Stress Testing the Corporate Loans Portfolio of the Swedish Financial Sector

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ABSTRACT

In this study, a macroeconomic credit risk model is applied to Sweden to judge the stability of the Swedish financial system to changes in the macroeconomic environment. Default rates for each industry are regressed against the macroeconomic variables to which Sweden has the greatest exposure and then stress tests are performed on the Swedish corporate loans portfolio to determine whether structural vulnerabilities are present in the financial sector. The findings of this study suggest that Swedish financial institutions are more susceptible to shocks in the real GDP than the real interest rate. Furthermore, the Swedish financial system is found to be only moderately affected by macroeconomic shocks to the corporate loans portfolio.

Keywords: Stress testing, macroeconomic credit risk, Monte Carlo simulation, value-at-risk, expected loss, vector autoregression

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1.0 Introduction

The current credit crisis has highlighted the necessity of measuring the systemic risk of the financial sector. Stress testing of the financial system is one method of identifying the structural weaknesses and aggregate risk exposure of a certain economy. A stress test of the financial system measures the sensitivity of the system towards changes in macroeconomic variables. Theoretically, a comprehensive stress test of the financial sector would indicate potential vulnerabilities in the financial system which can be corrected for with the information provided by the results.

The objective of this report is to identify the macroeconomic factors to which the financial sector in Sweden has the greatest exposure. Furthermore, the research attempts to determine the vulnerability of the financial system to shocks in these macroeconomic variables by stress testing the Swedish corporate loans portfolio. Using the knowledge acquired from this model, certain fiscal, financial, and corporate policies can be advised to strengthen the financial system. For example, the government could use the information obtained to advise or require financial institutions to increase their loan loss provisions.

The Swedish financial sector has domestic and foreign loan risk exposure. The aggregate loans portfolio has an approximate 20% contribution from Swedish households, an approximate 25% contribution from the domestic corporate sector, and more than half of the total value of the portfolio composed of loans to the foreign sector (Riskbanken 2009, 33-34). The foreign loan exposure is greatly concentrated in the Baltic States, and therefore the strength of the Swedish financial sector determined by the economic growth of these countries (Riksbanken 2009). Overall, the total exposure of the financial sector to all counterparties as of March 2009 is 7118 billion SEK.

This study will contribute to the ongoing macroeconomic credit research by testing the stability of Swedish financial system with a value-at-risk approach, utilizing recent data from the current credit crisis, and extending the number of investigated industries commonly used in the research. Furthermore, a program will be created to model and facilitate the stress testing of financial systems.

The validity of the results of a stress test is to a large extent dependent on the motivation behind the level of the chosen shocks. The magnitude of the shocks should be

sufficiently large to be considered abnormal, but remain plausible. The choice of magnitude for the shocks will follow the Boss (2002)[1] methodology which considers the strongest fluctuation in the data set of each macroeconomic variable as the test value.

The Dey *et al.* (2006) methodology to determine the exposure of the corporate loans portfolio of an economy to changes in important macroeconomic factors will be followed. This methodology corrects for several of the weaknesses of the pioneering Wilson (1997) approach, and the studies which have followed and modified this approach, to determine the macroeconomic credit risk of an economy. As Dey *et al.* (2006) highlight, three important changes have been made to the more recent Virolainen (2004) adaption of the Wilson (1997) approach. First, macroeconomic variables are treated as endogenous and interdependent rather than independent and exogenous. This modification has the benefit of aligning the model more closely with contemporary economic theory. Second, lagged default rates have been introduced in the industry-specific default rate regression. By introducing lags, the model is able to capture delayed effects on default rates from macroeconomic variables. Third, aggregate industry default data has been used instead of firm-specific data. While information will be lost through by not focusing on micro-level data, the model will be more easily applied to other economies.

In summary, this paper will provide an indication of the exposure of the Swedish financial sector to macroeconomic shocks and the information obtained may influence corporate and government policy decisions.

This study has been organized to first present a review of the macro stress testing literature. Second, the methodology employed to ascertain the sensitivity of the Swedish corporate loans portfolio to shocks in macroeconomic factors will be explained. Third, the data section and the empirical results will be presented. The paper will conclude with an interpretation of the results and a discussion of the limitations of the model.

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[1] Refer to Boss (2002, 78) for an important discussion of the necessity to specify plausible shock scenarios. If implausible shock scenarios are used, the empirical results will be biased. As a result, the level of loan loss provisions suggested by the model for banks to hold will be unreasonable.

2.0 Literature Review

This study is similar to other studies which attempt to identify and analyze the macroeconomic variables which affect the credit risk of banks in a certain country, and then stress test the corporate loans portfolio to shocks in these macroeconomic factors. Studies in this field may be classified, in accordance with Sorge *et al.* (2006), into two methodologies: balance-sheet models and value-at-risk (VaR) models.

2.1 Balance-sheet models

Balance-sheet models attempt to determine the macroeconomic credit risk of the financial sector by linking accounting measures of credit risk vulnerability with the business cycle and then performing macro stress tests using historically-determined sensitivity coefficients. These methods may be divided into two strands: *time series/panel regressions* and *structural models*.

The *prior* method estimates the sensitivity of the accounting measures of vulnerability to business cycles using reduced-form models with either time-series or panel data techniques. Examples of such studies which attempt to link banks' loan loss provisions (LLP) and non-performing loans (NPL) to macroeconomic variables include Pesola (2001) for Scandinavia, Kilirai *et al.* (2002) for Austria, Hanschel *et al.* (2003) for Switzerland, and Hoggarth and Sorensen *et al.* (2005) for UK. Some of the studies which use panel regression techniques have attempted to determine the reduced-form credit risk model for individual banks (refer to Carling *et al.* (2004), Quagliariello (2004), and Sorge *et al.* (2006) for an overview of these focused models). Generally, these studies conclude that a decrease in gross domestic product and or a rise in interest rate increase the level of LLPs and NPLs, but the effect of the corporate indebtedness is ambiguous. These models are generally quite simple to employ, but the results may be biased since data on LLPs and NPLs is influenced by income-smoothing provisions and other unrelated factors to credit risk (Sorge *et al.* 2006).

The *latter* method utilizes structural macroeconometric models to determine the fragility of the financial systems to changes in macroeconomic variables (Sorge *et al.* 2006). This model is much more data-intensive and is generally used by central banks to determine

monetary policy. Refer to Chirinko *et al.* (1991) for the US, Evjen *et al.* (2005) for Norway, and Hoggarth and Logan *et al.* (2005) for the UK, and De Bandt *et al.* (2004) for France to see examples of such studies. In 2009, the Swedish Central Bank (Riksbanken) employed a structural macroeconometric model to Sweden and found that the Swedish financial sector can be expected to lose 170-300 billion SEK between 2009 and 2010, which is a significant fraction of the credit portfolio value.

The advantages and disadvantages of employing balance-sheet models to determine macroeconomic credit risk have been extensively documented by Sorge *et al.* (2006). The advantages of such models are their simplicity and ease of use. The disadvantages are numerous with the most frequently cited being the rigid linear relationships assumed between macroeconomic variables and balance sheet credit risk vulnerability measures (LLPs, NLPs, etc) and that those same measures may be driven by factors unrelated to credit risk including income-smoothing provisions and risk management to contain future risks relating to the business cycle (Sorge *et al.* 2006, 119).

2.2 Value-at-Risk (VaR) models

Value-at-risk models to explain the macroeconomic credit risk of a financial system are based upon deriving a conditional portfolio loss distribution for a corporate credit portfolio to the financial sector and finding the expected and unexpected loss of this distribution. The loss distribution is obtained by determining the sensitivity of the credit portfolio to changes in the macroeconomic variables conditional on the current macroeconomic environment in a certain economy. Macro stress tests can then be applied by simulating shocks in the macroeconomic variables and finding the effect on the loss distribution. New expected and unexpected loss measures can then be retrieved.

The VaR approach to credit risk modeling has two strong advantages over the balance-sheet approach, as Sorge *et al.* (2006) highlights. First, the model can capture non-linear relationships between the loss function and macroeconomic variables, instead of assuming a linear relationship exists. The second advantage is the VaR model provides a framework for explicitly relating and analyzing market and credit risk, instead of relying on several different vulnerability indicators for financial institutions.

The disadvantages of the value-at-risk approach should be noted when choosing whether to use this approach and during the interpretation of the results. The main disadvantages to the VaR method are the non-additivity of value-at-risk measures across institutions, the limited use of the models over long-term horizons, and the disregard for feedback effects and parameter instability over long-term horizons (Sorge *et al.* 2006).

2.2.1 Wilson (1997) Methodology

The Wilson (1997) approach to macroeconomic credit risk modeling directly ties corporate sector default rates to macroeconomic variables. The obtained relationship may then be used to determine to the loss distribution of a corporate credit portfolio to the financial sector conditional on the current macroeconomic environment. Macroeconomic shocks can thus be modeled and the corresponding corporate sector default rates can be retrieved, whereby these new default rates can thus be used to determine the expected and unexpected loss to the credit portfolio. With the information retrieved from macro stress tests of the financial system, the level of required reserve capital by financial institutions to maintain stability in the financial system can be determined. The Wilson (1997) methodology is the basis for the Credit Portfolio View ® Model used by Mackinzie and associates.

Several studies have applied the Wilson (1997) approach for credit risk modeling and macro stress testing purposes. Boss (2002) employs a macroeconomic credit risk model to determine the corporate sector default rates for Austria and then uses this model for stress testing purposes on the Austrian corporate credit portfolio. He finds the level of industrial production, the inflation rate, the stock index, the nominal short-term interest rate of the previous year, and the oil price are found to be the most important determinants for the industry-specific corporate default rates in Austria. Virolainen (2004) and Sorge and Virolainen (2006) apply a Wilson (1997) macroeconomic credit risk model to investigate the causes of the industry-specific default rates in Finland, and then perform stress tests with domestic production and interest rate shocks on the Finnish corporate credit portfolio. The macroeconomic variables which explained the industry default rates to the greatest extent were found to be the domestic GDP, the one-year interest rate, and the level of corporate indebtedness.

Dey *et al.* (2006) modify the Wilson (1997) and Virolainen (2004) approach to account for macroeconomic variables influencing each other (using vector autoregressive models), delayed effects in the default rate regression from the macroeconomic variables, and aggregate sectoral data. At the authors note, this study utilizes industry-level data instead of firm-level data, and thereby may limit the explanatory power of the model. The conclusions from this study are that a decrease in the U.S. GDP would have the greatest impact on the portion of the credit portfolio investigated and that there are several, strongly significant arguments for not using the value-at-risk approach as it is currently being applied. The authors recommend a framework to be constructed which integrates a structural macroeconomic credit risk model with the corporate credit portfolio.

Caution must be taken when interpreting the results from the Wilson (1997) model as Dey *et al.* (2006; 2007) and Misina *et al.* (2008) underline, since implicit linear relationships exist in the definition of the industry-specific default rates and the credit portfolio loss distribution. Under the assumption the relationship between the economy and the shock scenarios is unchanging, and a very short VaR horizon (1-day) is used, then this model may be useful for stress testing purposes. However, such a short VaR horizon is generally not useful for macro-stress testing purposes.

2.2.2 Merton (1974) Methodology

An alternative to the Wilson (1997) approach is the firm-level Merton (1974) credit risk framework, which is based upon forward-looking equity prices instead of contemporaneous industry- or firm-specific default rates. A modified version of the Merton (1974) approach is employed by *Moody's-KMV®* using a historical database of corporate default rates to statistically measure the distance a firm is from default.

Several studies have extended the Merton (1974) framework to stress test the aggregate corporate sector. Drehmann and Manning (2004), Drehmann (2005), and Pesaran *et al.* (2005) employ a modified Merton (1974) framework to link firm-specific default probabilities with macroeconomic variables for macro stress testing purposes. Pesaran *et al.* (2005) use a global vector auto-regressive (GVAR) model to account for serial correlations between macroeconomic variables. This differs from the Drehmann *et al.* (2004) assumption that innovations in macroeconomic variables are IID, and thereby strengthens the model.

Jakubík *et al.* (2008) in a seminal work extend the Merton (1974) approach for country-by-country comparison of macroeconomic credit risk to a corporate credit portfolio. Gray *et al.* (2006) and Merton *et al.* (2008) modify the Merton (1974 approach) to analyze corporate and sovereign risk.

Compared with the Wilson (1997) methodology, the Merton (1974) approach has the advantage of using forward-looking equity prices, with the implicit (and general) assumption that equity markets are efficient. The disadvantages are the computational intensity and that equity prices may be noisy indicators of credit risk (Sorge *et al.* 2006, 125).

For an excellent overview of the balance-sheet and value-at-risk models used by central banks and other monetary authorities refer to Foglia (2008).

2.3 Comparison of studies to written work

Our work most closely follows the Dey *et al.* (2006) approach, which is based on a modified version of the value-at-risk methodology proposed by Wilson (1997). The motivation behind following this approach is to directly identify the sensitivity of industry-specific default rates to changes in macroeconomic variables. The recent credit crisis has arguably exposed inefficiencies in the equity market, and this had led us to question the explanatory power of the Merton (1974) framework. However, even a modified Wilson (1997) methodology has significant problems, which are possibly on the same level as and may even be worse than the Merton (1974) approach. These issues will be presented and discussed in this paper. The interpretation and validity of the results obtained will be shadowed by these problems.

3.0 Methodology

The methodology utilized in this report follows the Dey *et al.* (2006) modification of the Wilson (1997) portfolio approach for modeling macroeconomic credit risk. This methodology corrects for several of the underlying issues associated with the Wilson

approach, including the assumption of independent macroeconomic variables and the assumption lags for industry-specific default rates are unimportant.

The goal of the model is to estimate the expected loss of a credit portfolio consisting of corporate loans from the financial sector. The expected loss of the portfolio is determined by first calculating the expected loss in each industry s as a function of the defaults of companies in that industry (Dey *et al.* 2006, 4)

$$El_t^s = \pi_t^s \times ex_t^s \times l_t^s$$

where π_t^s denotes the default probability in industry s at time t, ex_t^s is the portfolio exposure to industry s at time t, and l_t^s is loss given default in industry s at time t. The total loss of the predefined credit portfolio is calculated as:

$$El_t = \sum_{s=1}^{S} \pi_t^s \times ex_t^s \times l_t^s$$

The results of the model will depend entirely on the specification of each input, and therefore it is very essential that each individual specification captures the variable movements as accurate as possible.

3.1 Probability of default

The Wilson (1997) framework relies on the empirical observation that the sensitivity to macroeconomic shocks and business cycles varies across different industrial and economic sectors. Therefore, to obtain accurate results, default probabilities are modeled for certain industrial sectors as a function of a set of macroeconomic variables. The function is specified by taking the log of the odds ratio, $\frac{\pi_t^s}{1-\pi_t^s}$, as a linear function of the explanatory variables (Dey *et al.*, 2006, 5)

$$ln\left(\frac{\pi_t^s}{1-\pi_t^s}\right) = X_{t-l}\beta^s + e_t^s, s = 1, \dots, S$$

where $X_{t-l} \equiv [1, x_t^1, \dots x_{t-L}^1, \dots, x_t^M, \dots, x_{t-L}^M]$ is a $1 \times (ML+1)$ vector of macroeconomic variables and their lags and $\beta^s \equiv [\beta_0^s, \dots, \beta_{ML}^s]$ is an $(ML+1) \times 1$ coefficient matrix. The motivation behind adopting a logistic dependent variable is that specifying a linear

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relationship between a probability and a set of variables is, in general, considered inappropriate (Dey *et al.* 2006, 5). This relation can be re-specified as a logistic function between the original probabilities and the macroeconomic variables (Dey *et al.* 2006, 6):

$$\pi_t^s = \left(1 + e^{-X_{t-l}b^s}\right)^{-1}$$

The marginal effects of each macroeconomic variable on the default probability, given the elements of $b^s \equiv [\beta_0^s, .., \beta_{ML}^s]$ is captured by the following relation (Dey *et al.* 2006, 6):

$$\beta_m^s = b_m^s \pi_t^s (1 - \pi_t^s)$$

This allows for industry-specific explanatory variables to be used in the model, and this may improve the fit of the regression.

The second step is to model the individual macroeconomic factors which are assumed to follow a vector autoregressive process (VAR) to take account for the interdependencies among the variables. The relationship is specified as (Dey *et al.*, 2006, 7):

$$X_t = \phi_1 X_{t-1} + .. + \phi_p X_p + u_t$$

with $u \sim n.i.d.(\mathbf{0}, \Sigma_u)$. The VAR specification of the macroeconomic variables allows for two channels of macroeconomic shocks on the default probabilities: a direct impact of a change in X_t^m and an indirect impact on the other macroeconomic variables (Dey *et al.* 2006, 7).

The aforementioned equations together define a system of equations governing the joint evolution of industry specific default rates:

$$ln\left(\frac{\pi_t^s}{1 - \pi_t^s}\right) = X_{t-l}\beta^s + e_t^s, s = 1, ..., S \quad (1)$$

$$X_t = \phi_1 X_{t-1} + .. + \phi_p X_{t-p} + u_t \quad\quad (2)$$

$$e_t \equiv [e_t^1 ... e_t^S] \sim N(\mathbf{0}, \Sigma_e) \quad\quad (3)$$

Once the parameter vectors $\widehat{\boldsymbol{\beta}}$, $\left(\widehat{\phi}_1, ..., \widehat{\phi}_p\right)$, and the covariance matrix $\widehat{\Sigma}_e$ of residuals from equation (1) for each industry have been estimated, it is possible to simulate future values of joint industry-specific default rates by dynamic simulation. Dey *et al.* (2006,7)

outlines the specific procedure of simulating industry-specific default rates by starting from a set of initial values of the variables X_{t-1} and then using equation (2) to obtain values of the variables in the next period. K iterations of this procedure will result in a K-period-ahead path for the macroeconomic variables:

$$X_{t+1} = \hat{\phi}_1 X_t$$

$$X_{t+2} = \hat{\phi}_1 X_{t+1} + \hat{\phi}_2 X_t$$

$$...$$

$$X_{t+K} = \hat{\phi}_1 X_{t+K-1} + \cdots + \hat{\phi}_K X_t$$

In this study, the endogenous variables included in the VAR system will be forecasted four periods ahead (one year). A vector of realized default probabilities for all industries, $\tilde{\pi}_t$, is obtained by substituting the iterated results into equation (1).

3.2 Exposures

The exposure of the banking industry to the different industries, required for constructing the credit portfolio that is representative of the bank's lending, is defined as the book value of loans to individual institutions or industries (Dey *et al.* 2006, 8). This definition is commonly used in the macroeconomic literature on the subject for the reason of avoiding the difficulty of tracing credit risk when off-balance sheets over-the-counter contracts are considered (Dey *et al.* 2006, 8).

3.3 Loss given default

The last component of the model specifies the proportion of the loan exposure that is likely to be lost in the event of default by a debtor. The loss given default at time *t* is defined as (Dey *et al.* 2006, 9)

$$l_t = 1 - rr_t$$

where rr_t denotes the recovery rate, which is the proportion of the loan exposure that can be expected to be recovered in the event of a default. In accordance with Dey *et al.* (2006) and maintaining the common industry assumption, the recovery rate was assumed to be 50%.

3.4 Generating loss distributions

The underlying assumptions of the model to be used for stress testing purposes are that the default probability is a function of macroeconomic variables, exposures are given for each industry and that loss given defaults are equal and constant across industries. Dey *et al.* (2006, 10) outline the specific procedure of generating loss distributions in four steps:

1) *Generate macroeconomic variables in the same manner previously mentioned*
2) *Generate a vector of s random variables with the variance-covariance matrix given by $\hat{\boldsymbol{\Sigma}}_e$. This is done by first generating a vector $\boldsymbol{Z} \sim N(\boldsymbol{0}, \boldsymbol{I})$, and then calculating $\tilde{\boldsymbol{e}}_t = A'Z_t$, where $\hat{\Sigma} = AA'$.*
3) *Substitute the results from the previous two steps into the sectoral default probability eqn.*

$$ln\left(\frac{\pi_t^s}{1 - \pi_t^s}\right) = \boldsymbol{X}_{t-l}\boldsymbol{\beta}^s + \tilde{\boldsymbol{e}}_t^s, \forall s$$

to obtain the values of default probabilities for each industry at a given point in time.
4) *For each value of simulated default probability for industry s, compute the expected loss in that industry according to*

$$El_t^s = \pi_t^s \times ex_t^s \times l_t^s$$

The value of the expected loss for the whole portfolio is obtained by summing the expected losses in all industries. By repeating this process by Monte Carlo simulation (to the desired accuracy level), the loss distribution of the corporate loans portfolio can be obtained.

3.5 Scenario Simulation

To determine the potential losses to be expected in a sudden macroeconomic crisis event, an artificial shock can be introduced in one of the macroeconomic variables utilized to explain the industry-specific default rates.

The stress test is implemented by first setting the scenario variable to an initial value and then tracing the impact of the shock on other variables through VAR processes to obtain realized values of the variables *k* periods ahead, which may then be used for calculating default rates specific to each industry. The obtained default rates can, in turn, be used to simulate the loss distribution of the corporate loans portfolio conditional on a certain macroeconomic environment by using Monte Carlo simulation (Dey *et al.* 2006, 19).

4.0 Data

The industry data utilized in this report was retrieved from *Statistiska Central Byrån* (SCB) and included: 1) the number of active companies in each industry (annual), 2) the number of defaults in each industry (monthly), and 3) long-term debt exposures for each industry (annual). Macroeconomic variables were collected from *Bloomberg* and included: 1) Swedish GDP (quarterly), 2) Stibor 1 year (quarterly), and 3) Stibor 3 months (quarterly). For the purpose of performing the testing, quarterly data was used.

Data interpolation was performed to match the frequency of the number of active companies data and the defaults in each industry. The number of active companies was found to linearly increase annually; therefore data interpolation could be performed with a reasonable level of certainty. Furthermore, exposure data for 2008 will not be available before this thesis is published and therefore to perform the tests using 2008 default rate data, the industry debt exposure was assumed to be identical for 2008 as for 2007.

To obtain the most accurate results from the stress tests, all industries in the Swedish economy should be regressed. However, due to periods of no defaults, several industries could not be included. The motivation for this is that the natural logarithm is not defined for the value of zero. Nevertheless, the value of the loan portfolio with the resulting thirteen industries represents the majority (59.1%) of the aggregate credit portfolio including all industries. Henceforth, the corporate loans portfolio will be defined as including thirteen industries of the Swedish economy:

Exhibit 4.1: Industries which define the Swedish Corporate Loans Portfolio

Industries included for stress tests
Wood Production (excl. furniture) [SCB: 20]
Publishing, printing and media [SCB: 22]
Manufacture of metal products [SCB: 28]
Construction [SCB: 45]
Sale, maintenance and repair of motor vehicles [SCB: 50]
Wholesale trade and commission trade [SCB: 51]
Retail trade [SCB: 52]
Hotels and restaurants [SCB: 55]
Transport/Tourist agencies [SCB: 60-63]
Real estate activities [SCB: 70]
Renting of machinery and equipment [SCB: 71]
Computer and related activities [SCB: 72]
R&D & other business activities [SCB: 73+74]

The four most important industries in terms of relative weights in the corporate loans portfolio are real estate (54.8%), R&D together with other service firms (16.1%), wholesale trade/commission trade (8.6%), and transportation/tourist agencies (6.3%). Of the industries which were not included in the loans portfolio, the electricity/gas/heating industry should me mentioned since it is relatively a little more important than the R&D industry. Refer to *Appendix A4* for the relative weights of all industries in Sweden in terms of long-term debt.

4.1 Default Rates per Industry

The default rates for each industry are calculated by dividing the total number of bankruptcies with the total number of active companies within the same industry. However the frequencies of these two series do not coincide since the number of bankruptcies is only available monthly whereas the number of active companies is only available annually. To obtain quarterly values for the number of bankruptcies in each industry, the number of defaults monthly was aggregated for each three month period. Data interpolation was performed to match the frequency of the data for the number of active companies and the defaults in each industry. The number of active companies was found to linearly increase annually; therefore data interpolation could be performed with a reasonable level of certainty. Hence, the annual change was linearly divided for each quarter to obtain the number of active

companies in each industry quarterly. Refer to the VBA code in Appendix D to see this adjustment.

Once the necessary transformations were completed to structure the data correctly, lognormal default rates for the selected industries were then calculated and plotted (see *Appendix B*). The most notable features of the data are that defaults rates for all industries have been declining since the recession in the early 1990s with a few exceptions such as the Asian crisis 97-99 and the global recession following the 9/11 terrorists attacks. The current economic crisis of 2008 and 2009 has not yet been fully realized in the default rate data, however, an indication of increasing rates of default has been observed in the last two quarters of 2008 in several industries.

Exhibit 4.2: Summary Statistics for each Industry

Industries	Mean	Std. Dev.	Skewness	Kurtosis
Wood Production (excl. furniture)	0,12%	0,08%	1,12	4,08
Publishing, printing and media	0,15%	0,08%	1,47	5,74
Manufacture of metal products	0,12%	0,06%	0,87	4,77
Construction	0,14%	0,07%	1,88	7,33
Sale, maintenance and repair of motor vehicles	0,15%	0,06%	1,45	4,94
Wholesale trade and commission trade	0,17%	0,08%	1,13	3,85
Retail trade	0,15%	0,06%	1,19	3,65
Hotels and restaurants	0,21%	0,10%	1,06	3,39
Transport/Tourist agencies	0,11%	0,05%	1,27	4,76
Real estate activities	0,09%	0,09%	1,84	6,39
Renting of machinery and equipment	0,14%	0,09%	1,12	3,97
Computer and related activities	0,10%	0,05%	0,79	3,54
R&D & other business activities	0,10%	0,05%	1,14	3,77

The industries that displayed the highest volatility in default rate were "Hotel, Restaurants", "Renting machinery and equipment" and "Real estate" with standard deviations of 0.097, 0.098 and 0.086 percentages respectively. The skewness and kurtosis values for all industries did not display the properties of a normal distribution and the Jarque-Bera test for normality concluded that the default rates for all industries are not normally distributed (see *Appendix A1*). However, normality could not be rejected for most industries once the industry default rates had been lognormally transformed (see *Appendix A2*).

A correlation matrix of the selected industries was calculated to determine the inner correlations across the industries (see *Appendix A3*). The results displayed a relatively high level of correlations across the industries which may present a systemic risk to the corporate sector of the Swedish financial sector. However, in determining the effects of the macro stress tests, each firm is assumed to have an equal impact of each bankruptcy on losses. As Dey *et al.* (2006) contend, this assumption is "clearly false", nevertheless the unavailability of firm specific data prevents this study from avoiding this assumption.

4.2 Sectoral exposures

The exposure of the Swedish banking industry to the different industries, required for constructing the credit portfolio that is representative of the bank's lending, is defined as the book value of loans to individual sectors. Furthermore, it is assumed that the loans exclusively come from the Swedish financial sector and thus the foreign proportion is not deemed significant. This assumption is false, since foreign loans have a slightly greater weight than domestic loans in the credit portfolio (Riksbanken 2009, 43-44), but this assumption was made due to the unavailability of foreign loan data for the financial sector. Exposure data for 2008 will not be available before this thesis is published and therefore to perform the tests using 2008 default rate data, the industry debt exposure was assumed to be identical for 2008 as for 2007.

4.3 Macroeconomic variables

The variables selected to explain the default rates for all industries included quarterly values of the Swedish GDP growth rate and the 1-year real STIBOR spanning the period 1993Q4 to 2008Q4. The GDP growth rate was calculated by taking the natural log difference between consecutive quarters. The real STIBOR 1-year change was computed by subtracting the log-differenced Swedish CPI from the nominal value of the 1-year STIBOR interest rate. These variables were found to be significant for the vast majority of industries by checking the adjusted R-squared values of the regressions and the p-values of the coefficients. Furthermore, other macroeconomic variables such as consumer confidence, oil price, retail sales, and car registration were regressed, however most of these were not found to add

explanatory power. Only consumer confidence was found to add some explanatory power, but not for the majority of the industries. Hence, the resulting VAR system was specified as having both GDP growth rate and the 1-year real STIBOR as being endogenous variables, and a constant as the exogenous variable. The VAR analysis was performed in EViews®.

To determine the correct lag length order for the VAR system the Likelihood Ratio (LR) Test, Residual Normality Test, and Residual Serial Correlation LM Test were performed. The conclusion from these tests was that a lag length of four was optimum (see *Appendices C1* and *C2*). The null hypotheses of (a) multivariable residual normality and (b) the presence of no serial correlation among residuals could not be rejected (see *Appendices C3* and *C4*).

5.0 Macroeconomic Scenarios and Results

For macroeconomic stress testing purposes, this study will follow the Boss (2002) and Virolainen (2004) scenario framework for specifying shocks to the Swedish GDP and interest rate. The shocks are selected to reflect the maximum, adverse historical movement in each data series. These shocks are sufficiently large to be considered abnormal, but remain plausible.

- Shock 1:Gdp shock 2,5% decrease in 2009Q1 and then normal growth determined by the VAR
- Shock 2: Interest rate shock of 150 basis point (increase) in 2009Q1 and then normal growth determined by VAR
- Shock 3: Extreme interest rate shock of 150 basis points in 2009Q1 and remaining at this level for the next three quarters
- Shock 4: Extreme GDP shock of 2,5% decrease for four consecutive quarters
- Shock 5: Combined shocks 1 and 2
- Shock 6: Combined shocks 3 and 4

5.1 Matlab program

A Matlab® program was created to perform the stress tests of the Swedish corporate loans portfolio and to obtain the corresponding portfolio loss distributions. The program consists of 5 steps in which the first step imports the data to be used for the tests (refer to *Appendix E* for the code). The second step involves the VAR forecasting which is carried out in an iterative process in which the four most recent values of the macroeconomic variables are multiplied with the corresponding VAR coefficient estimates and then summed with the constants of the VAR regressions. The resulting one-period ahead forecast of the macroeconomic variables are then included in the data series for each variable. Then this process is repeated for a specific number of steps ahead to obtain the corresponding desired final value for each of the macroeconomic variables. The third step involves a process of looping through each industry's empirical lognormal default rate data and then regressing these rates against the selected macroeconomic variables to obtain a matrix of coefficient estimates and a matrix of residuals.

The residuals from the default rate regression for each industry are then used to calculate the variance-covariance matrix which is then transformed into a correlation matrix for the Cholesky factorization. The Cholesky factorized matrix is then multiplied with a vector of 65000 generated values from the normal distribution to obtain a matrix of residuals which is then used to calculate new lognormal default rates for each industry.

The inverse of the 65000 calculated default rates for each industry are then multiplied with the corresponding industry's outstanding debt together with the loss given default, which is assumed to be 50%, to obtain 65000 different values of the expected loss. The distribution of the total expected loss of the Swedish financial sector is then obtained by aggregating the loss from each industry.

The shocks for the stress tests are introduced in the estimation process by replacing the empirical values with the specified shocks to obtain the VAR forecasts.

5.2 Baseline Loss Distribution

The Baseline Loss Distribution and values for the credit exposure measures are presented in Exhibit 5.1.

Baseline loss distribution
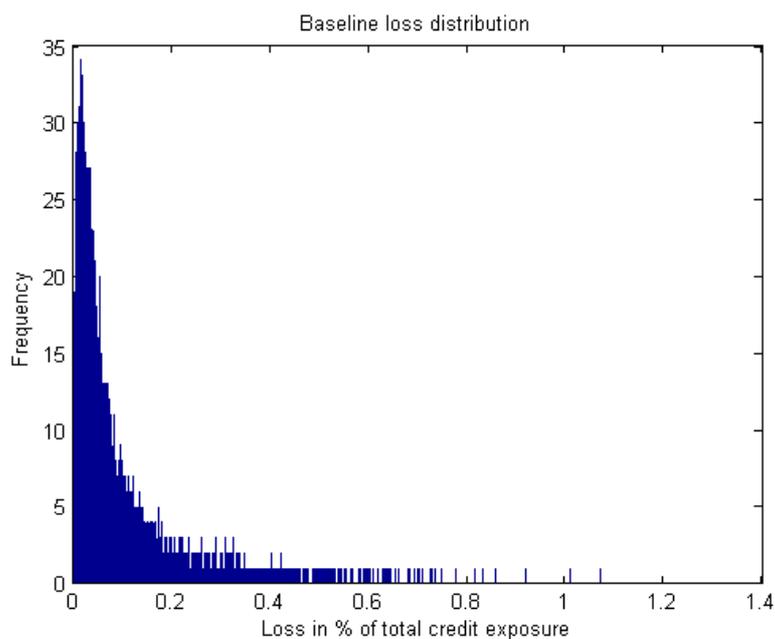
Baseline	
Expected loss	0,05%
Unexpected loss (99% VaR)	0,28%
Unexpected loss (99.9% VaR)	0,54%

Exhibit 5.1

The baseline losses represent only a small fraction of the value of the corporate loans portfolio. A series of six macroeconomic shock scenarios will be performed to judge the stability of the Swedish corporate loans portfolio to changes in the macroeconomic environment. If the LGD is varied between 0% and 100%, the Expected Loss has a range from 0% to 0.13%., the 99% VaR has a range from 0% to 0.7%, and the 99.9% VaR has a range from 0% to 1.40%. The exposure measures are quite sensitive to changes in the LGD.

5.3 Macroeconomic Shock Scenarios

5.3.1 Moderate Decrease in the Swedish Real GDP Growth Rate

A continuation of the 2.5 percent decrease in the Swedish real Gdp growth rate experienced in the final quarter of 2008 for one additional quarter may seem reasonable during the current credit crisis. This shock assumes that the GDP begins to revert to empirically normal states following the first quarter of 2009. This scenario is not considered

extreme in the light of the crisis and therefore if banks believe that this shock scenario is the most likely, then they may not put aside sufficient loan loss provisions for a more extreme macroeconomic shock.
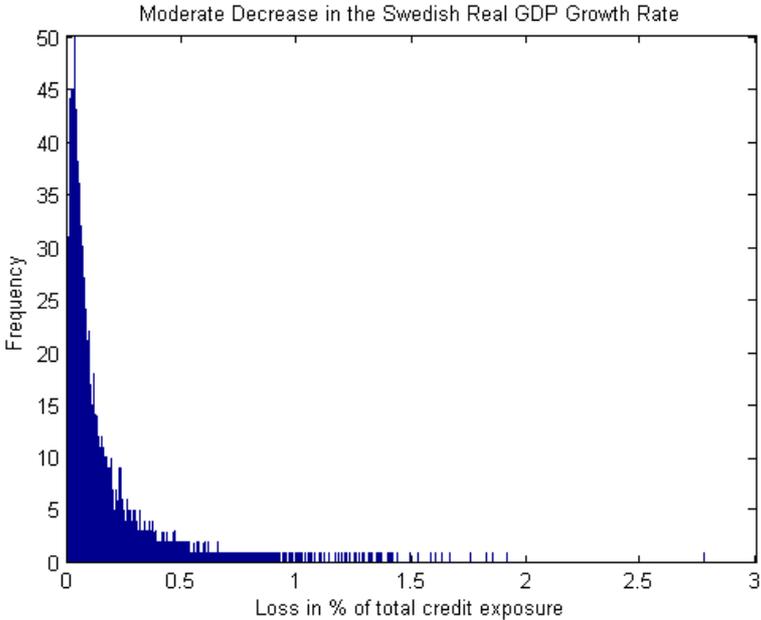
Moderate GDP shock	No stress	Stress
Expected loss	0,05%	0,09%
Unexpected loss (99% VaR)	0,28%	0,49%
Unexpected loss (99.9% VaR)	0,54%	1,02%

Exhibit 5.2

The simulated loss distribution under this scenario suggests that the impact of a single quarter production shock will have a minor effect on the corporate loans portfolio. In absolute terms, the expected loss is equivalent to 2 billion SEK and this does not strongly differ from the forecasted loss under normal conditions. The results from this simulation indicate that the Swedish financial sector is quite resilient to a short-term GDP shock and most financial institutions are expected to have sufficient reserves to cover such losses. If a tail event does not occur the maximum amount that is risked to be lost at the 99% confidence level is 0.49% of the total credit exposure.

5.3.2. Moderate Increase in the Real STIBOR Interest Rate

An increase in the real STIBOR interest rate by 150 basis points, as empirically observed in third quarter of 1994, for the first quarter of 2009 may be reasonable in the current credit crisis if a major global or Swedish financial institution defaults and leads to a more difficult credit environment. After the first quarter of 2009, the interest rate will be determined, as normal, by the VAR system. The GDP growth rate is assumed to be determined as normal by VAR forecasting.
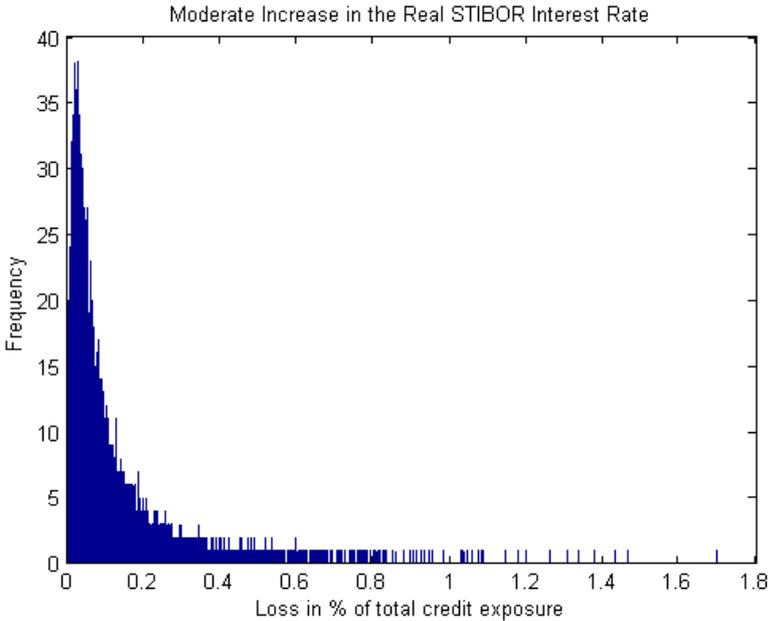
Moderate real Stibor shock	No stress	Stress
Expected loss	0,05%	0,07%
Unexpected loss (99% VaR)	0,28%	0,37%
Unexpected loss (99.9% VaR)	0,54%	0,72%

Exhibit 5.3

The results from this stress test suggest that the effects of an interest rate shock are minor and have relatively less negative consequences when compared with the GDP shock. The central bank of Sweden can affect Stibor through adjusting the domestic repo rate and thereby mitigate adverse effects from interest rate shocks. The repo rate is the rate in which a central bank offers to purchase government securities from commercial banks. If an interest rate shock occurred of the sufficient magnitude to be considered harmful to Swedish economy, the central bank can adjust the repo rate downwards to stimulate lending and

increase liquidity in the financial markets. A maximum loss of 0.37% of the portfolio value is at risk to be lost with 99% confidence if a tail event does not happen.

5.3.3 Extreme Decrease in the Swedish Real GDP Growth Rate

A macroeconomic shock of a decrease in the GDP growth rate of 2.5% for four consecutive quarters is employed to test the Swedish financial system to a severe recession. It is further assumed that the real Stibor is determined by the VAR system.
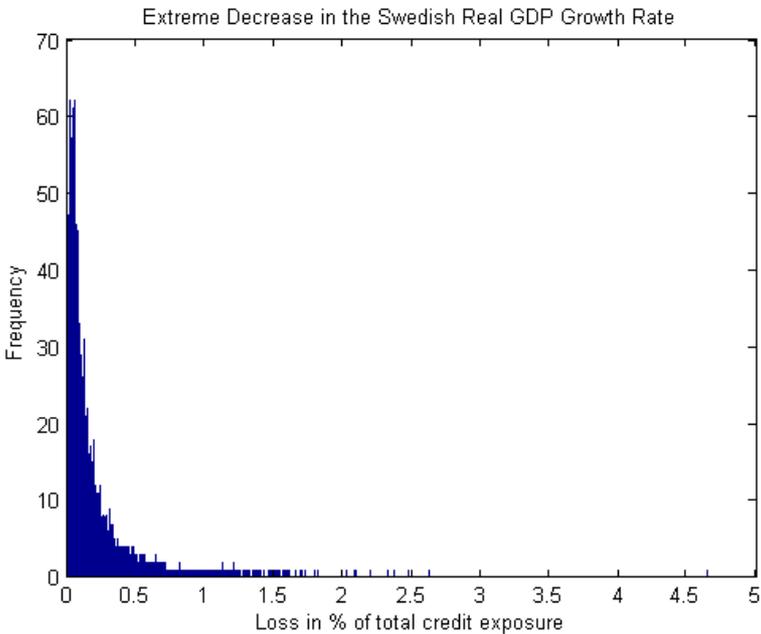
Extreme GDP shock	No stress	Stress
Expected loss	0,05%	0,12%
Unexpected loss (99% VaR)	0,28%	0,63%
Unexpected loss (99.9% VaR)	0,54%	1,29%

Exhibit 5.4

The outcome from this extreme stress scenario has strong, negative consequences for the aggregate credit portfolio relative to the single period shocks. Overall, the expected loss increases by 33% relative to the single quarter GDP shock. This scenario may appear empirically improbable, however the current recession of 2008-2009 has not been fully realized according to credible publications such as The Economist (The Economist: 23

April 2009). The results found by this stress scenario may suggest that the financial sector is at risk of having an insufficiently large capital buffer for protecting against such losses. If the financial system does not adjust to reflect these realities, then the stability of the financial system in the short-term may be jeopardized and financial institutions may have difficulty recovering after this period. The maximum value of the portfolio which is at risk to be lost at 99% confidence is 0.63% , which is relatively higher than the one-quarter shock scenarios.

5.3.4. Extreme Increase in the Real STIBOR Interest Rate

An increase in the real Stibor interest by 150 basis points and remaining at this level for all quarters of 2009 is considered extreme, but is plausible if the current credit crisis deepens and is driven by the defaults of many major global and domestic financial institutions. The GDP growth rate is assumed to be determined as normal by VAR forecasting.
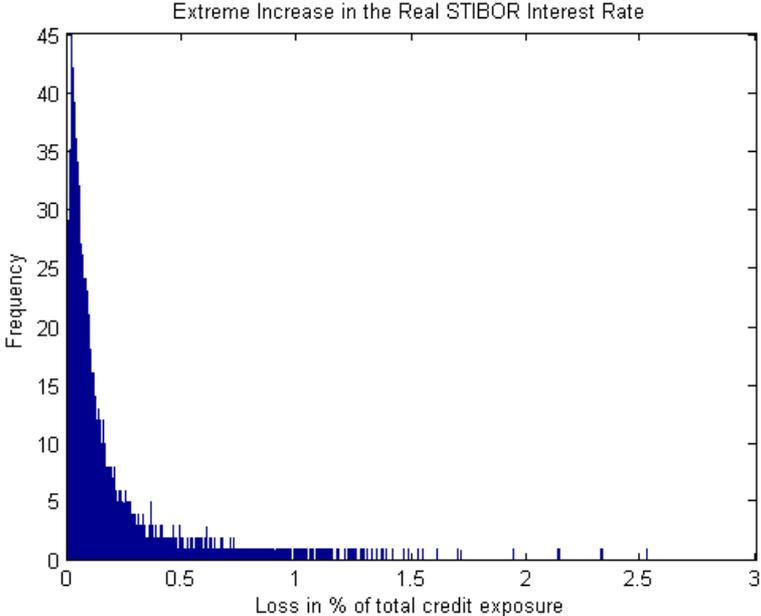
Extreme real Stibor shock	No stress	Stress
Expected loss	0,05%	0,08%
Unexpected loss (99% VaR)	0,28%	0,50%
Unexpected loss (99.9% VaR)	0,54%	1,01%

Exhibit 5.5

The results from this extreme interest rate stress scenario are not substantially worse from the single quarter interest rate shock and the difference in expected loss from the previous case was found to be only 14%. Furthermore as previously mentioned, the central bank of Sweden has the ability to mitigate the effects of this shock by adjusting the repo rate. A 0.5% loss is the maximum loss expected to be a risk to the portfolio with 99% confidence, which is only relatively lower than the extreme GDP shock scenarios.

5.3.5 Combination of Moderate Decrease in GDP Growth Rate and Increase in Stibor

A combined single quarter shock of a 2.5% decline in the GDP growth rate and a 150bp increase in the real Stibor represents a moderate worsening of the Swedish economy and this situation may occur if the global recession deepens in the first quarter of 2009 and there are no early signs of recovery until the next quarter. This scenario will simulate the potential impact of another global financial shock following the Lehman Brothers default in September 2008. The interest rate is increased to reflect the market expectations and fears of the lending environment and the decline in GDP is considered a consequence of this event. However, as more information and government assurances become available, the market begins to return to normal.
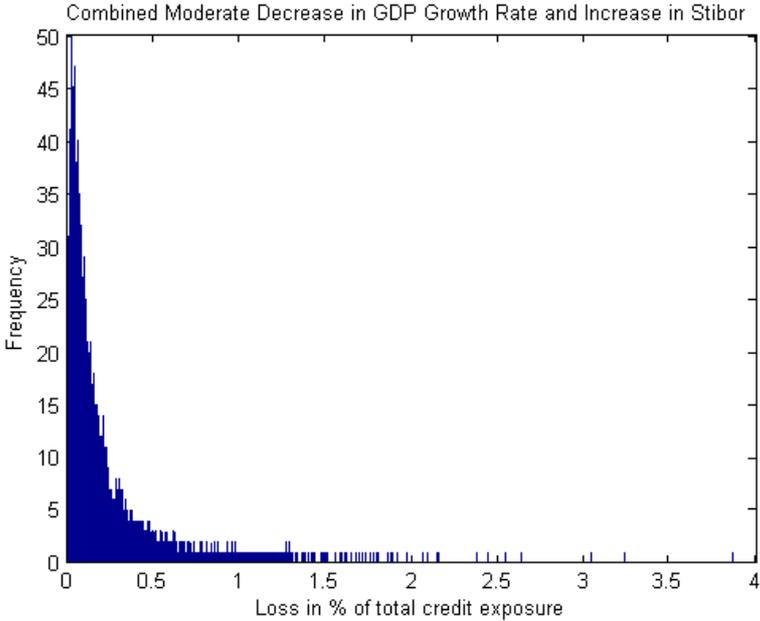
Moderate GDP and real Stibor shock	No stress	Stress
Expected loss	0,05%	0,13%
Unexpected loss (99% VaR)	0,28%	0,67%
Unexpected loss (99.9% VaR)	0,54%	1,30%

Exhibit 5.6

The results indicate that this combined stress scenario will have more severe consequences for the credit portfolio than the prior shocks in only one macroeconomic variable. This is an alarming sign which highlights that the financial sector is not well prepared for a combined moderate production and interest rate shock. The difference in 99% value-at-risk between this combined shock and the extreme GDP shock is 6%. The maximum value at risk with 99% confidence, 0.67%, is slightly higher for this combination scenario than from the extreme GDP shock scenario.

5.3.6 Combination of Extreme Decrease in GDP Growth Rate and Increase in Stibor

A combined shock of a 2.5% decline in the GDP growth rate for four consecutive quarters and a 150bp increase in the real Stibor which stays at this level for the year was chosen as the most extreme shock. This scenario reflects a severe contraction of the Swedish economy and a gloomy global credit environment. This state of the market may occur if the credit crisis deepens and government aid and assurances fail to raise expectations of a brisk return to a less volatile economy. The byproduct of this scenario is a more cautious credit environment, which is reflected in the higher and constant interest rate. Early expectations of recovery can hinder the recovery of global economies and may worsen and prolong the recession (The Economist 2009: 23 April 2009).

Exhibit 5.7

The results from the most extreme stress test to the corporate loans portfolio present the most severe losses. The 99% value-at-risk for this scenario is more than 10% greater than the value received from the other combined shock scenario and is several times greater than the VaR if there is no shock present. The macroeconomic environment portrayed in this scenario will critically affect the stability of the financial system in terms of the losses to the credit portfolio. The maximum loss to the portfolio if a tail event does not occur with 99% confidence, 0.74%, is the greatest all of scenarios.

5.4 Comparison of results with those from previous studies

The findings from this study differ from those of Dey *et al.* (2006) and Virolainen (2004). The resulting expected losses and value-at-risk from this study are substantially lower than those identified for Canada and Finland. Our results are closest to Virolainen (2004) for Finland in terms of expected loss and VaR. There are several possible reasons why the results from this study differ from the previous research. First, this study has

a much smaller fraction of the observations in recession or economic downturn periods. This leads to a downward bias in default rates, and thereby exposure levels. Furthermore, the data interval available from SCB displays a strong, declining trend in observed industry default rates. The same trend is not nearly as strong or is indiscernible in Virolainen (2004) and Dey *et al.* (2006), respectively. Finally, the current credit crisis has not been fully realized in terms of Swedish corporate default data. With the inclusion of 2009 data, the results may be more reasonable as compared with previous studies. Finally, the difference in models may also explain some of the results.

5.5 Critique of this Study

There are several issues with this study which may limit the value of the conclusions and the impact of these problems should be discussed. The major issue was the unavailability of data which covered economic downturn periods and this leads to a dramatic downwards bias in the default rates, and thereby value-at-risk measures. Furthermore, specific exposures for each financial institution in Sweden were not publicly available and this limits the accuracy of the results. Third, to the knowledge of the authors no research has been performed to identify the specific loan recovery rate for each industry in Sweden, and therefore the common assumption in the research of 50% for the LGD was used. Fourth, data on foreign loans was not publicly accessible and thus the relative importance of these loans to corporate loans could not be identified for the financial sector. Fifth, the lognormal default rates for each industry could have been regressed against macroeconomic variables specifically important to each industry. In the interest of estimation/model parsimony and following the previous research only GDP and Stibor were used for each regression. Finally, more frequent data on the number of active companies in each industry should ideally have been utilized. However, this data was not available in higher frequency and thus data interpolation had to be used.

5.6 Critique of the Model

There are many weaknesses inherent to the Dey *et al.* (2006) and Virolainen (2004) methodology and these drawbacks need to be considered when choosing such value-at-risk models. First, a strict linearity is assumed between lognormal default rates and the chosen macroeconomic variables, which may unjustifiably simplify the intricate relationship among the variables. Second, the forecasted evolution of the macroeconomic variables used to

explain the lognormal default rates is constrained by significant forecasts errors and uncertainties. If the forecasts are wrongly specified then the validity of the results is highly questionable. Due to these prominent forecast issues, this study employed only a short, four quarter forecasting period as compared with the eight to twelve quarter forecasting period used in the previous research. Third, the process of generating the loss distribution is restricted to an assumption that the residuals are normally distributed for each industry regression. Consequently, the residual generating process restricts the occurrence of extreme events, such as the current credit crisis, which could have severe impacts on the stability measures (expected loss and VaR). Fourth, many industries in Sweden had to be left out of the corporate loans portfolio due to the specification of the default rates in log form, and this led to conclusions which do not account for all industries. Furthermore, the specification of the default rate equation does not account for firms which do not have any debt from the Swedish financial sector, and thus the default rates will be biased downwards. Finally, the longer the data set used, the more likely the composition of the economy in a country has changed and thus including very old observations will bias the results. Ideally, a future model should have dynamic properties to account for changes in the economy of a country and include more industries.

6.0 Conclusion

The purpose of this study has been first to identify the macroeconomic factors to which the financial sector in Sweden has the greatest exposure and then to identify the vulnerability of the financial system to shocks in these macroeconomic variables by stress testing the Swedish corporate loans portfolio. The distinctive features of this study are the application of the Dey *et al.* (2006) macroeconomic credit risk model to Sweden, the inclusion of data from the current credit crisis, the introduction of a more extensive range of industries than commonly used in the research, and the development of a Matlab® program to facilitate the stress testing of financial systems.

The findings of this study suggest the Swedish financial sector is more susceptible to shocks in the real GDP than the real interest rate. Furthermore, the Swedish financial system was found to be only moderately affected by macroeconomic shocks to the corporate loans portfolio.

To determine the exposure and stability of the Swedish financial sector, the evolution of the default rates for each industry were modeled by a system of equations and the expected future losses to the loans portfolio were estimated by Monte Carlo simulation over one year.

The findings from this study differ from those of Dey *et al.* (2006) and Virolainen (2004) and the resulting value-at-risk measures and expected losses are substantially lower than those identified for Canada and Finland. There are several possible reasons why the findings from this study differ from the previous research. First, this study included a much smaller fraction of the data observations in recession or economic downturn periods, which may have led to a downward bias in default rates, and thereby exposure levels. Second, the current credit crisis had not yet been fully realized in terms of Swedish corporate default data before this study was completed. With the inclusion of 2009 data, the results may be more reasonable relative to previous studies. Finally, the difference in models may also explain some of the results.

There are several weaknesses in the model used to identify the vulnerability and stability of the Swedish financial system. First, the assumption of a linear relationship between lognormal default rates and the chosen macroeconomic variables may unjustifiably

simplify the intricate relationship among the variables. Second, the forecasted evolution of the macroeconomic variables used to explain the lognormal default rates is constrained by significant forecasts errors and uncertainties. Third, the process of generating the loss distribution is restricted to an assumption that the residuals are normally distributed for each industry regression. Consequently, the residual generating process restricts the occurrence of extreme events, such as the current credit crisis, which could have severe impacts on the stability measures (expected loss and VaR). Finally, the longer the data set used, the more likely the composition of the economy in a country has changed and thus including very old observations will bias the results.

Ideally, a future model should adjust for the aforementioned weaknesses and include dynamic properties to account for changes in the economy of a country and include more industries.

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Appendices

Appendix A: Default Rate Correlations and Normality Tests

Appendix A1: Default Rate Normality Test for each industry

Date: 05/16/09   Time: 14:36
Sample: 1994Q1 2008Q4

	_20_WOO	_22_PUB_	_28_MANU	_45_CONS	_50_SALE_	_51_WHOL	_52_RETAI	_55_HOTEI	_60_63_TR	_70_REAL_	_71_RENTI	_72_COMP	_73_74_R_
Mean	0.001233	0.001481	0.001178	0.001432	0.001483	0.001713	0.001507	0.002135	0.001141	0.000882	0.001418	0.001021	0.000954
Median	0.001106	0.001332	0.001096	0.001178	0.001265	0.001458	0.001318	0.001797	0.001017	0.000471	0.001124	0.000982	0.000804
Maximum	0.003872	0.004497	0.003329	0.004533	0.003603	0.004035	0.003473	0.005027	0.002768	0.004140	0.004407	0.002651	0.002549
Minimum	0.000148	0.000205	8.89E-05	0.000602	0.000669	0.000769	0.000710	0.000789	0.000194	0.000163	0.000178	0.000217	0.000319
Std. Dev.	0.000807	0.000836	0.000571	0.000729	0.000632	0.000778	0.000647	0.000971	0.000501	0.000865	0.000894	0.000525	0.000503
Skewness	1.117930	1.469070	0.870011	1.881526	1.454069	1.131950	1.194445	1.057347	1.273936	1.836907	1.122276	0.790731	1.137687
Kurtosis	4.083182	5.742231	4.769976	7.332306	4.943662	3.850819	3.651080	3.393685	4.756307	6.392897	3.969285	3.543944	3.772534
Jarque-Bera	15.43089	40.38122	15.40123	82.32361	30.58771	14.62284	15.32675	11.56729	23.94066	62.52164	14.94382	6.992238	14.43533
Probability	0.000446	0.000000	0.000453	0.000000	0.000000	0.000668	0.000470	0.003077	0.000006	0.000000	0.000569	0.030315	0.000734
Sum	0.073956	0.088881	0.070674	0.085900	0.088994	0.102803	0.090402	0.128080	0.068451	0.052903	0.085057	0.061252	0.057211
Sum Sq. Dev.	3.84E-05	4.12E-05	1.92E-05	3.14E-05	2.36E-05	3.57E-05	2.47E-05	5.56E-05	1.48E-05	4.41E-05	4.72E-05	1.63E-05	1.50E-05
Observations	60	60	60	60	60	60	60	60	60	60	60	60	60

Appendix A2: Lognormal Default Rate Normality Test for each Industry

Date: 05/16/09   Time: 14:44
Sample: 1994Q1 2008Q4

	_20_WOOL	_22_PUB_	_28_MANU	_45_CONS	_50_SALE_	_51_WHOL	_52_RETAI	_55_HOTEL	_60_63_TR	_70_REAL_	_71_RENTI	_72_COMP	_73_74_R_
Mean	-6.929215	-6.660836	-6.879044	-6.646422	-6.586775	-6.458337	-6.574885	-6.238964	-6.864437	-7.411536	-6.756621	-7.026486	-7.079925
Median	-6.805813	-6.620187	-6.815347	-6.743019	-6.671438	-6.529196	-6.630500	-6.319697	-6.889718	-7.660153	-6.789871	-6.925352	-7.124729
Maximum	-5.550220	-5.399913	-5.701601	-5.391781	-5.622452	-5.508584	-5.659386	-5.287963	-5.886974	-5.482920	-5.420069	-5.930285	-5.969565
Minimum	-8.818852	-8.492388	-9.328035	-7.414524	-7.308399	-7.169441	-7.249172	-7.143793	-8.545716	-8.720098	-8.634265	-8.435100	-8.048673
Std. Dev.	0.740781	0.565141	0.582986	0.428314	0.377500	0.422401	0.388951	0.425182	0.437336	0.847721	0.666580	0.558187	0.502775
Skewness	-0.632358	-0.409080	-1.355930	0.731436	0.596567	0.367745	0.537866	0.347300	-0.517822	0.519139	-0.421025	-0.412949	0.153693
Kurtosis	3.210385	3.871981	6.764597	3.028766	2.837832	2.246227	2.452242	2.294654	5.493855	2.139588	3.256603	2.621511	2.421698
Jarque-Bera	4.109422	3.574343	53.81593	5.352056	3.624666	2.772803	3.643098	2.449958	18.22968	4.545822	1.937234	2.063401	1.072301
Probability	0.128130	0.167433	0.000000	0.068836	0.163273	0.249973	0.161775	0.293764	0.000110	0.103012	0.379608	0.356400	0.584996
Sum	-415.7529	-399.6502	-412.7426	-398.7853	-395.2065	-387.5002	-394.4931	-374.3378	-411.8662	-444.6922	-405.3972	-421.5891	-424.7955
Sum Sq. Dev.	32.37660	18.84371	20.05248	10.82370	8.407889	10.52695	8.925684	10.66599	11.28449	42.39922	26.21538	18.38282	14.91418
Observations	60	60	60	60	60	60	60	60	60	60	60	60	60

Appendix A3: Correlation Matrix of Lognormal Industry Default Rates

	_20_WOOD	_22_PUB_	_28_MANU	_45_CONS	_50_SALE_	_51_WHOL	_52_RETAI	_55_HOTE	_60_63_TR	_70_REAL	_71_RENTI	_72_COMP	_73_74_R_
_20_WOOD_PROD___EXCL__FURNIT	1.000000	0.709386	0.618688	0.720804	0.675981	0.772243	0.748545	0.756930	0.701529	0.724731	0.738472	0.714427	0.768202
_22_PUB__PRINT__REPR MEDIA__	0.709386	1.000000	0.644318	0.729707	0.684162	0.726338	0.769042	0.694999	0.726717	0.758407	0.672823	0.752670	0.767422
_28_MANUF_METAL_PROD	0.618688	0.644318	1.000000	0.701060	0.618022	0.647371	0.650857	0.591215	0.612322	0.663780	0.585040	0.605121	0.713711
_45_CONSTRUCTION	0.720804	0.729707	0.701060	1.000000	0.895823	0.905713	0.908580	0.835109	0.852497	0.923326	0.861932	0.756363	0.923335
_50_SALE_SERV_VEHICLES__	0.675981	0.684162	0.618022	0.895823	1.000000	0.880634	0.891381	0.806906	0.824643	0.930201	0.848417	0.734110	0.908095
_51_WHOLESALE_COMMISS__TRADE	0.772243	0.726338	0.647371	0.905713	0.880634	1.000000	0.912404	0.888321	0.885905	0.938816	0.840275	0.785540	0.949417
_52_RETAIL_TRADE	0.748545	0.769042	0.650857	0.908580	0.891381	0.912404	1.000000	0.888731	0.906612	0.922138	0.848877	0.759659	0.945664
_55_HOTELS_RESTAURANTS	0.756930	0.694999	0.591215	0.835109	0.806906	0.888321	0.888731	1.000000	0.845268	0.865173	0.796573	0.680967	0.894644
_60_63_TRANSPORT__TOURISM	0.701529	0.726717	0.612322	0.852497	0.824643	0.885905	0.906612	0.845268	1.000000	0.872239	0.805914	0.715308	0.885401
_70_REAL_ESTATE_ACT_	0.724731	0.758407	0.663780	0.923326	0.930201	0.938816	0.922138	0.865173	0.872239	1.000000	0.861205	0.782247	0.940468
_71_RENTING_OF_MACH__EQUIP	0.738472	0.672823	0.585040	0.861932	0.848417	0.840275	0.848877	0.796573	0.805914	0.861205	1.000000	0.750649	0.858710
_72_COMPUTER___RELATED_ACT	0.714427	0.752670	0.605121	0.756363	0.734110	0.785540	0.759659	0.680967	0.715308	0.782247	0.750649	1.000000	0.814491
_73_74_R_D___OTHER_BUS__ACT	0.768202	0.767422	0.713711	0.923335	0.908095	0.949417	0.945664	0.894644	0.885401	0.940468	0.858710	0.814491	1.000000

Appendix A4: Total Long-term Debt for every industry in Sweden

Preliminära balansräkningsposter enligt Företagens ekonomi, mnkr efter näringsgren
SNI 2002, balansräkningsposter och tid

	2007	% of total
01 jordbruksföretag och serviceföretag till jordbruk	73450	1,94%
02 skogsbruk och serviceföretag till skogsbruk	100525	2,65%
05 fiskare, vattenbrukare inkl. serviceföretag	1005	0,03%
10 kolgruvor och torvindustri	857	0,02%
10+11 kolgruvor och torvindusti samt industri för utvinning av råpetroleum och naturgas	-	-
11 industri för utvinning av råpetroleum och naturgas inkl. serviceföretag	490	0,01%
13+14 metallmalmsgruvor och annan industri för mineralutvinning	11915	0,31%
15+16 livsmedels-, dryckesvaru-, och tobaksindustri	48035	1,27%
17 textilindustri	4093	0,11%
18 beklädnadsindustri; pälsindustri	3945	0,10%
19 garverier; industri för reseffekter, handväskor, skodon o.d.	269	0,01%
20 industri för trä och varor av trä, kork, rotting o.d. utom möbler	19522	0,51%
21 massa-, pappers- och pappers-varuindustri	73135	1,93%
22 förlag; grafisk och annan reproduktionsindustri	12201	0,32%
23 industri för stenkolsprodukter, raffinerade petroleumprodukter och kärnbränsle	1567	0,04%
24 kemisk industri	137276	3,62%
25 gummi- och plastvaruindustri	18257	0,48%
26 jord- och stenvaruindustri	27204	0,72%
27 stål- och metallverk	64237	1,69%
28 industri för metallvaror utom maskiner och apparater	24396	0,64%
29 maskinindustri som ej ingår i annan underavdelning	166228	4,38%
30 industri för kontorsmaskiner och datorer	913	0,02%
31+32 annan elektroindustri samt teleproduktindustri	87253	2,30%
33 industri för precisionsinstrument, medicinska och optiska instrument samt ur	80139	2,11%
34 industri för motorfordon, släpfordon och påhängsvagnar	66156	1,74%
35 annan transportmedelsindustri	9000	0,24%
36 möbelindustri; annan tillverkningsindustri	14591	0,38%
37 återvinningsindustri	1594	0,04%
40 el-, gas- och värmeverk	361788	9,54%
41 vattenverk	4193	0,11%
45 byggindustri	85645	2,26%
50 handel med och serviceverkstäder för motorfordon; bensinstationer	30009	0,79%
51 parti- och agenturhandel utom med motorfordon	192676	5,08%
52 detaljhandel utom med motorfordon; reparationsverkstäder för hushålls- och personliga artiklar	40350	1,06%
55 hotell och restauranger	35066	0,92%
60 landtransportföretag	44271	1,17%
61 rederier	37183	0,98%
62 flygbolag	8833	0,23%
63 serviceföretag till transport; researrangörer, resebyråer och transportförmedlare	50512	1,33%
64 post- och telekommunikationsföretag	152395	4,02%
70 fastighetsbolag och fastighets-förvaltare	1226815	32,36%
71 uthyrningsfirmor	30833	0,81%
72 datakonsulter och dataservicebyråer	40939	1,08%
73+74 forsknings- och utvecklings-institutioner samt andra företagsservicefirmor	359867	9,49%
80 utbildningsväsendet	2886	0,08%
85 enheter för hälso- och sjukvård, socialtjänst; veterinärkliniker	29372	0,77%
90 reningsverk, avfallsanläggningar, renhållningsverk	9717	0,26%
Total debt	3791603	100,00%

Appendix B: Default Rates per Industry 1994Q1-2008Q12
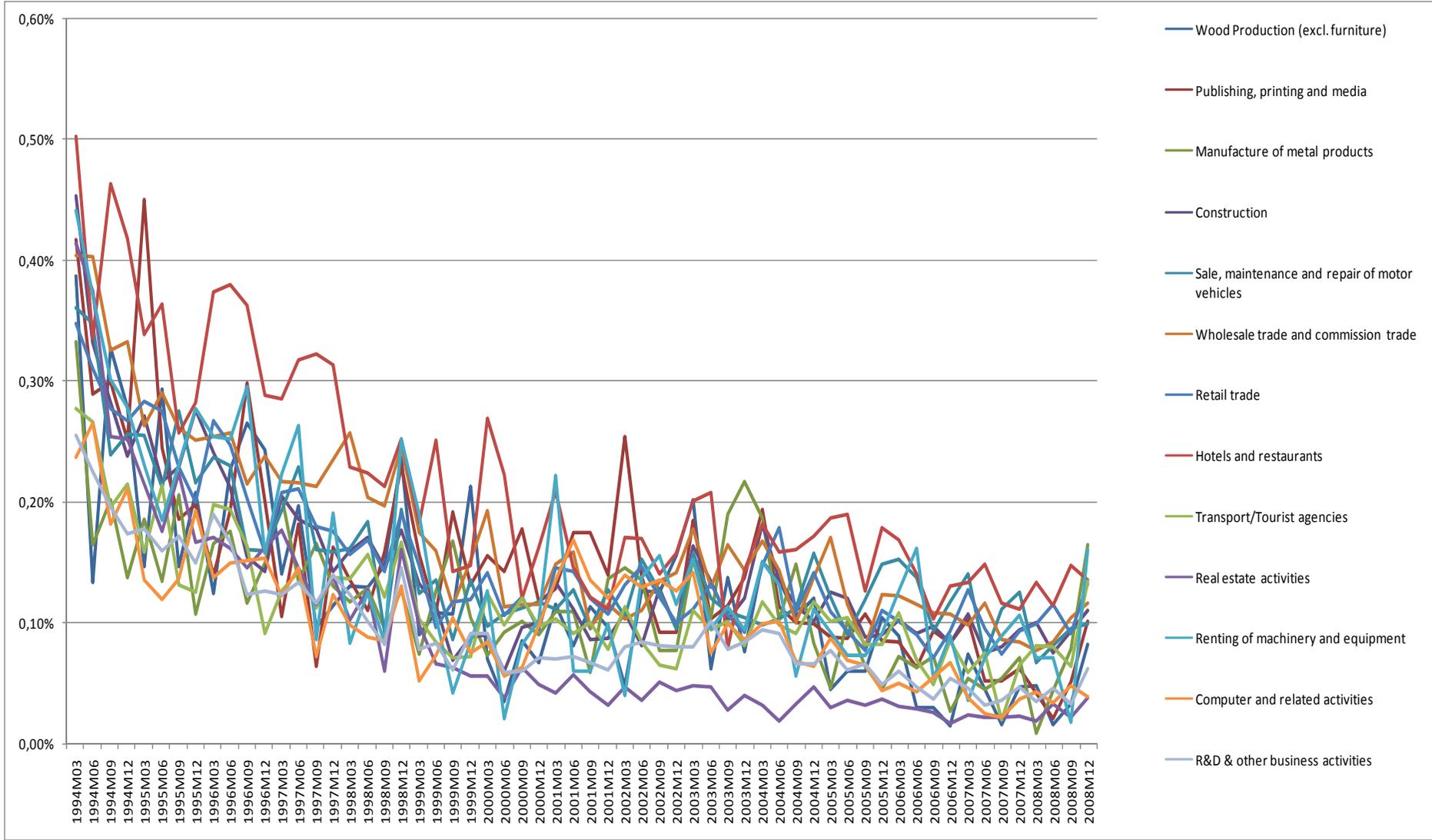
Appendix C: Vector Autoregression (VAR) System

Appendix C1: VAR Lag Order Selection Criteria

VAR Lag Order Selection Criteria
RGDP_GROWTH
Exogenous variables: C
Date: 05/17/09   Time: 12:12
Sample: 1993Q4 2008Q4
Included observations: 53

Lag	LogL	LR	FPE	AIC	SC	HQ
0	343.1140	NA	8.80e-09	-12.87223	-12.79788	-12.84363
1	382.8223	74.92135	2.29e-09	-14.21971	13.99666*	14.13394*
2	387.9827	9.347134	2.19e-09	-14.26350	-13.89175	-14.12054
3	389.1367	2.003108	2.45e-09	-14.15610	-13.63565	-13.95596
4	396.5267	12.27030*	2.16e-09	-14.28403	-13.61487	-14.02670
5	401.5376	7.941701	2.09e-09*	14.32217*	-13.50432	-14.00766
6	405.3474	5.750665	2.12e-09	-14.31500	-13.34844	-13.94330
7	408.6344	4.713465	2.21e-09	-14.28809	-13.17283	-13.85922

* indicates lag order selected by the criterion

LR: sequential modified LR test
    statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Appendix C2: VAR Estimate for the Optimal Lag Order

Vector Autoregression Estimates

Date: 05/17/09   Time: 12:13

Sample (adjusted): 1995Q1 2008Q4

Included observations: 56 after adjustments

Standard errors in ( ) & t-statistics in [ ]

	REAL_STIBOR_1Y	RGDP_GROWTH
REAL_STIBOR_1Y(-1)	0.730755	-0.007400
	(0.14655)	(0.12599)
	[4.98632]	[-0.05873]
REAL_STIBOR_1Y(-2)	0.253233	0.012836
	(0.18266)	(0.15703)
	[1.38634]	[0.08174]
REAL_STIBOR_1Y(-3)	-0.129487	-0.107087
	(0.18254)	(0.15693)
	[-0.70935]	[-0.68239]
REAL_STIBOR_1Y(-4)	0.009563	0.090657
	(0.13800)	(0.11864)
	[0.06930]	[0.76417]
RGDP_GROWTH(-1)	0.313034	0.325406
	(0.17578)	(0.15111)
	[1.78087]	[2.15341]
RGDP_GROWTH(-2)	-0.027114	0.603217
	(0.18901)	(0.16249)
	[-0.14345]	[3.71227]
RGDP_GROWTH(-3)	-0.171375	0.169683
	(0.19851)	(0.17066)
	[-0.86329]	[0.99427]
RGDP_GROWTH(-4)	0.009566	-0.494009
	(0.20488)	(0.17613)
	[0.04669]	[-2.80475]
C	0.004020	0.002695
	(0.00330)	(0.00284)
	[1.21681]	[0.94874]
R-squared	0.858380	0.424408
Adj. R-squared	0.834275	0.326435
Sum sq. resids	0.002292	0.001694
S.E. equation	0.006983	0.006003
F-statistic	35.60934	4.331878
Log likelihood	203.4444	211.9110
Akaike AIC	-6.944443	-7.246820
Schwarz SC	-6.618940	-6.921317
Mean dependent	0.040526	0.006309
S.D. dependent	0.017153	0.007315
Determinant resid covariance (dof adj.)		1.63E-09
Determinant resid covariance		1.15E-09
Log likelihood		417.4412
Akaike information criterion		-14.26576
Schwarz criterion		-13.61475

Appendix C3: VAR Residual Normality Tests

VAR Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
H0: residuals are multivariate normal
Date: 05/17/09   Time: 12:14
Sample: 1993Q4 2008Q4
Included observations: 56

Component	Skewness	Chi-sq	df	Prob.
1	-0.101509	0.096171	1	0.7565
2	-0.378191	1.334934	1	0.2479
Joint		1.431105	2	0.4889

Component	Kurtosis	Chi-sq	df	Prob.
1	2.382473	0.889792	1	0.3455
2	1.711525	3.873727	1	0.0490
Joint		4.763519	2	0.0924

Component	Bera	df	Prob.	
1	0.985963	2	0.6108	
2	5.208661	2	0.0740	
Joint	6.194624	4	0.1851	

Appendix C4: VAR Residual Serial Correlation LM Test

VAR Residual Serial Correlation LM Tests
H0: no serial correlation at lag order h
Date: 05/17/09   Time: 12:15
Sample: 1993Q4 2008Q4
Included observations: 56

Lags	LM-Stat	Prob
1	2.237380	0.6922
2	5.514553	0.2385
3	3.452165	0.4852
4	9.897140	0.0422
5	6.309505	0.1772
6	6.286184	0.1788
7	10.41816	0.0339
8	10.37153	0.0346
9	3.628136	0.4587
10	1.392524	0.8455
11	2.596851	0.6274
12	7.219282	0.1247
13	3.731707	0.4435
14	4.121023	0.3899
15	4.478025	0.3452
16	3.437235	0.4875

Probs from chi-square with 4 df.

Appendix D: VBA Code

```vba
Sub interpolatedata()

    Dim iCol As Integer, iOutput As Integer, i As Integer
    iOutput = 3


    Dim iSector As Integer: iSector = 5


    With Worksheets("Raw Active companies")
        For iSector = 5 To 37
            For iCol = 2 To 16
            .Range("T" & 2)(1, 1 + (iSector - 5)) = .Cells(iSector, 1)
            If iSector = 5 Then .Range("S" & iOutput) = .Cells(4, iCol)
    .Range("T" & iOutput)(1, 1 + (iSector - 5)) = .Cells(iSector, iCol)
                For i = 1 To 4
                    iOutput = iOutput + 1
                    .Range("T" & iOutput)(1, 1 + (iSector - 5)) =
    .Cells(iSector, iCol) + i * (.Cells(iSector, iCol + 1) - .Cells(iSector,
    iCol)) / 4
                Next i


            Next iCol
            iOutput = 3
        Next iSector



    End With
End Sub
```

Appendix E: Matlab® Code

```
function [Loss_dist]=loss_distribution2()



    %read input data

    readXlsInput;


    %Calc forecast of VAR

        startAt=1;

        noSteps=12;

        [Gdp_Stibor_forecast] =forecastVAR2(varCoefficients,
[gdp_growth,stibor], startAt, noSteps, shocks);

        x_f=[1,Gdp_Stibor_forecast(1,:)];

    %Regression for each industry

    r_matrix=[];

    coeffm=[];

    for i=1:13

[coefficients,confint,r]=regress(ln_defaults(:,i),[ones(size(gdp_growth,1),
1),gdp_growth,stibor] );

        r_matrix=[r_matrix,r];

        coeffm=[coeffm,coefficients];

    end


        cor=corr(r_matrix);

        A=chol(cor);

        noScenarios=65000

        random_matrix=(A'*randn(13,noScenarios))';
```

```matlab
    %Calculate expected loss for the number of scenarios selected

        for k=1:13

            for j=1:noScenarios

            ln_new=x_f*coeffm(:,k)+random_matrix(j,k);

            default_f=exp(ln_new)/(1+exp(ln_new));

            expected_loss(j,k) = default_f*longTermDebt(k,1)*0.5;

            end

        end


    %plot histogram

    Loss_dist=sum(expected_loss')'

    hist(Loss_dist,100);

    disp('end')

end
```

```matlab
function [Forecast] =forecastVAR2(varCoeff, gdp_stibor, startAt, noSteps,
shocks)

    Forecast=[];

    noLags=3;


    for i=1:noSteps

        if shocks(1,2)==1 && shocks(i+1,2)~=0

            Stibor_forecast = shocks(i+1,2);

        else

            Stibor_forecast = varCoeff(size(varCoeff,1),1)+
varCoeff(1:size(varCoeff,1)-1,1)'*[gdp_stibor(startAt:startAt+noLags,2) ;
gdp_stibor(startAt:startAt+noLags,1)];

        end

        if shocks(1,1)==1 && shocks(i+1,1)~=0

            Gdp_forecast = shocks(i+1,1);

        else

            Gdp_forecast = varCoeff(size(varCoeff,1),2)+
varCoeff(1:size(varCoeff,1)-1,2)'*[gdp_stibor(startAt:startAt+noLags,2) ;
gdp_stibor(startAt:startAt+noLags,1)];

        end

            gdp_stibor=[Gdp_forecast, Stibor_forecast; gdp_stibor];

    end

        Forecast= gdp_stibor(1:noSteps,:);

end
```

readXlsinput

```matlab
ln_defaults = xlsread('input v5.xls',1,'B2:N61');

gdp_growth=xlsread('input v5.xls',2,'C2:C61');

stibor=xlsread('input v5.xls',3,'H3:H62');

varCoefficients=xlsread('input v5.xls',4,'B4:C12');

longTermDebt=xlsread('input v5.xls',5,'B2:B14');

shocks=xlsread('input v5.xls',6,'B2:C12');
```