at time  $t$ ). This yields the following equation:

$$CS_{i,t} = \beta_0 + \beta_1 AV_{i,t} + \varepsilon_{i,t} \quad (2)$$

The last column of Table 1 shows that a higher average number of bank failures indicates a higher value of  $CS_{i,t}$ . The interpretation depends on the sign of  $CS_{i,t}$ . For a low average number of bank failures, the difference is negative, ie a stochastic LGD yields a more unstable system and an increase in  $AV_{i,t}$  moves  $CS_{i,t}$  towards zero. For a high average number of bank failures, the difference is positive, ie a constant LGD yields a more unstable system and an increase in  $AV_{i,t}$  also increases the difference between the results of a constant and a stochastic LGD. Again, all results are highly significant.

Intuitively, if the system is rather unstable (eg due to a low Tier I capital ratio of banks), a constant LGD leads to a higher average number of bank defaults than a stochastic LGD as it is not possible in the constant case to randomly draw a very low LGD that avoids

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<sup>10</sup>In this estimation, the cases where the constant and the stochastic LGD yield the same results are included ( $D_{i,t}$  takes on the value zero in these cases). As a robustness check we estimate the model without these data. However, there is hardly any change in the results.

Variable	Logit D	CS
$AV_{i,t}$	0.28*** (0.03)	0.23*** (0.02)
constant	-2.38*** (0.34)	-2.50*** (0.33)
Nobs	224	224
(Pseudo) $R^2$	0.30	0.20
AUR	0.76	-

Table 1: Logit regression with  $D_{i,t}$  being a dummy variable indicating that the failure of bank  $i$  at time  $t$  yields more bank failures under the assumption of a constant LGD compared to a stochastic LGD, and  $AV_{i,t}$  corresponding to the average number of bank failures with a constant and a stochastic LGD. OLS regression with  $CS_{i,t}$  being the difference of the (expected) number of failures under the assumption of a constant and a stochastic LGD. Robust standard errors. \*\*\* denotes significance at 1%-level. AUR gives the area under the ROC-curve.

contagion from one bank to another. In contrast, if the system is rather stable, a constant LGD leads to a lower average number of bank defaults compared to a stochastic LGD as it is not possible in the constant case to randomly draw a very high LGD.

Empirically, we find that the LGD is not rather constant, but markedly u-shaped (See Figure 4), ie the LGD is often low or high, but little probability mass is centered around the expectation of the distribution in the middle. Thus, the simplifying assumption of a constant LGD cannot be justified by empirical data, which has important implications for our contagion exercise. Under the assumption of a constant LGD, one tends to overestimate the extent of contagion in unstable systems and to underestimate it in rather stable systems. Memmel et al. (2011) investigate the extent of contagion for one point in time (the fourth quarter of 2010). In this context, they also compare the assumptions of a constant LGD and a stochastic LGD and find that the assumption of a constant LGD underestimates the extent of contagion. This is in line with the results of this section as Figure 5 shows a rather stable system in 2010q4.

## 4 Development of an Indicator

### 4.1 Stochastic dominance

As a next step, to evaluate our results from Section 3.2 in more detail, we have to find a measure that allows us to compare the different distributions (and not only single figures) of bank failures over time. One concept that makes this possible without many assumptions is stochastic dominance.<sup>11</sup> This measure can be eg used in decision theory if a preference relation between two assets with stochastic returns has to be found. In our case, we can also form preference relations by assuming that fewer bank failures are preferred to more bank failures. In this context, assume that there are two cumulative distribution functions  $F(\cdot)$  and  $G(\cdot)$ . The distribution  $F(\cdot)$  is said to have first-order stochastic dominance over the function  $G(\cdot)$  if

$$F(x) \geq G(x) \tag{3}$$

for all  $x$  and strict inequality for at least one  $x$ .<sup>12</sup> If there is first-order stochastic dominance, every individual preferring less bank failures to more bank failures and having the choice between two distributions, prefers the distribution that dominates the other one according to the definition given by Equation (3).

There are two main drawbacks of the concept of first-order stochastic dominance: First, there is no statement possible by how far one distribution is preferred to another (dominated) distribution and, second, the comparison is not complete in a mathematical sense, i.e. there is not always a dominance relationship between two distributions.

The results of the analysis of first-order stochastic dominance are shown in the appendix. The matrix that describes the results confirms our findings in Section 3.2. The most favorable distribution function of bank defaults is given in the second quarter of 2011.

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<sup>11</sup>See Bawa (1975) and Schmid and Trede (2006), chapter 8, for more information about the concept of stochastic dominance.

<sup>12</sup>Note, however, that the definition of stochastic dominance in this paper is not exactly the same as the standard definition which is based on the assumption that the respective utility function is increasing (and not decreasing as in this paper). However, we can redefine the utility function in a way that it is dependent on the number of solvent banks  $y := 16 - x$  (with  $x$  being the number of failed banks). Thus, it follows that  $\frac{\partial u}{\partial y} > 0$ . Using this assumption, the condition for first-order stochastic dominance is, that  $F(\cdot)$  dominates  $G(\cdot)$  if  $F(y) \leq G(y)$  for all  $y$  and strict inequality for at least one  $y$ . Redefining each CDF by making it dependent on  $y$  and using this standard condition for stochastic dominance yields the same results.

This distribution dominates the distribution function of all other points in time. The distribution function of the first quarter of 2009 does not dominate any other quarter but is dominated by 12 other quarters. This result indicates that in 2009q1 the distribution function of bank defaults was quite unfavorable. However, there is a dominance relationship between different points in time in only 70 of the 91 cases.<sup>13</sup>

Using a higher order stochastic dominance, one can mitigate the problem of completeness – at the expense of imposing additional assumptions.<sup>14</sup>

## 4.2 Whole distribution versus single figure

It is now possible (for most points in time) to compare the distribution functions of bank failures. To analyze the main determinants for the stability of the financial system it would, however, be much easier to use single figures as an indicator of financial stability. In the end, the question of whether a single figure is suitable to condense the information of a whole distribution needs to be answered with empirical data. Our aim is to show that a statement based on the comparison of two distribution functions is more or less equivalent to the comparison of the expectations. To do so, we proceed as follows: Having 14 different distribution functions (one for each quarter), we can make 91 (=14\*13/2) bilateral comparisons, i.e. we exclude comparisons with itself and double counts. Let  $F$  and  $G$  be the cumulative distribution functions of time  $t_1$  and  $t_2$ , respectively. Whenever there is a (first-order) dominance relationship between  $F$  and  $G$  (irrespective of the direction), the dummy variable  $D_{t_1,t_2}$  takes on the value one. The variable  $\Delta F_{t_1,t_2} := \text{abs}(F_{t_1} - F_{t_2})$  is the corresponding absolute difference in expected failures.

We model the probability of an existing dominance relationship with a logit model and

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<sup>13</sup>We also calculated the relationships of first-order stochastic dominance for the distributions of bank failures under the assumption of a constant LGD. In this case, we can even compare 87 of the 91 cases using the concept of first-order stochastic dominance.

<sup>14</sup>We additionally investigated the second-order dominance relationships. To be able to do this, we have to redefine each CDF to make it dependent on the number of solvent banks  $y$ . Under the assumption that individuals prefer more solvent banks to less solvent banks and are risk averse ( $\frac{\partial u}{\partial y} > 0$  and  $\frac{\partial^2 u}{\partial y^2} < 0$ ),  $F(\cdot)$  is preferred to  $G(\cdot)$  if  $\int_{-\infty}^y F(t) dt \leq \int_{-\infty}^y G(t) dt$  for all  $y \in R$  and strict inequality for at least one  $y$ . However, the number of dominance relationships (= 72) only slightly increases compared to first-order stochastic dominance.



explain this probability with the absolute difference  $\Delta F_{t_1, t_2}$ .

$$Pr(D_{t_1, t_2} = 1) = \frac{1}{1 + \exp[-(\beta_0 + \beta_1 \Delta F_{t_1, t_2})]} \quad (4)$$

We expect a positive coefficient for  $\beta_1$ : The larger the absolute difference in the expected number of bank failures, the more likely the existence of a dominance relationship. As a robustness check and to account for possible non-linearities, we also include the squared term  $\Delta F^2$  in the model. The results are displayed in Table 2. As expected, the coeffi-

Variable	Logit D	Logit D
$\Delta F$	0.45*** (0.13)	0.99*** (0.35)
$\Delta F^2$		-0.06** (0.03)
constant	-0.50 (0.40)	-1.14** (0.55)
Nobs	91	91
Pseudo $R^2$	0.25	0.27
AUR	0.85	0.82

Table 2: Logit regression where  $D_{t_1, t_2}$  is a dummy variable indicating (first-order) stochastic dominance between the distributions in  $t_1$  and  $t_2$  or vice versa, and  $\Delta F$  is the corresponding absolute difference in expected failures. Robust standard errors. \*\* and \*\*\* denote significance at 5% and 1%-level, respectively. AUR gives the area under the ROC-curve.

cient of the variable  $\Delta F$  is positive and highly significant. Additionally, to evaluate the discriminatory power of the model, we calculate the area under the ROC-curve (AUR). The ROC (receiver operating characteristic)-curve plots the type 1 error rate of the model against one minus the type 2 error rate of the model for different thresholds. The better the predictive power of the model, the lower the type 2 error rate for a given type 1 error rate and the higher the area under the ROC-curve. In the case of our model, the AUR is high with 0.85. Therefore, we conclude that, in this case, the comparison of two distribution functions on the one hand and the comparison of the two expectations on the

other hand yields rather similar results, i.e. the expected number of failures is a suitable indicator for measuring the vulnerability of a banking system to contagion. There is no use in including a quadratic term as done in the robustness check: the AUR is then even lower than in the case without this quadratic term.

## 5 Determinants

As shown in the previous section, the information included in the whole distribution can be summarized in one figure without much loss of information. This single figure is the expected number of failures  $F$  and will be our indicator for the vulnerability of the (German) interbank market. Drehmann and Tarashev (2011) show that highly sophisticated measures of systemic risk contribution can be well approximated by more objective figures like size and interbank lending. Following this idea, we try to replicate our indicator using relatively easily available measures. Following the results of the theoretical simulations in Sachs (2010), we look at four different determinants: the capital ratio  $CR$ , the extent of interbank lending  $IBL$ , the average loss given default  $LGD$  and the structure of the interbank market  $ENT$ , measured by the entropy of the matrix of bilateral interbank exposures. As outlined in Section 3.1, the entropy is a statistical tool that measures the degree of equality; the higher the entropy, the higher the degree of equality. Theoretical considerations as laid down in Sachs (2010) argue that a system *ceteris paribus* gets usually more stable the more equalized its linkages are, i.e. the higher the entropy is. We run the following linear regression:

$$F_{t,i,j} = \beta_0 + \beta_1 CR_{t,i,j} + \beta_2 IBL_{t,i,j} + \beta_3 LGD_{t,i,j} + \beta_4 ENT_{t,i,j} + \varepsilon_{t,i,j} \quad (5)$$

where  $CR_{t,i,j}$  is the Tier 1 capital ratio of the banking system at time  $t$  excluding bank  $i$ , which is originally and exogenously in distress. Accordingly,  $IBL_{t,i,j}$  is the cumulated interbank lending of the banking system over the aggregate total assets of the system at time  $t$  excluding bank  $i$ .  $ENT_{t,i,j}$  is the entropy of the matrix of bilateral interbank exposures at time  $t$ , excluding bank  $i$ . Figures 1 to 3 show the evolution over time for the three determinants (in contrast to our regressors, these figures show the determinants

for the whole financial system). On the one hand, the capital ratio in the system has increased significantly and interbank lending tends to decrease; these two developments are believed to make the system more stable. On the other hand, the exposures have become less equally distributed, which should lead to a less stable system.

By creating variables in the way described above, we not only have variation in the time dimension (as shown in Figures 1 to 3) but also in the cross-section (ie between banks). The descriptive statistics shown in Table 3 indicate that the endogenous variable  $F_{t,i,j}$  and two of the three exogenous variables are characterized by a substantial part of cross-sectional variation. This enables us to apply a panel analysis.

The index  $j = 1, \dots, 5$  denotes the different average LGDs, ranging from 25% to 65% in steps of 10 percentage points. As the variable  $LGD$  is set exogenously (at least its mean), we do not report its mean and standard deviation in Table 3. Table 4 shows the results of

Variable	Mean	Stand. dev.	Between variation (Percentage)
F	9.08	5.00	15%
CR (%)	10.12	1.11	1%
IBL (%)	12.83	1.51	74%
LGD	-	-	
ENT	4.21	0.10	39%

Table 3: Descriptive Statistics (for the case of an average LGD of 45%). The column “Between variation” gives the between variance of the given variable as a share of the total variance.

the linear regression (5) with bank dummies to account for possible bank-specific effects. The results are in line with expectations. We find that an increase in the capital ratio of the whole system by one percentage point reduces the expected number of failing banks by more than four. This result is highly significant. The exposure to the interbank market is also of great importance. When interbank lending (relative to total assets) increases by one percentage point, the number of expected failures will go up by 1.8 banks. When the LGD increases by one percentage point, then the number of expected bank failures will go up by 0.14 failures.

The capital ratio and interbank lending - although calculated for the whole system - are,

after all, the (weighted) average of the single ratios, i.e. these ratios are bank-specific measures by nature. The *LGD* is even specific to each borrower-lender-relationship. By contrast, the entropy of the system is a truly systemic measure. As mentioned above, it shows how equally interbank lending is distributed in the banking system. A higher entropy means that banks spread their interbank assets / liabilities more equally among other banks in the system. The simulation results in Sachs (2010) indicate that for a rather complete network a more equal distribution of interbank lending, i.e. a higher entropy of the matrix of interbank lending, leads (for not too extreme parameter values like an extremely low capitalization of banks) to a more resilient market. Indeed, we find that an

Variable	Coefficient	Stand. Dev.
CR	-4.02***	0.145
IBL	1.81***	0.127
LGD	0.14***	0.005
ENT	-24.13***	2.289
constant	130.07***	10.618
Adj $R^2$	0.813	
Nobs	1120	

Table 4: Results of the regression  $F_{t,i,j} = \beta_0 + \beta_1 CR_{t,i,j} + \beta_2 IBL_{t,i,j} + \beta_3 LGD_{t,i,j} + \beta_4 ENT_{t,i,j} + \varepsilon_{t,i,j}$ , where  $F_{t,i,j}$  is the expected number of failing banks in quarter  $t$  given that bank  $i$  fails exogenously and the LGD is drawn from beta distribution  $j$ . Pooled OLS regression with dummies for each bank and robust standard errors. \*\*\* denotes significance at the 1%-level.

increase in entropy (= a more equal distribution of interbank lending) leads to a reduction in the expected number of bank failures.<sup>15</sup> As the network we consider is also almost complete (for each point in time there are no more than two zero-entries in the  $16 \times 16$  matrix of interbank liabilities), our empirical results confirm the theoretical simulation results in Sachs (2010). These results are also in line with the theoretical findings of Allen and Gale (2000), who show that a complete network (with maximum entropy of the

<sup>15</sup>This finding is in contrast to Figure 3, which shows a more unequal distribution of claims over time although the stability of the system increased. However, it is quite likely that the negative effect of a decreasing entropy is outweighed by the effect of banks' capitalization and interbank lending.

matrix of mutual exposures) is more stable than an incomplete but perfectly interconnected network (with a lower entropy of the matrix of mutual exposures). The bank dummies also have a high explanatory power. All of them are highly significant as well. In total, the four determinants as well as the bank dummies can explain more than 80% of the variation in the indicator.

The relative importance of three of the four determinants can be assessed by assuming a change in each determinant by one standard deviation. For the LGD, we do not have a meaningful standard deviation because its variation is exogenously set by us. Using the standard deviations reported in Table 3 and the estimated coefficients in Table 4, we see a decrease of 4.5 in the number of expected failures when the capital in the system increases by one standard deviation (here: 1.11 percentage points). The corresponding figures for interbank lending and entropy are 2.7 and 2.4, respectively. Hence, the capital ratio is the most important determinant. However, some of the determinants show a rather high correlation among themselves, which has to be kept in mind when trying to quantify their exact contribution to system stability.

## 6 Conclusion

This paper investigates interbank contagion due to direct exposures for different points in time. We have data on mutual interbank exposures from the first quarter of 2008 to the second quarter of 2011. At first, following Memmel et al. (2011), we run contagion simulations by drawing the loss given default from a beta distribution that is fitted to a distribution of actually realized data of loss given default on the interbank market. As a result, we obtain for each point in time a whole distribution as well as the expected number of bank failures. We find that the system has become less vulnerable to domino effects over time. As a robustness check, we compare these results with the results obtained assuming a constant LGD and find that for a rather stable system, the assumption of a constant LGD tends to underestimate the extent of contagion, whereas for a rather unstable system the assumption of a constant LGD tends to overestimate the extent of contagion.

As a next step, we analyze whether the information of the whole distribution of bank failures can be summarized in a single indicator like the expected number of bank failures.

Using the concept of stochastic dominance to compare the distributions for different points in time, we find that the discriminatory power of the single indicator is sufficiently high. Finally, we investigate the main determinants of this indicator. We find that the banks' capital ratio, the share of interbank assets in the system in relation to total assets, the loss given default and the degree of equality in the distribution of interbank exposures (measured by entropy) are important determinants for financial stability. We are thus able to confirm the importance of these determinants derived from theoretical considerations. The results make it possible to investigate the stability of interbank markets, for which no detailed information is available.

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## Appendix 1: Beta distribution

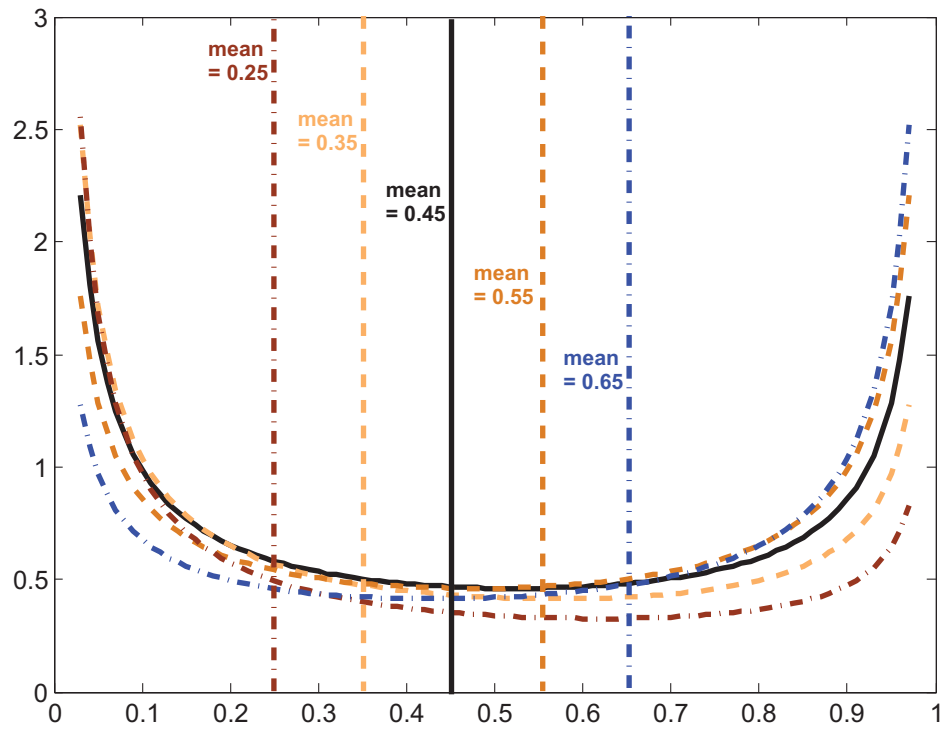


Figure 7: Different beta distributions of the loss given default used for the contagion simulations.

## Appendix 2: Dominance relationships

Analysis of dominance relationships from the first quarter of 2008 (08q1) to the second quarter of 2011 (11q2). If the element in row x and column y of the matrix is equal to one, the distribution function of time y (first-order) stochastically dominates the distribution function of time x.

	08q1	08q2	08q3	08q4	09q1	09q2	09q3	09q4	10q1	10q2	10q3	10q4	11q1	11q2
08q1	0	0	0	0	0	0	0	1	1	1	1	1	1	1
08q2	0	0	0	0	0	0	0	1	1	0	1	1	1	1
08q3	0	0	0	0	0	0	0	0	0	0	1	1	1	1
08q4	0	0	0	0	0	0	1	1	1	1	1	1	1	1
09q1	1	1	0	1	0	1	1	1	1	1	1	1	1	1
09q2	0	0	0	0	0	0	1	1	1	1	1	1	1	1
09q3	0	0	0	0	0	0	0	1	1	1	1	1	1	1
09q4	0	0	0	0	0	0	0	0	0	0	1	1	1	1
10q1	0	0	0	0	0	0	0	0	0	0	1	1	1	1
10q2	0	0	0	0	0	0	0	0	0	0	1	1	1	1
10q3	0	0	0	0	0	0	0	0	0	0	0	1	1	1
10q4	0	0	0	0	0	0	0	0	0	0	0	0	1	1
11q1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
11q2	0	0	0	0	0	0	0	0	0	0	0	0	0	0

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