State-Dependent Contagion Risk:
Using Micro Data from Swedish Banks

Lars Frisell*, Mia Holmfeldt, Ola Larsson, Malin Omberg, and Mattias Persson
Department of Financial Stability, Sveriges Riksbank

October 2007

PRELIMINARY AND INCOMPLETE

Abstract

In this paper we exploit a unique data set on banks' interbank exposures to estimate the risk of contagion between the four largest banks in Sweden - representing roughly 80% of total bank assets. For each quarter from 1999, the banks have reported their largest counterparty exposures broken down on (i) unsecured loans (ii) securities (iii) net and gross derivative positions and (iv) repo positions. Hence, contrary to earlier work, we can construct the actual matrix of bilateral, unsecured exposures between banks to study potential contagion effects. We first use market data to model the interdependence of banks' asset values, using the Gaussian copula. Following Merton's (1973) approach, a default is defined as when asset values shrink below the value of outstanding debt. Default events are then simulated through Monte Carlo simulation. Given an event of at least one default, we use the data on interbank exposures to estimate the likelihood of successive defaults. We show that, in striking contrast to when the initial default occurs for idiosyncratic reasons, state-dependent contagion is very likely. Our exposure data reveals that exposures between banks are very asymmetric. This means that attempts to re-construct bilateral exposures from totals - common in the literature - could underestimate the risk of default contagion.

*Corresponding author; lars.frisell@riksbank.se.

1. Introduction

The vulnerability of financial systems has been demonstrated with unpleasant regularity throughout the 20th century. Recent episodes include the S&L crisis in the US in the 1980s, the Nordic and Japanese banking crises in the early 1990s, and the debacle of LTCM in 1998. The economic and social costs of financial crises range from negligible, such as in the case of LTCM (where the Fed acted promptly to contain further contagion) to enormous, as during the Great Depression (where central banks in most countries affected stood idly by).[1] The risk of system-wide financial crises has two sources: firstly, banks in the same region or country are to a large extent exposed to common macroeconomic risks, such as interest rate and currency risks, or the health of the property sector. Secondly, the substantial exposures that financial firms have vis-à-vis each other create the risk of financial contagion: that one institution's default leads to losses for other financial institutions so substantial that these also risk default. Many scholars argue that preventing such domino effects in the financial system is the very raison d'être for central banks.[2] Recently, more and more effort within central banks, as well as a growing academic literature, has been devoted to the study of interlinkages between financial intermediaries and the risk of financial contagion.

In this paper we study contagion risk in the Swedish banking sector. Like many small countries in Europe, the banking market in Sweden is highly concentrated: four players control about 80% of assets, about 66% of the lending market and about 75% of the deposit market. Such a high concentration makes the issue of contagion critical for two reasons: first, each of the four major players is arguably of systemic importance for the Swedish payment system. During the Swedish banking crisis, when three of the four were on the brink of collapse, the government issued a general bank guarantee to avoid bank runs.[3] And even if one of the four large ones could be allowed to fail, it is almost unconceivable that the Swedish government would allow a second default among them. Second, the concentrated bank market means that interbank exposures mostly tend to be very large between the four. Many of these

[1] Hoggarth et al. (2002), for example, estimate that output losses during banking crises average 15-20 % of GDP.

[2] For example, in a seminal paper Bernanke (1983) argues that the Fed's refraining from containing bank defaults, rather than its alleged tight monetary policy, was the more important factor contributing to the Great Depression.

[3] Another testimony to the systemic importance of the large Swedish banks is the upgrading of their credit rating when Moody's introduced their "joint default analysis" rating in early 2007. This rating system (now modified) explicitly took into account the probability of government support into the rating. This rating system led to an upgrading of many banks, particularly in small economies with relatively concentrated banking markets, such as the Nordic countries.

exposures is unsecured, in terms of (net) derivative exposures, holdings of securities and deposits or other uncollateralized lending. As we will show, a default by one of them, triggered by a general deterioration of banks' asset quality, with significant probability leads to another default.

To examine the risk of contagion we take into account both the correlation in banks' asset values (due to correlated exposures) and the direct exposures between the banks in the interbank market. Hence, we examine the likelihood of contagion *given* the state of the economy that gave rise to the initial default. With the exception of Elsinger et al (2006b), the previous literature has focused on the second step, and studied the risk for contagion when the initial default occurs for idiosyncratic reasons. Intuitively, since the banks' lenders are affected by similar macroeconomic conditions, conditioning on the state of the economy substantially increases the risk of default contagion. We argue that it is in particular in economic recessions that authorities mostly should worry about financial contagion and systemic risk. Using interbank exposures to quantify the risk of state-dependent contagion could give central banks and supervisors a sense for how important, or how urgent, proactive action (such as liquidity support) could be in a crisis situation.

To our knowledge there are no previous studies that include all interbank exposures, nor any that have access to the full structure of bilateral exposures. The majority of studies on contagion use public balance sheet data. One exception is Furfine (2003) who uses data from the U.S. federal funds market. However, this only accounts for a relatively small (10-20%) share of total interbank exposures. Some studies include regulatory data on large exposures, but these include only extremely large exposures.[4] In addition, exposures between financial institutions that are of shorter term than one year are exempted from these reporting rules. It could be argued that short-term exposures are less relevant for the study of contagion as they could be quickly withdrawn in case of an imminent crisis. However, we believe it is unlikely that banks' interbank funding would change much during a recession. First, interbank relations have been built up over the course of a long time, and are unlikely to change until problems in a specific institution are evident, such as a significant downgrade of the institution's credit ranking. Second, in a general recession, where all the four large banks are

[4] In the EU regulatory framework, banks are not allowed to have individual counterparty exposures that are larger than 25 per cent of their capital base.

affected, each of the banks may have difficulties in finding cheap funding alternatives outside Sweden.

Our analysis is performed as follows. We first model the interdependence of banks' asset values using the Gaussian copula. We use individual default probabilities for each quarter from Moody's KMV. KMV uses the distance-to-default (DD) measure introduced by Merton (1973), and maps the DDs into default probabilities using historical default distributions. The correlation structure from the copula is then used to simulate the other banks' asset values given the event of at least one default. Our results indicate a much higher probability of contagion risk, for a given assumed loss-given-default, compared to previous literature. For example, with an assumed LGD as low as 20%, we find that the contagion risk ranges from 5% to as high as 40%. Elsinger et al. (2006b) also demonstrate an increased probability of contagion compared to previous studies, but their results seem to rely on the assumption that interbank debts are junior to all other claims, which makes a quantitative comparison between their and our results difficult.

The rest of the paper is organized as follows. Section 2 reviews the related literature. In Section 3 we explain the procedure for modelling defaults with a review of Merton's option-pricing approach to estimate default probabilities. Section 4 describes the data and section 5 includes an analysis and presents the results. Section 6 concludes and discusses possible extensions.

2. Related Literature

Several recent papers have analyzed interbank linkages and contagion risk, including e.g. Sheldon and Maurer (1998), Furfine (2003), Upper and Worms (2004), Degryse and Nguyen (2004), Elsinger et al. (2004). Although data availability and methodology differ among these studies, they all have in common that they assume the failure of one bank (at the time) for idiosyncratic reasons, and, given an assumed loss-given-default, examine the probability of successive defaults. The overall conclusion of this literature is, in a nutshell, that contagious defaults are very unlikely.[5]

[5] Kaufman (1994) finds that the recovery ration in the failure of Continental Illinois was as high as 95%, and argues that the risk of contagion in the banking market should not significantly differ from that in other industries.

Furfine (2003) uses daily interbank exposures from the Fedwire system to estimate the risk of contagion. This has a major drawback, as these exposures only cover a relatively small part of total interbank exposures. However, like the current study, it allows the author to focus on unsecured positions (e.g., not the funding legs of repo transactions). Furfine finds that aggregate assets at failing banks never exceed 1% of total assets of the commercial banks.

Upper and Worms (2004) use balance sheet data to estimate a matrix of bilateral credit exposures between German banks divided on different maturities. Like much of the literature, they do not have access to off-balance sheet exposures such as securities, deposits or derivative positions. In the absence of actual exposure data, the authors assume that interbank lending is as “widely dispersed as possible”, given the observed distribution of loans and deposits. They assume that one bank fails for idiosyncratic reasons, and use (estimated) interbank exposures to simulate possible contagion effects. If one or more banks fail in the second round, the process is repeated. Although Upper and Worms show that significant contagion effects are possible, this is not very likely. For example, with an assumed loss-given-default ratio at 40%, the average percentage of affected assets in the banking system amounts to 0,58%.

Degryse and Nguyen (2004) use a very similar approach to Upper and Worms on Belgian data. With a LGD assumption of 40% the authors conclude that “banks accounting for more than 90% of the assets lose less than 40% of their tier-I capital”. Even with an assumed loss-given-default of 100%, only 5% of total bank balance sheet assets would be affected by contagion in the worst scenario.[6]

Elsinger et al. (2004) have access to both balance sheet data and monthly supervisory data. Access to supervisory data allows the authors to reconstruct more than 70% of actual bilateral exposures. Still, this only covers on-balance sheet exposures. The authors find that 97 per cent of insolvencies in the Austrian banking system would occur for fundamental reasons, while 3 per cent would occur due to contagion. It should be noted that the authors assume that

[6] The authors refer this to the fact that Belgian banks are very internationally diversified, where less than 15% of interbank exposures were to other banks.

interbank liabilities are junior to all other claims.[7] According to the authors, this implies a median recovery rate of 66 per cent.

Most closely related to the current paper is Elsinger et al. (2006b). The authors study ten large UK banks and - like the current paper - combine an analysis of asset correlations and direct interlinkages from interbank borrowing to assess the full risk of systemic crisis. The authors use weekly stock data from 2003 to estimate a process governing the banks' asset values. This is combined with balance sheet data on liabilities to derive one-year distance-to-defaults and, by assuming a log-normal asset price process, probabilities of default. Finally, default events are simulated and combined with estimated interbank liabilities to estimate the probability of successive defaults. The authors find that the probability of contagion due to a default in one bank caused by a systematic shock ranges from 2,5 % up to as much as 67 %, although it is unclear what is the effective LGD assumed.

The current paper improves on Elsinger et al. (2006b) in two important respects. First, we have access to actual bilateral exposures between the four largest banks (and also other large counterparties). This may be valuable for estimation of contagion risks if interbank exposures are very asymmetric, also when accounting for the banks' relative sizes. Second, this data allows us to single out all unsecured lending that imposes credit risk including non-balance sheet items, such as credit guarantees and credit commitments.

3. Modelling defaults with market data

3.1 The Merton model for estimating asset values

In Merton (1974) the default probability of a firm measures the likelihood of the asset value of a firm falling below a certain threshold. This default probability is mainly determined by four variables, the firm asset value and a distribution of its future values, the volatility of the asset and the level of the default point. The firm defaults when its market value of assets falls below the default point. The total value of the firm assets can be decomposed into the value of its debt and the value of the equity. While the value of equity is observable for a publicly traded firm, the value of debt is in general not. However, using the model suggested by Merton (1974), in which he connects a firm's market value of total asset to its market value of

[7] If a bank is declared insolvent it honours all non-bank liabilities first and then allocates proportionally the remainder of its capital to its debtor banks.

equity, the value of its debt can be estimated using an option pricing based approach. By assuming that the debt of the firm consists of one single discount bond maturing in T periods, then its equity can be treated as a call option expiring in T periods. The total assets of the firm represent the underlying asset and the strike price is equal to the nominal value of the debt. Following the rational of a call option, the firm's equity is worthless when its asset value at time T is below the nominal value of the debt, and the firm goes into default. Hence the nominal value of the debt is often referred to as the default point.

The Merton model is to a large extent based on the Black and Scholes model for option pricing. Assume that the asset value of a firm follows a geometric Brownian motion,

$$dV_t = \mu V_t dt + \sigma_V V_t dW_t, \tag{1}$$

where V_t is the asset value, μ is the drift term, σ_V is the volatility, and dW is a standard Wiener process. Together with the standard assumption of the Black and Scholes model, the equity value E is given by,

$$E_t = V_t \Phi(d_1) - e^{-rT} DPT \Phi\left(d_1 - \sigma_V \sqrt{T}\right), \tag{2}$$

where,

$$d_1 = \frac{\ln(V_t / DPT) + \left(r + 0.5\sigma_V^2\right)T}{\sigma_V \sqrt{T}}, \tag{3}$$

where $\Phi(\cdot)$ is the cumulative standard normal distribution, DPT is the default point, corresponding to the strike price in the standard Black and Scholes option pricing model and r is the risk free interest rate. Equation (2) expresses the value of the equity as a function of the total value of the firm and is one of the main equations in the Merton model.

From the setup in Black and Scholes model, it follows that there is an explicit relation between the asset and equity volatilities. This expression is the other important equation used in the Merton model and looks as follows,

$$\sigma_E = \left(\frac{V_t}{E_t}\right)\Phi(d_1)\sigma_V. \tag{4}$$

Given an estimate of the firm's equity volatility, using equation (2) and (4) simultaneously, allow one to solve for both the asset value and volatility. Solving for the asset volatility from the volatility equation and proceeding by plugging this expression into the call price equation yield the final asset value, *V*. Repeating the same procedure for various dates will produce a time series of asset values.

Given the assumption in (1), the probability that the asset value will be below the default point (DPT) at time T is given by,

$$PD = \Pr(V < DPT) = \Phi(-DD), \tag{5}$$

where *DD* (Distance-to-Default) is calculated as:

$$DD = \frac{\ln(V / DPT) + \left(\mu - 0.5\sigma_V^2\right)T}{\sigma_V \sqrt{T}}. \tag{6}$$

Hence, using the two nonlinear equations in (2) and (4) make it possible to translate the value and volatility of a firm to an implied probability of default.

In the original Merton model, the default point, *DPT*, is defined as the nominal value of debt of the firm. However, in practice it is often defined as the amount of short-term loans of the firm plus 50 % of its long-term loans. Another drawback of the original Merton model is that the Brownian motion assumption is not the most appropriate for the asset value process as it understates the actual probability of default of the firm. This implies that (5) is not an appropriate estimate of the *PD*. An empirical study by Moody's KMV shows that the defaulted firms instead have a leptokurtic distribution ("fatter tails"). KMV solves the problem by using an alternative estimate of the distance-to-default, *DD*,

$$DD = \frac{V - DPT}{V \times \sigma_V}. \tag{7}$$

This quantity is measured as the number of standard deviations the asset value is away from the default point. Finally they insert the estimated *DD* into an empirical distribution relating the *DD* quantities to a great number of firms to the number of defaults during the following year. This procedure results in an estimate of the probability of default, referred to by KMV as an empirical default frequency, *EDF*.

A common critique against the Merton model and structural models in general, is that the estimated probability of default for short time horizons is considered too small, relative to the observed credit spreads (see e.g. Amato and Remolona (2003)). However, empirical research suggests that the credit spreads are driven by several factors besides credit related ones (see Collin-Dufresne, Goldstein and Martin (2001)). Furthermore, research shows that the inconsistency between the spreads and the estimated probability of defaults disappears when the estimated probabilities are compared to spreads from the CDS market instead of the bond market (see Ericsson, Reneby and Wang (2006)).

In order to estimate the firm's asset value, we use data on equity value and nominal debt for each individual bank included in our analysis collected from Bloomberg. In addition we use the EDF-data for each individual bank from the Moody's KMV database.

3.2 Correlation due to common economic factors

Based on the Merton model, our objective in step one is to estimate a multivariate distribution of the asset values of the banks in our sample. The dependence structure between the asset values comes from the exposure to common economic factors, and at this moment the interbank exposure is disregarded. In a one-factor model this can be written as,

$$V_{i,t} = \mu + \omega_i F_t + \sqrt{1-\omega_i^2}\,U_{i,t}, \tag{8}$$

where $V_{i,t}$ is the asset value of bank i at time t, F_t and $U_{i,t}$ are two standard normally distributed random variables, which are independent of each other, and ω_i is the factor loading of bank i on the common factor F. Since the factor F is common to all banks, it follows that the asset value correlation between two banks i and j is given by,

$$Corr(V_i, V_j) = \omega_i \omega_j. \tag{9}$$

Furthermore, the probability of default, conditional on the factor F, is given by,

$$\left(PD_i \middle| F = f\right) = \Pr\left(V_i < DPT_i \middle| F = f\right) = \Phi\left(\frac{DPT_i - \omega_i f}{\sqrt{1-\omega_i^2}}\right). \tag{10}$$

Integrating over the common factor, we get the unconditional probability of default,

$$PD(V_i) = \Pr(V_i < DPT_i) = \Phi(DPT_i).$$

In step two our objective is to add the contagion risk. In the same setting as above, this can be written as,

$$V_{i,t} = \omega_i F_t + \sqrt{1-\omega_i^2}\,U_{i,t} - \sum_{j \neq i} 1_{\{V_{j,t} < DPT_{j,t}\}} LGD_{j,t} EXP_{i,j,t}, \tag{11}$$

where $1_{\{\cdot\}}$ is an indicator function, generating a one whenever firm i defaults, $LGD_{j,t}$ is the loss-given-default for firm j at time t and $EXP_{i,j,t}$ is the exposure of bank i to bank j at time t. Equation (11) states that the asset value of bank i at time t depends on a systemic factor, F, an idiosyncratic factor, U, and a term that controls the losses due contagion effects.

There is no straightforward method to estimate the dependence due to common economic factors. One approach would be to estimate and specify some functional relation between the asset values and a set of macroeconomic variables. However, it is not obvious how to choose the macroeconomic variables, nor is it obvious how to specify the functional relation.

In this study, we do not attempt to identify the common economic factors. Instead, we use a simple but yet plausible model and examine how sensitive our results are to the underlying assumptions. We simply assume that the correlation in asset values, conditional on exposures to the common factors but disregarding the interbank exposures, follows a Gaussian copula and we estimate the variance-covariance matrix based on the estimated asset values. Hence, following the previous notation we have,

$$\omega_i \omega_j = Corr(V_i^*, V_j^*), \qquad (12)$$

where V^*_i is the estimated asset value of bank i.

The assumption of multivariate normally distributed returns in asset values is standard in the finance literature. One possible alternative to the Gaussian copula is to estimate a *t* copula. The *t* copula, compared to the Gaussian copula, assigns a higher probability to joint extreme events. Hence the probability of a joint default should be higher with the *t* copula compared to the case with the Gaussian copula, ceteris paribus.

One possible critique to our two step procedure is that if the market is fully efficient, the estimated correlation in the first step should also reflect the risk of contagion. Roughly expressed, if this is the case it would imply that our approach will include the contagion effects “twice”. However, we motivate our two-step procedure with the following arguments. First of all, the exposures are not publicly known. Hence in order to take the effects of contagion into account the market needs to make an estimate of the size of the exposures. Second, given the low probability of default for the time period examined, the contagion effects, unconditionally, should be highly limited. Hence it is likely that the market do not price these effects unless the probability of default is relatively high. The deficiency in our approach lies in its ad hoc nature, with no real connection to economic intuition. However, we deem the approach as sensible and reasonable.

4. Data

Credit risk in the Swedish banks is partly due to traditional (on balance) loans, but also of contingent liabilities such as credit commitments, letters of credit, guarantees and counterparty risks arising in derivatives and foreign exchange contracts – most of which are off-balance sheet items. Looking at the total credit risk exposure of the Swedish banks, the off-balance sheet items make up around 20 per cent but between banks this share is often much higher. For each quarter from 1999, the four major banks in Sweden - representing roughly 80% of total bank assets in Sweden - have reported their 15 largest counterparty exposures. The banks have reported both gross exposures and any risk-mitigating instruments to enable an analysis of the exposure at risk. In particular, it may be worth noting that repurchase agreements in the Swedish inter-bank market are not included. Repurchase agreements have government bonds as underlying assets and in most cases, there would be no losses on these exposures if a counterparty failed. If repurchase agreements were not excluded, they would risk dominating the data.

The most important items in the exposure data are:

- Unsecured lending, for example overnight lending and deposits. This includes non-collateralised securities lending.
- Securities exposures: the market value of securities held by the reporting bank per counterparty less any risk-reducing instruments (such as credit default swaps).
- Derivative exposures: all derivative exposures that have a positive market value, less any netting agreements and/or other mitigants.

It is worthwhile to reiterate that the structure of large exposures varies enormously over time, and that different banks can have very differing degrees of concentration in their interbank exposures – also with regard to the other major banks. Hence, an attempt to estimate interbank exposures with some publicly know metric, such as balance sheet sizes, would be seriously flawed, and most likely lead to an underestimation of contagion risks. For example, in 2006, an assumption that total interbank exposures were distributed proportionally to other banks' share of lending in Sweden would underestimate the largest exposure by 40% or som SEK 6 Bn.

Table 1 - Concentration measures for the four largest banks. Average of the Q1 and Q2 2007 reports.

	A	B	C	D
largest exposure/total exposure	6%	7%	8%	2%
5 largest exposures/total exposures	18%	16%	26%	6%
15 largest exposures/total exposures	31%	22%	51%	9%

5. Analysis of state-dependent default contagion

As the main object of this paper is to study state-dependent default contagion between the four major Swedish banks, one of the most important factors influencing the outcome is the correlation structure between the banks asset values. If the banks asset values are positively and highly correlated it increases the probability of multiple defaults. As mentioned earlier in section 3 our analysis proceeds in two steps. In the first step we estimate the correlation structure between the four banks in our sample where we assume that the dependences are caused by the exposure to common economic factors. In the second step, we combine theses estimated correlations with default contagion in a Monte Carlo simulation where we also use the banks' EDF.

In order to obtain a correlation structure we need, in the first step, to estimate a multivariate distribution for the bank's asset values. We assume the changes in asset values to be multivariate Gaussian distributed. The asset values that we need in order to estimate the variance-covariance matrix are estimated using the Merton model described in section 3. Another approach would be to use the bank's equity values as proxies for their asset values. In order to check for any potential differences we estimate the correlation structure based on both these approaches. However, according to Lehar (2003) the correlation based on the banks' asset values are superior to equity value correlation as they are not affected by changes in the capital structure. In table 1 we show the estimated correlations calculated from the asset values of the banks that are estimated using the Merton model.

Table 2 – Asset Value Correlation

Bank	A	B	C	D
A	1			
B	0,624	1		
C	0,144	0,396	1	
D	0,315	0,465	0,287	1

Note: Table 1 shows the estimated correlation matrix based on the asset values estimated using the Merton model.

The correlation based on the estimated asset values results in a rather wide range of correlations. However, one important feature is that they are all positive, indicating that contagion is an important issue. One bank, B, display higher correlation to the other banks relative to the other three. In table 2 we show the estimated correlations calculated from the equity values of the banks. From this we see that the correlations for all banks are close to 0.5 and hence are on average higher compared to the asset value based correlations.

Theses values are somewhat smaller compared to equity correlations between Euro-area banks (estimated between the period of 1999-2004 by the Danish Nationalbank). (Corresponding values among the largest Danish banks show a much lower correlation structure with values ranging between -0.05 to 0.51.) According to Lehar (2003) who studied the correlation structure between banks in different regions concludes that US banks on average show higher median correlation between banks' asset values, calculated using the Merton model, compared to European banks. One given explanation is that European banks are more diversified which might reflect that they be less integrated compared to the US banks.

In the remaining part of the paper, we will use the asset values calculated using the Merton model if nothing else is explicitly mentioned.

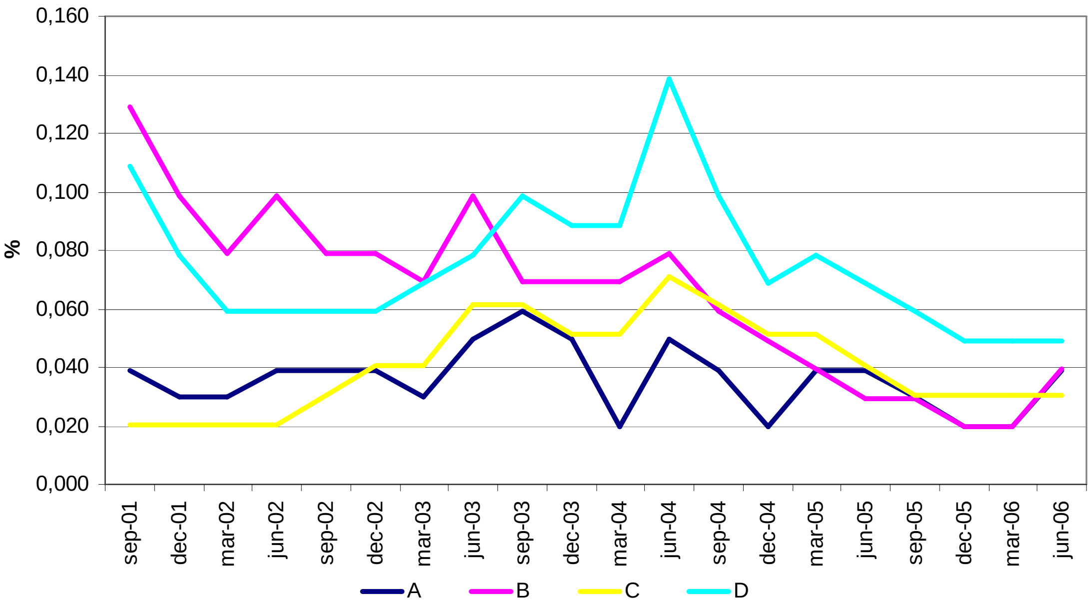
We proceed by creating a multivariate distribution for each point in time, which in our case is quarterly. The dependencies in the distribution are modelled using the estimated copula where we assume both the copula and its parameters to be constant over the time period examined. The univariate distributions that enter the estimation are modelled as normal with a mean equal to the arithmetic mean of the logarithmic returns and with an asset volatility obtained from the Merton model. The simulated asset values obtained based on the multivariate distribution is then compared to the default point, *DPT*, in order to evaluate potential default. If a simulated asset value is below the default point, the corresponding bank is assumed to have defaulted.

Before the default analysis is conducted we need to find an appropriate default point. If the normal distribution is assumed, and the asset volatility derived from the Merton model is used, the implied probability of default will not be in accordance with the EDF reported by KMV, as their model is based on an empirical distribution, based on a proprietary data set. Hence, we need to adjust the default point in order to correct for the miss-specification. This adjusted default point is obtained by assuming normality and use the asset value volatility and the mean vector together with the EDF obtained from KMV. Assuming normality, the new default point is,

$$DPT_t^{Adj} = V_t \exp\left(\mu + \sigma_V \Phi^{-1}\left(EDF_t\right)\right). \tag{13}$$

Through this adjustment, the simulated number of defaults will be close to the number of defaults implied by the EDF. The EDF for each individual bank is displayed in figure 1 below. These values also correspond to the simulated number of defaults for each bank.

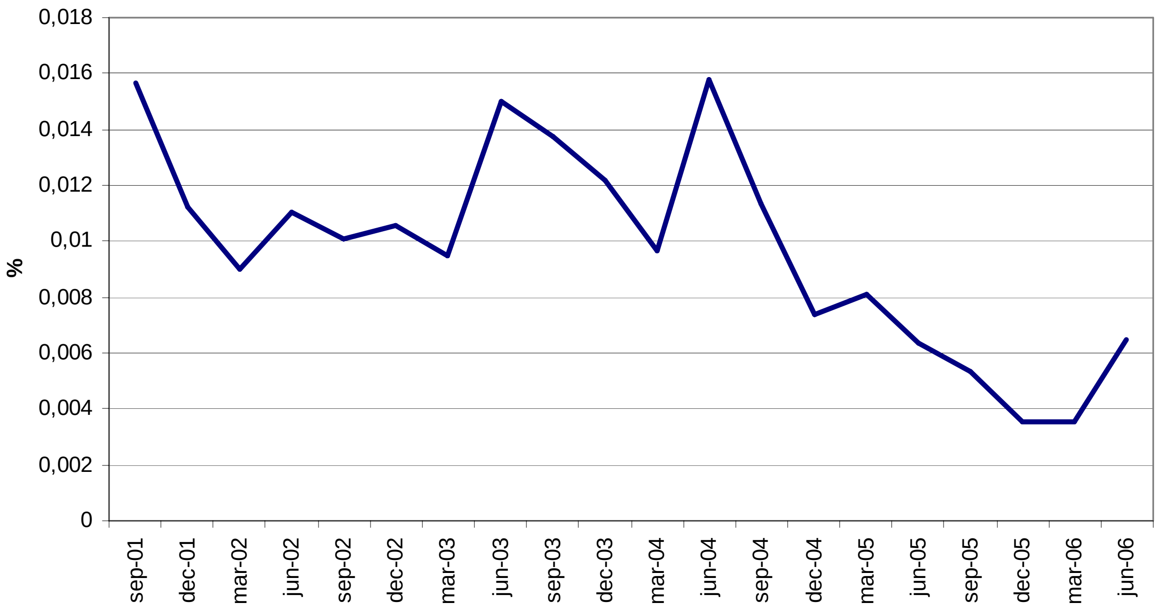
Figure 1 – Probability of default. EDF in % for each bank.



In the analysis we assume that no netting takes place in case of default. One effect of a netting agreement is that the seniority structure of the bank's debt changes. The consequences that any netting agreements have on contagion are ambiguous. Bilateral netting agreements might either increase or decrease the effects of contagion, depending on the data examined. In a paper by Elsinger et al. (2006b) the majority of the UK banks in their sample were harmed by bilateral netting.

Before we run the analysis for contagion, we analyse the probability of joint defaults (without contagion effects). These probabilities are obtained through Monte Carlo simulation. For each quarter, we estimate the joint defaults using the Gaussian copula together with the univariate EDFs. Figure 1 shows a time series of the probability of 2 simultaneous defaults.

Figure 2 – Probability of 2 simultaneous defaults



Note: Figure 2 shows the probability of 2 simultaneous defaults measured in %.

According to figure 1, the probability of 2 simultaneous defaults is very low and the probability of 3 or more simultaneous defaults (not shown in the graph) is essentially zero.

The next step in our analysis is to simulate the asset values of the bank from the multivariate distribution. We simulate 10 million asset values for each bank and for each time period. For each simulated vector, we compare the asset values to the adjusted default point. The bank is assumed to be in default if the value of its assets is below this point.

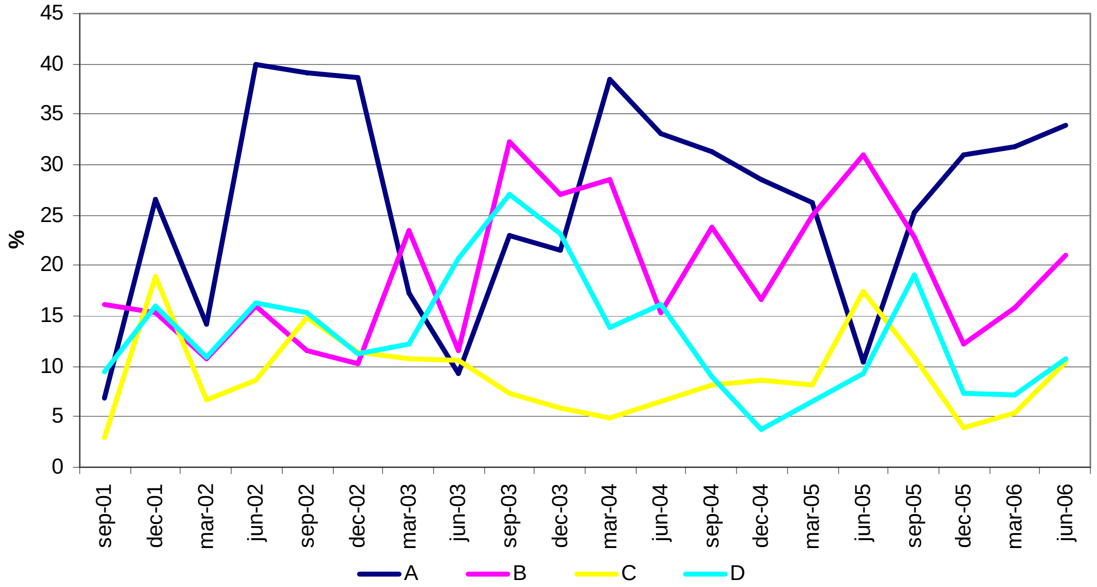
In the case one banks default, the other banks are assumed to lose some of their exposure to the defaulted bank. This loss reduces their asset values, which, in turn, might result in asset values below the adjusted default point for the any of the other banks. If this is the case, we consider the simulated scenario to be an instance of contagion.

The probability of contagion depends to a great extent on the structure of the interbank exposures. It has been shown theoretically by Allen and Gale (2000) that the more symmetric the exposures between banks are the less likely is the probability of contagion. This is also confirmed empirically in Upper and Worm (2002) who find that banks with symmetric exposures are less at risk of contagion. Due to the documented asymmetric exposures between the four banks in our sample the risk of contagion after one banks default increases. The exposures are highly asymmetric even after conditioning on the banks relative sizes.

Another important determinant for the degree of contagion is the loss given default, LGD. The choice of LGD is not apparent. Evidently the effect of contagion is increasing with a higher value of assumed LGD. This value was estimated by James (1991) to be approximately 40 %, with 30 % representing the average losses of the failed bank’s assets and 10 % corresponding to the direct expenses associated with the bank closure. It was further argued by Degryse and Grégory (2004) that since a significant part, more than 50 % for the Belgian banks (see Degryse and Grégory (2004)), of the interbank loans are secured they find a reasonable LGD to range between 20 and 40 %. The chosen LGD should reflect the degree of secured interbank exposures for the banks analysed, the LGD should decrease as the proportion of guaranteed loans increase. According to Upper and Worm (2004) the number of banks affected by contagion is rather insensitive for LGDs ranging between 5 and 40 % whereas they identify a jump in the severity of contagion for values above 40 %. Based on this reasoning we assume two different degrees of loss given default, 20 and 40 %.

The Monte Carlo simulation produces, for each time period and bank, the number of default events in combination with the number of events when one bank’s default caused the default of another bank (i.e., how often contagion occurred). By dividing the number of times a default in one specific bank caused contagion in another bank by the total number of times that bank defaulted we obtain an estimate of the likelihood of contagion effects for each bank. In figures 3 and 4 we display a time series of the estimated probabilities of contagion under the respective assumed LGD.

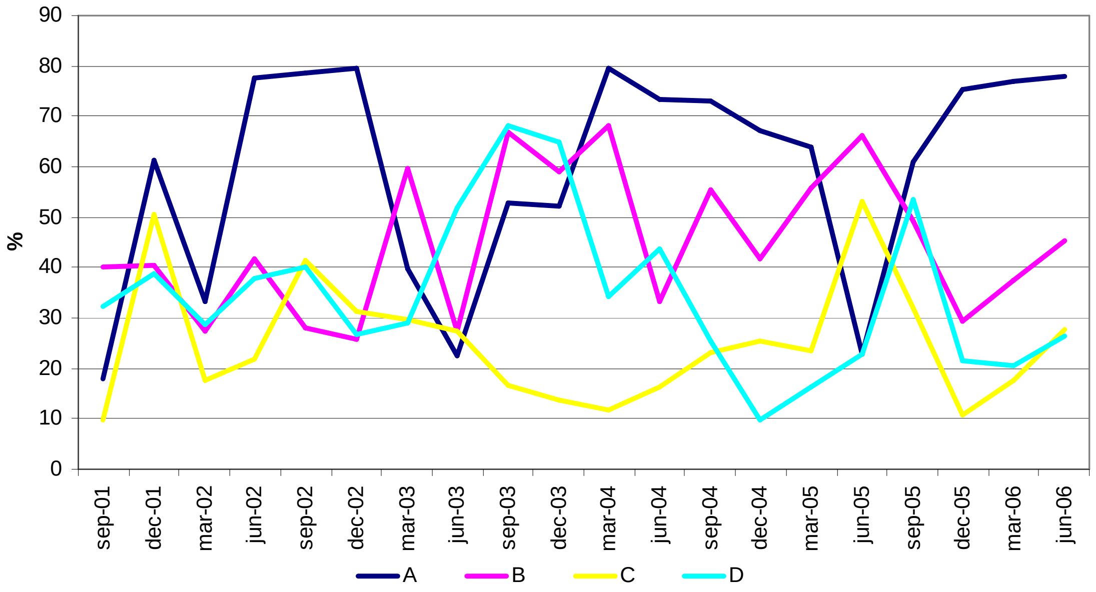
Figure 3 – Probability of contagion (Assumed LGD of 20 %)



Note: Figure 3 shows the probability (in %) of contagion due to a default in one of the four banks. The labels identify the bank that started to default, i.e. the origin of the contagion. The loss given default is assumed to be 20 % of the bank exposure. The results are based on the asset values calculated from the Merton model.

Assuming a LGD of 20 %, figure 2 shows that the probability that a default in bank A causes a default in one of the other banks ranges from 7 % in the beginning of the sample to 40 % in 2002. The probability for this bank fluctuates between these values throughout the sample period. Least likely to cause contagion in the Swedish banking system is, according these results, bank C with probabilities never above 20 % for an assumed LGD of 20 %. The result for this bank is much more stable during the sample period compared to the other banks. The results for the alternative assumed LGD, 40 %, are quite similar, with more or less a parallel shift in the probabilities. One difference is that the higher LGD induce stronger fluctuations in the probabilities for this time period. For both levels of assumed LGD, a much higher probability of default contagion is achieved compared to most results in the previous literature.

Figure 4 – Probability of contagion (Assumed LGD of 40 %)



Note: Figure 4 shows the probability (in %) of contagion due to a default in one of the four banks. The labels identify the bank that started to default, i.e. the origin of the contagion. The loss given default is assumed to be 40 % of the bank exposure. The results are based on the asset values from the Merton model.

6. Conclusions

The crucial importance of the financial system for the functioning of the market economy should be in little doubt. If major financial institutions default, and people lose confidence in the safety of their deposits and investments, the economic and social costs may become enormous. The main cause of these very large costs is that when many financial institutions fail, their funding of new investments is thwarted. This leads to a reduction in consumption which, in turn via a multiplier effect, further reduce investments and consumption. One of the, perhaps, most apparent example of this are the great depression during the 1930s.

If major financial institutions fail or are weakened, the functioning of the credit channel can be severely impaired for a long time, which thwarts firms' funding and reduces output and consumption. Before the trust in the system is restored, and consumption and investment return to normal levels, the economic and social costs may become enormous. [8]

[8] Hoggarth et al. (2002) estimate that output losses during banking crises average 15-20 % of GDP.

In this paper we analyse contagion risk in the Swedish banking sector. One of the main contributions of this paper is the unique data set on the largest counterparty exposures for four major Swedish banks. The data include unsecured lending, securities and derivative exposures. The Swedish interbank market is highly concentrated, four banks together account for about 80 % of the total assets, which makes the issue of contagion imperative. The two main sources of the risk for a system-wide financial crisis are banks' exposures to common economic factors and the exposures between the institutions themselves. When analyzing systemic risk one should take into account both factors.

Taking into account the correlation between banks' asset values substantially increases the risk of default contagion. Our simulation study results in a probability of state-dependent contagion, for an assumed LGD of 40 %, to range from 10 % to 80 % for the four banks for the time period studies. There is a range of issues left for future work, let us mention just a few of them. Can one attempt to explain the large variation in interbank exposures, and do different banks have different strategies when it comes to interbank lending and borrowing? Is there a straightforward explanation to the varying correlations between different banks' asset values, such as in exposure to different industries and countries? How significant are second- and third round contagion risks? Partly depending on the answers to these questions, what policy tools can and should be used by central bank and supervisory authorities to contain the risk of interbank contagion?

References

Allen, F. and D. Gale, 2000, “Financial Contagion”, Journal of Political Economy, 108(1), 1-33.

Amato, J. and E. Remolona, 2003, “The Credit Spread Puzzle”, Quartely Review BIS, December, 51-63.

Bernanke, B. S., 1983, “Nonmonetary Effects of the Financial Crisis in the Propagation of the Great Depression,” American Economic Review, 73(3), 257-76.

Blåvarg, M. and P. Nimander, 2002, “Interbank Exposures and Systemic Risk”, Sveriges Riksbank Economic Review 2002:2.

Collin-Dufresne, P., R. Goldstein and J. S Martin, 2001, “The Determinants of Credit Spread Changes”, Journal of Finance, 56, 2177-2208.

Degryse, H. and G. Nguyen, 2004, “Interbank Exposures: An Empirical Examination of Systemic Risk in the Belgian Banking System”, CentER Discussion Paper 2004-04, Tilburg.

Elsinger, H., A. Lehar, and M. Summer, 2004, **“**Risk Assessment for Banking Systems”, OeNB Working Paper 79.

Elsinger, H., A. Lehar, and M. Summer, 2006a, “Systemically Important Banks: An Analysis for the European Banking System”, International Economics and Economic Policy, 3, 73-89.

Elsinger, H., A. Lehar, and M. Summer, 2006b, “Using Market Information for Banking System Risk Assessment”, International Journal of Central Banking, 137-165.

Ericsson, J., J. Reneby and H. Wang, 2006, “Can Structural Models Price Default Risk? Evidence from Bond and Credit Derivative Markets”, Working Paper McGill University.

Furfine, C., 2003, “Interbank Exposures: Quantifying the Risk of Contagion”, Journal of Money, Credit and Banking, 35, 111-128.

Hoggarth, G., R. Reis and V. Saporta, 2002, “Costs of Banking System Instability: Some Empirical Evidence”, Journal of Banking and Finance, 26, 825-855.

Kaufman, G., 1994, “Bank Contagion: A Review of the Theory and Evidence”, Journal of Financial Services Research, 8, 123-150.

Lehar, A., 2005, “Measuring Systemic Risk: A Risk Management Approach”, Journal of banking and Finance, 29 (10), 2577-2603.

Merton, R., 1973, “A Rational Theory of Option Pricing”, Bell Journal of Economics and Management Science, 4, 141–83.

Merton, R., 1974, “On the Pricing of Corporate Debt: The Risk Structure of Interest Rates”, Journal of Finance, 29, 449-470.

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.

Upper C. and A. Worms, 2004, “Estimating Bilateral Exposures in the German Interbank Market”, European Economic Review, 48, 827-849.