Stockholm School of Economics

Master Thesis in Finance

An Application of Macroprudential Capital Requirements in Sweden

May 23, 2013

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Abstract

The adverse effects of the recent financial crisis have highlighted the need to reform bank regulation. In this paper we investigate the suitability of capital requirements based on measures that account for systemic risk. We analyse the effects that such requirements would have had historically for the Swedish banking system, had they been employed, using a network based structural model of the banking system and simulated credit portfolio losses. We analyse the potential efficiency gains that reallocation of capital across banks within the Swedish banking system could have by looking at the individual probabilities of default and the unconditional expected losses given default. The analysis builds on detailed data on the four largest banks in Sweden, focusing on four points in time; Q4 2012, Q2 2009, Q2 2007 and Q1 2005. Based on our analysis we conclude that optimal systemic capital allocations differ substantially from current. Further, by applying macroprudential capital requirements individual probabilities of default can be decreased by approximately 10% in Q4 2012, but even more in periods when the crisis was more prominent. Perhaps most important is that the risk of a systemic crisis, with more than three banks defaulting simultaneously, can be decreased by 37% and expected losses almost halved.

KEYWORDS: Systemic Risk, Macroprudential, Capital Requirements, Bank Regulation, Financial Stability

Acknowledgement: We would like to thank our tutor and supervisor Peter Englund for his valuable input and guidance during the writing process.

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1 Introduction

"Going forward, a critical question for regulators and supervisors is what their appropriate field of vision should be. Under our current system of safety-and-soundness regulation, supervisors often focus on the financial conditions of individual institutions in isolation. An alternative approach, which has been called system-wide or macroprudential oversight, would broaden the mandate of regulators and supervisors to encompass consideration of potential systemic risks and weaknesses as well..."

Federal Reserve Chairman, Ben Bernanke (2008)

The recent financial crisis and the high social cost it has so far incurred, both in terms of bail-outs and forgone potential economic output, have shattered the public's confidence in the financial system, the intermediaries, and perhaps most of all, its regulation. The incumbent regulatory framework is extensive but fragmented and has some apparent and extremely important short-falls, mainly in that instead of acting as a second line of defence, it exacerbated the crisis in important ways. As banks are extremely important players in the financial system, and even more so in the Nordic region, their role in the previous crisis, their activities as well as capital requirements should be reviewed.

The mentioned regulatory shortcomings have been frequently discussed in academia as well as news media but no resolutions with substantial advances have yet been introduced. In both the U.S. and European Union, lawmakers have introduced liquidity requirements with related funding demands and vetted some bold ideas on capital regulation, but their plans are regularly shot down for various reasons - most commonly undesirable side-effects. Under the current bank regulation, banks are required to hold capital according to guidelines that are used to classify assets by risk-weights and bank capital of different quality. The ratio of such capital over the risk-weighted assets is the commonly discussed capital ratio. The Basel III framework revolves around a minimum requirement on the capital ratios and is enacted in legislation on the national level. In essence, the focus of regulation has been the risk of the individual bank.

Recent history and academic research have proved this focus to be a big regulatory issue. Systemic risk is a concept that accounts for the effects that any individual bank failure has on other banks and therefore on the banking system as a whole. Systemic risk is created endogenously by the existence of interbank relationships, feedback effects and other externalities. Hanson *et al.* (2010), concludes that the regulatory framework has been too microprudential in nature because current regulation is partial-equilibrium in its concept, aimed at preventing costly failure of individual banks. In response to this regulatory shortcoming, the concept of macro-prudential regulation has emerged. The latter do by definition account for individual bank risk as well as systemic risk.

More specifically, the concept of a chain not being stronger than its weakest link is too simplistic in the context of financial regulation. Since banks are limited liability companies but their failures are usually resolved by the government footing the bill, it is in the best interest of society to use regulatory mechanisms that align bank incentives with the general public as much as possible while maintaining an efficient and functioning financial system.

When regulation prove insufficient and banks actually do fail to cover their losses, precise measures of distress costs are hard to find but indicative estimates do exist. For example, Englund (1999) estimated the costs to the tax-payer under the 90s crisis in Sweden. In other countries costs of shoring up a financial system has ranged between 0% and 50% of GDP in previous crisis periods according to Reinhart & Rogoff (2009).

An alternative measure proposed in literature is the estimated potential output lost in perpetuity, presented in Boyd *et al.* (2005). Using this approach, the costs of the financial crisis that hit Sweden in the 1990s is estimated at 7.5% of the discounted value of future GDP. Due to these high costs associated with financial breakdown, governments are rarely willing to sit by. Hence, there is an implicit guarantee of being bailed out, in the event of a crisis, in most countries across the globe. To optimally align incentives, banks' individual capital requirements should account for the systemic risk inherent in the financial system.

Scenario stress testing is the main tool currently used in monitoring stability and is applied by many different parties. It is commonly employed to determine what macroeconomic scenarios could cause a systemic crisis (see, Misina & Tessier (2007)) and evaluate the current state of a financial system of some scope. The importance of stress testing is widely recognized, however, in the wake of the recent financial crisis, macroprudential practitioners agree on that stress testing could not enforce an adequate policy response (see Haldane (2009), Cihak (2007) and Galati & Moessner (2011)). We believe that capital regulation based on macro prudential risk measures could prove to be the best alternative, and will attempt to evaluate different measures using simulations.

In Wagner (2010), a model of the banking system was presented to illustrate the dire effects of banks diversifying. The heart of the issue is that when the correlation of pay-offs, in particular the negative pay-offs, is non-zero, the risk of a systemic collapse becomes apparent. In his version, the pay-offs and correlations were lines of business but it is equally applicable to banking portfolios. However in reality, compared to the Wagner model, banks are heterogeneous and thus differ in size and risk which increases complexity.

The rationale for reform of bank regulation should be that the higher the probability of a bank causing a systemic event, the more capital should this bank hold in order to target the endogenously created systemic risk instead of incentivizing banks to diversify and potentially increase risk. Wagner raises the concern of higher capital requirements incentivizing banks to seek riskier investments, i.e. shift to riskier assets. This relates to how regulation should account for the interconnectedness and size of banks. The current scope of regulation is therefore insufficient from a macroprudential stand-point.

In augmenting the framework of bank capital regulation, or introducing alternative measures, two questions are of main concern:

1. The total amount of capital needed in the system, determining the aggregate shock it could withstand, and

2. How to optimally distribute capital among the parties in the system

To limit the scope of our thesis our focus is not on the prior, which is chosen by the banks in isolation subject to a minimum regulatory threshold, but rather the latter, which is an allocation problem. We ask the question if there is any macroprudential allocation rule that is more efficient than the current regime, both in terms of loss risk but also incentivizing behaviour.

We will apply capital allocation frameworks on the Swedish banks, based on a number of thoroughly researched macro-prudential risk measures. The aim is to evaluate how appropriate and effective these risk measures would have been in previous periods representing different states of the economy as well as different states of the chosen banks. Furthermore, we attempt to explain differences in risk contributions across banks with the heterogeneous nature of banks. We will also evaluate the validity of common arguments such as the importance of bank size to risk and the related debate on classifying systemically important banks within the G-SIB framework (see, BCBS (2009)). To our knowledge this is the first study that derives macro-prudent capital requirements, unambiguously accounting for the endogeneity of systemic risk and applying these to historical data on the Swedish banking system.

The Swedish banking system is composed of over a dozen counterparties but clearly dominated by four publicly traded banks. These four encompass almost 80% of total bank assets in the economy which tells of high concentration. With total assets approximating 400% of GDP, the Swedish banking system is a behemoth in comparison to the Swedish economy (yet not unparalleled in other countries), which is of importance in a potential bail-out scenario.

To simplify our model and optimize data availability we select the four large banks; SHB, Nordea, SEB and Swedbank, to proxy the Swedish banking system as a whole. Swedbank has its roots in the early 19th century but its current form is a result of a series of consolidations of troubled Swedish savings banks in the Swedish financial crisis in the 1990s. SHB was founded in Stockholm back in 1871 and has since established itself as one of the leading Nordic banks. SEB was founded through the merger of Skandinaviska Banken and Stockholms Enskilda bank in 1972, while Nordea was created through a merger of four Nordic banks in 2001. By and large, all of the banks have either survived a number of severe crisis events or emerged from them. The banks have also grown out of Sweden into several adjacent markets, with Nordea being more Danish and Finnish than Swedish measured in assets. However since they are all headquartered and incorporated in Sweden it is where the regulatory burden lies. We primarily use data extracted from quarterly reports from which each bank's balance sheet composition, income statement, sectoral and geographic credit portfolio exposures, and credit losses have been extracted.

In this paper we employ an approach similar to that used by Gauthier *et al.* (2012), in which an iterative process is applied to find the fixed point solution to the problem regarding optimal capital allocation. We solve for this fixed point in four historical points in time representing important events for the broader economy as well as the banks. To explain the importance of a fixed point solution, we need to distinguish our approach from *risk attribution* which is merely a task of measuring overall risk as an exogenous entity and distributing it properly among the banks. Our approach however, is a dynamic problem, in the sense that, reallocating the capital endowment within a system changes the overall risk of the system in addition to that of the individual banks. Therefore, estimating macroprudential capital requirements is by virtue a fixed point problem. It is due to the dynamism of the fixed point problem that we need a form of operational model of the banking system to keep track of bank behaviour and balance sheets. This more meticulous approach is the prudent alternative when looking at the macroprudential capital requirements as a serious policy candidate for real world application. To exemplify, risk attribution would encompass calculation of risk measures on the given parameters of a certain period and the only useful analysis could be the ex post risk that the banks have contributed. By using risk allocation in our dynamic context, we will redistribute bank capital among the banks to minimize risk represented by the different measures. This could imply that increasing the risk of some banks by moving capital to other parties is rational as long as the net effect on systemic risk has decreased. Such a redistribution of bank capital obviously have no useful application in reality but is very useful to evaluate the efficiency of the different risk measures.

To explain and evaluate the different macroprudential capital requirements, we have divided the proceedings into three sequential parts. First we simulate the macroeconomic conditions and record the corresponding credit portfolio losses under each selected time period. Second, the banks' reaction to the losses from the first step is modelled to determine the propagation caused by Asset Fire Sales (AFS) and direct contagion between banks. In the third and final step we compute the macroprudential risk measures and reallocate capital according to the capital requirement rules for simulations of a counterfactual reality where capital is allocated using different rules.

Having completed these steps we evaluate current regulation and suggested complements and provide inference of the special conditions valid for the Swedish banking system. Of importance is analysing applicability and feasibility of the macro-prudential risk measures as regulation. The rest of the paper is organized as follows: Section 3 contains a detailed and focused literature review. Section 4 describes the procedures used to derive macroprudential capital requirements. Section 5 contains a description of the data used and a critical discussion of data sources. Section 6 outlines our results and main findings and Section 7 concludes our analysis.

2 Literature Review

In this literature review we focus on the main building blocks of our analysis, *credit losses*, and *macroprudential capital requirements*. Together, these provide a solid understanding of our paper and justify assumptions made.

2.1 Credit Losses

Financial indicators are commonly linked to macroeconomic variables when simulating credit loss distribution. As outlined by Misina *et al.* (2006), there are two main approaches to relating financial indicators (i.e. sectoral default probabilities) to macroeconomic variables:

- the Balance-sheet approach, popularized by Wilson (1997a,b), and
- the Portfolio-approach, based on the Merton (1974) credit risk model

Both approaches seek to explain a set of financial indicators in terms of some underlying risk factors. In the majority of the literature associated with stress testing aggregate credit risk, macroeconomic shocks are assumed to affect financial institutions through their effect on sectoral default probabilities. While the precise links and circumstances vary, Jimenez & Mencia (2007) provides a good platform, linking default probabilities to growth in GDP and changes in the three-month interest rate. Similarly, Virolainen (2004), models default probabilities on GDP, interest rates and corporate indebtedness in Finland. However, compared to our approach, these focus on the aggregate credit portfolio of the economy while we explicitly model that of each bank.

Under the asset-pricing oriented *Portfolio approach*, assets of an institution, sector, or similar, are grouped into a portfolio for which certain risk characteristics are used to find a loss distribution. Initial methods used forward-looking equity prices while more recently, models using contemporaneous industry- or firm-specific default rates are growing in popularity. The underlying idea is to relate the portfolio loss distributions to a set of macroeconomic variables, and find what effect changes in these variables have on the loss distribution. A frequently employed version is Moody's

KMV framework that utilizes a historical database of corporate default rates and credit rating history to statistically estimate the risk of any given company defaulting. This approach is applicable primarily for actively traded assets. Corporate loan portfolios of Swedish banks do not fit this description, hence, we will not explore this approach any further.

Under the Wilson (1997a,b) approach, balance-sheet indicators are modeled in terms of macroeconomic variables with the purpose of directly tying corporate sector default rates to macroeconomic indicators. Chosen financial indicators as well as the chosen macroeconomic variables vary across applications. The macroeconomic variables most commonly incorporated are GDP, short-term interest rates, inflation measures and unemployment rates. The bulk of the studies use a single indicator, for example: Dey (2006) uses returns on equity, Hoggarth *et al.* (2005) writeoffs-to-loans ratio, and Kalirai & Scheicher (2002) loan-loss provisions. An interesting adjustment, introduced by Monnin (2005) and Illing & Liu (2006) and used in Misina & Tkacz (2008), is to replace individual indicators with a single financial stress index (FSI) composed of both balance-sheet and financial indicators, and to explain the index in terms of macroeconomic variables.

It is also worth mentioning that the popular Credit Portfolio View (CPV) model by *McKinsey and Associates* is built on the above mentioned balance-sheet approach. The CPV hold default probabilities dependent on a set of macroeconomic variables' future values that are subsequently used to derive loss distributions. However, this approach is more suited for traded asset classes with robust data. Virolainen (2004) and Sorge & Virolainen (2006) uses an approach similar to this model for assessing aggregate credit risks in the Finnish banking sector, which is similar to the Swedish banking system, while Gauthier *et al.* (2012) apply their version on the individual level for Canadian banks. The criticism of classic stress testing introduced during the recent crisis has led to the development of a new generation of stress testing models. For examples of such models we refer you to Foglia (2009) and Yang & Tkachenko (2009).

2.2 Macroprudential Risk Measures

In Borio (2002), it is argued that strengthened macroprudential regulation is required to improve the defence against financial instability going forward. He further highlights the important distinction between measuring contributions to risk of individual banks (cross-sectional) and measuring the evolutions of systemic risk over time (time-dimensional). However, Wagner (2009) argues that the lack of this systemic focus in regulation is a result of the poor theoretical foundation for such regulation.

To incorporate systemic risk, macroprudential regulation requires methods to properly measure systemic risk inherent in a financial system. Value at Risk (VaR) is a widely used tool for measuring risk, and is defined as the worst expected loss for some time horizon at a given statistical level of confidence. However, this measure fails to incorporate all aspects of systemic risks. Different VaR extensions and adjustments are presented and discussed in Jorion (2007). The most important extensions include Component VaR ($CVaR$), Incremental VaR ($IVaR$), Marginal Expected Shortfall (MES) and the concept of change in Conditional Value at Risk ($\Delta CoVaR$). Löffler & Raupach (2011) examine the reliability and robustness of some of these.

Due to the restrictions of above mentioned risk measures, recent literature has proposed new methods for measuring the systemic risk that is based on observed stock returns, most prominently Acharya *et al.* (2010). However, they acknowledge the problem of finding a systemic risk measure that is practically relevant and completely justified by the theoretical frameworks available, similar to Wagner (2009). The gap between practical needs of regulators and theoretical models has been so wide that suboptimal measures, such as VaR, have persisted as the main measurement. In summary, there are many different systemic risk measures proposed in literature. However, as mentioned by Sylvain *et al.* (2013), many of these are untested and complex by nature, thus the quest for better systemic risk measures continues.

3 Theory

In this section we will present the theory underlying the methods applied in this thesis and discuss their advantages as well as short-comings. We start by describing the basics of macro-prudential regulation, the relevant risk measures and their application as capital regulation for a proper frame of reference. This is followed by an explanation of the process of credit loss simulation based on macroeconomic indicators. After the description of credit loss simulation we turn to a detailed description of our model of the banking system. The output from the credit loss simulation and bank system model will then be classified and accompanied by an explanation of how to interpret its function. Finally, based on the output from previous steps, designated macroprudential capital requirements will be calculated and form the basis for the reallocation rule.

3.1 Capital requirements

We assume that for a given vector of bank capital endowments $C = (C_1, \cdots C_n)$, the banking system's joint loss distribution is represented by $\Sigma(C)$. Using a given capital allocation mechanism $f(\Sigma)$, we can allocate the overall risk, and effectively capital, across individual banks. For each given risk allocation mechanism f, we define a macroprudential capital requirement C^* as;

$$C^* = f(\Sigma(C^*)) \tag{1}$$

which can be compared to risk attribution that is concerned with calculating $C^* = f(\Sigma(C^0))$ for some currently observed level of capital C^0. The difference between the static risk attribution and the dynamic fixed point method we use can be substantial for the stability of the financial system. In mathematics the fixed point is often referred to as an invariant point. To measure risk we will take stance in the economic capital realm of value-at-risk, or VaR, which is a uniform measure of risk accepted as the paradigm by most of the developed world.

3.1.1 Value-at-Risk

Since April 1995, the Basel Committee on Banking Supervision has required commercial banks to calculate VaR for most of their assets as basis for capital adequacy requirements. Since then, banks have had to report their VaR to regulators on a daily basis and keep a designated amount of capital as safety for that risk. In short, VaR can be explained as the worst expected loss in a given time horizon at some given statistical confidence interval. To compute it one therefore needs to know statistical properties of a portfolio and its components, such as the moments and distributional properties of its return. A very good presentation of VaR and its derivation is provided in Jorion (2007).

The most straightforward application is that on actively traded portfolios of listed assets, where prices changes frequently and the statistical aspects of computing VaR are easily accessible and trustworthy. However, Yamai & Yoshiba (2005) highlight a number of important shortcomings of VaR:

1. VaR takes no notice of loss beyond the VaR level as it only measures percentiles of profit-loss distribution, and

2. VaR is not subadditive and thus non-coherent

Consequently, since the emergence of VaR, different versions and extensions have been designed to suit other applications, for example credit risk. We will not employ a VaR based capital requirement but focus on its evolutions that better account for systemic risk.

3.1.2 Component VaR

Component VaR measures each bank's contribution to overall risk, calculated as the beta (see below) of the losses for each bank with respect to the losses of a portfolio of all banks - which is why it is often referred to as beta, as used in asset pricing and portfolio management. Portfolio VaR is defined as the sum of all banks' individual VaR, $VaR_P = \sum_{i=1}^{n} VaR_i$. In calculating Component VaR, the underlying theory of Marginal VaR and Incremental VaR is applied. For a more detailed description and derivation of the measure we refer to Jorion (2007).

To estimate the measure, we use the losses $l_{i,s}$ of each bank i in each scenario s and the losses of the system as a whole, written as $l_{p,s} = \Sigma_i l_{i,s}$. Then, similar to classic asset pricing theory beta is calculated as $\beta_i = \frac{cov(l_i l_p)}{\sigma^2(l_p)}$. Letting C_i be the Tier 1 capital observed for each of the banks, we reallocate it according to a risk sharing rule built on the calculated β_i such as:

$$C_i^{\beta} = \beta_i \sum_{i=1}^{n} C_i \tag{2}$$

where C_i^{β} is the capital of each bank reallocated under the Component VaR rule. A convenient property is that the sum of the banks' betas will sum to one implying that redistribution is straightforward.

3.1.3 Incremental VaR

By aggregating the individual losses across banks in each scenario we find the joint loss distribution for the whole system. In simulation, we use a confidence level of 95% and $10,000$ scenarios. The portfolio VaR, VaR_p therefore becomes the 500th largest loss of the aggregate losses l_p. Next, we repeat the procedure of computing VaR of the joint distribution, but excluding bank i. This yields VaR^{-i} which is the 500th largest value as $l_s^{-i} = \Sigma_{j=1,j\neq l}^{n} l_{j,s}$ which is used to find the Incremental VaR for bank i as:

$$iVaR_i = VaR_p - VaR^{-i} \tag{3}$$

Effectively, the incremental VaR can therefore be interpreted as the increase in risk, measured in VaR, generated by the inclusion of bank i in the system.

Compared to Component VaR, which computes the marginal impact of increasing bank i's balance sheet, Incremental VaR represents the risk that the inclusion of an additional given bank adds to the total risk inherent in the financial system. The obvious disadvantage of Incremental VaR in this application is that the sum of $iVaR$ is not the VaR of the system and therefore the capital allocation rule must be scaled:

$$C_i^{iVaR} = \frac{iVaR_i}{\Sigma_i iVaR_i} \sum_{i=1} C_i \tag{4}$$

3.1.4 Marginal Expected Shortfall

Marginal Expected Shortfall (MES) is defined as the conditional expectation of losses beyond the VaR level such as described in, Acharya *et al.* (2010):

$$MES_i = -E(l_i | l_i < -VaR_i) \tag{5}$$

They explain that one can circumnavigate the main shortcomings of VaR by adopting MES. However, as with VaR, there are certain disadvantages with MES. More specifically, when the underlying distribution is fat-tailed, the estimation errors of MES are much larger than those of VaR. Consequently, Yamai & Yoshiba (2005) conclude that the most effective measure is a combination of VaR and MES. They suggest that the use of a single risk measure should not dominate financial risk management.

The capital allocation rule based on MES is scaled similar to incremental VaR and is defined as follows:

$$C_i^{MES} = \frac{MES_i}{\Sigma_i MES_i} \sum_{i=1} C_i \tag{6}$$

3.1.5 Benchmark Capital Requirements

In analysing the macroprudential risk measure based reallocations of bank capital we have a suitable benchmark provided by the banks themselves - their actual risk-weighted assets. As the banks in Sweden were relatively unharmed by the recent economic turmoil and even issued equity, they are well-capitalised with capital levels far above the minimum requirements. By using the reported risk-weighted assets (RWA) and Tier 1 capital, we can compute a benchmark for each period:

$$C_i^{Basel} = \frac{RWA_i}{\Sigma_i RWA_i} \sum_{i=1} C_i. \tag{7}$$

Such a requirement appropriately evaluates the macroprudential performance of the Basel framework, separated from the individual banks' preferred excess capital levels. In fact, due to the previous equity issues, comparisons based on Tier 1 capital levels within our framework would be severely distorted both over time and across banks.

3.2 Macroeconomic Credit Risk Model

Banks today are increasingly interested in, but also required to monitor their credit portfolios very closely. The goal of the credit loss modelling is to arrive with the loss distributions on which the rest of our analysis will build on. Banks use a plethora of internal risk assessment models for the purpose of credit risk estimation, that according to Frye & Jacobs (2012), by-and-large, share four key components: probability of default, loss given default, exposure at default and loan maturity. We will define and present the theory underlying the first three components. This section will explain how the macroeconomic environment is connected to loan loss simulations. Below follows a detailed description of the process and assumptions underlying credit risk modelling.

For each bank b, the losses incurred due to default of some individual companies in sector s, is:

$$El_t^{s,b} = \pi_t^{s,b} \times \delta_t^{s,b} \times l_t^{s,b} \tag{8}$$

and the expected loss of the portfolio of assets is:

$$El_t^b = \sum_{s=1}^{S} \pi_t^{s,b} \times \delta_t^{s,b} \times l_t^{s,b} \tag{9}$$

where π is the default probability in industry s at time t, δ is the individual bank b's portfolio exposure to industry s at time t and l is some loss given default in industry s at time t so that the total losses in the system equals:

$$El_t = \sum_{b=1}^{B} El_t^b \tag{10}$$

We will now sequentially break down the three components of Equation 8 and explain them in detail to illustrate how we arrive with the simulated losses.

3.2.1 Probability of default

Chan-Lau (2006), divide the techniques of estimating default probabilities into two categories:

1. market-based techniques, which rely on security prices and ratings, and

2. fundamental techniques, which rely on financial statement data and economic factors

Furthermore, Chan-Lau (2006) reviews a number of different techniques for estimating default probabilities using market-based information. These techniques can be applied whenever there is a relatively liquid secondary market for securities issued by the obligor of interest. However, the author highlights a common critique raised against market-based default probabilities - that they do not reflect real-world probabilities because they are likely to be upward biased due to the existence of default risk premium. In a separate paper, Chan-Lau (2006) reviews fundamental techniques used to estimate default probabilities. These techniques are particularly useful when the obligor of interest do not have publically traded securities. In this sense, these techniques are appropriate for default probabilities estimation associated with loans, in particular the balance sheet approach we have opted for. Another aspect highlighted is that macroeconomic factors are clearly connected to default rates which supports our choice of method.

More specifically, we assume that the default probability in each industry is a function of some set of macroeconomic variables such that:

$$\pi^s = f(x) \tag{11}$$

where x_t is a vector of macroeconomic variables. One issue is finding a suitable functional form for f which effectively relates macroeconomic variables to default probabilities. Since our dependent variable is a probability, using a linear relationship would in general be considered unsuitable. Instead, we specify it as an odds ratio, $\frac{\pi_t^s}{1-\pi_t^s}$, for which a linear relationship of the underlying macroeconomic variables is prudent:

$$\ln(\frac{\pi_t^s}{1-\pi_t^s}) = \mathbf{X}_{t-l}\beta^s + e_t^s, s = 1, \cdots, S \tag{12}$$

in which $X(t-l) \equiv [1, x_t^1, \cdots, x_{t-L}^1, \cdots, x_t^M, \cdots, x_{t-L}^M]$ is a lagged series of the macro variables, including an intercept. It is therefore an $1 \times (ML+1)$ sized matrix, where L is the number of lags used and M is the number of series included so that $\beta_s \equiv [\beta_0^s, \cdots, \beta_{ML}^s]$.

To build the different $\mathbf{X}(t-l)$ used in each scenario, we need to estimate its statistical properties and we opt for a VAR set-up. To determine the appropriate lag lengths we use the Akaike Information Criterion (AIC), Hannan-Quinn Information Cirterin, the Schwartz-Bayesian Information Criterion (SBIC), and Likelihood-Ratio Test. In general the original functional form can be written as:

$$X_t = \phi_1 X_{t-1} + \cdots + \phi_p X_{t-p} + u_t \tag{13}$$

After choosing the lag order of the model, we estimate the model of Equation 12 and find estimates for $\hat{\beta}$ and $\hat{e}$. After estimating, $\hat{\beta}$,($\hat{\phi}_1, \cdots, \hat{\phi}_p$) and $\hat{\Sigma_e}$, we can construct a T period long path of X, which models the macroeconomic factors in previous periods as:

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

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

$$\cdots$$

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

The resulting N, K-period long, paths for each scenario represent the prevailing macroeconomic conditions for which different scenarios of probability of default exists at each period of time t. Using these, we have the X_t^s

as described earlier, and by applying the estimated $\hat{\beta}^s$, $(\hat{\phi}_1, \cdots, \hat{\phi}_p)$ and $\hat{\Sigma}_e$ that we retrieved estimating the original series, we can compute N series of the log-odds ratio. While default data is not publicly available bankruptcy statistics provide a good proxy.

3.2.2 Exposures

The second component used to determine losses related to Equation 8 and the banks' credit exposures to the different industries. This step is important and effectively utilizes the banks' sectoral lending exposures to construct a proxy for the credit portfolio as a whole and introduce further heterogeneity that decreases modelling risk of depicting banks as being too homogeneous.

When only using plain vanilla loans as credit instruments in the portfolio under consideration, as proposed by Misina *et al.* (2006), defining exposure is relatively easy and most commonly coincides with the book value of the same assets. Through the inclusion of off-balance sheet exposures, derivatives and other more exotic contracts it becomes far more complicated. Especially since it is not often clear who is the ultimate counterparty, such as in over-the-counter (OTC) derivative positions (see Izzi *et al.* (2012)). In stress-testing literature, it is more common to focus on plain loans, a path which we will follow here.

3.2.3 Loss given default

The final component linking the probability of default and exposure to actual losses is the loss given default l. That is, what amount of money or percentage of exposure is lost to the lender in the event of default of an obligor. For the individual obligor, loss given default at time t is defined as:

$$l = 1 - rr$$

where rr is the recovery rate, representing the amount of money recovered from a loan in the event of its default. Since we are using book value of exposures, it is appropriate to define the recovery rate as a percentage of the par value of the loan. For a given industry, an average recovery rate is most often applied on loans in that industry. The recovery rate for each of the banks' portfolio is defined in a similar manner, such that the average loss given default is valid for the modelled default in the entire credit portfolio.

In comparison to the well-researched default probabilities, exposure at default and loss given default lag behind in terms of both theoretical and practical insight according to Yang & Tkachenko (2012). Several papers have scratched the surface of the usual problems and restrictions associated with EAD and LGD modelling, some are presented in Marrison (2002) and Gupton & Stein (2002). The concept of recovery rate is easy to grasp but problems and challenges arise in its estimation. de Servigny & Renault (2004) discuss these thoroughly, but in summary, the many definitions of what constitutes a default is the main culprit. In the Basel II framework, a default was defined as payment or interest 90 days past due on financial instruments or provisioning but with the possibility of banks' internal assessment of a firm. The legal definition is on the other hand related to the bankruptcy of a firm, whereas the market definition links defaults to financial instruments and corresponds to interest or principal payment past due.

Apart from the definition of bankruptcy, recovery rates depend on a number of factors, such as debt renegotiation, collateral, seniority, industry and legal framework of the obligor. To complicate matters further, there is no commonly used measure for level of recovery. One definition of recovery rate is what the debtor will recover after debt is settled, another is the price of debt immediately after default, but the latter is only applicable to publicly traded debt.

According to Mora (2012), it is more commonplace to either assume constant recovery rates, or draw them stochastically from a particular distribution, independent of prevailing default rates. While work in the area is limited, it seems recovery rates are not constant and that there is a link between default rates and recovery rates. In Sorge & Virolainen (2006) and Gauthier *et al.* (2012) they were, however, assumed constant at 33%.

In light of the low added value from more thorough estimation of recovery rates, and the relevance of both Sorge & Virolainen (2006) and Gauthier *et al.* (2012) to our application, we will also assume constant recovery rates at the same level.

3.2.4 Generating Loss Distributions

Having determined the basic components used to simulate credit losses:

- default probability as a function of macroeconomic factors
- exposures for each bank to each sector
- constant loss given default, assuming homogeneity across industries

we have a solid platform for continuing our search for the credit loss distribution. The procedure that we employ to simulate credit losses entails:

1. Generating N paths for the macroeconomic variable as described in Equation 13
2. Generating the random variables for each sector s using the variance-covariance matrix given by $\hat{\Sigma}_e$ in accordance with the method presented in Wilson (1997a,b), where one generates a vector $\mathbf{Z} \sim N(\mathbf{0}, \mathbf{1})]$ and calculate $\hat{e} = A'Z_t$ such that $\hat{\Sigma} = A'A$.
3. Substituting the resulting macroeconomic paths and random variables into the previously defined $\ln(\frac{\pi_t^s}{1-\pi_t^s})$, yielding the odds ratio of each industry at each point in time. The probability of default can then be calculated from this odds ratio.
4. For each simulated sectoral default probability, on each path, insert the components into the equation to find expected losses:

$$El_t^s = \pi_t^s \times \delta_t^s \times l_t^s \tag{14}$$

By aggregating the expected losses at time t across industries, the credit portfolio expected losses are found as:

$$El_t = \sum_{s=1}^{S} \pi_t^s \times \delta_t^s \times l_t^s \tag{15}$$

By repeating these steps for a large number of realizations of generated π we will obtain the sought after loss distribution of designated size $N \times K$.

3.3 Model of the Banking System

A network model of interbank claims is solved to find the fixed point using iterations that determine ultimate losses. At this point each bank's risk contribution equals each bank's optimal capital requirement by some risk measure, and we can assess how the overall risk of the banking system changes when capital is redistributed between the banks. This network model unambiguously models contagion effects through network and asset fire sales externalities and has been built to suit the data available. We account for the interbank market through two main channels:

1. *Asset Fire Sales (AFS)*, and
2. *Direct Contagion*

After a period for analysis has been chosen, the first step is to expose the banks' credit portfolio to the credit portfolio shocks, which is the El_t^s modelled earlier, now represented by ε_i. In summary, for losses large enough to wipe out a sufficient part of the capital buffer, regulatory requirements cannot be met unless the balance sheet is shrunk and the affected bank sells assets. Given an inelastic demand curve for these assets, prices will fall and cause mark-to-market losses for the other banks holding the same class of assets.

The side-effect of other banks' capital position being hurt enough to force them to sell assets as well is what initiates the stereotypical downward spiral in asset prices. Our approach to modelling these AFS externalities is derived from Cifuentes *et al.* (2005). In the case of a bank defaulting and thus failing to pay its liabilities in the interbank market, other banks are hurt by direct contagion as they are forced to write-down their claims on the defaulting party. This network externality is modelled explicitly through a clearing mechanism for the interbank market. We begin by explaining the network model representing the interbank market.

3.3.1 The network model

Similar to Gauthier *et al.* (2012) we build our model of the banking system on the model developed by Eisenberg & Noe (2001). However, we modify it in several aspects, most prominently to include bankruptcy costs and uncertainty in line with Elsinger *et al.* (2003). This step is the key in determining the net-worth of the banks simultaneously and makes inference on losses from different sources. The ingenuity of the model is that it lets us model all multilateral exposures among the banks across scenarios, instead of mapping each of the bilateral exposures sequentially. This decreases computation by a factor N, which is the number of nodes modelled. For large systems with more than four nodes this would be extremely important.

The suggested method to find this vector involves employing a so called *fictitious sequential default algorithm* which is a process of dynamic adjustment, introduced in Eisenberg & Noe (2001), where the existence and uniqueness of such a payment clearing vector is proven. Since the solution in our case is non-linear due to AFS externalities we will apply an iterative approach. In each round of iteration, an attempt is made to clear the system assuming that all non-defaulting nodes from the previous round will stay in their survival state. The algorithm is terminated either when all of the banks have defaulted, or when the adjustments to the banks' net-worth are very small. The fictitious sequential default algorithm produces a natural measure of *systemic risk* as exposures of a given node in the system is affected by defaults of other banks and losses are exacerbated by effects prevalent in real-world banking systems.

In essence, the approach is based on limited liability and absolute priority; constraints that in combination means that either the creditors are paid in full, or any residual value is distributed proportionally within a certain class of creditors. For the sake of simplicity bank balance sheets are reclassified to suit modelling needs.

In detail this means that for a set $\mathcal{N} = \{1, \cdots, \mathcal{N}\}$ banks, we classify the balance sheet of each bank $i \in \mathcal{N}$. First of all, the assets are divided into external assets A_i, which include the claims external to the banking system, and inter-bank assets corresponding to other banks within the system, denoted x_i. The assets within A_i should be interpreted as the banks' non-bank loans and securities. Furthermore, each bank uses funding from both within and outside the banking system. Senior debt and deposits from outside investors are grouped in D_i while the obligations to other banks $j \in N$ are represented by their nominal liabilities x_i. That means that we distinguish the banks' internal and external funding balances, $(A_i - D_i)$ from $(x_j - x_i)$ and the owners' equity contribution E_i, which the losses will ultimately accrue to.

In the numerical analysis, the loan portfolio A_i is exposed to a shock ε_i, generated from simulations in Section 3.2.4. The residual value of the bank is by definition the outside assets minus the outside liabilities adjusted for the interbank assets and liabilities after adjustments for payments to and from the banking system, $A_i - \varepsilon_i - D_i + x_j - x_i$. If the residual value becomes negative the bank is insolvent and a proportial bankruptcy cost Φ is incurred on the residual value. Assuming seniority of outside debtors, any remaining value after these have been paid off, are distributed among the creditor banks. The total initial obligations of bank $i \in \mathcal{N}$ to the rest of the system is denoted $d_i = \Sigma_{j \in \mathcal{N}} X_{ij}$, and we define a new matrix $\Pi \in [0, 1]^{N \times N}$, containing elements π_{ij} that is found by normalizing x_{ij} by total obligations:

$$\pi_{ij} = \begin{cases} \frac{x_{ij}}{d_i} & \text{if } d_i > 0 \\ 0 & \text{otherwise} \end{cases}$$

To comply with the AFS method designed by Cifuentes *et al.* (2005), we further need to divide each banks' external assets A_i into liquid and illiquid assets. The liquid assets are denoted λ_i and constitutes cash and government securities. For the sake of simplicity, the exposures between banks are also assumed liquid but kept separated. Assets not included in λ_i are deemed illiquid and denoted e_i. The price of liquid assets are constant and normalized to 1 while the price of e_i, p_i, is determined in equilibrium.

The interbank clearing vector is represented by X^*. This component takes the aggregate payments of each bank to the interbank market, limited liability constraints and seniority into consideration. An important aspect here is the proportional sharing of losses in case of default. As in David & Lehar (2011), we also include the liquidation cost at this stage and define each component x_i^* of X^* as:

$$
\begin{aligned}
x_i^* = \min\Big[d_i, \max\Big((p_i e_i + \lambda_i - \varepsilon_i) \\
\times \Big(1 - \varPhi \mathbf{1}_{\left[p_i^* e_i + \lambda_i - \varepsilon_i + \sum_j \pi_{ij} x_j^* - D_i < d_i\right]}\Big) \\
+ \sum_j \pi_{ij} x_j^* - D_i, 0\Big)\Big] \quad (16)
\end{aligned}
$$

This guarantees that a bank's aggregate payment x_i^* to the interbank market will always be non-negative and not more than the face value of its obligations d_i. This also implies it will neither exceed its net wealth, calculated as $p_i e_i + \lambda_i - e_i$, less the liquidation costs $\varPhi$ conditional on default, plus payments from the other banks $\Sigma_j \pi_{ij} x_j^*$, minus the bank's senior deposits D_i. This guarantees that the limited liability constraint is not violated.

Due to the price dynamics of the illiquid and liquid assets external to the system, banks will sell illiquid assets for cash and cash equivalent assets to comply with regulatory requirements on capital ratios. We will use the basic capital ratio constraints put forth by the Basel II Accord. This means that since liquid assets are assumed to carry a government guarantee, they have a zero risk-weight in this model. Illiquid assets on the other hand are assumed to carry the average risk-weight of each bank i's illiquid assets, ω_i. The ratio of Tier 1 capital to risk-weighted assets of each bank is a prespecified minimum r^*, which a bank cannot violate. To comply with the minimum r^*, the bank is forced to sell assets for losses ε_i above some level. This minimum capital requirement ratio constraint is given by:

$$\frac{\upsilon(p_i e_i + \lambda_i - \varepsilon_i + \Sigma_j \pi_{ij} x_j - x_i - D_i)}{\omega_i p_i (e_i - s_i) - \varepsilon_i} \geqslant r^* \quad (17)$$

The numerator is the residual value of the bank, weighted by a factor υ, which is the ratio of reported Tier 1 capital to equity E_i of bank i [1]. Notice also that interbank claims and liabilities are calculated in realized terms. The mark-to-market risk-weighted value of the banks' assets, after any sale of illiquid assets s_i, are found in the denominator. Selling illiquid assets have effect in this set-up as the denominator decreases due to the sale, as these assets carry a risk-weight while the cash received carry a risk-weight of zero, the numerator remain unchanged, and thus selling illiquid assets improves the capital ratio. To include heterogeneity in asset prices across banks, the price of illiquid assets, p_i, is assumed to be a linear function of the equilibrium average price p and the deviation of each bank's regulatory risk-weight from the average across the system, ω, to find:

$$p_i = \min(1, p + (\bar{\omega} - \omega)\kappa) \tag{18}$$

where $\kappa > 0$ to ensure that assets sold by riskier banks receive higher discounts. In Table 14 in the Appendix we present the descriptive statistics of risk-weighted assets and the relationship to total assets. Average prices p are determined by the inverse demand curve for the illiquid asset:

$$p = e^{-\alpha\left(\frac{\Sigma_i s_i}{\Sigma_i e_i}\right)} \tag{19}$$

where α is a positive constant. Notice that s_i is divided by e_i in calculating average prices to make the pricing historically consistent as illiquid asset total changes. To include a floor in this pricing function we introduce a minimum price $p_{\min}$. Note also that the Eisenberg & Noe (2001) model is simplified by removing the cross-equity ownership aspect since this is not prevalent among the Swedish banks. The key take-away is that prices depreciate as more illiquid assets are sold. In the sensitivity analysis in Section 5.4 we present the scale of effects from the choice of α and κ [2].

[1] Equity is weighted to correspond to the minimum capital requirements in practice since these are not necessarily the same in all periods. These are not exchangeable in the formula as losses accrue to equity and not directly to capital

[2] After testing a range of values for the parameters α and κ we opted for using $\alpha = 0.4$ and $\kappa = 0.0005$ as the combination provided more consistent results over time, yet guaranteed some cases of losses spiralling to bankruptcies that we needed for

3.3.2 Aggregating losses

In each scenario, defined by a set of loan losses for the banks, we find for each bank i the smallest sale of s_i^* that guarantees that the minimum capital requirement is satisfied. For clearing in the interbank market, x_i^* is determined and the average price p_i^* is determined in Equation 19. The total losses $l_{i,s}$ for each of the banks in every scenario can now be computed for use in the macroprudential capital requirements such as:

$$l_{i,s} = \left((p_i^* e_i + \lambda_i - \varepsilon_{i,s}) \left(1 - \Phi \mathbf{1}_{[x_i^* < d_i]}\right) + \sum_j \pi_{ij} x_j^* - D_i - x_i^* \right) - v_i^0 \quad (20)$$

where,

$$v_i^0 = A_i + \sum_j \pi_{ji} d_j - D_i - d_i \quad (21)$$

This v_i^0 represents the net worth of a bank before any external shock or other exacerbating market effects. A scenario s is defined by a particular draw of $e_{i,s}$ of the bank specific shocks. The total losses are therefore efficiently calculated in isolation, by using net-worth after total losses less the net-worth of the bank before any losses are accounted for. Since book values are used, v_i^0 equals the actual C_0 reported equity capital.

A final remark is that in our search for a fixed point, we assume banks will shrink their asset portfolio to comply with minimum capital requirements, not issue equity. While it is hard to see an issue being completed in a severe distress scenario without government intervention it is definitely not impossible but very hard to incorporate within this modelling environment where we are looking for defaults. If a bank could always issue equity defaults would not occur.

By clearing the market for interbank claims and balancing the system from the initial shock, we record further information useful in analysing systemic stability, apart from the aggregate losses incurred by the banks. For example, the type of bankruptcy events and their relative importance which

further analysis of macroeconomic risk. Some alternative combinations are displayed for comparison.

have systemic implications. All in all, in each scenario, the banks in the system can reach five different states after the interbank market has been cleared:

1. *Survival*
2. *Fundamental default*
3. *Contagious default*
4. *AFS default*
5. *Combined Contagious-AFS default*

Survival is the obvious outcome where the equity reserves of the banks are sufficient to withstand the aggregate losses from the initial shock and the propagation of the other effects. We define a bank bankrupt when its interbank claims are worth less than their nominal amount ($x_i^* < d_i$), since these are assumed to be the most junior claims in this model. Fundamental default for bank i occur when it is unable to honour its promises assuming all other banks will pay their claims and that market prices for the illiquid asset is at par value ($p = 1$):

$$e_i + \lambda_i + \sum_j \pi_{ji} d_j - D_i < d_i \tag{22}$$

If a bank is not in fundamental default, by loosening the constraint on the price for the illiquid assets we define an AFS default as the event when:

$$\begin{aligned} e_i + \lambda_i + \sum_j \pi_{ji} d_j - D_i > d_i \quad \text{and} \\ p_i^* e_i + \lambda_i + \sum_j \pi_{ji} d_j - D_i < d_i \end{aligned}$$

A pure contagious default occurs only when bank i defaults due to the inability of other banks in the system to pay their claims such that:

$$\begin{aligned} e_i + \lambda_i + \sum_j \pi_{ji} d_j - D_i > d_i \quad \text{but} \\ e_i + \lambda_i + \sum_j \pi_{ji} x_j^* - D_i < d_i \end{aligned}$$

Finally, a combined Contagious-AFS default occur when:

$$\begin{aligned} p_i^* e_i + \lambda_i + \sum_j \pi_{ji} d_j - D_i &> d_i \quad \text{and} \\ e_i + \lambda_i + \sum_j \pi_{ji} x_j^* - D_i &> d_i \quad \text{but} \\ p_i^* e_i + \lambda_i + \sum_j \pi_{ji} x_j^* - D_i &< d_i \end{aligned}$$

This means that our network model will be able to capture the two most important properties: spillover effects and feedback loops, as well as their combination. The first emerges when the distress of one bank leads it to sell assets or default on its interbank claims which eventually results in negative externalities for the other banks. Therefore, the increase in a bank's PD will increase the likelihood of such events and thus also increase the PD of other banks in the system. The spillover effect makes the correlation of bank asset values dependent on the health of the system as a whole, as measured by the entities in it.

When all banks are healthy, AFS and interbank defaults are not likely to occur and the correlation of the asset portfolios are driven by correlation in the assets external to the system, e_i, which is the loan portfolios in isolation. When the AFS or contagion scenario occurs, all prices decrease and correlation approaches one. At the same time, with capital decreasing, the probability of AFS and contagion increases, and with them the ex-ante asset and default correlation. In this fashion, the insights made by Wagner (2010) are valid for the approach used in our analysis.

4 Data

Using non-public central bank data on credit portfolios and bilateral bank exposures in the Canadian banking sector, Gauthier *et al.* (2012) simulated credit losses and determined the relevant macroprudential risk measures for the Canadian banking sector. Their data is perhaps the best imaginable but nothing like it is available in our application. To conduct this study, we have instead used information from the banks' quarterly reports. The analysis is targeted on the most recent period, Q4 2012, but also involve three periods for reference:

- Q2 2009: representing a period when the system was exposed to extraordinary amounts of stress that eventually forced the banks to issue equity

- Q2 2007: being one of the last quarters before the havoc when markets were still at peak levels

- Q1 2005: the most recent period sufficiently normal to be used as reference

In the following sections we will detail the sources and use of data.

4.1 Interbank claims

Bilateral exposures between banks are the most important part in modelling propagation through the contagion channel. A matrix specifying all bilateral exposures would be optimal but since we only know the nominal interbank assets and liabilities for each bank we have to use a proxy. It is also assumed that the system encompass only the four large banks. We have thus estimated the bilateral exposures by assuming that the banks spread their lending and borrowing as diverse as possible across all other banks using what is called an entropy maximization algorithm, described in Blien & Graef (1997).

This method implies that banks diversify completely within the system and have no preferred partners. The banks as a group are however net borrowers in the interbank market in our sample as the liabilities are greater than the corresponding assets reported in the quarterly reports. Due to this we assume that there is a fifth party external to the system that holds the balance of what is left after the bilateral interbank assets has been matched with the liabilities, but is not part of the system as such.

A pitfall of this approach is that the severity of contagion could be underestimated and such suspicion is further affirmed by the fact that the banks have international activities that could also render losses not particular to the external assets. Such losses will never be incurred by the fifth party within this model, which is a limitation related to size of chosen system and, obviously, exposure data.

Even with perfect information this step requires significant consideration. For example, exposures fluctuate significantly over short periods, especially in times of distress, because of inherently short maturities on the interbank market. How to measure off-balance sheet exposures consistently with on-balance sheet assets and liabilities is another issue.

The varying characteristics and activities also have effect at this stage. For example, it is a very active foreign exchange counterparty which implies that SEB has a larger balance sheet exposure to other banks related to this activity relative to other banks of similar size. Reliance on deposit funding is another characteristic that varies across banks and the less risk prone, the more of the bank's assets are held in liquid and safe interbank assets. Such low risk behaviour could in fact be punished within our model as the interbank exposures are larger in nominal terms, making the bank more exposed to contagion.

4.2 Bankruptcy statistics

Using public data from Statistics Sweden, we first compile it to be historically consistent in reported time periods. We further collapse the data into 10 different sectors that best matches exposures reported by the banks. Descriptive statistics together with historical peaks, defined as 12-month rolling averages, for the entire period of Q1 2001 - Q4 2012 are presented in Table 1 below[3].

Table 1: Swedish corporate bankruptcy rates by sector (1999 Q1 - 2012 Q4)

Name	Number	Min	Mean	Max	Peak	Std. dev.
Construction	1	0.21%	0.31%	0.48%	0.40%	0.06%
Property & Real Estate	2	0.05%	0.09%	0.19%	0.16%	0.03%
Forest & Agriculture	3	0.00%	0.02%	0.03%	0.03%	0.01%
Manufacturing	4	0.12%	0.24%	0.39%	0.33%	0.07%
Transportation	5	0.11%	0.29%	0.47%	0.40%	0.08%
Public Sector	6	0.04%	0.08%	0.14%	0.12%	0.02%
Retail	7	0.23%	0.34%	0.46%	0.40%	0.05%
Renting & Other Fin.	8	0.08%	0.21%	0.39%	0.30%	0.07%
Services	9	0.08%	0.17%	0.26%	0.24%	0.05%
Utilities	10	0.04%	0.16%	0.55%	0.25%	0.10%
All		**0.12%**	**0.20%**	**0.27%**	**0.25%**	**0.04%**

Mean default rates vary significantly across sectors. As expected, sectors commonly depicted as less risky, for example Forest & Agriculture, Public Sector and Property & Real Estate, all have extremely low mean default rates and virtually no variation. Over a longer period Property & Real Estate would probably have a much higher variation and higher average values as well due to the Swedish crisis in the 90s - in which real estate assets were a big culprit. In stark contrast, Retail and Construction exhibit minimum default rates higher than the average across the sectors albeit with relatively low variation over time. Also, as expected, the more cyclical industries such as Transportation and Manufacturing, experience relatively higher variation in default rates over time. The Peak column represents the highest 12-month average within any sector. It appears that almost all of the sectors experience prolonged periods of high default rates

[3]Financial sector bankruptcies are excluded as these are modelled endogenously in our network model

at close to peak level except Utilities, where the maximum value possibly represent an extreme event, also expected due to relatively fewer companies in that sector could mean individual defaults boost statistics a lot.

In Figure 3 in the Appendix we compare historical default rates per sector to the macroeconomic factors. An important event clearly took place in early to mid-2009, where default rates increased substantially in the cyclical and more high-risk sectors, with a similar pattern in the bank-specific macro factors. This motivates our choice of using Q2 2009 as a period representing severe financial distress.

4.3 Credit Exposures

The credit exposures have been extracted from the banks' financial reports. However, inconsistencies in reporting exist over time which causes apparent problems. For example, in Table 16 in the Appendix, we have compiled the different sectoral classifications reported by the banks, the main issue is that the banks change their reporting practices over time and do not disclose the criteria used for sector assortation. This means that the sectors reported by banks do not match the sectors used for default statistics by Statistics Sweden. Further complicating the matter is that the sectors do not match across banks. This necessitates the reclassification into the 10 different master sectors we presented in Section 4.2 and is conducted to match the categorization of the default statistics. For the small balance of the credit portfolios not matching the sectors we create a residual "Other" sector for which average default rates is assumed appropriate. Historically the banks have reported exposures at different intervals. Swedbank for example publishes credit exposures in each quarterly report while Nordea excludes data on credit exposures in most quarterly reports. For the cases when only semiannual frequencies are available, we have assumed that the exposures reported in the annual report is valid for the last two quarters of the report period and the following two quarters of the incumbent period because the credit portfolio balance reported are closing accounts and this minimized average error in time.

4.4 Historical Credit Losses

Net loan losses are plotted over time in Figure 1 and the characteristic peak from late 2008 to mid 2010 is visible, representing a period when the crisis had spread from the financial markets to the wider economy. The link to default rates is apparent, yet this series is visibly smoother due to its construction. By monitoring their credit portfolios, banks set aside reserves to cover losses. If realized losses are larger than reserves, an additional loan loss charge must be made in that particular period. If the opposite is true, a recovery from the loan loss provisions can be made.

This method means that variations in net loan losses will be smoothened by the use of reserve balances, depending on banks' ability to predict such events. As seen in Figure 1, short-time deviations from the path occur mainly in periods of surprising events. In the figure we can also see SEB's and Swedbank's net loan losses are negative from mid 2010 and onwards, implying that they overestimated losses to the extent that ex-post recoveries are larger than the actual losses and new provisions. The data also confirms the common perception that SHB is a more risk-averse lender. The low level of deviations proves good monitoring practices and forecasting skills.

Figure 1: Bank-specific historical net loan losses

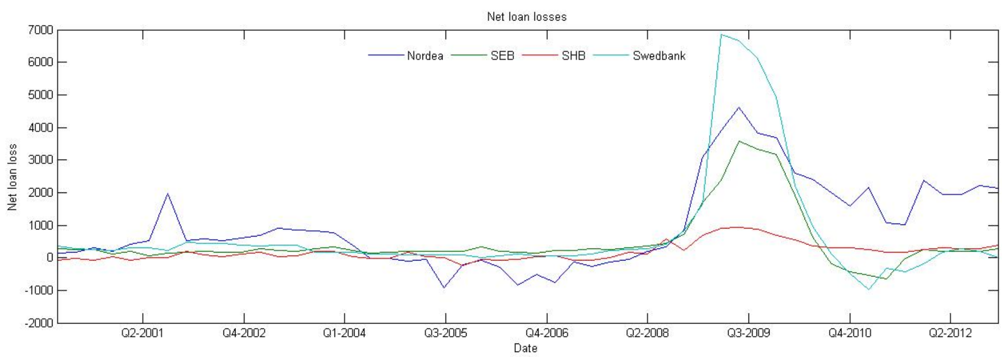


Figure 2: Bank-specific macroeconomic factor time series

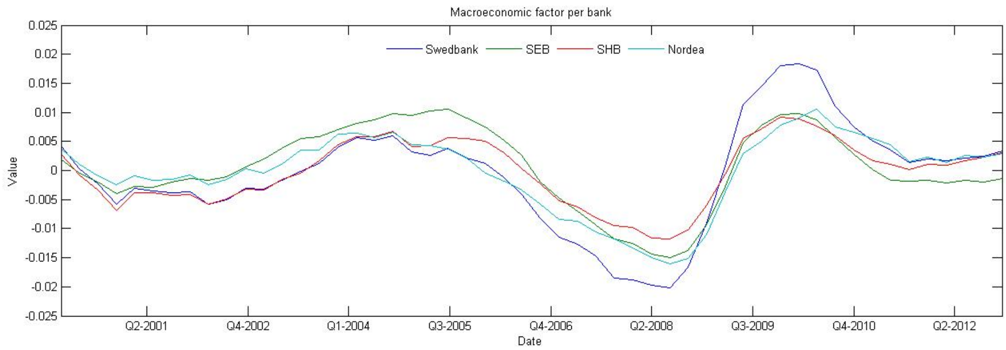


Table 2: Descriptive statistics of historical credit losses

Bank	Min	Mean	Max	Std. dev	Skew	Excess kurtosis
Nordea	-0.60	0.41	1.60	0.51	0.41	-0.09
SEB	-0.58	0.44	2.71	0.69	2.11	4.20
SHB	-0.27	0.14	0.62	0.19	0.80	0.54
Swedbank	-0.82	0.63	5.32	1.32	2.71	6.40

Table 3: Descriptive statistics of simulated credit losses

Bank	Min	Mean	Max	Std. dev	Skew	Excess kurtosis
Nordea	0.14	0.47	2.00	0.34	0.49	-0.14
SEB	0.18	0.31	2.81	0.76	1.05	2.30
SHB	0.13	0.19	0.84	0.29	0.54	-0.07
Swedbank	0.11	0.35	3.91	1.16	1.24	2.87

4.5 Macroeconomic factor

To find the macroeconomic factor used for estimation and simulation of credit losses we have vetted several different alternatives, such as GDP, different interest rates, unemployment, and combinations thereof. After choosing unemployment, we collected data for each of the banks' main geographical exposures. These countries and regions are presented in Table 15 in the Appendix and divergence from average is the functional form used. Then, using balance sheet data, the series was weighted into an individual variable for each of the banks, representing their unique risk exposure, which are plotted in Figure 2 above.

We applied the Hodrick-Prescott (H-P) filter (see Hodrick & Prescott (1997), or originally Whittaker (1923)) on each of the independent variables which splits each of their trend and cyclical components into new series. This step improves robustness and quality of the subsequent VAR forecasts, given that there is an I(2) trend present with normally distributed noise. Results from tests for order of integration and normality are favourable and shown in Table 17. The VAR length was chosen after consulting Akaike, Hannan-Quinn, Schwartz-Bayesian information criteria in combination with the LR test. The results are displayed in Table 18 in the Appendix along with the results from estimation of the VAR model in Table 19, and tests for residual normality and serial correlation in Table 20 and Table 21.

5 Results

Output resulting from the loss simulations and clearing the interbank market is presented and analysed in detail in this section. Linked to the systemic risk in real-world application, and therefore of great importance, will be the pattern of defaults and the intricate way it will spread. We will therefore begin discussing the contagion channels. After this we will move on to analyse the different risk measures and their efficiency in capital regulation applications.[4] We will analyse the characteristics most relevant to risk in the Swedish banking system. For the sake of diligence and concreteness, we will focus on Q4 2012 but also reflect on information pertinent to the other periods. This section is arranged so that we will begin analysing the contagion channels and their role and importance, followed by the main question of economic efficiency in Subsection 5.2, before looking at the main theme of this thesis, the effects of Macroprudential capital requirements. This part will then be concluded by a sensitivity analysis.

[4]The results are valid for internal comparison between risk measures and allows for important inferences. However, when analyzing the results one need to remember that the absolute values of default probabilities are not applicable in reality beacuse the parameters are not estimated properly.

5.1 Contagion channels

In Table 4 below we present the results from the our simulations. For the sake of comparability, these are all generated using a minimum price for the illiquid asset, $p_{min} = 0.94$, which means that the stock of illiquid assets can at most fall 6% in value even if the banks offload all of their holdings. The scale of such losses are considerable but without central banks and governments worldwide supporting pricing we believe it is not all too unlikely.

By trial and error we have concluded that parameters κ and α values of 0.0005 and 0.4 respectively, are appropriate for the modelling associated with Equations 18 and 19. The α represent price elasticity of the illiquid asset and the value used corresponds to an elasticity close to the average of the most common goods and services in the economy. Since the combination is also applicable in all of the periods chosen we are satisfied. The probability refers to default occuring in the quarter of a year chosen.

Table 4: Unconditional PDs given $p_{min} = 0.94$, $\kappa = 0.0005$ & $\alpha = 0.4$

Q4 2012 Bank	Fundamental (%)	Contagious (%)	AFS (%)	Contagious-AFS (%)	Total (%)
Nordea	0.00	0.59	0.20	0.01	0.80
SEB	0.00	0.06	0.10	0.64	0.80
SHB	0.04	0.00	0.76	0.00	0.80
Swedbank	0.08	0.71	0.00	0.00	0.79
Q2 2009 Bank	Fundamental (%)	Contagious (%)	AFS (%)	Contagious-AFS (%)	Total (%)
Nordea	0.00	0.95	0.21	5.40	6.56
SEB	0.00	0.01	5.52	0.01	5.54
SHB	0.04	1.50	0.00	5.02	6.56
Swedbank	0.03	4.53	0.01	8.80	13.37
Q2 2007 Bank	Fundamental (%)	Contagious (%)	AFS (%)	Contagious-AFS (%)	Total (%)
Nordea	0.00	0.03	0.05	1.77	1.85
SEB	0.00	0.05	1.43	0.44	1.92
SHB	0.00	0.05	1.13	0.74	1.92
Swedbank	0.00	0.73	0.02	1.09	1.84
Q1 2005 Bank	Fundamental (%)	Contagious (%)	AFS (%)	Contagious-AFS (%)	Total (%)
Nordea	0.00	0.01	0.01	0.25	0.27
SEB	0.00	0.00	0.19	0.13	0.32
SHB	0.00	0.02	0.01	0.22	0.25
Swedbank	0.00	0.02	0.24	0.13	0.38

As defined in Equation 22, a fundamental default occurs when credit losses are too large for the individual bank to absorb using its capital reserves. Throughout all of the periods, this event is rare which stems from the fact that the idiosyncratic risk in bank credit losses is relatively mild. However when taking into account the contagion aspect the PD increases somewhat. In all of the periods presented, SHB and Swedbank are those most prone to a fundamental default as well most probable to fail due to contagion from the first event. For Swedbank this is explained by the large losses that it suffered in the crisis and the effects these have on the credit loss simulations.

Simply put, actually realising large losses makes such losses more probable and therefore more often recurring in simulations. This might therefore be partially attributed to the method applied. In SHB's case the answer is not as certain, but by looking at the different risk measures, it is likely related to correlation. Similar to SHB and Swedbank, most of Nordea's risk stem from contagion. This is explained by their dependence on market funding, a concern that the Riksbank has voiced repeatedly[5], and the Federal Reserve have increasingly focused on, in the discussion of regulation in the U.S.

Apart from Swedbank, the other banks are more resilient to the first two of default causes, but rather more exposed to the AFS and Contagious-AFS defaults. What contagion channel proves most important to which bank sheds some light on how losses could propagate in the system during a crisis event. When trying to prevent a systemic crisis it seems rational to establish the root cause of such a crisis, limit the severity with sufficient capital but not forget that managing events and appropriately preparing interventions is extremely important as well.

When looking at aggregate risk of default in each period but Q2 2009, the banks are, by-and-large, equally probable to default. Looking at other

[5] See for example Eklund *et al.* (2012)

periods, we find that PDs actually change substantially over time but remain consistent across banks. This is a reflection of banks being regulated under the same regime and that they all minimize PDs within same frame of reference while the economic environment, their capital cushions, and perhaps even underlying parameters change over time.

The difference in PD between Q2 2007, and Q2 2009 as well as Q4 2012, should be viewed in light of the equity issues completed by all of the banks between the first two periods. By our account, dividing PD in half on the individual level is an impressive feat, although the total amount of capital in the banking system is not a prioritized topic for discussion in this thesis. More interesting is that the issues seem to have decreased the PD significantly, in comparing Q4 2012 and Q2 2007, the PD measured in Q2 2009 is still extremely high. While the banks were not very keen on the issue and mandatory government private placement, the alternative might have rendered a more traumatic experience judging by these numbers.

Similiarly to previous studies in other countries, the Swedish system looks very robust before considering the effects of AFS. In all of the periods, the bulk of the risk measured in PD is not related to fundamental default but contagion, AFS, and their combination. As outlined before, banks have to sell illiquid assets to comply with capital requirement rules within our model when sufficiently large losses are incurred, which causes the price of that asset class to fall, implying losses on all other banks' balance sheets. The dynamism of this effect is that it exacerbates the initial losses and makes all of the banks weaker and even more susceptible to contagion. We find that SEB, SHB and Swedbank have had significantly higher PDs from AFS than Nordea, which is consequently more likely to survive write-downs. However, Nordea has a comparatively higher PD of contagion.

We believe this is an effect of being substantially larger than the other banks in combination the maximum entropy rule applied to calculate exposures. This method causes Nordea to carry substantially larger exposures to the other banks in nominal terms within our model than in reality, as it most likely has other bank counterparties, in Sweden but also internationally. While the AFS represents a substantial part of default probabilities within this modelling environment; one aspect must be further discussed. The market price floor assumes that a central bank or similar authority would always intervene and supply the liquidity needed after some point. Market pricing is applied until prices have fallen 6% after which the price is capped. The importance of liquidity is further highlighted in Subsection 5.4 on sensitivity, in which the minimum price in Q4 2012 is allowed to drop 33% less compared to the standard case ($p_{min} = 0.96$).

An important observation is also that the pattern of default causes and magnitude is changing a lot over time. In this model, the fundamental driver is the unemployment in a given period causing losses that is then either soothened or exacerbated by exposures and capital cushion. Since capital held by banks is far but fixed and lending exposures as well as stock varies a lot as well, probability of default should also be expected to vary using the same parameters, even if default statistics remain largely unchanged.

5.2 Probability of financial crisis

Earlier we looked at the individual PDs of the banks in different periods, however the probability of a financial crisis is somewhat a different concept. To identify the systemically important banks, we will therefore address the probability of a systemic collapse. It is very unlikely that a major Swedish bank would collapse without being affected by a full-scale financial crisis already.

To analyse which bank contributes what to the probability of a systemic crisis, Table 5 is useful as it shows the probability of a default for the banks, conditional on the default of another bank. From this perspective a default of either Nordea or SEB are less likely to cause the other banks to default.

This is especially interesting due to the size of Nordea. SEB and SHB are the most systemically important from this perspective, as they are almost certain to cause the other banks within the system to default given their own default.

Table 5: Individual bank default probability conditional of default of specific bank in Q4 2012, given $p_{min} = 0.94$, $\kappa = 0.0005$ & $\alpha = 0.4$

Default of bank	Probability of involvement of bank Nordea	SEB	SHB	Swedbank	Average
Nordea	-	46.67	28.38	100.00	58.35
SEB	100.00	-	60.81	100.00	86.94
SHB	100.00	100.00	-	100.00	100.00
Swedbank	57.14	26.67	16.22	-	33.34

5.3 Macroprudential capital requirements

By applying capital requirements corresponding to the macroprudential risk measures we find that the banking system could be more efficiently regulated. The results presented in Table 6 illustrates the amount of capital allocated to the banks under the different rules in nominal terms.

Table 6: Capital allocations in Q4 2012, given $p_{min} = 0.94$, $\kappa = 0.0005$ & $\alpha = 0.4$

Bank	Incremental VaR	Component VaR	MES	RWA	Reported
Nordea	206.13	184.81	188.62	239.53	259.05
SEB	118.75	188.17	178.54	105.63	107.19
SHB	126.95	72.56	78.18	122.03	90.10
Swedbank	73.77	80.06	80.25	58.40	105.76

Compared to the incumbent regulation, all of the alternative allocations suggest Nordea is over-capitalized. Similarly, all but the reference allocation suggests that so is Swedbank. The Incremental VaR rule and the reference rule suggest that SHB is under-capitalized. All of the allocation rules signals that SEB is severely under-capitalized from the systemic perspective.

Table 7 illustrates the same output but in percentage terms, and it suggests that variations measured in equity ratios are very different from the capital ratios actually in place. Another important aspect is that bank size is less important under the macro-prudential capital measures than within the incumbent regulation and the proposed complements to it.

Table 7: Capital ratios in Q4 2012, given $p_{min} = 0.94$, $\kappa = 0.0005$ & $\alpha = 0.4$

Bank	Incremental VaR (%)	Component VaR (%)	MES (%)	RWA (%)	Reported (%)
Nordea	10.17	9.59	9.67	12.28	13.08
SEB	14.14	20.07	16.65	12.28	12.85
SHB	13.16	9.12	12.37	12.28	9.06
Swedbank	15.24	15.68	14.63	12.28	21.38

It is important to analyse the effects capital reallocation has on the banks' individual PDs. In Table 8 these are presented along with those of the actual capital held. Notice that while the individual PD is very stable at around 0.80 across banks under the current rule, alternative macroprudential capital regimes perform even better on the individual level. This is somewhat surprising because this is in essence what microprudential regulation is concerned with.

Table 8: Unconditional PDs under different capital allocations in Q4 2012, given $p_{min} = 0.94$, $\kappa = 0.0005$ & $\alpha = 0.4$

Bank	Incremental VaR	Component VaR	MES	RWA	Actual
Nordea	0.80	0.85	0.81	0.75	0.80
SEB	0.59	0.57	0.60	0.75	0.80
SHB	0.75	0.85	0.86	0.76	0.80
Swedbank	0.80	0.56	0.57	0.75	0.79

The different allocation mechanisms have obvious effects on the contagion and AFS aspects of regulation. Looking at Table 9 we see that introducing rules based on Component VaR and MES could substantially decrease risk of more than three banks collapsing. The Incremental VaR alternative however seem to cause even higher risk of systemic default, albeit decreasing risk of less than four defaults. The reference allocation, by risk-weighted assets, seems to decrease risk of system-wide defaults.

Table 9: Probability of multiple defaults under different capital allocations in Q4 2012, given $p_{min} = 0.94$, $\kappa = 0.0005$ & $\alpha = 0.4$

Defaults	Incremental VaR	Component VaR	MES	Basel	Actual
1	0.07	0.32	0.10.	0.46	0.48
2	0.49	0.68	0.72	0.40	0.41
3	0.12	0.13	0.02	0.17	0.15
4	0.37	0.19	0.31	0.31	0.36
≥ 3	0.49	0.32	0.33	0.48	0.51

The expected losses conditional on default found using the reference allocation is also noteworthy and in Table 10 we see that this alternative is not as alluring as it seemed when looking at basic PDs. All three of the macro-prudential allocation rules imply lower expected losses given default than the actual allocation of capital. The difference in magnitude of losses between the different alternatives alone motivates further research.

Table 10: Conditional expected loss as % of total assets under different capital allocations in Q4 2012, given $p_{min} = 0.94$, $\kappa = 0.0005$ & $\alpha = 0.4$

Defaults	Incremental VaR	Component VaR	MES	Basel	Actual
1	0.20	0.18	0.18	0.47	0.57
2	0.14	0.18	0.32	0.42	0.79
3	0.32	0.20	0.34	0.47	0.74
4	0.73	0.97	1.24	1.55	1.26

5.4 Sensitivity

To analyze the sensitivity of our results, we need to consider both the aspects of modelling and realistic application. To begin with, the modelling environment is very sensitive to very small incremental changes in κ, α and p_{min}. Unsuitable combinations causes all banks to either default in every scenario, or to practically always survive without harm.

Neither of the outcomes are useful in this thesis as we need to investigate crisis scenarios, but more importantly it creates difficulties in interpreting the results for practical implementation and comparing different periods. In Table 11 we let the price fall 4%, less than the base case of 6%, that is $p_{min} = 0.96$, which corresponds to a smaller decrease in market liquidity than in our base case scenario. As expected, the number of bankruptcies decreases, but the patterns are also affected. The magnitude of the decrease in defaults illustrate that our analysis is very sensitive to the minimum price on illiquid assets.

The problem with applying too low minimum prices within this modelling environment is that AFS defaults across the board causes default correlation to approach one. This partially explained by the fact that the higher the minimum Tier 1 capital ratio used, the earlier the banks will be forced to sell illiquid assets. In modelling we used the minimum Tier 1 capital requirements of 7% required and not the 10% suggested for the Swedish banks which makes realistic interpretation harder but is preferable when comparing the different measures, especially at different periods of time.

Table 11: Sensistivity of default probability to minimum price in Q4 2012, given $\kappa = 0.0005$ & $\alpha = 0.4$

	$p_{min} = 0.94$			$p_{min} = 0.96$		
Bank	AFS	AFS-Cont.	Total	AFS	AFS-Cont.	Total
Nordea	0.20	0.01	0.80	0.03	0.12	0.18
SEB	0.10	0.64	0.80	0.02	0.40	0.45
SHB	0.76	0.00	0.80	0.57	0.02	0.74
Swedbank	0.00	0.00	0.79	0.00	0.00	0.33

Table 12: Price sensitivity of illiquid asset to individual bank deviation from system average risk-weighted to parameter values of κ, histoical average divided by total assets

	Average	Hypothetic parameter values for κ				
Bank	deviation	0.0003	0.0004	0.0005	0.0006	0.0007
Nordea	-0.024	-0.0007	-0.0010	-0.0012	-0.0015	-0.0017
SEB	0.066	0.0020	0.0027	0.0033	0.0040	0.0046
SHB	-0.048	-0.0014	-0.0019	-0.0024	-0.0029	-0.0034
Swedbank	0.006	0.0002	0.0003	0.0003	0.0004	0.0004

To put the contents of Table 12 into perspective, a κ of 0.0005 would imply a discount of 0.24% on the illiquid assets to the prevailing efficient market price. While the effect could seem meagre, it actually translates into a SEK 7.4bn mark-to-market loss for Nordea in Q4 2012, which is approximately three times larger than the net loan losses at SEK 2.3bn the same period.

The amplitude of such effects is probably not very realistic, but still a straightforward method to account for heterogeneity which affirms the concept that banks in worse shape would attain lower prices for their assets in a crisis. Still we believe that the effect arising from κ is subordinated and should be kept limited, which motivates our choice of parameter value. From Table 13 we see that α is chosen so that offloading small portions of bank holdings affect prices significantly.

Table 13: Price sensitivity of illiquid asset to parameter values of α at different levels of fire sales

	Hypothetic parameter values of α				
$\Sigma_i s_i / \Sigma_i e_i$	0.3	0.4	0.5	0.6	0.7
2%	0.994	0.992	0.990	0.988	0.986
4%	0.988	0.984	0.980	0.976	0.972
6%	0.982	0.976	0.970	0.965	0.959
8%	0.976	0.969	0.961	0.953	0.946
10%	0.970	0.961	0.951	0.942	0.932

6 Discussion

Regulatory guidelines, including Basel III, have been very ambitious and designed to address a variety of risks. The risks that such capital regulation addresses can generally be divided into three categories:

1. **market risk** that arises due to price uncertainties of assets traded in competitive markets

2. **credit or default risk** relates to specific credits and loans where the risk arises due to probability of future defaults and is our main concern throughout this paper

3. **liquidity and counterparty risk** which arises due to events that makes entering or exiting positions difficult, especially for large quantities, at reasonable prices and period of time

Albeit the comprehensive scope, past regulation has been argued to be too microprudential in nature. We introduce regulatory tools that not only incorporate market risk, default risk and liquidity risk, but also systemic risk.

The main objective of macroprudential regulation is to ensure that banks internalize externalities inherent in a financial system. Our results show that a complete overhaul might not be necessary to accomplish that goal, but actually that simply augmenting the measurement practices yields significant deduction in systemic risk by aligning interests among the banks, and between them and society.

Through diligent application of appropriate macroprudential capital requirements to the Swedish banking system we conclude that such measures stabilize the system as modelled in this application, yet sensitivity somewhat conceals the true extent. The Swedish banking system is well-capitalised from an international perspective and very robust before considering the effects of AFS, a characteristic inherent to its concentration. We find that default probabilities are in essence not very dependent on the classic fundamental default, but rather the systemic externalities of AFS and contagion, and the combination of the two. Our analysis illustrates that capital could in fact be reallocated among the four Swedish banks in our sample to decrease overall probability of default as well as expected losses, and albeit such a manoeuvre is a silly notion in reality, it shows that the banks could be met half-way because under more efficient regulatory rules, a better allocation of less capital could still benefit society.

Two of the risk allocation mechanisms that we investigate, Component VaR and MES, yield substantial decreases in default probabilities of individual banks as well as the probability of multiple bank defaults, which is extremely important in decreasing expected costs of financial distress. Furthermore, all risk allocation mechanisms investigated yield lower expected losses given default compared to current capital regulation. The outtake is that bank size seems less important in terms of capital regulation based on macroprudential risk measures. However, as banks are heterogeneous and differ in other characteristics than size, the optimal regulatory framework should probably utilize certain macroprudential capital requirements in combination with rules on other risks arising from bank activities or characteristics that such measures fail to account for. Recently, size has recieved considerable focus and the G-SIB framework targets important and large banks for their, suggestively, excessive implicit burden on society by applying an extra capital charge on top of current regulatory minimum requirements. In this respect Conditional VaR would, as mentioned, be counterproductive as it incentivizes growing balance sheets and Marginal Expected Shortfall or Incremental VaR would both be more suitable and not unwind progress made in this area.

One practical aspect in measuring risk, especially VaR, is validity of the underlying assumptions and whether or not they are realistic in a given application. A number of financial strategies rely on the estimation of dynamic models for asset returns. For example, the very popular option pricing model from Black & Scholes (1973) assumes that asset prices follow a geometric Brownian motion and that returns are normally distributed. That is not necessarily the case, and we believe one should expect that any theoretical model is by definition misspecified to some extent compared to reality. Further as applying theoretical models typically involves estimation of unknown parameters and data constraints are prominent, the results presented in this paper must be interpreted with caution. Especially minding the limited data our analysis is built on compared to what authorities could force the banks to supply. This analysis should therefore be primarily viewed as a good point to pick up future research.

Actually implementing macroprudential capital requirements would not be an easy task. Large quantities of data would have to be collected by regulators, especially on interbank exposures. Further, in light of the need for more research in the area we urge regulators to force the banks to disclose, or themselves collect the necessary information. We would also like to highlight the potential ambiguity that could be created by combining measures, which could allow banks to seek out regulatory arbitrage.

The final obstacle to regulators we consider to be important is the behavioural aspects related to deriving bank capital requirements not merely based on individual bank's characteristics and actions, but to motivate the fairness of that banks' capital position being a function of their competitors. We expect that banks would complain over the lack of predictability and themselves losing power over their fate, as the moves and actions would have effects on capital requirements of other banks and thereby their rate of return.

The weaknesses aside, to avoid future crises, any changes in regulation must ensure than banks do internalizes the endogenously created systemic risk. Based on the assumptions made in our analysis we have put forward several risk allocation mechanisms that should be seriously considered by regulators.

7 Appendix

7.1 Figures

Figure 3: Historical bankruptcy rates per sector

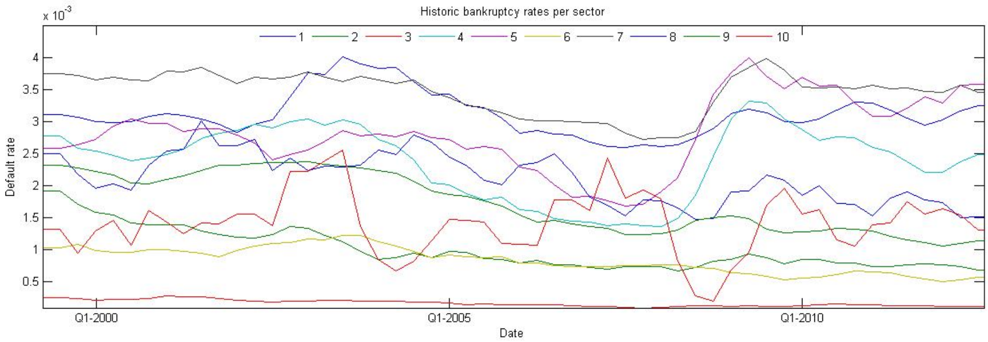
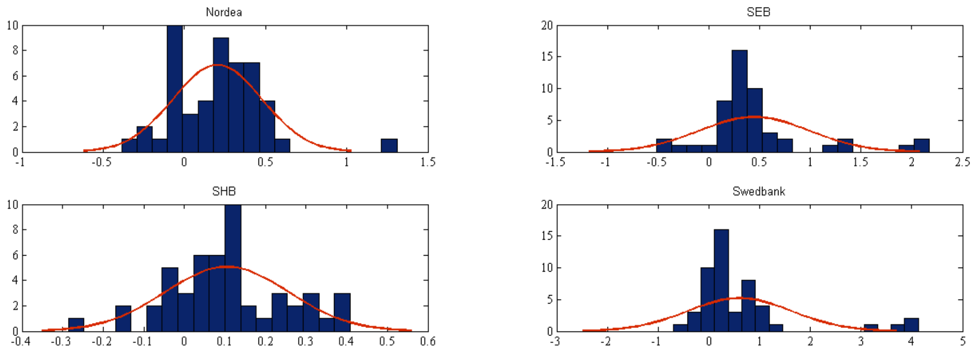


Figure 4: Histogram of bank credit losses incurred in period



7.2 Tables

Table 14: Descriptive statistics of average risk-weight per total assets and individual bank deviations

	System average	Deviations			
		Nordea	SEB	SHB	Swedbank
Min	0.327	-0.090	-0.031	-0.160	-0.086
Average	0.453	-0.024	0.066	-0.048	0.006
Median	0.470	-0.035	0.080	-0.021	-0.020
Max	0.527	0.071	0.119	0.059	0.092
Q4 2012	0.337	0.014	-0.021	-0.068	0.075
Q2 2009	0.421	0.034	0.057	-0.132	0.041
Q2 2007	0.451	-0.090	0.080	-0.036	0.045
Q1 2005	0.470	-0.055	0.116	-0.017	-0.044

Table 15: Bank-specific geographic credit portfolio, historical average levels

Country	Nordea %	SEB %	SHB %	Swedbank %
Denmark	27.2		3.1	3.4
Finland	22.6		5.3	1.5
Norway	17.5		8.9	
Sweden	29.4	44.5	78.1	83.2
Baltics	0.9	6.3		11.4
Russia				
North America			1.0	
United Kingdom			0.9	
Germany		28.1		
Rest of Nordics		8.7		
Emerging Markets		1.1		
Other		11.2	2.7	0.6

Table 16: Sectoral exposure matching bankruptcy statistics and bank sectoral lending

Sector	Nordea	SEB	SHB	Swebank
Construction	Construction Other material sectors	Construction		Construction
Real estate & property mgmt.	Real estate	Property mgmt.	Construction & prop. mgmt Housing co-operatives	Property mgmt. Housing co-operatives Real estate mgmt.
Forestry & agriculture	Agriculture & fishing Metals & mining Paper & forest companies		Agriculture, hunting & forestry	Forestry & agriculture
Manufacturing	Manufacturing Industrial capital goods Telecom equipment	Manufacturing	Industrial, trading & services Manufacturing	Manufacturing
Transportation	Shipping Transport Shipping	Transportation Off-shore	Transport & communication Shipping	Transportation Shipping
Public sector	Public sector	Municipalities Public sector	Local authorities Public sector	Public sector & utilities Municipalities
Retail	Consumer staples Retail trade Media & leisure Consumer durables	Wholesale & retailing	Trade & retail Hotels & restaurants	Retails, hotels & restaurants Retail Hotels & restaurants
Renting & other financial services	Financial operations Renting & consulting	Finance & insurance	Insurance Holding companies Investment trusts Mutual funds	Finance & insurance
Services	Trade & services Health care Telecom operators Information technology	Other services	Trade, hotel & restaurants Other corporate services	Professional services Other service business Information & communication
Utilities	Energy Utilities		Utilities	

Table 17: KPSS test for order of integration and Jarque-Bera test for normality on residuals.

	I(0)	I(1)	I(2)	Normality
Bank	D-statstic	D-statstic	D-statstic	JB-stat
Nordea	0.366***	0.170**	0.028	6.843*
SEB	0.326***	0.200**	0.044	6.497*
SHB	0.285***	0.152*	0.022	10.986**
Swedbank	0.484***	0.182**	0.020	17.214**
$D^c_{0.05} = 0.146$, $D^c_{0.025} = 0.176$, $D^D_{0.01} = 0.216$				
$JB^c_{0.05} = 5.004$, $JB^c_{0.025} = 7.605$, $JB^D_{0.01} = 33.490$				

Table 18: Optimal VAR lag order selection criteria

Nordea

Lag	Log L	AIC	HQC	SBIC	LR
0	-44.1094	-11.1028	-11.0880	-11.0638	-
1	-44.1092	-12.2390	-12.2243	-12.2000	213.3399
2	-44.1091	**-12.8211**	**-12.7769**	**-12.7041**	**14.2921**
3	-44.1091	-12.8055	-12.7466	-12.6496	4.4625
4	-44.1091	-12.7011	-12.6716	-12.6231	0.9163
5	-44.1091	-12.7670	-12.6933	-12.5721	5.1845

SEB

Lag	Log L	AIC	HQC	SBIC	LR
0	-44.1094	-11.9825	-11.9677	-11.9435	-
1	-44.1092	-12.1633	-12.1485	-12.1243	134.0722
2	-44.1091	**-13.6219**	**-13.5925**	**-13.5440**	**9.1512**
3	-44.1091	-13.5869	-13.5428	-13.4700	3.0534
4	-44.1091	-13.5571	-13.4982	-13.4012	4.1035
5	-44.1091	-13.5461	-13.4725	-13.3512	0.8554

SHB

Lag	Log L	AIC	HQC	SBIC	LR
0	-44.1094	-12.3691	-12.3543	-12.3301	-
1	-44.1091	**-13.2776**	**-13.2334**	**-13.1606**	41.1084
2	-44.1092	-12.9733	-12.9439	-12.8954	5.9402
3	-44.1091	-13.2724	-13.2135	-13.1165	0.6694
4	-44.1091	-13.2072	-13.1335	-13.1123	**6.7287**
5	-44.1091	-13.2243	-13.1360	-13.0904	4.3843

Swedbank

Lag	Log L	AIC	HQC	SBIC	LR
0	-44.1097	-10.4239	-10.4091	-10.3849	-
1	-44.1093	-11.4762	-11.4615	-11.4373	59.0566
2	-44.1091	**-12.4556**	**-12.4114**	**-12.3386**	**8.8015**
3	-44.1091	-12.3138	-12.2843	-12.2358	3.3928
4	-44.1091	-12.4350	-12.3761	-12.2791	4.1035
5	-44.1091	-12.4105	-12.3368	-12.2156	1.8548

Table 19: VAR Estimates for chosen model

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

		Nordea				**SEB**	
		X_{trend}	X_{cyc}			X_{trend}	X_{cyc}
AR(1)	X_{trend}	2.0116	-0.0060	AR(1)	X_{trend}	1.8774	-0.076
		(0.0236)	(0.0040)			(0.0741)	(0.0121)
		[98.7959]	[-1.4990]			[25.3286]	[-0.6282]
	X_{cyc}	0.6243	1.4592		X_{cyc}	0.5524	1.6939
		(0.6006)	(0.1171)			(0.4971)	(0.0814)
		[1.0394]	[12.4593]			[1.1112]	[20.8153]
AR(2)	X_{trend}	-1.0254	0.0000	AR(2)	X_{trend}	-0.8955	0.0018
		(0.0214)	(0.0041)			(0.0741)	(0.0121)
		[-47.9826]	[0.0061]			[-12.0880]	[0.1512]
	X_{cyc}	-0.5843	-0.5869		X_{cyc}	-0.4465	-0.8313
		(0.6304)	(0.1203)			(0.4968)	(0.0814)
		[-0.9268]	[-4.8768]			[-0.8986]	[-10.2168]

		SHB				**Swedbank**	
		X_{trend}	X_{cyc}			X_{trend}	X_{cyc}
AR(1)	X_{trend}	0.9748	-0.0002	AR(1)	X_{trend}	1.4874	0.0180
		(0.0586)	(0.0202)			(0.1279)	(0.0247)
		[16.6454]	[-0.0078]			[11.6327]	[0.7277]
	X_{cyc}	0.0602	0.9167		X_{cyc}	0.3691	1.1641
		(0.1736)	(0.0600)			(0.4747)	(0.0918)
		[0.3469]	[15.2763]			[0.7775]	[17.8767]
				AR(2)	X_{trend}	-0.4818	-0.0263
						(0.1334)	(0.0251)
						[-3.6133]	[-1.0440]
					X_{cyc}	-0.3239	-0.7760
						(0.4951)	(0.0934)
						[-0.6542]	[-8.3123]

Table 20: VAR model residual normality tests

Nordea	Skewness	g-statistic	Prob.	**SEB**	Skewness	g-statistic	Prob.
X_{trend}	-0.1104	-0.1139	0.7228	X_{trend}	0.1677	0.1729	0.5911
X_{cyc}	-0.3127	-0.3224	0.3219	X_{cyc}	0.0496	0.0511	0.6483
Joint		-0.3151	0.3327	Joint		0.0643	0.8732

	Kurtosis	g-statistic	Prob.		Kurtosis	g-statistic	Prob.
X_{trend}	2.0907	-0.8769	0.1865	X_{trend}	2.7436	0.4561	0.6483
X_{cyc}	2.5360	-0.3837	0.4411	X_{cyc}	2.3041	1.0751	0.2823
Joint		-0.4067	0.4240	Joint		1.0080	0.3169

	Jarque-Bera	Prob.		Jarque-Bera	Prob.
X_{trend}	1.8241	0.2582	X_{trend}	1.0295	0.5000
X_{cyc}	1.2632	0.4061	X_{cyc}	0.3712	0.5000
Joint	1.1930	0.4304	Joint	0.7198	0.5000

SHB	Skewness	g-statistic	Prob.	**Swedbank**	Skewness	g-statistic	Prob.
X_{trend}	0.1596	0.1646	0.6089	X_{trend}	0.2836	0.2925	0.9011
X_{cyc}	0.3643	0.3756	0.2511	X_{cyc}	-0.0364	-0.0376	0.9067
Joint		0.3307	0.3100	Joint		0.0297	0.0927

	Kurtosis	g-statistic	Prob.		Kurtosis	g-statistic	Prob.
X_{trend}	2.5679	-0.3483	0.4685	X_{trend}	2.7559	-0.1401	0.6628
X_{cyc}	2.5393	-0.3800	0.4438	X_{cyc}	2.2066	-0.7485	0.2336
Joint		-0.3805	0.4435	Joint		-0.6422	0.2816

	Jarque-Bera	Prob.		Jarque-Bera	Prob.
X_{trend}	1.5479	0.3253	X_{trend}	1.3224	0.3875
X_{cyc}	0.6013	0.5000	X_{cyc}	0.7946	0.5000
Joint	1.0238	0.5000	Joint	1.2371	0.4148

Table 21: LM test for residual serial correlation

Nordea			**SEB**		
Lags	LM-statistic	Prob.	Lags	LM-statistic	Prob.
1	1.5418	0.4626	1	1.2816	0.5269
2	1.8689	0.6001	2	3.3081	0.3465
3	2.8386	0.5852	3	4.3279	0.3634
4	2.5070	0.7754	4	4.5098	0.4786
5	5.3504	0.4996	5	6.3895	0.3810

SHB			**Swedbank**		
Lags	LM-statistic	Prob.	Lags	LM-statistic	Prob.
1	5.1516	0.0761	1	1.4763	0.4780
2	4.4419	0.2175	2	1.6882	0.6396
3	4.8411	0.3040	3	1.7708	0.7778
4	9.3497	0.0959	4	2.4988	0.7767
5	8.9824	0.1746	5	2.6133	0.8556

Table 22: Capital allocations in Q2 2009, given $p_{min} = 0.94$, $\kappa = 0.0005$ & $\alpha = 0.4$

Bank	Incremental VaR	Component VaR	MES	RWA	Reported
Nordea	82.24	107.57	100.77	205.83	255.22
SEB	34.10	161.85	52.66	89.43	97.00
SHB	345.21	105.30	291.62	125.43	75.73
Swedbank	28.76	115.58	45.26	69.39	85.30

Table 23: Capital ratios in Q2 2009, given $p_{min} = 0.94$, $\kappa = 0.0005$ & $\alpha = 0.4$

Bank	Incremental VaR (%)	Component VaR (%)	MES (%)	RWA (%)	Reported (%)
Nordea	4.01	5.24	4.91	9.90	12.44
SEB	4.23	20.08	6.53	9.90	12.03
SHB	29.09	8.88	24.58	9.90	6.38
Swedbank	4.74	19.03	7.45	9.90	14.04

Table 24: Capital allocations in Q2 2007, given $p_{min} = 0.94$, $\kappa = 0.0005$ & $\alpha = 0.4$

Bank	Incremental VaR	Component VaR	MES	RWA	Reported
Nordea	134.00	83.93	87.27	174.89	177.48
SEB	61.48	95.05	89.77	78.13	66.03
SHB	83.79	87.69	93.16	91.53	76.46
Swedbank	65.27	77.89	74.35	59.26	83.83

Table 25: Capital ratios in Q2 2007, given $p_{min} = 0.94$, $\kappa = 0.0005$ & $\alpha = 0.4$

Bank	Incremental VaR (%)	Component VaR (%)	MES (%)	RWA (%)	Reported (%)
Nordea	7.55	4.73	4.92	9.60	10.00
SEB	7.75	11.99	11.32	9.60	8.33
SHB	9.02	9.44	10.03	9.60	8.23
Swedbank	10.85	12.95	12.36	9.60	13.94

Table 26: Capital allocations in Q1 2005, given $p_{min} = 0.94$, $\kappa = 0.0005$ & $\alpha = 0.4$

Bank	Incremental VaR	Component VaR	MES	RWA	Reported
Nordea	92.32	71.92	78.96	116.30	135.65
SEB	66.55	90.97	75.05	50.09	58.73
SHB	68.70	52.24	56.16	57.80	74.88
Swedbank	42.71	55.15	60.12	46.10	44.26

Table 27: Capital ratio in Q1 2005, given $p_{min} = 0.94$, $\kappa = 0.0005$ & $\alpha = 0.4$

Bank	Incremental VaR (%)	Component VaR (%)	MES (%)	RWA (%)	Reported (%)
Nordea	6.98	5.43	5.97	8.79	10.25
SEB	11.67	15.96	13.17	8.79	10.30
SHB	10.45	7.94	8.54	8.79	11.38
Swedbank	8.14	10.51	11.46	8.79	8.44

Table 28: Bank sectoral credit portfolio exposures (%)

Nordea

Sector	1	2	3	4	5	6	7	8	9	10	11
Min	2.59	22.92	3.65	7.93	9.26	2.68	6.29	5.01	7.17	0.00	5.02
Average	4.07	24.76	5.94	12.98	10.44	4.47	9.49	8.90	10.17	0.00	8.79
Median	3.32	24.83	5.61	13.03	10.30	3.39	10.13	9.41	9.99	0.00	8.23
Max	6.09	26.75	8.36	18.49	13.51	18.07	12.23	10.66	12.93	0.00	15.43

SEB

Sector	1	2	3	4	5	6	7	8	9	10	11
Min	1.14	25.98	0.00	6.82	5.17	7.16	5.56	3.13	4.15	0.00	2.85
Average	1.49	29.91	0.36	10.90	7.13	19.74	6.24	4.50	8.43	1.30	10.00
Median	1.50	28.61	0.00	9.70	6.87	22.75	6.07	3.99	7.35	0.00	11.48
Max	1.98	36.35	1.08	18.66	9.07	30.57	7.58	8.58	13.12	5.11	15.72

SHB

Sector	1	2	3	4	5	6	7	8	9	10	11
Min	0.00	34.86	0.00	0.00	0.00	1.19	0.00	0.00	0.00	0.00	21.51
Average	0.00	46.42	0.52	6.10	3.44	2.10	5.37	4.51	1.99	0.93	28.63
Median	0.00	43.08	0.70	6.83	2.80	1.83	5.42	1.73	1.82	0.00	28.41
Max	0.00	67.63	1.14	8.05	6.57	3.90	8.05	13.41	7.61	2.71	35.30

Swedbank

Sector	1	2	3	4	5	6	7	8	9	10	11
Min	2.98	40.39	8.66	6.79	3.45	0.00	5.66	0.00	0.00	0.00	0.00
Average	3.47	49.09	11.80	11.15	5.25	3.12	8.53	0.95	5.81	0.00	0.81
Median	3.47	49.36	11.81	9.78	4.69	4.16	8.44	0.00	6.15	0.00	0.00
Max	4.27	57.48	16.49	16.89	9.73	5.39	10.41	4.91	11.28	0.00	5.25

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