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Contagion at the interbank market with stochastic LGD

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Abstract

This paper investigates contagion at the German interbank market under the assumption of a stochastic loss given default (LGD). We combine a unique data set about the LGD of interbank loans with data about interbank exposures. We find that the frequency distribution of the LGD is u-shaped. Under the assumption of a stochastic LGD, simulation results show a more fragile banking system than under the assumption of a constant LGD. There are three types of banks concerning their tendency to trigger contagion: banks with strongly varying impact, banks whose impact is relatively constant, and banks with no direct impact.

Keywords: Interbank market, contagion, stochastic LGD

JEL classification: D53, E47, G21

Non-technical summary

The interbank market is believed to be a channel through which the distress of one bank spreads to other banks. At this market, large and sometimes unsecured loans are granted among banks. The failure of one bank can thereby lead to the distress of the creditor banks, which themselves can become the starting point of additional failures. With the help of network models, the contagion effects at the interbank market are assessed.

In this paper, we investigate these contagion effects on the German interbank market, limiting the analysis to 15 systemically relevant German banks. From data of the German credit register, we establish the matrix of mutual exposures. The assumptions about the loss given default (LGD) are important as well. We have only little information about the LGD of a single interbank loan. However, our dataset makes it possible to precisely derive the statistical distribution of the LGD of interbank loans. The simulation proceeds as follows: At first, we assume that one of the 15 banks fails. Then, we determine the losses of the creditor banks. In the event that some of these banks fall into distress themselves, a contagious process starts. This contagion process comes to an end when no new failures occur in one round.

The results of the simulation study can be summarised in three core statements:

1. The empirical frequency distribution of the LGD at the interbank market is markedly u-shaped, i.e. there are many observations with a very low loss rate (LGDs of up to 10%) and many observations with a very high loss rate (LGDs of more than 90%). By contrast, there are relatively few observations in between (LGDs of 10% to 90%).

2. The simulations are run twice, once with a constant LGD in the amount of the empirical average in our data (45%) and once with a stochastic LGD, drawn from a distribution that is close to the empirical frequency distribution. The simulations under the assumption of a stochastic LGD generally yield a more unstable system than the simulations under the assumption of the corresponding constant LGD. Thus, assuming a constant LGD, which is often done in the literature, leads to an underestimation of the effects of contagion.

3. We can identify three groups of banks concerning their impact on the financial system in the event that they are falling into distress: banks whose failure leads to strongly

varying contagion effects, depending on the actual realisation of the stochastic path; banks whose failure leads to a relatively constant number of further failures; and banks, having only a small amount of liabilities to the other banks, whose failure does not result in further failures even in the most adverse situation.

Nichttechnische Zusammenfassung

Der Interbankenmarkt gilt als ein Kanal, über den sich Schieflagen einer Bank auf andere Banken ausbreiten. Auf diesem Markt werden großvolumige, mitunter unbesicherte Kredite zwischen den Banken vergeben. Die Schieflage einer Bank kann dadurch zu Schieflagen der Gläubigerbanken führen, die dann selbst zum Ausgangspunkt weiterer Schieflagen werden. Mit Hilfe von Netzwerkmodellen versucht man abzuschätzen, mit welchen Ansteckungseffekten am Interbankenmarkt gerechnet werden muss.

In diesem Papier untersuchen wir die Ansteckungseffekte für den deutschen Interbankenmarkt, wobei wir uns auf 15 systemrelevante deutsche Banken beschränken. Aus Daten des Kreditregisters ermitteln wir die Matrix der gegenseitigen Kreditbeziehungen. Wichtig sind auch die Annahmen über die Verlustrate bei Ausfall (LGD). Wir haben nur wenige Informationen über die Verlustrate eines bestimmten Interbankenkredits. Jedoch ermöglicht es unser Datensatz, präzise Aussagen über die statistische Verteilung der Verlustrate von Interbankkrediten zu treffen. Die Simulation läuft folgendermaßen ab: Zunächst nehmen wir an, eine der 15 Banken fällt aus. Danach bestimmen wir die Verluste bei den Gläubigerbanken. Sofern einige dieser Gläubigerbanken selbst in Schieflage geraten, beginnt ein Ansteckungsprozess. Dieser Ansteckungsprozess setzt sich solange fort, bis in einer Runde keine weiteren Ausfälle auftreten.

Die Ergebnisse der Simulationsstudie lassen sich in drei Kernaussagen zusammenfassen:

1. Die empirische Häufigkeitsverteilung der Verlustrate am Interbankenmarkt ist ausgeprägt u-förmig, d.h. es gibt viele Beobachtungen mit sehr geringer Verlustrate (LGDs bis 10%) und viele Beobachtungen mit sehr hoher Verlustrate (LGDs von mehr als 90%), dagegen relativ wenige Beobachtungen im Bereich dazwischen (LGDs von 10 bis 90%).

2. Die Simulationen werden zweimal durchgeführt: einmal mit einer konstanten Verlustrate in Höhe des empirischen Mittelwertes in unseren Daten (45%) und einmal mit einer zufälligen Verlustrate, wobei wir aus einer statistischen Verteilung ziehen, die nahe an der empirischen Häufigkeitsverteilung ist. Die Simulationen unter der Annahme der zufälligen Verlustrate ergeben in der Regel ein instabileres System als die Simulationen unter der Annahme der entsprechenden konstanten Verlustrate.

Somit führt die in der Literatur häufig unterstellte konstante Verlustrate dazu, das Ausmaß der Ansteckungseffekte zu unterschätzen.

3. Wir können drei Gruppen von Banken unterscheiden, was die Auswirkungen einer Schieflage auf das Bankensystem angeht: Banken, deren Ausfall zu stark unterschiedlichen Ansteckungseffekten führt, und zwar abhängig davon, welcher Zufallspfad gerade eingetreten ist; Banken, deren Ausfall zu einer relativ konstanten Zahl von weiteren Ausfällen führt; und Banken mit geringen Verbindlichkeiten gegenüber den anderen Banken, deren Ausfall selbst im ungünstigsten Fall keine weiteren Ausfälle nach sich zöge.

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Contagion at the Interbank Market with Stochastic LGD[1]

1 Introduction

The collapse of Lehman Brothers turned the 2007 / 2008 turmoil into a deep global financial crisis. The tremendous effects of the Lehman default were largely contagion effects which propagated and intensified the Lehman shock. In particular, the fear of contagion via interbank markets played a crucial role in this process. While banks could gauge their direct losses from transactions with Lehman Brothers, they could not assess their counterparties' losses and creditworthiness and were therefore not willing to lend money to other banks, causing the breakdown of interbank markets. This led to unprecedented liquidity extension of central banks and government rescue packages (see Stolz and Wedow (2010)) which, however, could not avoid deep recessions in many countries of the world. From an economic perspective, it is therefore essential to have a tool allowing to assess potential contagion risks via interbank markets.

This is the aim of this paper. We study contagion at the German interbank market, one of the largest interbank markets in Europe. We carry out a simulation exercise where we assume that a certain bank fails and examine how this failure affects other banks' solvency via direct effects and chain reactions in the banking system. Throughout this paper, our focus is on 15 systemically relevant German banks. We analyze in particular the role of the loss given default (LGD) in the contagion process and examine how the assumption of a stochastic LGD affects the results.

The LGD is a key factor for the extent of contagion. The LGD, multiplied by the total exposure of a creditor bank to a debtor bank, gives the actual loss of the creditor bank in the event of the debtor bank failing. The LGD can vary between 0% (eg in the event that the defaulted loan is fully collateralized) and 100% (which is equivalent to a zero recovery rate of the defaulted loan). As there is usually only sparse information about recovery rates in the case of bank defaults, the standard approach in the literature on interbank contagion is to assume a fixed value of the LGD and repeat the simulation exercise with

[1]The views expressed in this paper are those of the authors and do not necessarily reflect the opinions of the Deutsche Bundesbank. We thank Gabriel Frahm, Ulrich Krüger, Peter Raupach and the participants of the research seminar of the Deutsche Bundesbank for valuable comments.

different values of this LGD. The literature generally finds that losses in the total banking system crucially depend on the LGD value. Below a certain threshold of LGD, potential losses are minor. However, as soon as the LGD exceeds a certain threshold, there are considerable risks of large parts of the banking system being affected and heavy losses in the banking system occurring (see eg Upper and Worms (2004) and van Lelyveld and Liedorp (2006)). Therefore, the standard approach has the considerable drawback that an assessment of contagion risks in the real world is difficult and associated with great uncertainties. In our paper, we overcome this shortcoming by using a unique dataset of realized LGDs of defaulted interbank exposures.

Our contributions are as follows. First, using this dataset of realized LGDs on the interbank market, we are able to investigate the empirical pattern of actual LGDs. Second, unlike the vast majority of papers in the literature, we do not need to estimate the amount of interbank exposures nor do we rely on incomplete information from very large interbank exposures. Instead, we are able to precisely quantify interbank exposures (including off-balance sheet and derivative positions) within the national market. Third, in contrast to most papers in the literature, we conduct the simulation exercise with a *stochastic* LGD derived from the observed distribution of LGDs (instead of a stepwise increase of *constant* values). We thereby obtain a distribution of the number of contagious bank defaults which allows a more realistic assessment of contagion risks.

Our main findings are, first, that LGDs follow a u-shaped distribution, which can be reasonably well approximated by a beta distribution. Second, using the precise information about interbank exposures and the distribution of LGD, we find that the number of bank defaults may increase substantially when we assume a stochastic LGD instead of a constant one. Third, we observe three types of banks concerning their tendency to trigger contagion: Banks with a u-shaped distribution of subsequent bank failures, banks with an unimodal distribution of subsequent bank failures and banks where no subsequent bank failure occurs.

The paper is structured in the following way: In Section 2, we give a brief overview of the literature on interbank contagion as well as LGD modelling and state our contribution to the literature. Section 3 deals with the description of the contagion exercise and its main components (bilateral exposures, modelling of the LGD). In Section 4, we show the results of the contagion exercise and in Section 5 the conclusion is presented.

2 Literature

Our paper relates to three strands of the literature. The first strand is about empirical simulation studies of interbank contagion (see Upper (2007) for an overview). Especially national European interbank markets have been the focus of empirical studies (see, for instance, van Lelyveld and Liedorp (2006) for the Netherlands, Sheldon and Maurer (1998) for Switzerland or Mistrulli (2007) for Italy). In addition to studies based on national interbank markets, there are cross-border contagion simulations. These studies are either based on BIS data on consolidated banking statistics (see Espinosa-Vega and Solé (2010) and Degryse et al. (2010)) or analyze international sector interlinkages (see Castrén and Kavonius (2009)). Most papers in this strand do not have direct access to information on interbank exposures, but apply either statistical methods to derive the bilateral exposures or rely on data which cover only part of the interbank exposures. We have a certain advantage compared to these studies since we are able to precisely quantify the amount of bilateral exposures for a system of 15 large German banks. Our data set is based on the German credit register and includes off-balance-sheet and derivative positions. It contains all bilateral exposures of the 15 banks above a threshold of EUR 1.5 m. This threshold is not relevant for the purpose of our study since interbank exposures are typically large.

The second strand of literature we contribute to deals with extensions of the usual contagion exercises. Cifuentes et al. (2005) introduce additional stress due to declining asset prices as a result of fire sales; Elsinger et al. (2006) integrate the interbank contagion model in a stress testing setting that includes macroeconomic shocks. Espinosa-Vega and Solé (2010) and Chan-Lau (2010) do not only consider credit risk, but funding risk as well. They argue that the banks' funding is hindered when the interbank market does not function properly. Aikman et al. (2009) incorporate various of these aspects into one quantitative model of systemic stability. Degryse and Nguyen (2007) explicitly model the LGDs, deriving them endogenously from the banks' balance sheet composition. Our extension is about LGD modelling as well. However, we model the LGDs as stochastic.

The third strand of literature deals with the distribution of LGDs. Huang et al. (2009) and Tarashev and Zhu (2008) choose a stochastic setting for the LGD. They assume a triangular distribution with the probability mass concentrated in the center of the distribution (more precisely at 55% and 50%, respectively). Crouhy et al. (2000) model a stochastic LGD with the help of a beta distribution. They estimate the parameters by using bond market data. Their estimations yield the result that the LGD follows an uni-modal beta distribution. Our contribution consists in estimating the distribution of the LGDs of *interbank exposures*. We have a unique data set of realized interbank LGDs at our disposal. This data suggests a u-shaped density for the LGD, ie a distribution with much probability mass at zero and 100 per cent. This finding is in line with Dermine and de Carvalho (2006) and Bastos (2010) who use a dataset of defaulted loans provided by a large Portuguese bank and find a u-shaped LGD distribution for non-financial firms.

3 Round-by-Round Algorithm

3.1 General procedure

In the event of a bank failing, the banks that have given credit to this bank suffer losses from their exposures. The contagion process in the interbank market may stop after the first round, but may also propagate further through the system. Banks, which fell in distress as a consequence of the initial distress, may now themselves become a source of contagion. This process will continue round by round until the banking system reaches a new equilibrium with a possibly huge number of failures or until the supervisory authorities manage to put an end to this process.

In this section, we describe a simulation exercise so as to study the extent to which the German banking system may be prone to such a contagious process. We apply the round-by-round algorithm as described in Upper (2007).

1. Initially, bank i fails exogenously.

2. As a result, banks whose exposure to bank i multiplied by the loss given default (LGD) exceeds their buffer of tier-1 capital, also fail. We define a bank to be in default in the event that its tier-1 capital ratio is below 6 per cent of its risk-weighted assets. This default definition is in line with the new Basel accord where the minimum capital requirement is also set at 6%.[2] We do not take into account potential reactions of the lender banks. For example, the lender banks may have hidden reserves which they release to increase their tier-1 capital. Instead, we assume

[2] See Basel Committee on Banking Supervision (2010), paragraph 50.

that write-offs on interbank loans decrease the lender's tier-1 capital by the same amount.

3. Further banks may fail if their combined exposure to the banks that have failed so far (times the LGD) is greater than their capital buffer.

4. The contagious process stops when no new failure occurs and a new equilibrium is reached.

Thus, bank j is in distress, if

$$\frac{E_j - \sum_k (LGD_{jk} \cdot x_{jk} \cdot 1_{k \in D})}{RWA_j - 0.2 \cdot \sum_k (x_{jk} \cdot 1_{k \in D})} < 0.06 \tag{1}$$

In this context, E_j is the tier-1 capital of bank j, x_{jk} is the exposure of bank j to bank k, $1_{k \in D}$ is an indicator variable that takes on the value 1 in the event that bank k is in distress (and 0 otherwise), LGD_{jk} is the loss given default associated with the exposure of bank j to bank k and RWA_j are the risk weighted assets of bank j. We assume that interbank claims receive a weight of 0.2 in banks' risk weighted assets.[3] When calculating the tier-1 capital ratio, we also take into account that every claim to a bank that failed completely disappears from the creditor bank's risk weighted assets.

We carry out this simulation exercise for each of the 15 systemically relevant banks in Germany. We do not include the rest of the banks in Germany because previous studies have already shown that only a small number of banks form the so-called core of the German interbank market and that these core banks act as an intermediary for numerous small banks (see Craig and von Peter (2010)). Thus, the failure of a systemically relevant bank will most likely trigger a huge amount of smaller banks to fail. However, the small banks do generally not trigger contagious reactions. In our analysis about the vulnerability of the German interbank market, we therefore deal only with the interconnectedness of the systemically relevant banks.

To run the round-by-round algorithm, information is needed on (i) the pairwise exposures between the banks and (ii) the appropriate loss given a bank fails. Concerning the pairwise exposures, we have detailed information on exposures within the German interbank market (see Section 3.2). This leaves the question of determining the loss given

[3] The risk weight of 0.2 follows from the Basel I and Basel II framework applied to German banks.

default. From the literature we know that this is crucial for the contagion exercises (see eg Upper and Worms (2004)). Different solutions are possible.

1. Constant *LGD*. The loss given default is exogenously set to a constant value, say 40% or 45%.[4] To account for the fact that the LGD crucially drives the results, one can vary the constant loss given default over a wide range of values. The contagion exercise is then run for each different value of the LGD.

2. Endogenous *LGD*. If information on the actual over-indebtedness of the distressed bank, the bankruptcy cost and the degree of collateralisation were available, it would be possible to endogenously calculate the loss given default.

3. Stochastic *LGD*. Our supervisory data concerning the write-offs of interbank loans show that the loss given default considerably varies, with a large portion of the probability mass at 0% and at 100%. A possible explanation for this quasi-dichotomy may be that the loans are either fully collateralised (as in the Repo-market) or completely unsecured. This finding is not in line with the assumption of a constant LGD (solution 1). Solution 1 would rather be in line with a distribution of the LGDs concentrated in one point.

In this study, we start with the first solution, ie the solution in which the loss given default is deterministic and takes on the value of the mean of our dataset.

This exercise is our benchmark. The method with stochastic LGDs (solution 3) should then provide information on how the stochastic nature of the LGD drives the results. The exact properties of the LGD-distribution are investigated in Section 3.3. We discard the solution with an endogenous LGD since we lack the necessary data. Besides, our data on realised LGDs suggest that the borrower banks' balance sheet composition and other bank specific variables only explain a small fraction of the LGD variation. Most LGD variation seems to stem from the extent of collateralisation of the interbank exposures.[5]

[4]Kaufman (1994) gives an overview of loss given default estimates for bank failures; the estimates vary considerably. James (1991) finds that the average loss of failed US banks during the period of 1985 to 1988 was about 30%. In addition, there were direct costs associated with the bank closures of 10% of the assets. In our data set, the mean LGD is about 45%.

[5]We carried out a variance decomposition of the LGDs. We find that most of the variation is due to the lender bank (about two thirds), ie the variation owing to the balance sheet composition of the borrower bank is less important, which is another argument for not using solution 2.

3.2 Exposure at Default (EAD)

As outlined above, the first step for running the round-by-round algorithm consists of establishing the matrix of mutual interbank exposures. We use Bundesbank data from the German credit register (MiMiK) to obtain the necessary information.[6] Unlike credit registers in most other countries, the German credit register also includes interbank loans and is not confined to non-financials. This data base offers us a certain data advantage compared to other studies since we are able to determine the complete matrix for the systemically relevant banks. By contrast, balance sheet data only show (for each bank) the aggregate amount lent to or borrowed from all banks. Moreover, payment data or large exposure data are in general less comprehensive than credit register data and include, for example in the case of payment data, only information about short-term lending.

The German credit register contains quarterly data on large exposures of banks to individual borrowers or single borrower units (eg groups). Banking institutions located in Germany are required to report if their exposures to an individual borrower or the sum of exposures to borrowers belonging to one borrower unit exceeds the threshold of EUR 1.5m at least once in the respective quarter. We think that the threshold of EUR 1.5m does not cause a serious bias since the typical interbank loan is relatively large and exceeds the threshold of EUR 1.5m.

The credit register applies a broad definition of loan. Loans in this sense include traditional loans, bonds, off-balance sheet positions and exposures from derivative positions. However, trading book positions are excluded. We analyze gross exposures, as opposed to netting bilateral exposures. We do not net, because, in the event of a bank failing, it is not clear whether a netting can be enforced.[7] For the simulation exercise, we use data from the second quarter 2010.

3.3 Stochastic Loss Given Default (LGD)

The second key component for the contagion exercise is the loss given default (LGD). We have some information about the loss rate banks face in the event of a borrowing bank's default. While we do not know the LGD of the lender bank for a default of a specific

[6]See Schmieder (2006) for more details about this database.

[7]See Mistrulli (2007) for this and other arguments concerning the simulation method.

borrower bank, we know for each lender bank the average LGD of interbank exposures (at an annual frequency). Specifically, for each bank and each year, we have data on the volume of non-performing interbank loans and on the corresponding write-downs. From this data, we can derive the realization of the LGD in the interbank market for a given bank in a given year. The data are taken from the quantitative supervisory reports for banks in Germany, collected by the Bundesbank.[8] Based on this data, we can estimate the distribution of LGDs.

Since our simulations of the contagion exercise only consider systemically relevant banks, we focus on data of private commercial banks and the large central institutions of the savings and cooperative banks. Regional savings and cooperative banks, which are generally small and medium-sized, are left out. The reason is that we consider their position in the German interbank market as less representative for our stability analysis because these banks' interbank market activities are very much characterized by relationships to their central institutes. This is not the case for smaller private banks that we therefore included in the data set. Our dataset of LGDs consists of 344 observations for the period 1998-2008. Figure 4 shows the frequency distribution of the LGDs.[9]

Visual inspection of the LGD distribution suggests to use a a beta distribution for modelling the stochastic LGDs. The density of the beta distribution is given by

$$f(x) = \frac{1}{B(\alpha,\beta)} x^{\alpha-1}(1-x)^{\beta-1} \quad x \in (0,1) \tag{2}$$

with

$$B(\alpha,\beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}, \tag{3}$$

where $\Gamma(\cdot)$ is the Gamma-function. The parameters $\alpha > 0$ and $\beta > 0$ determine the shape of this distribution.[10] The beta distribution is especially suitable for modelling LGD because (i) the domain is confined to the economic sensible interval from 0 to 1, (ii) it is highly flexible and (iii) nests other distributions.[11] For instance, when both parameters equal one, then the beta distribution becomes a uniform distribution. When both of the

[8] For more details on these data see Memmel and Stein (2008).

[9] The data set that includes all banking groups also has a u-shaped frequency distribution with slightly more probability mass at zero and slightly less probability mass at one.

[10] Figure 5 summarizes the possible shapes of the probability density function dependent on the parameter values.

[11] See eg Hahn and Shapiro (1967), pp.91.

parameters are smaller than one, the probability density function is u-shaped with a large portion of the probability mass close to zero and one. For parameter values close to zero, this distribution converges to the binomial distribution. By contrast, the density is unimodal in the case of both parameters α and β being greater than one. For very large parameter values, it converges to the degenerate distribution, where the entire probability mass is concentrated on one point. The expectation and the variance of a random variable X following a beta distribution are functions of the parameters α and β:

$$\mathrm{E}(X) =: \mu = \frac{\alpha}{\alpha+\beta} \tag{4}$$

and

$$\mathrm{var}(X) =: \sigma^2 = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)} \tag{5}$$

Given estimates for the expectation and the variance, estimators for the parameters α and β are obtained by solving the equations (4) and (5) for α and β, respectively:[12]

$$\hat{\alpha} = \hat{\mu}\left(\frac{\hat{\mu}(1-\hat{\mu})}{\hat{\sigma}^2} - 1\right) \tag{6}$$

$$\hat{\beta} = (1-\hat{\mu})\left(\frac{\hat{\mu}(1-\hat{\mu})}{\hat{\sigma}^2} - 1\right) \tag{7}$$

Using the sample mean $\hat{\mu}$ and variance $\hat{\sigma}^2$ as an estimator for the population mean and variance, we obtain $\hat{\mu} = 0.45$ and $\hat{\sigma}^2 = 0.15$. Inserting $\hat{\mu}$ and $\hat{\sigma}^2$ into equation (6) and (7) yields $\hat{\alpha} = 0.28$ and $\hat{\beta} = 0.35$. These parameter values suggest a u-shaped distribution (see Figure 5).

Figure 4 also contains the probability density function of a beta distribution with the estimated parameters. Compared to the empirical frequency distribution, only small deviations can be observed. Statistical tests confirm this observation. The null hypothesis of a χ^2 goodness-of-fit test that our data follow a beta distribution with estimated parameters $\hat{\alpha}$ and $\hat{\beta}$, cannot be rejected on a 5% significance level. Choosing ten equidistant intervals and comparing the observed frequency to the expected frequency within the intervals yields a p-value of ≈ 0.075.[13]

[12]This procedure is called method of matching moments, see eg Hahn and Shapiro (1967), p.95. We do not use maximum likelihood-estimation because there is a considerable amount of observations which equal exactly 0 and 1 and for which, therefore, the likelihood function is not defined.

[13]The result of this test gives strong evidence that the assumed distribution is very close to the observed

As an additional robustness check for the use of the beta distribution with estimated parameters, we also run simulations by drawing from the discrete distribution observed by the data. For this purpose, we randomly choose observations out of the data set with each observation number occurring with equal probability (see Section 4.3).

The results obtained from our dataset may also have further implications for the literature on LGD modelling. As already mentioned, the null hypothesis that our data sample follows a beta distribution with parameters $\hat{\alpha} = 0.28$ and $\hat{\beta} = 0.35$ cannot be rejected on a 5% significance level. However, in the literature, LGDs are often not modelled as following a u-shaped beta distribution (i.e. $\alpha < 1$ and $\beta < 1$), but as following an unimodal distribution (in the case of the beta distribution, this implies that $\alpha > 1$ and $\beta > 1$) or as being constant. Thus, our next step is to explicitly test whether the LGD distribution is really u-shaped, i.e. we test the null hypothesis that $\alpha \geq 1$ or $\beta \geq 1$. We carry out a sequence of two t-tests with the two null hypotheses $\alpha \geq 1$ and $\beta \geq 1$, respectively. In the event that we can reject both null hypotheses, we accept the hypothesis $\alpha < 1$ and $\beta < 1$. Given the same significance level in both t-tests, the significance level of the joint hypothesis $\alpha < 1$ and $\beta < 1$ is at least as strong (see Frahm (2010)).

Using the delta-method and the relations given in Equations (6) and (7), we derive the asymptotic distribution of the estimates for $\hat{\alpha}$ and $\hat{\beta}$, respectively. Using a first-order Taylor expansion, the delta method gives us a relation between the variance-covariance matrix of the estimators $\hat{\mu}$ and $\hat{\sigma}^2$, and the variance-covariance matrix of $\hat{\alpha}$ and $\hat{\beta}$:

$$Var\begin{pmatrix} \hat{\alpha} \\ \hat{\beta} \end{pmatrix} \approx \nabla \begin{pmatrix} f_1\left(\hat{\mu}, \hat{\sigma}^2\right) \\ f_2\left(\hat{\mu}, \hat{\sigma}^2\right) \end{pmatrix}^T \cdot Var\begin{pmatrix} \hat{\mu} \\ \hat{\sigma}^2 \end{pmatrix} \cdot \nabla \begin{pmatrix} f_1\left(\hat{\mu}, \hat{\sigma}^2\right) \\ f_2\left(\hat{\mu}, \hat{\sigma}^2\right) \end{pmatrix} \tag{8}$$

with $f_1\left(\hat{\mu}, \hat{\sigma}^2\right) = \hat{\alpha} = \hat{\mu}\left(\frac{\hat{\mu}(1-\hat{\mu})}{\hat{\sigma}^2} - 1\right)$ and $f_2\left(\hat{\mu}, \hat{\sigma}^2\right) = \hat{\beta} = (1-\hat{\mu})\left(\frac{\hat{\mu}(1-\hat{\mu})}{\hat{\sigma}^2} - 1\right)$.

distribution, as the test is very sensitive due to the large number of observations. To illustrate the correlation between the number of observations and the sensitiveness of the test, we run simulations with a sample randomly drawn from a beta distribution. Drawing $10,000$ times 344 observations from a beta(0.28,0.35)-distribution and testing each sample against a beta(0.18,0.25)-distribution yields a probability of making a type II error (ie the error of falsely accepting the null hypothesis) of around 18%. Repeating this exercise for only half of the sample (ie drawing 172 observations each time) leads to a probability of making a type II error of 62%. Thus, the larger the sample, the more sensitive the test becomes to only small deviations from the distribution tested.

The variance-covariance matrix of $\hat{\mu}$ and $\hat{\sigma}^2$ is given by:

$$Var\begin{pmatrix}\hat{\mu}\\ \hat{\sigma}^2\end{pmatrix}=\begin{pmatrix}\sigma^2_{\hat{\mu}} & \sigma_{\hat{\mu},\hat{\sigma}^2}\\ \sigma_{\hat{\mu},\hat{\sigma}^2} & \sigma^2_{\hat{\sigma}^2}\end{pmatrix}=\begin{pmatrix}\frac{1}{N}\sigma^2 & \frac{1}{N}\mu_3\\ \frac{1}{N}\mu_3 & \frac{1}{N}\left(\mu_4-\frac{N-3}{N-1}\sigma^4\right)\end{pmatrix} \tag{9}$$

where μ_3 and μ_4 denote the third and fourth central moments, respectively.[14] For implementation purposes, we replace the true moments by their estimators, i.e. $\hat{\sigma}^2$, $\hat{\mu}_3$ and $\hat{\mu}_4$ are given by $\frac{1}{N-1}\sum_{i=1}^{N}(x_i-\hat{\mu})^2$, $\frac{1}{N}\sum_{i=1}^{N}(x_i-\hat{\mu})^3$ and $\frac{1}{N}\sum_{i=1}^{N}(x_i-\hat{\mu})^4$, respectively.[15] From the Equations (8) and (9), we see that the variances of $\hat{\alpha}$ and $\hat{\beta}$ are linear combinations of $\sigma^2_{\hat{\mu}}$, $\sigma_{\hat{\mu},\hat{\sigma}^2}$ and $\sigma^2_{\hat{\sigma}^2}$:

$$Var(\hat{\alpha})=\left(\frac{\partial f_1}{\partial\hat{\mu}}\right)^2\cdot\sigma^2_{\hat{\mu}}+2\cdot\left(\frac{\partial f_1}{\partial\hat{\mu}}\right)\cdot\left(\frac{\partial f_1}{\partial\hat{\sigma}^2}\right)\cdot\sigma_{\hat{\mu},\hat{\sigma}^2}+\left(\frac{\partial f_1}{\partial\hat{\sigma}^2}\right)^2\cdot\sigma^2_{\hat{\sigma}^2} \tag{10}$$

$$Var\left(\hat{\beta}\right)=\left(\frac{\partial f_2}{\partial\hat{\mu}}\right)^2\cdot\sigma^2_{\hat{\mu}}+2\cdot\left(\frac{\partial f_2}{\partial\hat{\mu}}\right)\cdot\left(\frac{\partial f_2}{\partial\hat{\sigma}^2}\right)\cdot\sigma_{\hat{\mu},\hat{\sigma}^2}+\left(\frac{\partial f_2}{\partial\hat{\sigma}^2}\right)^2\cdot\sigma^2_{\hat{\sigma}^2} \tag{11}$$

Calculations based on our dataset yields $Var(\hat{\alpha})=0.0007$ and $Var\left(\hat{\beta}\right)=0.0013$. As a next step, we use these values to calculate the test statistics T for the t-test with the null hypothesis that $\alpha>1$ and $\beta>1$. The results $T_\alpha\approx-27$ and $T_\beta\approx-18$ clearly show that the null hypothesis can be rejected. Thus, we can conclude that, contrary to the common assumption of an unimodal LGD distribution in the literature, our dataset of the LGD follows a u-shaped distribution.

4 Results

4.1 Aggregate results

We start with simulations using a constant LGD (see discussion in Section 3.1). Results are then taken as benchmark to simulations using stochastic values.

In the simulations with a constant LGD, we assume a value of 45%, which is equal to the mean of our actual LGD values. The initial assumption is that one of the 15 banks fails. This could trigger a cascade of failures, if the ratio of tier-1 capital to risk weighted assets of one of the creditor banks falls below 6%. For a constant LGD, we obtain *one*

[14]See, for example, Mood et al. (1974), pp. 228, and Zhang (2007) for the variances and covariances of the estimators $\hat{\mu}$ and $\hat{\sigma}^2$.

[15]See Hahn and Shapiro (1967), pp. 48.

number of bank defaults occurring in the system, dependent on the bank that fails first. We repeat this exercise by varying the bank that fails first from bank number 1 to 15. As a result, we obtain a frequency distribution of the number of bank failures. Figure 1 shows that in 47% of the cases, which is equivalent to 7 out of 15 initial bank defaults, no further bank failure occurs. In 13% of the cases we have one subsequent bank failure (ie in total two bank defaults). Figure 2 illustrates that in only 13% of the cases more than six bank defaults occur. The failure of one of the 15 systemically relevant German banks thus leads to an average of 3.7 bank defaults altogether.

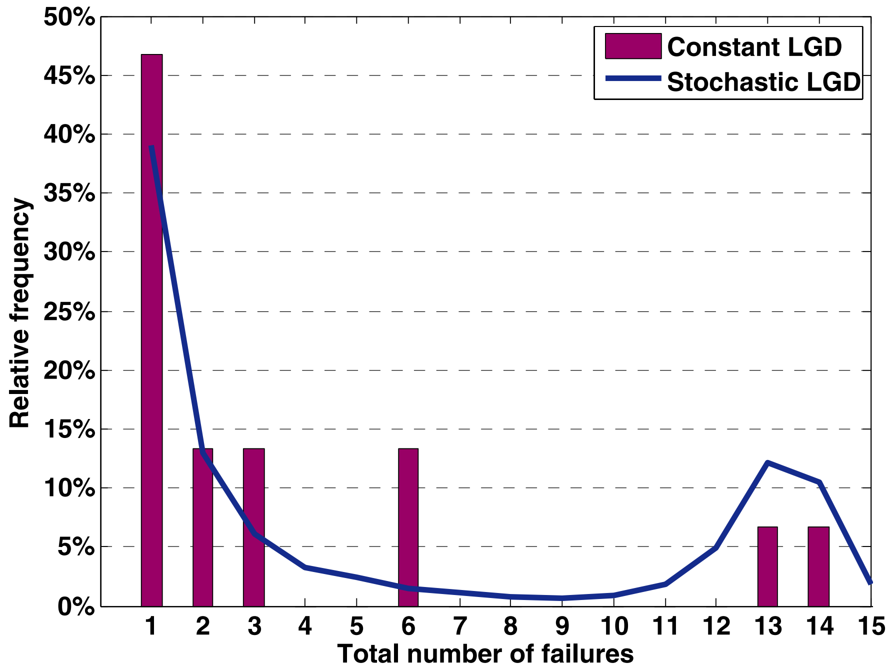

Figure 1: Frequency distribution of bank failures for constant LGD and stochastic LGD.

The second set of simulations (based on a stochastic LGD) is carried out by drawing from a beta distribution with parameters $\alpha = 0.28$ and $\beta = 0.35$. This means that, for each exposure of a creditor bank to a bank in distress, we randomly draw an LGD value from the beta distribution estimated in Section 3.3. Again, we simulate by varying the bank that fails first exogenously. In contrast to simulations based on a constant LGD, the approach with a stochastic LGD yields for each of the 15 banks a *distribution* of the number of banks in distress (and not only one single number of subsequent failures). We repeat the contagion exercise $100,000$ times for each bank, each time another of the 15

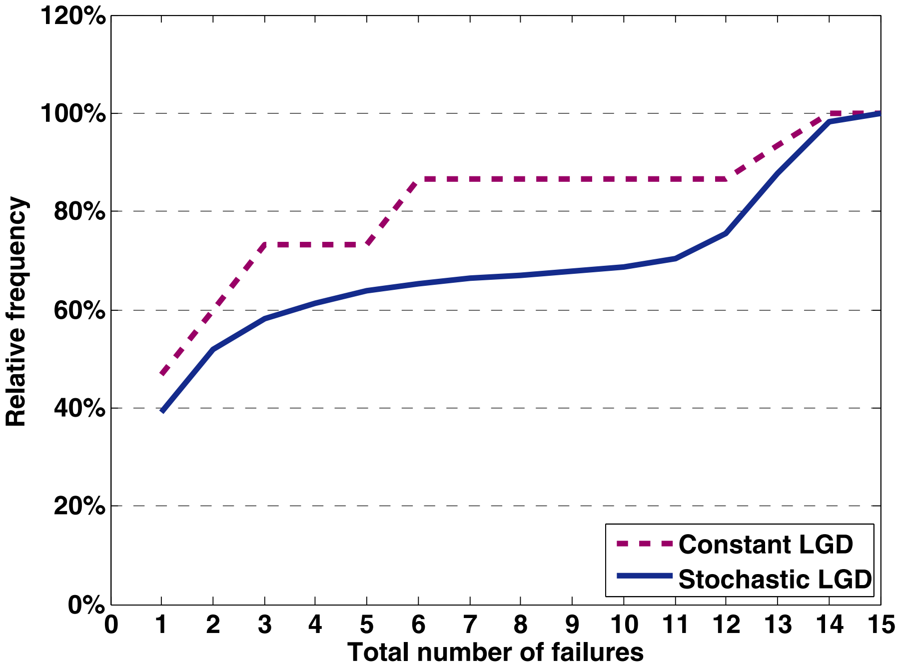

Figure 2: Distribution function of bank failures for constant LGD and stochastic LGD.

banks starts the contagious process.

Figure 1 gives the relative frequency of the number of bank failures, where we assume that the probability of the initial failure is the same for all of the 15 banks. The figure shows that, in 39% of the 1,500,000 simulation runs, no further failure occurs. By contrast, in case of a constant LGD of 45%, 7 out of 15 banks (= 47%) do not initiate a contagious process. Moreover, the overall expected number of bank defaults, given the failure of one of the 15 banks, is higher in the case of a stochastic LGD (5.6 banks in distress) than in the case of a constant LGD (3.7 banks in distress).

However, the comparison of entire distributions, only on the basis of their expected values, may neglect important parts of the distributions. This is especially true for distributions with a large amount of probability mass at the boundaries, as in our case. A stronger concept is the concept of stochastic dominance which is often used, for instance, in decision theory when the outcomes of two risky projects have to be compared (see eg Bawa (1975)). A cumulative distribution F is said to stochastically dominate the distribution G, if $F(x) \leq G(x)$ for all x (and strict inequality for at least one point). Figure 2 shows that the empirical cumulative distribution function of the results for the stochastic

LGD $F_{stoch}(\cdot)$ dominates the one for the constant LGD $F_{const}(\cdot)$, ie the distribution function $F_{stoch}(\cdot)$ is always below the function $F_{const}(\cdot)$. In this context, (first order) stochastic dominance means that any society preferring less failures to more failures considers the case of stochastic LGDs as inferior to the case of constant LGDs. In other words, with only few assumptions about the society's preferences (especially non-saturation), we are able to show that the loss distribution with the assumption of stochastic LGD is less desirable than the loss distribution under the assumption of a corresponding constant LGD.

From an economic perspective, figure 2 illustrates that simulations based on a constant LGD tend to underestimate the risks to financial stability by a bank failure. Contagion effects and therefore potential losses in the banking system may be substantially larger, implying a more fragile banking system. Since simulation studies on interbank contagion usually assume a constant LGD, this suggests that contagion risks have often been underestimated in the literature so far.

4.2 Identifying banks with similar contagion patterns

After examining aggregate results of the banking system, we investigate the disaggregate simulation results dependent on the trigger bank. We focus on the simulation results with a stochastic LGD. There are three possible patterns for the distribution of the number of bank failures, given a certain trigger bank.

1. A distribution with a large portion of probability mass concentrated on the boundaries of the distribution, ie in most of the $100,000$ iterations either a very low or a very high number of banks fail. This is the case for 7 of the 15 trigger banks. In all these cases, the expected number of bank defaults is higher in the stochastic model compared to the constant LGD of 0.45. Figure 6 shows an example for this pattern.

2. An almost unimodal distribution with a large portion of probability mass concentrated on one point. In two cases, the peak of the distribution is at a high number of bank failures (see Figure 7). It is remarkable that only in these two cases, the expected number of bank defaults is lower in the stochastic model. In four cases, the peak of the distribution is at a low number of bank failures (see Figure 8). These remaining four cases have again a higher expected number of bank defaults in the stochastic case.

3. A degenerate distribution with all probability mass concentrated on the left boundary (see Figure 9), ie those banks do not initiate a contagious process. This happens in two cases. By definition, the results of the stochastic and the constant LGD are then identical.

In Table 1 we give an overview of summary statistics of the three groups. This table reads

Group	Number	Bank failures (average across groups)	
	of banks	mean	standard dev.
1	7	7.0	5.3
2	6	5.5	3.2
3	2	1.0	0.0

Table 1: Average mean and average standard deviation of bank failures for the three groups of banks (group 1 = large probability mass at the boundaries of the distribution, 2 = unimodal distribution, 3 = degenerate distribution).

as follows. The first group consists of seven banks. We choose each of the seven banks as the bank that exogenously fails, and then calculate the mean and the standard deviation of the number of banks in distress in the simulation runs. The average across these seven means is 7.0, the average standard deviation is 5.3.

When we compare the standard deviations in the first and second group, we find that the standard deviations in the first group are considerably higher. This difference is due to the finding that banks in the first group have a bimodal distribution concerning the frequency of banks in distress, while those in the second group have an unimodal distribution. In the third group, as no subsequent bank failures occur, the mean of bank failures is one and the standard deviation is zero.

Our findings overall indicate a high degree of heterogeneity in the results. First, the exact distribution of bank failures depends on the trigger bank. Whether the simulations with a constant LGD over- or underestimate the results on average compared to the stochastic LGD, depends on the shape of the distribution of bank failures. Second, for a given trigger bank, different scenarios occur. Especially in case of the u-shaped distribution of the number of bank defaults (ie pattern 1), a fortunate combination of LGDs indicates a stable system, ie a low number of subsequent bank defaults. If there is an unfortunate combination of LGDs, however, the number of bank defaults increases sharply. Thus, while the simulations with a constant LGD yield only one single result of bank defaults, the simulations with a stochastic LGD enable to distinguish between different scenarios.

4.3 Robustness checks

We carry out robustness checks concerning two issues. First, to investigate the sensitivity of our results with respect to the assumed distribution, we draw from the discrete distribution observed by the data instead of the beta distribution. For this purpose, one observed LGD value is randomly allocated to each exposure of a creditor bank to a bank in distress. Compared to drawing the LGD from a beta distribution, the results of this exercise do not differ much. The average amount of bank failures in the stochastic case is 5.5 (compared to 5.6 in Section 4.1). Furthermore, if we look at the relative frequency distribution as well as the cumulative distribution function of the total number of bank failures, there are virtually no differences to the results of the simulations with the beta-distributed LGD. Hence, the empirical cumulative distribution function of bank failures with a stochastic LGD still stochastically dominates the cumulative distribution function of bank failures with a constant LGD. Moreover, the distribution of the number of bank failures for a given trigger bank reveals for each bank the same pattern as in Section 4.2. We can therefore conclude that drawing from the beta distribution is a good approximation for our observed LGD values.

Second, we examine the impact of including off-balance sheet positions in our simulations. Most literature on interbank contagion ignores off-balance-sheet exposures, while we have considered them in our above simulations. We therefore repeat the simulation exercise by excluding off-balance sheet positions. According to our dataset, the share of off-balance-sheet exposures to total exposures varies considerably between banks. Not surprisingly, banks with a high amount of off-balance-sheet positions on their liability side trigger much less bank failures when ignoring these exposures. In total, the average amount of bank failures is only 4.1 (compared to 5.6 when considering all exposures). Again, the cumulative distribution function of bank failures using a stochastic LGD stochastically dominates the cumulative distribution function of bank failures using a constant LGD. The shape of the distribution of bank defaults for a given trigger bank, however, changes for two banks. These two banks exhibit the highest share of off-balance-sheet positions on

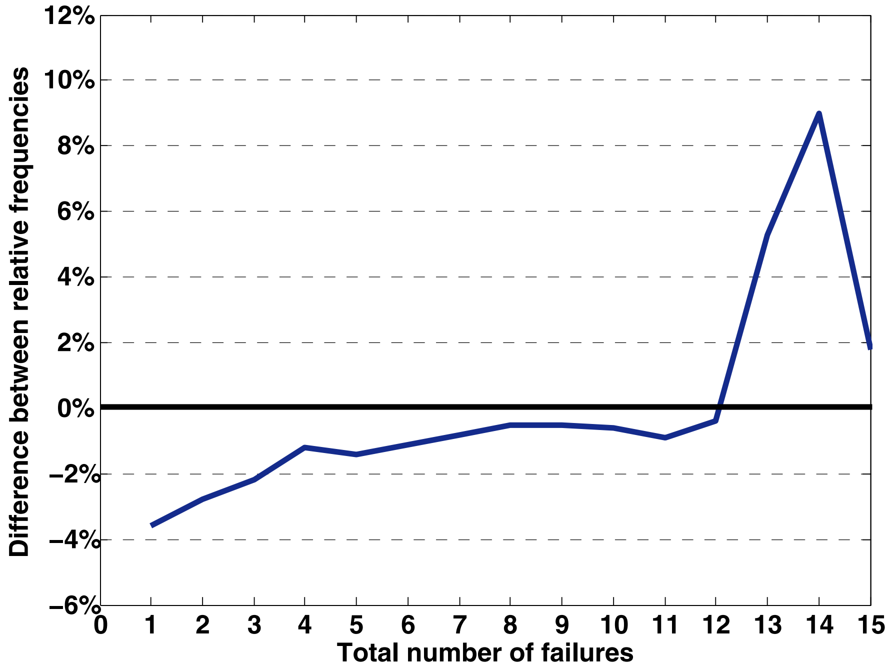

Figure 3: Difference between the relative frequency distributions of bank failures considering total exposures and considering only balance sheet exposures.

their liability side.

To elaborate the differences between the simulation results with and without off-balance-sheet exposures, we calculate the difference between the two relative frequency distributions of bank failures (see Figure 3). Figure 3 shows, for example, that the overall probability of observing only one bank failure (ie contagion effects not occurring) is four percentage points higher when only considering balance sheet exposures. For high numbers of bank defaults, the result is reversed. For instance, the overall probability of observing 14 bank failures is nine percentage points higher when off-balance-sheet exposures are considered. Thus, Figure 3 shows that the inclusion of off-balance-sheet exposures leads to a higher probability of observing extreme events and therefore captures tail risk in a more adequate way. Therefore, we can conclude that off-balance-sheet exposures considerably contribute to the interdependence of banks and possibly change the results of the stability analysis in a remarkable way.

5 Conclusion

In this paper, we investigate contagion risk in the German interbank market. We have access to a unique data set about loss given defaults (LGDs) of interbank exposures. Our data reveal that the frequency distribution of the LGD is u-shaped, ie defaults of interbank loans often imply either a loss of 0 or 100 per cent. This bimodal distribution stands in contrast to the assumption of an unimodal LGD distribution in the literature.

Next, we run simulations investigating the extent of potential contagion in the German interbank market. For this purpose, we focus on 15 systematically relevant German banks. For our simulations, we compare the outcome of two different assumptions. First, we run simulations assuming a constant LGD that equals the average LGD value in our dataset. The assumption of a constant LGD is the standard approach in the literature. Second, we use a stochastic LGD by drawing from a beta distribution. The shape of the beta distribution is derived from our LGD data set. With the help of the concept of stochastic dominance, we show that contagion effects tend to increase when we replace a constant LGD with a stochastic one. This finding indicates that the traditional literature with the assumption of constant LGDs underestimates the severity of contagious processes.

On the bank level, we identify three types of banks: banks whose initial failure either leads to a high or low a number of further failures, depending on the probability path; banks whose initial failure leads to an unimodal distribution of subsequent failures; and banks that even in the worst scenarios do not trigger any further bank defaults because other banks' exposures are not high enough. For banks belonging to the first group, the number of subsequent bank failures is not predictable for eg a regulatory institution without knowing the exact LGD-values. For these banks it is reasonable to have a more detailed look at the data and eg identify the crucial interbank exposures that drive the results. Though the danger of domino effects caused by a bank from the second group can be high (when the peak of the distribution is at a high number of bank failures), there is not much uncertainty about it. Thus, it is not difficult to predict the number of subsequent bank failures. The failure of one of the banks belonging to the third group looks, at first sight, unproblematic for the rest of the financial system as no further systemically relevant bank fails for sure. However, one has to be careful with this assessment as we did not take into account the numerous small banks that have direct exposures to the systemically relevant banks. Furthermore, we only consider direct domino effects in our analysis and abstract from other effects that can occur in times of crisis.

An open question for future research is to compare the loss distribution at different points in time and to develop an indicator showing by how far the interbank market is prone to contagious processes.

References

Aikman, D., P. Alessandri, B. Eklund, P. Gai, S. Kapadia, E. Martin, N. Mora, G. Sterne, and M. Willison (2009). Funding liquidity risk in a quantitative model of systemic stability. Working Paper Bank of England No 372.

Basel Committee on Banking Supervision (2010). Basel III: A global regulatory framework for more resilient banks and banking systems. Bank for International Settlements.

Bastos, J. A. (2010). Forecasting bank loans loss-given-default. *Journal of Banking and Finance 34*, 2510–2517.

Bawa, V. S. (1975). Optimal rules for ordering uncertain prospects. *Journal of Financial Economics 2*, 95–121.

Castrén, O. and I. K. Kavonius (2009). Balance sheet interlinkages and macro-financial risk analysis in the euro area. ECB Working Paper Series No. 1124.

Chan-Lau, J. A. (2010). Balance sheet network analysis of too-connected-to-fail risk in global and domestic banking systems. Working Paper IMF 10/107.

Cifuentes, R., G. Ferrucci, and H. S. Shin (2005). Liquidity risk and contagion. *Journal of the European Economic Association 3*, 556–566.

Craig, B. and G. von Peter (2010). Interbank tiering and money center banks. Working Paper Bank for International Settlements (BIS) No 322.

Crouhy, M., D. Galai, and R. Mark (2000). A comparative analysis of current credit risk models. *Journal of Banking and Finance 24*, 59–117.

Degryse, H., M. A. Elahi, and M. F. Penas (2010). Cross-border exposures and financial contagion. *International Review of Finance 10*, 209–240.

Degryse, H. and G. Nguyen (2007). Interbank exposures: An empirical examination of contagion risk in the Belgian banking system. *International Journal of Central Banking 3*, 132–171.

Dermine, J. and C. N. de Carvalho (2006). Bank loan losses-given-default: A case study. *Journal of Banking and Finance 30*, 1219–1243.

Elsinger, H., A. Lehar, and M. Summer (2006). Risk assessment for banking systems. *Management Science 52*, 1301–1314.

Espinosa-Vega, M. A. and J. Solé (2010). Cross-border financial surveillance: A network perspective. Working Paper IMF 10/105.

Frahm, G. (2010). The likelihood-ratio test for v-hypotheses. Discussion Paper, Department of Economic and Social Statistics, University of Cologne.

Hahn, G. J. and S. S. Shapiro (1967). *Statistical Models in Engineering*. New York: John Wiley & Sons.

Huang, X., H. Zhou, and H. Zhu (2009). A framework for assessing the systemic risk of major financial institutions. *Journal of Banking and Finance 33*, 2036–2049.

James, C. (1991). The losses realized in bank failures. *Journal of Finance 46*, 1223–1242.

Kaufman, G. G. (1994). Bank contagion: A review of the theory and evidence. *Journal of Financial Services Research 8*, 123–150.

Memmel, C. and I. Stein (2008). The prudential database BAKIS. *Schmollers Jahrbuch 128*, 321–328.

Mistrulli, P. E. (2007). Assessing financial contagion in the interbank market: Maximum entropy vs. observed interbank patterns. Bank of Italy Discussion paper No 641.

Mood, A. M., F. A. Graybill, and D. C. Boes (1974). *Introduction to the Theory of Statistics* (Dritte Auflage ed.). New York et al.: McGraw-Hill.

Schmieder, C. (2006). The Deutsche Bundesbank's large credit database (BAKIS-M and MiMiK). *Schmollers Jahrbuch 126*, 653–663.

Sheldon, G. and M. Maurer (1998). Interbank lending and systemic risk: An empirical analysis for Switzerland. *Swiss Journal of Economics and Statistics 134*, 685–704.

Stolz, S. and M. Wedow (2010). Extraordinary measures in extraordinary times: Bank rescue operations in Europe and the US. Discussion Paper, Series 1, No 13/2010, Deutsche Bundesbank.

Tarashev, N. and H. Zhu (2008). Specification and calibration errors in measures of portfolio credit risk: The case of the asrf model. *International Journal of Central Banking 4*, 129–173.

Upper, C. (2007). Using counterfactual simulations to assess the danger of contagion in interbank markets. Working Paper Bank for International Settlements (BIS) No 234.

Upper, C. and A. Worms (2004). Estimating bilateral exposures in the German interbank market: Is there a danger of contagion? *European Economic Review 48*, 827–849.

van Lelyveld, I. and F. Liedorp (2006). Interbank contagion in the Dutch banking sector. *International Journal of Central Banking 2*, 99–133.

Zhang, L. (2007). Sample mean and sample variance: Their covariance and their (in)dependence. *The American Statistician 61*, 159–160.

Tables and Figures

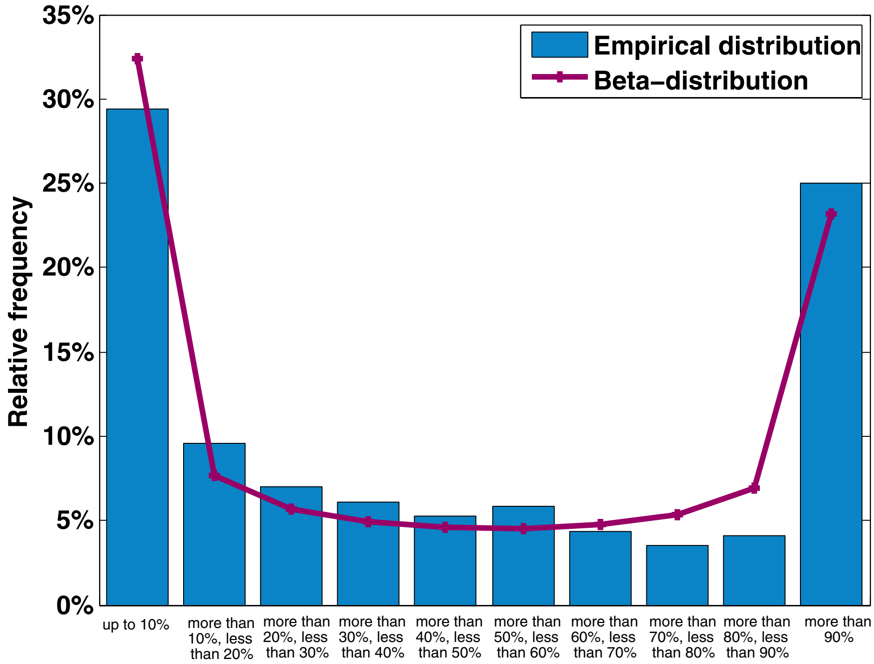

Figure 4: Relative frequency of the loss given default for interbank loans, derived from data on German private commercial banks and the central institutions of the savings and cooperative banks. 344 observations for the period 1998-2008.

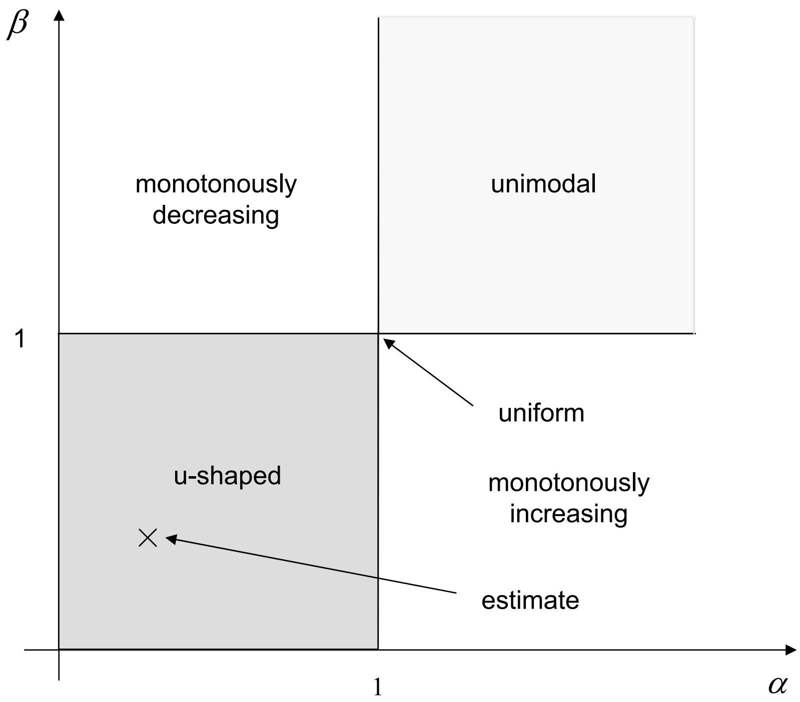

Figure 5: Shapes of the probability density function of the beta distribution dependent on the values of α and β.

Figure 6 to 9: Different distribution patterns

Note: These pictures show different distribution patterns of bank failures dependent on which bank fails first. Each picture is created by assuming that one particular bank fails first. The total number of bank failures occuring because of domino effects is then calculated by drawing an LGD value from the beta distribution for each interbank exposure. This exercise is repeated $100,000$ times for each bank. In this context, three contagion patterns can be observed dependent on the trigger bank: A u-shaped distribution of bank failures (see Figure 6 and pattern 1 in Section 4.2), an unimodal distribution of bank failures (see Figures 7 and 8 and pattern 2 in Section 4.2) and a degenerate distribution of bank failures (see Figure 9 and pattern 3 in Section 4.2).

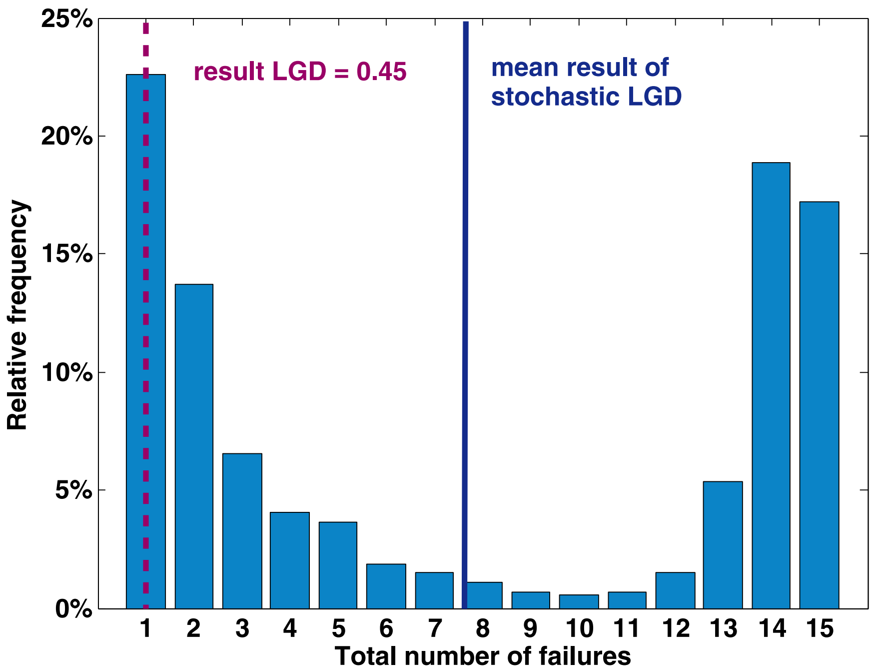

Figure 6: Example of a distribution of bank failures with a large amount of probability mass at the boundaries of the distribution.

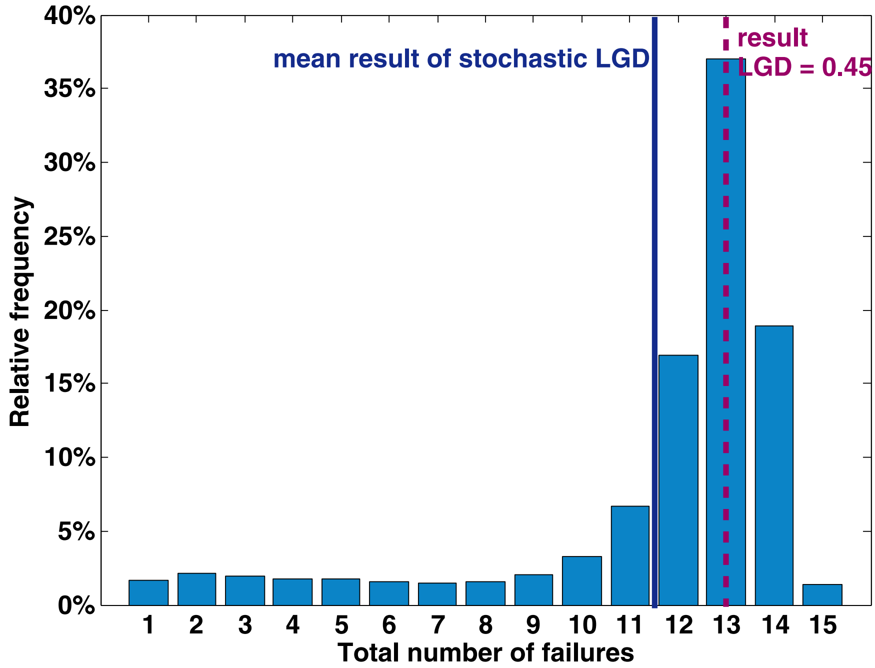

Figure 7: Example of a distribution of bank failures with a large amount of probability mass concentrated on a high number of bank failures.

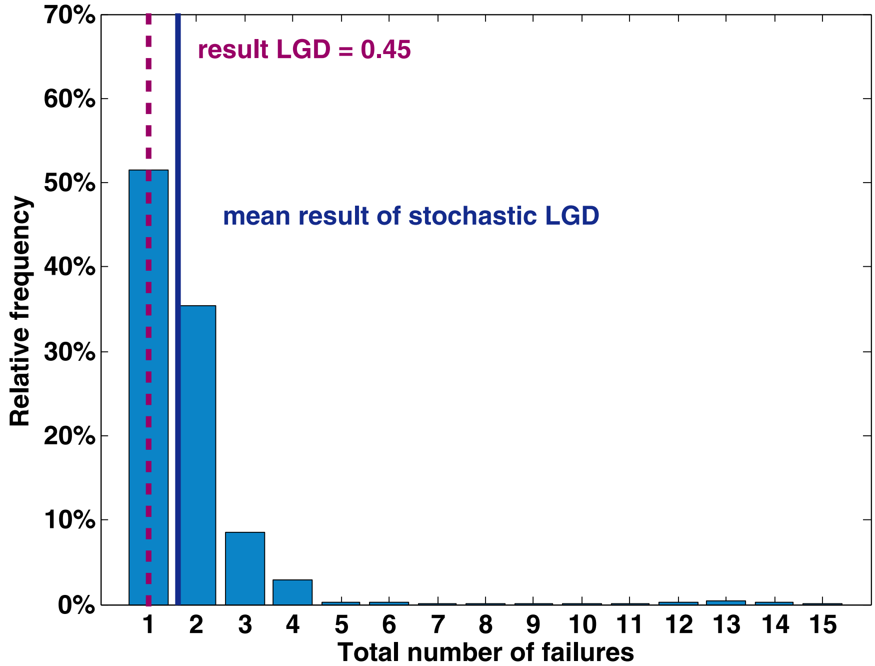

Figure 8: Example of a distribution of bank failures with a large amount of probability mass concentrated on a low number of bank failures.

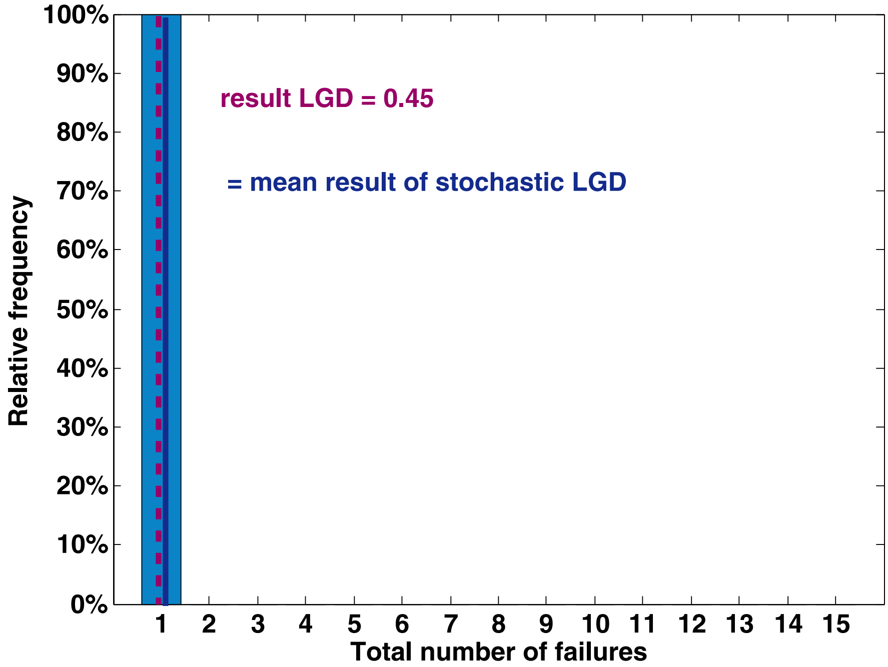

Figure 9: Example of a degenerate distribution of bank failures.

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