



KUNGLIGA TEKNISKA HÖGSKOLAN

Modeling Downturn LGD for a Retail Portfolio

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Abstract

Loss given default is a very important measure in credit risk. This measure however might be affected by the state of the economy, especially in downturn conditions. The Basel II accord requires financial institutions to calculate the expected loss for their credit portfolio in downturn conditions. As a part of this, downturn loss given default has to be estimated. The Swedish FSA define downturn conditions as the conditions during the 90s crisis. This leads to the need to create a model for quantifying the loss given default factor during downturn conditions. The modeling is complicated by the lack of saved data from this period. This paper will discuss numerous different approaches on how to solve this problem and as we will see, most approaches do not give any reasonable results with our dataset. Instead this paper recommends a multifactor model to be used until sufficient data have been amassed.

Sammanfattning

Förlust givet konkurs är ett mycket viktigt mått inom kreditrisk. Detta mått är dock inte konstant utan kan påverkas av saker så som ekonomins tillstånd, speciellt under recessioner. Basel II kräver att finansiella institut beräknar förväntade förluster för sin kreditportfölj i en recession-period. Som en del i detta måste recessionsförlust förorsakad av konkurs (EN:Downturn Loss Given Default) skattas. Finansinspektionen definierar recession i det här sammanhanget som det tillstånd som rådde under nittiotalskrisen. Det här leder till behovet att kvantifiera förlust förorsakad av konkurs under dessa förhållanden. Denna modellering kompliceras av bristen på data från nittiotalskrisen. Den här uppsatsen diskuterar flera olika sätt att komma runt denna problematik men vi kommer att se att de flesta modeller inte ger några rimliga resultat. Istället rekommenderas en linjär multifaktormodell tills dess att en större datamängd samlats in.

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Chapter 1

List of Abbreviations

AIRB	- Advanced Internal Rating Based
CCF	- Credit Conversion Factor
DCCF	- Downturn Credit Conversion Factor
DLGD	- Downturn Loss Given Default
EAD	- Exposure at Default
EL	- Expected Loss
FRIB	- Foundation Internal Rating Based
FSA	- Financial Supervisory Authority
LGD	- Loss Given Default
PD	- Probability of Default
RWA	- Risk Weighted Assets
SME	- Small and Medium Enterprises
UL	- Unexpected Loss

Chapter 2

Introduction

The Theoretical Background section below will go through a number of terms and definitions that are needed to get this section well defined. Any reader not familiar with the area is strongly recommended to read the Theoretical Background before reading this section.

2.1 Background

A bank is a very complex environment that have many different types of risk that must be handled such as credit risk, market risk and operational risk. There are several reasons for this, firstly to be able to make a profit, losses due to risk must be handled. Secondly the government and society at large also has an interest to limit risk in banks and other financial institutions. This due to the systemic effects if a financial actor goes into bankruptcy due to excessive risk taking. An example of this is Lehman Brothers which took excessive risk, the market went against them and thus they went into bankruptcy. This led to that all the liquidity in the financial system dried up overnight, since no one knew if anyone else was sitting on toxic assets. This caused major disruptions in the world economy and the effects can still be felt. To avoid this from happening, banks are required to have a certain amount of capital that can absorb losses so that the bank can avoid to go into bankruptcy if things goes bad.

The Basel II Accord, initially published 2004, is an international recommendation on banking laws and regulations and as such they discuss the subject of required capital thoroughly. The

Basel II accord has three pillars:

- The first pillar deals with the required capital for credit risk, market risk and operational risk.
- The second pillar deals with how the regulating authority should deal with the requirements in pillar one and also discusses how other risks such as legal risk, systemic risk and concentration risk should be handled.
- The third pillar requires banks to publish certain information about their risk management, this to promote stability in the system.

2.2 Scope

The scope of this paper is to look at a method that can be used by Nordea for calculating downturn LGD for both internal use and to be used in the capital requirement calculations.

This paper will not discuss how to calculate downturn PD and therefore refer interested readers to existing extensive academic research already performed in the area. The reason for excluding PD is to limit the amount of work.

This paper is limited to use Nordea's internal data on the retail portfolio and data that is publicly available. For more through description of the data and its scope, please see the Data section below.

We also limit this to models that are based on some kind of data. While purely theoretical models might be interesting, it is hard to corroborate from a economic perspective why they should be able to predict the downturn LGD in real scenarios.

This means that this paper will only look at the downturn scenarios, while calculating the variables in a normal (non-downturn) scenario is outside the scope of this paper.

2.3 Method

This paper will go through a number of different modeling paradigms and discuss if and why are feasible to use. If we are able to use the model and our data to predict a downturn LGD value

we will do so and discuss from an economic perspective if the result is reasonable.

This means that the work on this essay will be split into two distinctive parts. First we will perform a thorough literature study to find good models. In the second phase we will test these models with our dataset.

2.4 Purpose

The purpose of this paper is to find a way to model the downturn LGD factor in a way that is both mathematically correct and that is acceptable for FSA. The model will mainly be used to improve Nordea's internal calculations of these factors, due to new internal demand on development.

A requirement is that the model must be able to stress the LGD with a crisis scenario like the 1990's crisis.

2.5 Hypothesis

The hypothesis is that the LGD for the retail portfolio is not significantly affected by an economic downturn. I.e. $LGD \approx DLGD$. The intuition for this is the fact that defaults by physical person's carries severe consequences in all the Nordic countries, hence obligors in distress will try everything before defaulting. Default of a physical person does not mean that the loans are written off like in the case of a juridical person. Since the retail portfolio consists mainly of mortgages to physical persons for which the bank has both good collaterals covering the loan and obligors with high motivation to avoid default.

Chapter 3

Theoretical Background

3.1 Basel II

The Basel II accord is a collection of recommendations on banking laws and financial regulations issued by the Basel Committee on Banking Supervision. The purpose with these recommendations is to create standards regarding how much capital a bank needs to hold against financial risk and other types of risk.[1][paragraph 1,4]

To decide the capital that a financial institution need to hold against credit risk one must calculate expected loss (EL) and unexpected loss (UL), where EL is seen as a cost of doing business and UL represents the potential for unexpected losses.

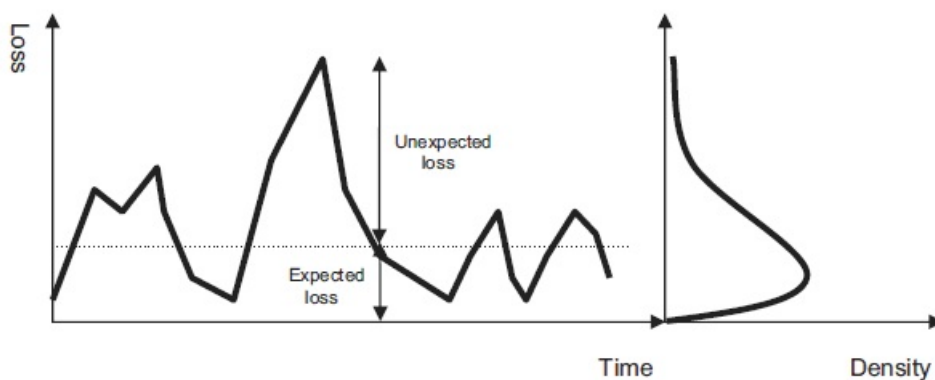


Figure 3.1

[3]

EL is calculated by the formula:

$$EL = PD * LGD * EAD \tag{3.1}$$

Where PD is probability of default, LGD is loss given default and EAD is exposure at default.

3.2 Probability of Default

Probability of Default (PD) is the probability that an obligor will default over a period of one year. A lot of research has been done on how this factor should be modeled and stressed. One reason for this might be that in the FIRB the banks are only required to estimate PD themselves.

3.3 Loss Given Default

Loss given default (LGD) is defined as the credit loss that is incurred if an obligor defaults expressed as a percentage of the exposure at default.[1]

According to the Basel II accord AIRB approach, a bank's estimation of LGD may not be lower than the historical long run default weighted average. This can be calculated as:

$$LGD = 1 - \frac{EAD + \sum(NPV(Increases)) - \sum(NPV(Decreases))}{EAD} \tag{3.2}$$

cashflows after the default is discounted back to the time of the default using an interest rate that takes the risk and uncertainty of the cashflows into account. This method is based on the statement:

"When recovery streams are uncertain and involve risks that cannot be diversified away, net present value calculations must reflect the time value of money and a risk premium appropriate to the undiversifiable risk."[1][paragraph 468]

The quote is extracted from the Guidance on Paragraph 468 of the Framework Document by the Basel Committee on Banking Supervision.

This discount rate can be determined in many ways and one example is using the rate on government bonds and adding a risk premium. Others have tried to calculate the correct rate backwards by using the price of defaulted publicly traded bonds before and after default and the actual recoveries, to determine which rate this implies.[26]

In addition to these criteria the bank also has taken into account that the LGD may be higher during an economic downturn. This is taken into account by calculating a downturn LGD.[1][paragraph 468] How this should be done is however not defined in the accord.

3.4 Credit Conversion Factor

Exposures can be split in two categories, on balance and off balance. On balance means that some kind of exposure they is included in the balance sheet. An example of this is a mortgage. Off balance means items that are not currently on the balance sheet but which could lead to items on the balance sheet in the future.. An example of this is a mortgages in principle (SV: länelöfte.) This means that the bank promise to lend money to a prospective homebuyer if he buys anything within a specified time period, this could lead to a loan that ends up on the balance sheet and is thus classified as off balance. For the on balance the entire amount of the exposure is used in the capital calculation. In the case of off balance exposures however capital must only be held against a part of the exposure. This part is calculated by multiplying the off balance with a credit conversion factor (CCF). This factor should capture how much of the off balance that has been utilized at the time of default.[1][paragraph 82]

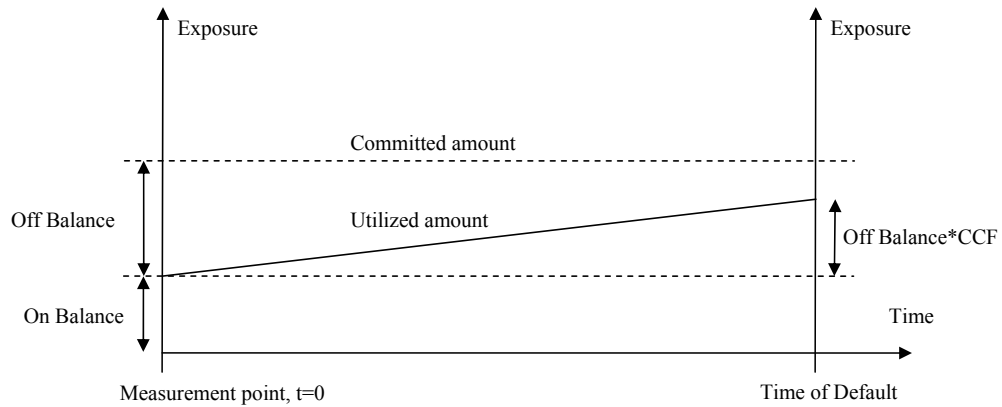


Figure 3.2

Exposure at default (EAD) can thus be calculated using the formula:

$$\text{EAD} = \text{On Balance} + \text{CCF} * \text{Off Balance} \quad (3.3)$$

[1][paragraph 308-310]

If the equations 3.3 is solved for CCF we get:

$$\text{CCF} = \frac{\text{EAD} - \text{On Balance}}{\text{Off Balance}} \quad (3.4)$$

Where the on balance and off balance are known quantities but the CCF factor must be calculated using historical data. According to the Basel II accord banks must take into account that the CCF factor might be higher during an economic downturn.[1][paragraph 474-479] This is done by calculating a downturn CCF factor and test if it deviates from the average historical CCF factor.

The Basel II accord can be interpreted to support the view that the CCF must be expressed in this way. The EU implementation of the Basel II, the Capital Requirements Directive (CRD), implicitly states that the CCF factor must be higher than zero.[5][p 81]

The CCF factor is called Loan Equivalent (LEQ) or Usage Given Default (UGD) in some literature. Some American literature even defines the term CCF differently than we do and use one of

the above terms for what we would call CCF.[5][p 81] In this paper however only the definition in equation 3.4 is used.

3.5 Risk Weighted Assets

Risk weighted assets (RWA) is given by the formula:

$$\text{RWA} = K * 12.5 * \text{EAD} \quad (3.5)$$

Where K is the capital requirement. K is given by different formulas for different asset classes. For retail the formula is:

$$K = \text{LGD} * \Phi[(1 - R)^{-0.5} * \Phi^{-1}(PD) + \left(\frac{R}{1 - R}\right)^{0.5} * \Phi^{-1}(0.9999)] - PD * \text{LGD} \quad (3.6)$$

This formula is derived from an Asymptotic Single Risk Factor (ASRF) model. This means that we model the loss rate as only dependant on a single factor and that the individual idiosyncratic risk factors of individual exposure do not have any effect. The reasons for choosing this model is that the Basel Committee wanted a portfolio invariant measure, i.e. only the characteristics of the new loan should matter. There should be no marginal effects based on the portfolio it is added to. One of the reasons for this is that it would be difficult for the employees in the branch network to know how they are supposed to run their business if the conditions changes because of the portfolio. It would be even hard to explain to the customer why the loan they were as good as promised last week can not be done suddenly. The demand for a portfolio invariant model more or less limited the choice to an ASRF model. [4]

The term $\Phi^{-1}(PD)$ in the equation above represents the default threshold and the $(1 - R)^{-0.5}$ factor is a penalty based on the default correlation R. The $\Phi^{-1}(0.9999)$ term represents a conservative value of the systematic risk factor and $\left(\frac{R}{1 - R}\right)^{0.5}$ is a penalty based on the default correlation R.

The correlation R in the capital requirement formula above is set to 0.15 for retail mortgages by the Basel II Accord. The formula for qualifying revolving credit facilities is the same with the difference that R=0.04. Retail exposure not covered by these two categories uses the formula:

$$R = 0.03 \left[\frac{1 - \exp(-35 * PD)}{1 - \exp(-35)} \right] + 0.16 \left[1 - \frac{(1 - \exp(-35 * PD))}{1 - \exp(-35)} \right] \quad (3.7)$$

to calculate R.[1][paragraph 328] This formula gives a correlation between 3% (when PD=1) and 16% (when PD=0). The factor 35 decides how fast the correlation decreases when PD decreases and the choice of 35 here mean that the decline is slower than the equivalent case for corporate where it is set to 50.

The Basel II accord has three different approaches to measure credit risk: Standardized, Foundation Internal Rating Based (FIRB) and Advanced Internal Rating Based (AIRB).

If using the standardized approach the banks are required to use the credit ratings of an external credit rating agency to quantify the required amount of capital.

The banks using the FIRB approach are allowed to quantify their own PDs but are required to use the regulators LGD and banks using the AIRB approach are allowed to estimate their own PDs, EADs and LGDs.

In general the AIRB requires less capital than FIRB and FIRB requires less capital than the standardized approach. This since the more advanced methods only can be used if the bank has sufficient historical data. This means that the bank can replace conservative estimations with historical values that in general show less credit losses than the conservative estimations.

3.6 Previous research

When Basel II was implemented, both financial institutions and researchers focused on how to estimate PD. As when some improvements had been discovered focus shifted to LGD. This means that in the case of LGD, a comparison of model suitability can be conducted and subsequently tested with data.

While there have been numerous studies modeling downturn LGD, most of these have focused on corporate credit portfolios, mainly publicly traded bonds. The reason for this is simple, data on and about corporation issuing public bonds is easily available and market values of publicly traded bonds are readily available.

The Vasieck model used in the Basel II accord does not take the correlation between LGD and PD into account. This has led to a large number of researchers trying to correct this, by

suggesting models that take this correlation into account. The largest group of such models is the factor models group. This group of models assumes that both PD and LGD are driven by some kind of common latent variable. An example of this kind of model is Frey 2000 with one systematic and one idiosyncratic factors, Hillebrand 2006 two systematic factors, Barco 2007 with two systematic factors and Chabane Laurent and Salomon with two systematic and two idiosyncratic factors.

There are also attempts to model downturn LGD with copulas and an example of this is Hui Li 2010 which discusses a copula model for only two loans but which could theoretically be extended to any number of loans.

Others, such as Chalupka et al 2008, discuss numerous simpler models. Most of these however are not relevant since they are not based on data or are based on data that are not available. Ozdemir and Miu 2009 suggest three approaches of which two will be tested in this paper, namely stress LGD by macro factors and a PD-LGD correlation model. A good example of an article building of a macro-stressable model is Caselli et al 2008 which comes to the conclusion that three macro factors are the main determinants for LGD.

Another interesting approach is to model LGD based on micro-data such as employment status, income, marriage, etc for each obligor. This has been done by Belloti and Cook 2009 and this kind of model is also supported by Roszbach at Riksbanken. This kind of data is not available to the author and will thus not be explored in this paper. Basing a model on this type of data and changing the status of people, for example from employed to unemployed, would probably be a very good model for downturn LGD and further research in the area should be done as data become available.

3.7 What does "downturn" mean?

An important aspect of this task is to determine how to define "downturn". According to the Swedish FSA there are no periods during the twenty-first century that can be seen as downturns in this regard.[8][p 12] This guideline was however published in 2007, i.e. before the financial crisis. While one could argue that the recent financial crisis was severe enough, the credit losses for Swedish banks have not been significant if we disregard the Baltic exposures. An example of this is that for private persons in Sweden that were not laid off, there has been no crisis at all.

Instead they have experienced lowered taxes and extremely low interest rates. Since this paper is based on data from Nordea's retail portfolio in the Nordic countries we have to look at another crisis. This implies that the best period to look at is the years during the nineties crisis. This is in line with the FSA that states that

"...the nineties can give good guidance on how such a (downturn) period might look." [8][p 12]

We define a period of crisis for each country of interest in the table below.

Denmark	2008 - Q2 2010
Finland	1990 - 1994
Norway	1987 - 1992
Sweden	1990 - 1994

We note that the recent financial crisis was worse for Denmark than the crisis in the nineties. As opposed to Sweden, Denmark had major decline in housing prices and numerous of smaller banks filed for bankruptcy.[30] For this reason we choose to use the period 2008-2010 as a model crisis for Denmark. Since the last data point on Danish macro data available when this paper was written is June 2010 the dataset might be censored, however looking forward from now, all predictions points upwards so using the censored dataset should only lead to more conservative estimates and is thus no problem. The Norwegian parliaments commission into the property crisis also seem to support the choice of these time intervals(Obviously it does not support the Danish time interval since the report was published in 1998).[28]

We have looked at how three factors develop to determine the crisis periods namely: GDP, property prices and unemployment and consider a crisis to have ended when they have stopped decreasing(Increasing in the case of unemployment). This definition gives periods that correspond to the periods commonly seen as deep crises. The reason for choosing to end the period when the conditions stops to get worse instead of when they start to improve is that it is sudden negative events that drives defaults and thus LGD. This means that the worst should be over when things start to stabilize hence this should be a conservative assumption.

3.8 What characterized the Swedish property crisis

Since we will use the property crisis in the nineties as our model crisis, we will make some observations about experiences from it. While the crisis was characterized by substantial credit

losses for most banks, most of the credit losses came from corporate exposures. Credit losses from private persons were comparably small. The loans to private individuals represented 2% of credit losses in 1992. In 1993 this had increased to 26% of losses and was 23% in 1994. In money the amounts were 385 MSEK 1992, 1098 MSEK 1993 and 500 MSEK 1994. The large increase private persons share in total loan losses can partly be explained by the transfer of assets to Securum in 1993. The transferred assets were mainly non performing corporate loans meaning that it changed the portfolio composition, this however can not explain the whole increase. [14][15][16]

There are several reasons for this, firstly the most common reason that private persons default is sudden unemployment or sickness. In many cases these are temporary conditions and default can be handled by simply lowering amortization until the person gets a new job/recovers. Secondly, residential mortgages have the residence as collateral, and in the few cases where the residence is actually sold, the proceedings from the sale covers most of the debt. This means that any remaining debt probably can be repaid by the obligor's salary. This was true even during the crisis.[31]

In the cases where the property did not cover most of the debt, the collateral was mainly very remote houses that are problematic to sell, however in those cases the property did not cost the defaulted that much either. The main category of private persons that defaults and leads to actual losses is SME owners that have guaranteed their firm's loans with private property. Unfortunately the loan losses above can not be separated into losses on residential mortgages and losses due to SME failure.

It is also important to note that the crisis was caused by a number of structural changes. Since then, people have either become accustomed to the changes or further changes have been made. This means that the economy, regulations and the banks have changed since.[31] Firstly, during the eighties the credit market in Sweden was de-regulated. Before this, the bank was only allowed to increase net lending by a certain percentage each year. This led to a large unfilled demand for credit by the households. When the market was de-regulated the households borrowed heavily, quickly increasing their leverage. This at the same time as the banks accustomed to the regulation did not have an adequate credit process in place. Secondly, until 1990 interest rates were fully deductible in Sweden. This coupled with high marginal taxes on income made debts cheap financing. During the beginning of the nineties there was a change from pegged currencies, and full employment to floating currencies and inflation targeting, causing a major macro-economic

shift. However, it took time for the economy to adjust. The years after the change, interest rates remained on the same nominal level as before, leading to a large increase in real interest rate.[23]

Although it would have been interesting to investigate how the crisis in the nineties affected the other Nordic countries, this has not been done due to the practical problems involved. The differences however, should not be so large that the description above is an unreasonable approximation even if it does not fit in every aspect. Especially in Denmark this might be an issue since we use a total different time period for Denmark. All macro data used however, is from the respective country.

3.9 Downturn LGD

There has been some research done into calculating LGD factors in downturn scenarios. This research however focuses mostly on deriving purely theoretical models (as in no or very little connection to real world data) or is based on publicly traded debt, almost always US corporate bonds.[3] In the case of a traded bond one might see LGD as one minus the bond price after default through the bond price before default. This however requires a market value, something that is not available for mortgages. While this kind of research might be very interesting it is not applicable without modification, since our model has to be based on real world data and market prices are not available.

In general, many banks have problems calculating LGD and especially downturn LGD since they lack sufficient data. There has been some research done on how to work around this problem. Part of the solutions offered are the theoretical models mentioned above, and part are Monte Carlo approaches or macro-economic models.

Chalupka et al state some approaches they think might be good ways to calculate downturn LGD.[11] These are:

1. Use a different(read higher) discount factor
2. Work with default weighted LGD instead of exposure weighted or time weighted LGD
3. Take into the consideration the non-closed files, where the recovery is lower
4. Use macro-economic factors within several stress scenarios

5. Choose 5 worst years out of last 7 years

While 1. might partially serve to calculate downturn LGD, it clearly is not enough and impossible given our dataset since the data only a single final LGD value is saved. Using only 1. disregards several important factors. 2. are already done with the normal LGD so that would not change anything. Currently, Nordea assumes that all recoveries are made within three years of the default. Later recoveries are not considered. While 3. might imply an even shorter limit it does not appear like a good way to estimate downturn LGD for several reasons. Most importantly that it is a very subjective method and that it is not based on actual, accurate data. 4. is an interesting approach which this paper will try to apply. 5. do not seem to capture a downturn very well since if the last seven years have been good the result will be biased.

The methodology of picking the worst, might hold some value in some sense but for it to be actually useful, it would have to be modeled differently. One might for example create a new portfolio consisting of actual loans from the real portfolio but overweight the loans with high LGDs. This might for example be done with the bootstrap method. While this methodology might be interesting as a comparison it does not fulfill the criteria of being based on actual downturn data since we can not know which quantile of the loss distribution that correspond to an actual downturn.

Ozdemir and Miu suggest three different approaches to downturn LGD:

1. Use historical LGD from a stressed period
2. Use a stressable LGD model such as a macro model
3. Explicitly incorporate PD and LGD correlation

As said before, 1. is impossible with the data available but would probably be the best method if they were available, while 2. and 3. will be tested in this paper.[19]

Chapter 4

Data

The data used to produce this paper is derived from Nordea's retail portfolio. The portfolio contains data for loans to private persons and some SME. The portfolio as of the end of 2009 (numbers from the Nordea Annual report 2009) has an on-balance exposure of 130248 mEUR with household mortgages making up 96615 mEUR of the on-balance. The off-balance exposure was 11479 mEUR which gives a total exposure of 141776 mEUR. [13]

Nordea has useable and representative data from 2002 which is available on a loan basis. The data before 2002 is very aggregated and only available in the form of annual reports of the banks that merged to create Nordea. This makes it very hard to use this information since we have to separate the net losses into PD and LGD. Also note the fact that it takes a three year workout period from default to get the final LGD. This means that we have data with final LGD values from 2002-2006 i.e. five years.

The on balance items are dominated by mortgages which make up about 74% of the on balance.[13] This means that focus of this paper will be to model mortgages correctly.

The dataset contains the realized LGD for all defaults during 2002-2006. It is important to note that the criterion used by Nordea to determine defaults is that a payment is more than 90 days late. This means that a default only indicates that a payment has not been made, it says nothing about the lenders fiscal situation. I.e. someone who has the ability to pay but who forgets to will be classed as a default and then as a default that recovered when the obligor pays.

The data has been split into different pools according to the type of the loan, i.e. residential

mortgages in one pool, credit cards in another. This gives us a large number of pools, however the number of observations is not equally distributed in these pools. Instead some pools contains a large share of the exposure and/or default observations.

While each of these pools contains a large number of defaults some pools contain only a fraction of loans that actually incurred losses. Between 45-95% of the defaults in each pool was cured, meaning that no losses were incurred since the loan became performing again. Of the remaining non-recovered loans there is a large share that did not lead to any losses. This because the sale of collaterals covered the debt. The large number of loans which did not lead to losses might cause a modeling problem if not considered properly.

While some pools contains few observations these pools also have a very small share of both exposure and losses, this means that we should have enough observation to be able to get reliable results. It is also important to note that we have very high granularity in our data since the exposure to each costumer is very small compared to the size of the portfolio. While we do not have perfect granularit we are close enough to be able to use model based on perfect granularity.

In this paper we have reduced the number of pools to three per country to preserve commercial confidentiality and make it easier to follow. Please refer to Appendix C for a specification of these pools and to section 5.5 for a description of the characteristics of each pool.

Chapter 5

Models

We will go through a number of different models, which of some will be tested and some we will dismiss without testing because of lack of data or demand of computer power. We will go through the FSA's suggested model, a multiplicative factor model, different regression models, latent variable models, copula models, an additive factor model and finally a micro data model based on the characteristics of every obligor. But first we will look at the distribution of LGD.

Most studies on LGD and downturn LGD (for example Chalupka et al 2008) seem to show a similar pattern where most observations either have a LGD of 0% or 100%. This means that some defaults do not imply any losses at all. Examples of this are when the collateral is worth more than the loan or when then obligor has just forgotten to pay the bills. There are also a percentage of loans that imply that more than the entire amount is lost. It is possible for the LGD to be higher than 100% because of the recovery costs, loans with an LGD over 100% are mostly unsecured. 5.1 show a simulation on how a ordinary LGD distribution looks.

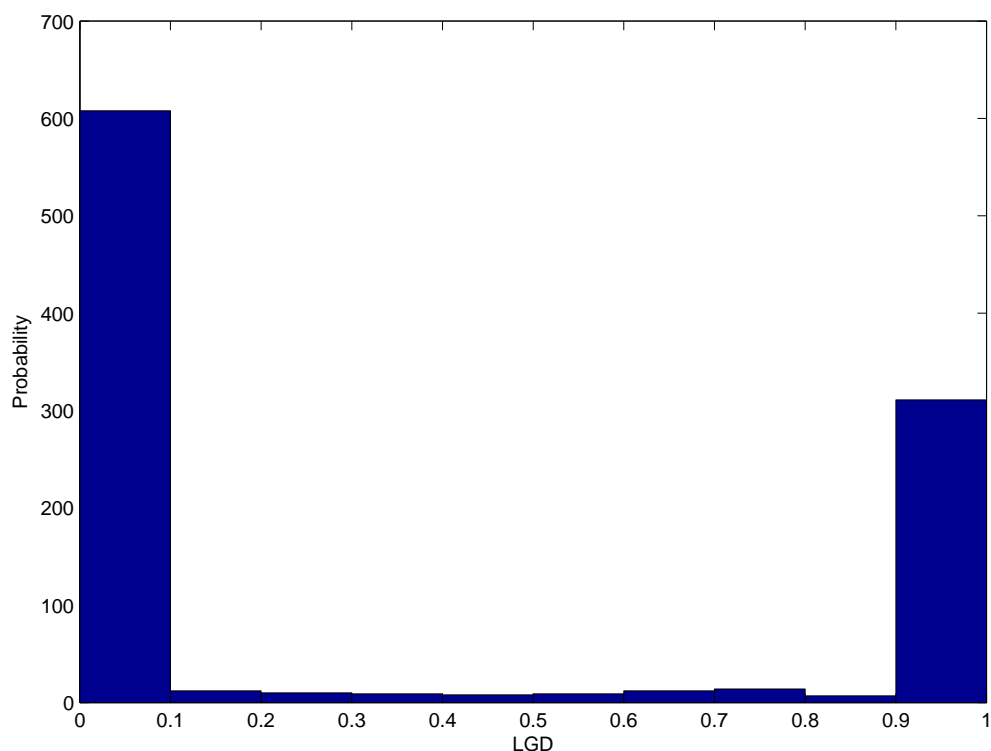


Figure 5.1: The plot shows the distribution: $X=0$ with $p=0.6$, $X=1$ with $p=0.3$ and $X=U(0,1)$ with $p=0.1$

5.1 Multiplicative Factor Model

One way to factorize LGD is to use the formula

$$\text{LGD} = (1 - C)(1 - S)(1 - O) \quad (5.1)$$

where: C is the cure rate, i.e. loans that stop being in default S is recoveries from collaterals ratio, i.e. sales of collaterals O is recoveries from obligor ratio, for example repayment from the salary of the obligor. This is the model suggested by the Swedish FSA in their report "Att mäta kreditrisk - erfarenheter från Basel 2".[8]

Using this framework allows us to separate the sources that can be used to repay the loan in case

of default. This means data for which we can model the variables independently. For instance, one might presume that recoveries from collaterals ratio, S , is dependent on housing prices while recoveries from obligor ratio, O , is dependant on unemployment. This however still leaves the problem regarding how to quantify the C , S and O parameters and more importantly how to stress them. One way to solve this is to make them dependent on macro-economic data and then stress these.

According to the Swedish FSA, the most important and most common factor for mortgages is the loan to value ratio. This is however not taken into account in the model which they suggest for calculating LGD.[8]

5.2 Copulas

While this area in general is very suited to be modeled by copulas, this paper will not use copula models to calculate downturn LGD. This due to the fact that the size of the portfolio used would create big computational problems for very little gain. A copula with hundreds of thousands dimensions is extremely computer intensive to calculate at the same time as the size make good estimations of parameters such as correlation impossible. Instead one would have to make the assumptions that all correlations are the same and equal to some more or less arbitrary numbers. This makes copula models difficult to use in practice on such a large portfolio. This reasoning was confirmed by Filip Lindskog in a discussion about model choice. One good example of this type is the one suggested by Hui Li 2010. This model however only looks at two loans at the same time.[21] While it is possible to expand that model to cover more loans, it is not possible from a practical sense with a portfolio containing as many loans as Nordea's retail portfolio.

It is possible that this kind of model could be used for large corporate costumer since they are limited in numbers and it should be easier to estimate correlations. For example if a firms largest costumer defaults the risk that the firm defaults will increase a lot. To investiget this however is outside the scope of the paper since we only look at retail costumers.

5.3 Latent variable single factor model

There are numerous sources that claim that PD and LGD are correlated, especially in downturn. [20] This has led to a number of models based on the basis that the correlation between PD and LGD comes from a dependence on a common factor. One example of these single factor models is the model presented by Frye 2000. The reason for choosing this model is that it is simpler form than the others and thus should be more robust.

We begin with describing this model before defining it in a more formal manner. We assume that the PD is driven by two factors, one systematic factor representing the state of the economy and one idiosyncratic factor unique to each obligor. We then assume that it is the same systematic factor that drives LGD. However the level of correlation between the systematic factor and PD or LGD respectively might differ. We then use historical data to solve an ML estimation to gain the PD-Economy correlation and which historical values this implies for the latent state of the economy variable. We then make an assumption on how the LGD depends on mean, standard deviation, and correlation with the economy and use the implied values for the state of the economy to solve another ML problem. This second problem gives us the LGD-Economy correlation, mean LGD and standard deviation of LGD. We can now choose a sufficiently stressed quantile of the latent variable and calculate which LGD values this implies, these LGD values are our DLGD.

First we define the relationship

$$A_j = pX * \sqrt{(1 - p^2) * X_j} \tag{5.2}$$

A_j is the asset level index for the j :th firm in the portfolio, while A_j might be mapped against asset value in money, this is not necessary for the model. X is a systematic risk factor often seen as the "state of the economy" and X_j is an idiosyncratic risk factor specific for the j :th firm. Both these are assumed to be independent and normally distributed.

The correlation factor p , controls how much the state of the economy affects the loan. A p close to zero will mean that the idiosyncratic risk factor is a more important driver of LGD and that we will not see any credit cycles. A value of p close to 1 will mean that the firms is closely tied to the state of the economy and that we will see severe credit cycles since many firms will default at the same time. The firm is considered to be in default if A_j is less than some threshold value,

defined with help of PD_j which is the long term average probability of default for firm j . We now define the default indicator D_j . This indicator is 1 if the firm is in default and 0 otherwise. i.e:

$$D_j = 1 \text{ if } ; A_j < \Phi^{-1}(PD_j); D_j = 0 \text{ Otherwise} \quad (5.3)$$

If we assume that we have a large and well diversified portfolio, which is a very reasonable assumption since our data are mortgages and bank loans to SMEs. This means that each loan is very small compared to the size of the portfolio and that it is close enough to a homogenous portfolio that assuming homogeneity does not make any unreasonable restrictions. We can hence use the law of large numbers which implies that conditional on a level of X , the observed default frequency for loan j , DF_j , approximates its conditionally expected rate. Given this information we solve the next problem to determine

$$\begin{aligned} DF_j &= P [A_j < \Phi^{-1}(PD_j) | X = x] = P [px * \sqrt{(1-p^2)} * X_j < \Phi^{-1}(PD_j) | X = x] \\ &= \left[X_j < \frac{\Phi^{-1}PD_j - px}{\sqrt{(1-p^2)}} \right] = \Phi \left[X_j < \frac{\Phi^{-1}PD_j - px}{\sqrt{(1-p^2)}} \right] \end{aligned}$$

Looking at the recovery side we define recoveries R_j :

$$R_j = \mu_j + \sigma * qX + \sigma\sqrt{(1-q^2)} * Z_j \quad (5.4)$$

Where Z_j is an idiosyncratic risk factor, X is the state of the economy, same as above, q is the recovery rates dependence on the state of the economy. I.e. a q close to zero will imply that recoveries do not depend on the state of the economy and a value close to the opposite. σ_j is the long term average recovery rate and σ_j is the volatility of the recovery rate. We also not that:

$$Corr(A_j, X) = p \text{ and } Corr(R_j, X) = p \quad (5.5)$$

To fit the single factor model to data we first define

$$DF_{t,r} = \Phi \left[X_j < \frac{\Phi^{-1}PD_j - pX_t}{\sqrt{(1-p^2)}} \right] \quad (5.6)$$

Where $DF_{t,r}$ is the default rate in pool r in year t and PD_r is the long term average default rate for firms in pool r . Instead of just separating into pools we could separate into groups of firms with rating x in pool r . This is however impossible in practice, since it would result in very few observations in each group. It would also be hard to get these data without making so restrictive assumptions that the analysis becomes meaningless.

We can then calculate the default rate in year t , DF_t , with the formula:

$$DF_t = \sum_{r=1}^R h_{t,r} D_{t,r} = g_p(X_t) \quad (5.7)$$

Where $h_{t,r}$ is the share of total defaults in pool r in year t .

Since g is monotonic and we know that X is normal distributed, we can use the change variable technique. i.e if then:

$$F_Y(y) = \left| \frac{1}{g'(g^{-1}(y))} \right| * f_X(g^{-1}(y)) \quad (5.8)$$

And in our case we have $DF_t = g_p(X_t)$ which implies that

$$f_{DT_t}(DT_t) = \left| \frac{1}{g'(g^{-1}(DT_t))} \right| * f_X(g^{-1}(DT_t)) = [X_t = g^{-1}(DT_t)] = \left| \frac{1}{g'(X_t)} \right| * f_X(g^{-1}(DT_t)) = \left| \frac{1}{g'(X_t)} \right| * \frac{\exp\left(\frac{-(g^{-1}(DT_t))^2}{2}\right)}{\sqrt{2*\pi}}$$

If we then calculate the derivate of g implicitly and assume independence between years, we can get the joint density function for the default rates:

$$f_{DF_1, \dots, DF_t}(DF_1, \dots, DF_t) = \prod_{t=1}^T \left| \frac{1}{g'(X_t)} \right| * \frac{\exp\left(\frac{-(g^{-1}(DF_t))^2}{2}\right)}{\sqrt{2*\pi}} = \left[g'(DF_t) = \frac{d}{dx} \sum_{r=1}^R h_{t,r} \Phi \left[\frac{\Phi^{-1} PD_j - p X_t}{\sqrt{(1-p^2)}} \right] = \frac{p}{\sqrt{1-p^2}} \sum_{r=1}^R h_{t,r} \Phi \left[\frac{\Phi^{-1} PD_j - p X_t}{\sqrt{(1-p^2)}} \right] \right] = \prod_{t=1}^T \frac{\sqrt{1-p^2} * \exp\left(\frac{-(g^{-1}(DF_t))^2}{2}\right)}{p \sqrt{2\pi} * \sum_{r=1}^R h_{t,r} \Phi \left[\frac{\Phi^{-1} PD_j - p X_t}{\sqrt{(1-p^2)}} \right]}$$

I.E.

$$f_{DF_1, \dots, DF_t}(DF_1, \dots, DF_t) = \prod_{t=1}^T \frac{\sqrt{1-p^2} * \exp\left(\frac{-(g^{-1}(DF_t))^2}{2}\right)}{p\sqrt{2\pi} * \sum_{r=1}^R h_{t,r} \Phi\left[\frac{\Phi^{-1}PD_j - pX_t}{\sqrt{(1-p^2)}}\right]} \quad (5.9)$$

We note that the joint density function 5.9 is a function of DF_t , the default proportions $h_{t,r}$ and the long term average default rates PD_r and the unknown parameter p . We also note that we can calculate all these parameters using our dataset. We get p by maximizing the joint density function with respect to p ; i.e. by using maximum likelihood. This can be done since we can invert g numerically with respect to X_t since g is monotonic. I.e. seek X_t such that:

$$DF_{t,r} = \Phi\left[X_j < \frac{\Phi^{-1}PD_j - pX_t}{\sqrt{(1-p^2)}}\right] = 0 \quad (5.10)$$

Where we use the p value in the current iteration of the maximum likelihood maximization.

After we have found our p we can use the equation

$$DF_{t,r} = \Phi\left[X_j < \frac{\Phi^{-1}PD_j - pX_t}{\sqrt{(1-p^2)}}\right] \quad (5.11)$$

and solve it for X_t since all other parameters are known. This then gives us implicit values for X_t .

Now define $R_{t,r}$, the recovery rate year t for loans in pool r .

$$R_{t,r} = \mu_r + \sigma q X_t + \sigma \sqrt{1-q^2} * Z_{t,r} \quad (5.12)$$

The average recovery rate in year t can be calculated as

$$R_t = \frac{\sum_{r=1}^R R_{t,r}}{\sum_{r=1}^R N_{t,r}} \quad (5.13)$$

Where $N_{t,r}$ is the number of recoveries year t in pool r .

If $R_{t,r}$ in 5.13 is replaced by 5.12 we get:

$$R_t = \frac{\sum_{r=1}^R N_{t,r} \mu_{t,r}}{N_t} + \frac{\sum_{r=1}^R N_{t,r} \sigma q^2}{N_t} + Y_t \quad (5.14)$$

Where Y_t is normally distributed with zero mean and variance

$$Var [Y_t] = \frac{\sum_{r=1}^R N_{t,r} \sigma^2 (1 - q^2)}{\left(\sum_{r=1}^R N_{t,r}\right)^2} \quad (5.15)$$

This leads to the likelihood function for the recovery data by using the change of variable technique again.

$$f(R_t) = \exp\left(\frac{-\frac{1}{2Var[Y_t]} * \left[R_t - \frac{\sum_{r=1}^R N_{t,r} \mu_{t,r}}{N_t} - \frac{\sum_{r=1}^R N_{t,r} \sigma q^2}{N_t}\right]}{\sqrt{2\pi Var[Y_t]}}\right) \quad (5.16)$$

Maximizing $\prod_r f(R_t)$ with respect to μ_j , σ and q gives estimates of these parameters. What remains to adapt this model for the purpose of this paper, is to decide how severe the crisis in the nineties was with respect to our X parameter. It is important to note here that we have assumed that X is normal distributed and this is probably not the best distribution to model a crisis as severe, as the one in the nineties since the distribution has very little weight in the tails.

The formulas above is presented as in Frye however when deriving them I got slightly different results. Note the extra square in the formula below:

$$Var [Y_t] = \frac{\sum_{r=1}^R N_{t,r}^2 \sigma^2 (1 - q^2)}{\left(\sum_{r=1}^R N_{t,r}\right)^2} \quad (5.17)$$

And that the q^2 has been changed to q in the formula below.

$$f(R_t) = \exp\left(\frac{-\frac{1}{2Var[Y_t]} * \left[R_t - \frac{\sum_{r=1}^R N_{t,r} \mu_{t,r}}{N_t} - \frac{\sum_{r=1}^R N_{t,r} \sigma q}{N_t}\right]}{\sqrt{2\pi Var[Y_t]}}\right) \quad (5.18)$$

How one should determine a value of X that represents a downturn scenario is also an important question. One idea here is to look at some variable such as change unemployment or property prices and assume that it is normal distributed. We then normalize the variable and calculate in which quantile a data point that we know, comes from a downturn end up. If we do this for a couple of variables we should have an idea of which value to use.

5.4 Regression models

While it is certainly possible to select a large number of macro-economic factors and then use model selection theory and choose to use the factors which have the highest significance, this is not a good idea.

We have available data from a normal (i.e. non downturn) period from an economic standpoint. We are going to use this data to calibrate a regression model based on macro-economic factors and then use the value of these factors during the nineties crisis to calculate a downturn LGD. While certain relationships may exist during the normal period it is not certain that they behave in the same way during a stressed period. This means that we have to be certain that we use factors that actually do affect LGD and that the relationship does not change significantly if the economy deteriorates.

5.4.1 Macroeconomic Drivers, Previous Research

Caselli et al have done a study examining the relation between LGD and macro-economic factors with the help of a dataset of 11649 loans from the Italian market. According to the study, the best predictors for LGD on loans to households are the default rate of households, unemployment rate and household consumption. For SME LGD they assert that the best predictors are GDP growth rate and the number of employed. [10] They also come to the conclusion that there are no set of parameters that fits all LGD pools. Instead the macroeconomic factors must be chosen so that they fit the LGD pool in question i.e. Household disposable income affect mortgage LGD a great deal more than foreign guarantees to SMEs.

An important factor that prevents the comparison of results between countries is bankruptcy law. For example in the US a mortgage is tied to the property, not the person. I.e. a person can leave the house key to the bank and be free of the mortgage. In Sweden however the mortgage is tied to the person, not the property and a person can be in debt even after the lender has liquidated the property. This means that a Swedish obligor is less probable to default since the legal consequences are much more severe. Which implies that while you might use the same method in different countries the results can not be compared in a good way. Otherwise a comparison between the results in this study and that of Caselli et al would be very interesting, especially since they also focus on a retail portfolio. The legal situation in the Nordic countries

is however similar, which helps simplifying the analysis.

Torbjörn Isakson, chief analyst at Nordea, suggests another set of factors. He suggests that the debt to disposable income and interest rate payments to disposable income, probably are the two most driving factors for mortgage LGD and that other important factors might be interest rate level, household financial savings and employment or unemployment. [29]

The importance of these factors is supported by Troels Thiell Eriksen, senior analyst at Nordea, specialized in the Nordic housing market. He also suggests that forced sales might be a good variable since forced sale of real estate should be closely tied to defaulted mortgages. [30]

Another source of inspiration for choosing macro-economic variables is Riksbankens report on financial stability 2009:2. In this report Riksbanken makes an analysis of the lending and credit risk of the large Swedish banks and base their level of credit losses on a macro-economic scenario of three variables, namely industrial production, consumer price index and 3 months interest rate. [7]

In the report "Alla vill göra rätt för sig" the Swedish Enforcement Agency investigates the reasons for over indebtness. Their conclusions are that while it is hard to quantify specific reasons for over indebtness important factors are sudden negative events and low margins. Sudden negative events mean events that lower income and are hard to predict. Examples are unemployment, long term sickness and divorce. Having low margins lowers a person's ability to handle these changes. Low margins however does not mean that it only concerns persons with low income as persons with high income may also have low margins. [22]

According to a study by the Swedish Riksbank SMEs show less reaction to macroeconomic changes as well as changes in firm specific risk factors. The Riksbank uses this to reach the conclusion that the unexpected loss is smaller for SMEs than for larger corporations.[24] What is interesting in this for our model, is that since SMEs show less reaction to changes in the macro economy, however it also means that the losses should be more stable around the mean than larger corporation making the intercept more important, so this should not cause a problem.

5.4.2 Macroeconomic factors

The main source of the macro-economic data is Ecwin, a databank that compiles time series of financial and economic data. The advantages of using this data source are that almost all

macro-economic data comes from a single source which makes collection easier and that we get comparable data series for the different countries or as close to comparable as possible. However not all factors used were available from Ecwin some come from Eurostat and the national statistics agencies. Please refer to appendix A for tables over data sources and from which year they were available.

5.4.3 Time Lags

It is important to note that there might be lag effects in the relationship between LGD and macro data, i.e. if we have LGD data from Q2 2002 it is not certain that it is the unemployment data from Q2 2002 we should use in our regression. Instead it might be the unemployment data from Q1 2001 that show the best correlation with changes in LGD. One explanation for this is that most people have some kind of buffer they will use before defaulting and that the unemployment subsidies decrease after one year of unemployment. To be certain that we use optimal time lags one might compare the correlation between LGD and the macro data and choose to use the time lags that show the highest correlation.

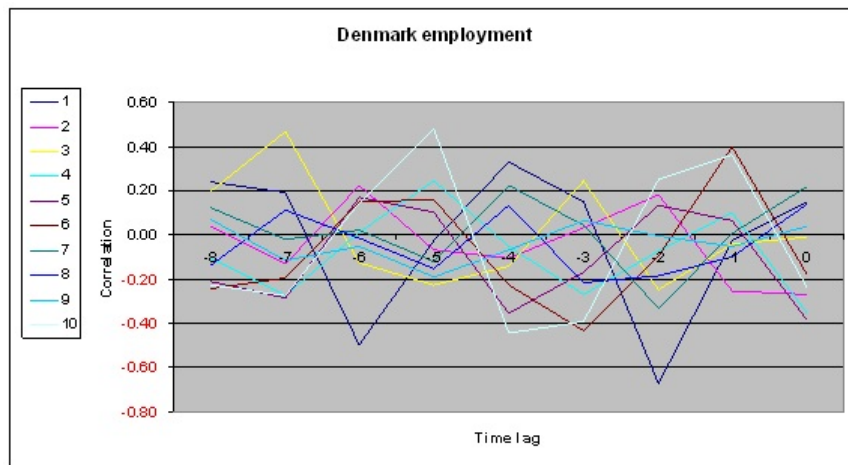


Figure 5.2

The plot shows the correlation between the LGD of 10 Danish pools and employment for 9 different time lags of the employment. The values on the x-axis correspond to the number of quarters for which the employment data has been shifted. So if the value is -4, we have checked the correlation between the LGD values and the unemployment one year before.

However as we see in the plot above, it is impossible to determine which time lag is optimal. Firstly we have the problem that the correlation for each pool changes sign more or less randomly for different time lags. This together with the small data sample used to calculate the correlations in the first place raises the question whenever we can draw any reliable conclusions from this at all. The second problem is that the correlation for the different pools does not seem to follow the same pattern, for example, for time lag -4 we have some pools that have the highest correlation while some have the lowest. This can partly be explained by the fact that the pool contains different kinds of loans and that these loans are affected differently. But the most probable reason is that we simply do not have enough data. Unsecured loans should probably be affected earlier than mortgages. Because of this problem and arbitrariness of choosing time lags based on the available data, all time lags were set to zero. This is not true since it takes some time for things such as decreased employment to cause actual increases in LGD. But it is the most reasonable assumption we can make under the circumstances.

5.4.4 Macroeconomic Drivers

Debt to disposable income ratio This ratio measures how the debt compares to the income which could be used to pay it. This means that it is a measure of long term viability. I.e. if this measure is high, the households will be very sensitive to interest rate increases. While it is intuitive to assume that a higher debt to income ratio leads to a higher LGD, this might not be the case, since the ratio increases mostly when the economy is going up. Likewise a decline in debt ratio is a sign of an economic downturn, and the level of decrease is dependent on the level of credit losses and the difficulty of getting new financing. As we see in the picture, the ratio decreased during the property crisis and increased during good years. It is also probable that the ratios long term average has been changed since inflation targeting was introduced, making comparisons difficult.

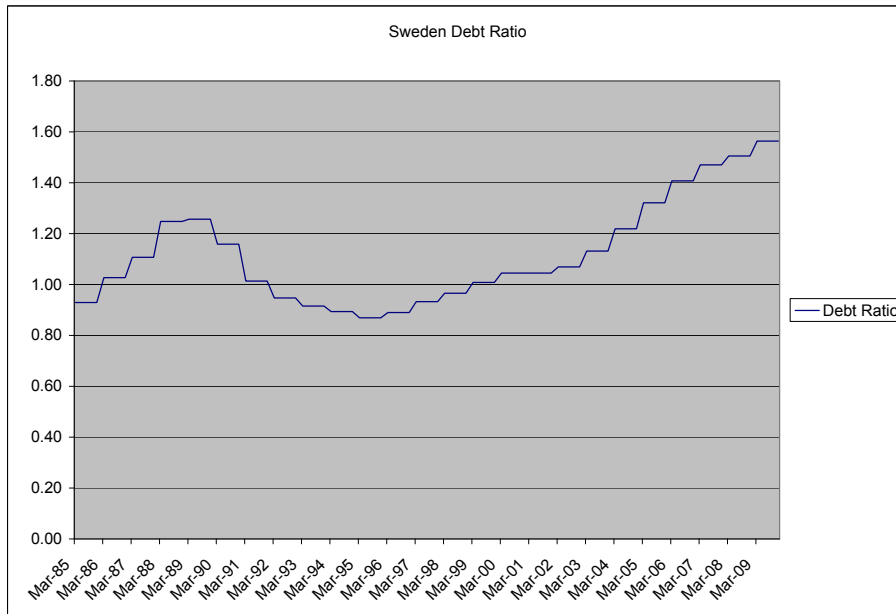


Figure 5.3

Property prices are an important indicator since most of the collaterals for our portfolio is housing. A decrease in this variable will decrease the value of the collaterals, increasing the LGD. Ideally this measure should contain both houses and condominiums prices in the right proportions but such measures are hard to get. This however is not possible since the required price data/price index for condominiums and the historical distribution between houses and condominiums does not exist. The price of houses and condominiums is highly correlated so the error of only using house prices should no be that large.

Interest rate payments to disposable income ratio should be more a short term indicator of the loan defaults. A high value of this variable should imply a higher number of defaults since a higher ratio is more difficult to maintain if something negatively affect payment ability, for example unemployment or sickness. This variable should also be a trend sensitive indicator since the number of people with floating interest rates on their mortgages is record high. [17] While this variable should be a good indicator, the fact is that it is not. This is because the

shift to inflation targeting by the central banks after the property crisis. This has led to lower inflation which in turn has led to lower nominal interest rate. So this variable shows a steadily decreasing trend from 1990 to the 2006 where our dataset ends.

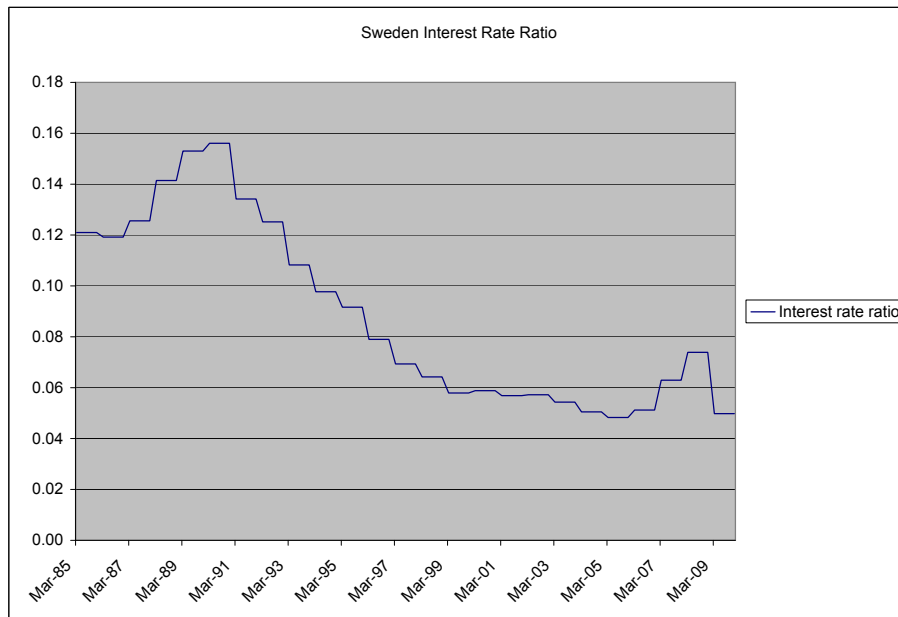


Figure 5.4

Forced Sales of real estate This is the number of sales on executive auctions. The number of forced sales should have a very high correlation to defaulted mortgages since a defaulted mortgage is a very common reason for a forced sale. This statistic is however only available in Denmark. In the other countries we will try to use bankruptcies as a proxy for this variable.

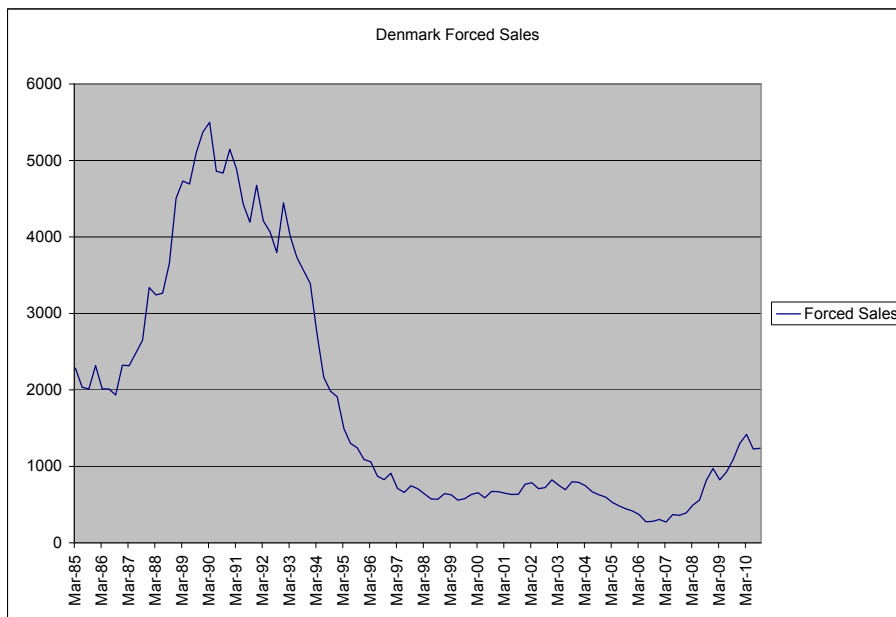


Figure 5.5

Employment and unemployment, employment is the share of the workforce that is currently employed and unemployment is the share of the workforce that currently has no employment. As these variables measure more or less the same thing we will discuss them together. A decrease in employment will lead to an increase in unemployment and while it is not a 1:1 relationship the effect it has on LGD is the same since in general an employed person earns more than a person that is not. This means that LGD will increase with increasing unemployment (decreasing employment) as people will not be able to pay their loan, especially mortgages in our case.

Interest rate level. The level of interest rate do affect the number of loans that default and will probably have some effect on the LGD. It is hard to see whether nominal or real rate that will be more useful; which should also be true for long and short rates. To be certain to get the best result we will try all of these variables.

Household financial savings is defined as disposable income minus consumptions. If the

households have higher savings that means that they have a higher buffer against a downturn. This means that high savings should mean fewer defaults among households. The problem with this assumption is of course that savings are not equal distributed among the households and it is the households that save the least that have the highest risk of default.

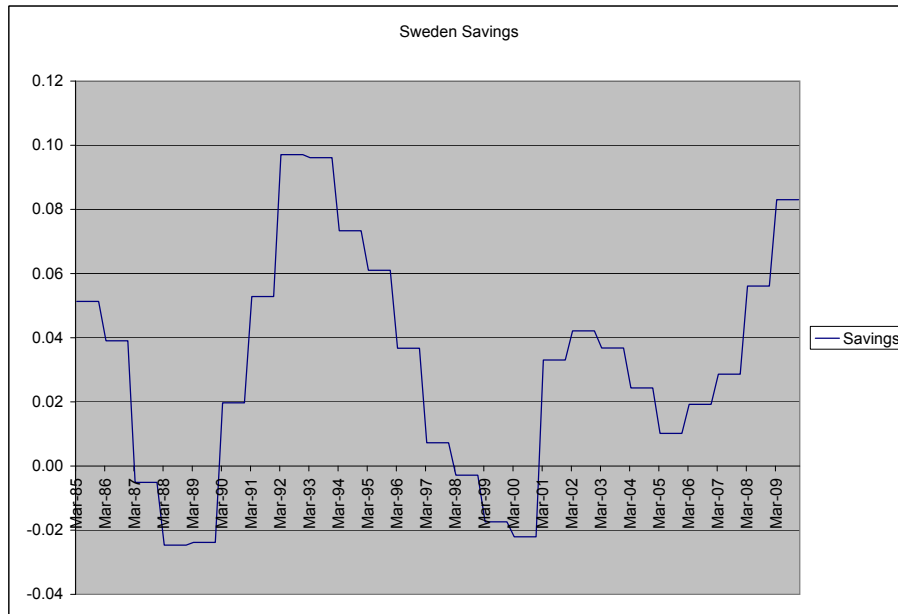


Figure 5.6

GDP is a measure of overall economic output and is defined as the market value of all finished goods and services produced in a country in a year. As such, GDP is a good measure of the level of economic activity inside a country. Given this, it makes a reasonable assumption that GDP should be negatively correlated to LGD in the SME segment and while it probably have some effect on the household LGD level, it is probably small compared to both the effect on SME and the effect other factors have on households.

Disposable income is defined as personal income minus taxes. This measure is probably negatively correlated to household LGD since if households earn more it is reasonable to assume

that loss given default will decrease. It is important to note that since personal default has very severe consequences and does not mean that the debt does not have to be repaid, a mortgage is one of the first things that get paid.

Consumer price index is defined as the price level for a basket of goods and services. The basket is based on the goods bought by consumers and should show how prices develop. Since we use a retail portfolio it makes sense to use this index, if it were a corporate portfolio, a price index based on another good basket would probably have been more appropriate. It is not really clear what effect on DLGD this measure should have, if any at all.[29]

Government bond yield. This variable is a proxy for mortgage interest rates. Increases in interest rate should increase the PD since some households will not be able to afford the increase. However how this should affect LGD is not clear. One might argue that increases in interest rate leads to lower housing prices, however, this should be captured better by the property price variable.

5.4.5 Non Macro Drivers

While macro-economic factors can be very useful to estimate LGD and CCF, there are other factors that can be used as well. Most of these factors are micro factors and need to be applied on a loan level while the macro factors can be used on pooled data. This means that the computer intensity of the calculations increase significantly as do the difficulty in obtaining data.

In a study of micro data Chalupka et al finds that the most important factors driving LGD are relative value of the collateral, loan size and year of origination. [11]

Probability of default numerous academic studies such as Hu 2002 finds that PD and LGD are correlated. This implies that PD can be used as driver for LGD. Other studies such as Frey 2000 says that the correlation between PD and LGD comes from dependence on common factors. If that is the case it might be problematic to have both the macro-economic variables and PD at the same time since it could cause multicollinearity problems. [27]

Credit Rating. The credit rating of the individual obligor depends on both qualitative factors such as personal knowledge of the bank employee that grants the loan and quantitative factors such as income. As such, credit rating is probably a very good indicator for PD and LGD, while use of credit rating probably would produce good results. However, it is not possible too use for

two reasons; 1) using rating groups would make each group too small, 2) the credit rating data cannot be obtained for all years. Therefore using this would further limit the already small data sample. Taking both these effects into account the degradation of the results would probably be larger than any potential gain at this stage. The author supports the idea of investigating this area further when more data is available.

Geographic region/Country. Different regions have different structural conditions and cultures that can affect LGD and CCF. For example two countries might have a system where private persons might default and be free of their debt in one country however it is socially unacceptable to default. In this case the countries would have different PDs and LGDs despite similar laws. Franks et al finds that recovery rates in France, Germany and the UK differ significantly and attribute this to the different bankruptcy laws in these countries.[12] In this paper the data has been separated in four geographic groups, Denmark, Finland, Norway and Sweden. This should capture the most important differences in legal situation and debt culture. Further subdivision is not possible since this would lead to too few observations in each group.

Industry. Chalupka et al concludes that there are significant differences in LGD dependent on industry. The reason for this is that different industries have different structure and different amounts of physical capital.[11] For example a steel mill has a lot of physical capital that can be used as collateral, while an IT-consultant hardly has any physical capital at all. Different industries are also affected differently by a crisis as are the values of the collaterals they provide. For example a steel mill might be good collateral in a normal market environment but in a deep recession with very low steel demand the collateral value will be much lower than usual, increasing the LGD. This is more or less equivalent to the split according to pool we have done with our dataset. The pools are based on that there are certain groups of loans with similar characteristics such as type of collateral.

Default on credit card It seems reasonable to assume that an obligor in distress would choose to default on credit card debt before defaulting on a mortgage. Therefore it would be interesting to see if credit card defaults could be used as a driving factor from mortgages defaults. This however will probably be difficult to test due to data inadequacies.

5.4.6 Regression

One method to tie the macro-economic factors together with the LGD is by using regression. Which kind of regression specification that is appropriate is hard to decide a priori, so instead the model that gives the best significance will be chosen.

There are economic reasons to suspect that some of these factors may be correlated and probably should not be used simultaneously to avoid problems with co-linearity. For example the variables interest rate and disposable income should not be used in the same regression as interest rate payments to disposable income ratio.

5.4.7 OLS

In OLS regression the linear model

$$Y = X * \beta + \varepsilon \tag{5.19}$$

where;

$$Y = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}, X = \begin{pmatrix} x_{1,1} & \dots & x_{1,k} \\ \vdots & \ddots & \vdots \\ x_{n,1} & \dots & x_{n,k} \end{pmatrix}, \beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_n \end{pmatrix}, \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

is assumed.

We can then use the least squares method to approximate β which yields:

$$\hat{\beta} = (X'X)^{-1} * X'Y \tag{5.20}$$

Which is unbiased and we use the heteroskedasticity consistent covariance estimator:

$$\hat{\Sigma} = \left(\frac{1}{n}X'X\right)^{-1} * \left(\frac{1}{n}X'DX\right)^{-1} * \left(\frac{1}{n}X'X\right)^{-1} = \left(\frac{1}{n}X'X\right)^{-1} * \left(\frac{1}{n}X' \sum_{i=1}^n (x_i x_i \hat{e}_i^2) X\right)^{-1} * \left(\frac{1}{n}X'X\right)^{-1} \tag{5.21}$$

[18] To be certain to get a good specification of the regression model, the forward selection method with a significance level of 0.05 was used for each pool. The purpose of this is to make certain that the model can be used for other periods than the one the data are from. While using

all available variables would have led to a better fit of the model during the years 2002-2006, it would also have meant that it could not be used in a more stressed scenario since the result would have been unreasonable.

5.5 Linear Multifactor Model

As we can see in the result section below, regression did not work very well since it gave a number of degenerated results. The idea of using linear models is however a good one, and instead of basing the linear model purely on quantitative data we will try one that also take some economic common sense aspects into account.

Other

The other group consists of loans with either some kind of property or other assets (mainly assets from SMEs) as collateral. Bearing this in mind we use unemployment and GDP as stress factor. Unemployment should capture the the effects of changes in employment while the GDP captures the more conditions for SMEs.

Residential

As this pools contains mainly mortgages, natural choices of factors to stress factors are employment and property prices. Like in the regression model above, the interest rate ratio and debt ratio probably should be very good explanatory variables here. Unfortunately we have the same problem as above here. The change in these variables are dominated by the effects caused by the change too inflation targeting which make them hard to use with our given data.

Unsecured

The pools in this group do not have any collateral. This kind of loans is mainly affected by the state of the economy in general and thus we use employment and Stock Index as stress factors. We choose to use the stock index instead of GDP as the index should be more volatile and better capture quick changes in the economy,

If we add up the above we get the table below:

Group	Unemployment	Property Prices	Stock Index	GDP
Other	x			x
Residential	x	x		
Unsecured	x		x	

We specify this model as:

$$DLGD = (1 - C)_{DT} * (E(LGD) + \beta_1 x_1 + \beta_2 x_2) \quad (5.22)$$

Where C is the cure rate and $E(LGD)$ is the mean historical LGD value. The betas are coefficients and the x 's are macro variables. The macro variables are defined as the change rate of the variable on a yearly basis using the geometric average in the downturn period defined for each country.

We will use the following decreases in non-cured rate to simulate our downturn. The reason for not using the same stress factor is that not all pools are affected equally by a downturn.

$$(1 - C)_{DT} = (1 - C) - \Delta GDP - \Delta Employment \quad (5.23)$$

5.6 Microdata Model

This is a kind of model that is based on data for every single loan instead of using aggregated indicators. This however means that to use this kind of model, large amount of data must be available at a granular level. This kind of model is also favored by Kasper Roszbach, deputy head of research at Sverige's Riksbank.

Since this kind of data required is not available to the author we will only go through the main features of the model.

Assume that we have a credit portfolio of retail loans but in addition to the data we have available, we also have data on how much each obligor earns and how much the collateral of the loan is worth (at the time the loan was issued). This makes it possible to calculate the loan to value ratio for each loan. We then model a downturn with the following simple algorithm:

Microdata Model Flowchart

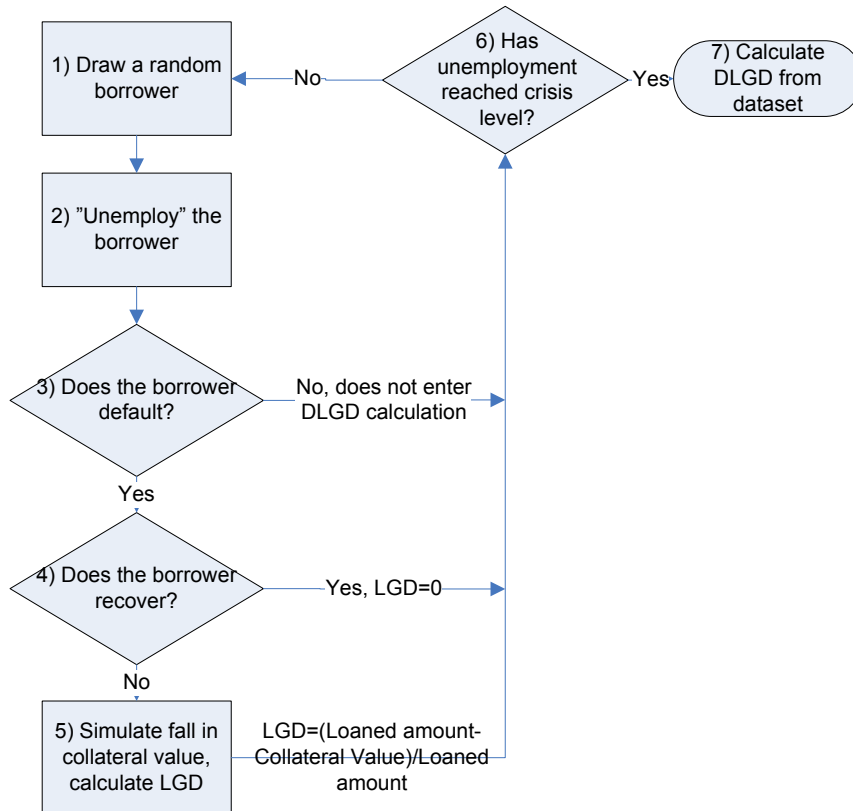


Figure 5.7

And an explanation to each step

1. Select a random obligor (without return)
2. If the obligor earns more than the highest amount in the unemployment benefit, lower the income to what he would get if he was unemployed. weighted LGD
3. Randomly determine if this leads to a default. The probability of default is based on how

much the income was lowered, on how high the interests rates are of the new income

- a) If 3) does not leads to a default go to 6.
 - b) If 3) does leads to a default go to 4.
4. Calculated the risk for reemployment during the next year and randomly determine if this obligor is reemployed,
 5. If the obligor is reemployed $LGD=0$ and $recovery=1$ go to 6)
 6. If 3) does not recover go to 5)
 7. If he is not re-employed, simulate the fall in the value of the collateral by looking at how much housing prices has fallen during historical recessions (or other indexes if the collateral is not housing). If the new collateral value is still higher then the loaned amount the $LGD=0$. Otherwise $LGD=(\text{Loaned amount}-\text{new collateral value})/\text{Loaned amount}$. Go to 6.
 8. Repeat the steps above until the "unemployment" has been raised to a level that is similar to the unemployment level in a historical crisis. So if the current unemployment is 4% and the historical level of crisis unemployment is 10% we repeat these steps until we have selected $10\%-4\%=6\%$ of the loans portfolio and simulated them losing their jobs.

We then calculate the LGD we have in this scenario and use it as our downturn LGD.

This is of course a short overview on how this kind of model might work. If one were to use one in real life one would have to define the distributions and refine the model.

Chapter 6

Results

6.1 Regression models

Using the regression model discussed above selecting which regression coefficients to use for each pool by forward selection with a significance level of 0.05 we get the result in the tables below. Please note that the intercepts are all numbers between 0 and 1. They have been left out for confidentiality reasons since the intercept is very close to the average historical LGDs in our dataset.

Modeling Downturn LGD for a Retail Portfolio

Country	Pool	Intercept	GDP	CPI	Employment	Unemployment	Property Prices
Denmark	Residential	0.xx					
Denmark	Unsecured	0.xx	0.28499	3.9392	-0.441		0.3159
Denmark	Other	0.xx					9.3612
Finland	Residential	0.xx				3.7915	
Finland	Unsecured	0.xx	1.16791	17.2707			-3.0182
Finland	Other	0.xx					
Norway	Residential	0.xx			3.6544	-0.49612	1.4438
Norway	Unsecured	0.xx	-0.56812		-7.4129	-1.06481	2.1792
Norway	Other	0.xx					
Sweden	Residential	0.xx					
Sweden	Unsecured	0.xx	0.19944				
Sweden	Other	0.xx				0.63988	

Table 6.1

Country	Pool	Stock Index	Yield 10Y	Yield 5Y	Yield 2Y	Yield 3 months
Denmark	Residential	0.33025				
Denmark	Unsecured	0.1148	-0.37061		0.27136	
Denmark	Other					
Finland	Residential					1.44616
Finland	Unsecured	0.93215		0.02122		-0.48625
Finland	Other			0.7527		
Norway	Residential			0.21316	-0.07645	-0.23496
Norway	Unsecured	0.26361	-1.23574	1.0491	0.04746	-0.21879
Norway	Other					
Sweden	Residential					-0.21204
Sweden	Unsecured	-0.22528	-1.9865	1.06287		
Sweden	Other					

Table 6.2

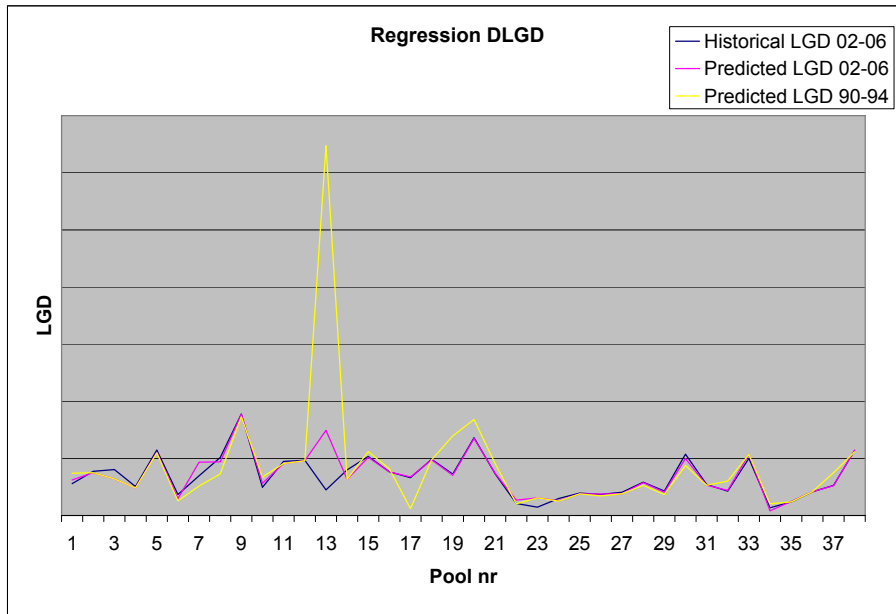


Figure 6.1

While regression models are a good idea in theory, they are not useful in practice to estimate downturn LGD given the conditions in this paper. This is because, while the dataset used contains hundred of thousand default observations, they are not representative for a downturn period. This means that if we calculate the regression coefficients from these data, the coefficients cannot be used to predict the LGD level in a downturn.

The results in table 6.1 and 6.2 is an aggregation of the full results some of the reasoning here might not have support in these tables but are instead based on a larger table with a lot more pools. The reason for censoring the results this way is commercial confidentiality.

The regression coefficients do show values that are clearly unreasonable. For example the coefficients for employment should all be negative, i.e. an increase in employment leads to a decrease in LGD. This is however not the case, instead a number of pools for which employment is significant, have a positive coefficient for employment. This means that if employment increases,

the LGD increases. This is clearly an unreasonable result and we can see the same pattern in unemployment and property prices. We also have that increasing stock prices increases the LGD for a number of pools.

If all the pools had the wrong sign it probably would depend on some other kind of error such as omitted variable bias or multi-co-linearity. But when the signs are more or less randomly distributed we have to draw the conclusion that regression is not usable with our dataset. In the examples discussed above about 50 % of the pools has a positive coefficient and 50% has a negative coefficient. While the regression coefficients above obviously work reasonably well to forecast the data that was used to calculate them, we cannot make any assumptions that they can be used for anything else. This is based on what is reasonable with regards to how the economy works and that all common sense speaks against such results. If the signs of the regression coefficients were as expected, one might discuss using it to forecast a downturn but as it is, that assumption cannot be made in good faith.

It is also important to note that the regression above is the specification that gives the best results. All other specifications have given results that were worse, most of them a lot worse. For example Appendix D contains the regression coefficients of all pools that are secured by private housing on unemployment and property prices. As we can see, in the table, the sign and size of the regression coefficient vary wildly, meaning that a small decrease in unemployment may increase the LGD a lot in one pool and lower it in another. It is easy to achieve even worse result by changing the specification even more.

While the variables debt ratio, interest rate ratio and savings ratio should be good predictors from an economic common sense perspective, the results speak otherwise. If these variables are added to the regression, we get degenerated results that are clearly unreasonable. This also strengthens the reasoning above, i.e. our regression cannot be used to forecast downturn LGD.

A good example of this is that the LGD predicted in a crisis like the nineties crisis gives a negative LGD in the area 2 to 6 for some pools. This is clearly unreasonable. You do loss 200%-600% more if a loan defaults in a crisis values of 1.05-1.15 might have been reasonable but you do not spend 6 millions to get back 1 million from a non performing obligor. There are two possible reasons for this, 1) these macro-economic variables are only available on a yearly basis which is a problem since we do our regressions on a quarterly basis. 2) that the development of these variables in the period 2002-2006 is not representative for a full economic cycle; instead

they only capture the behavior in a very good period. This might affect these variables more since the number of observations is just a fourth of the number of observations of the other macro-economic variables.

The same thing can be said about the variable forced sales in Demark, it shows a decreasing trend during the period 2002-2006 while the LGD for residential mortgages, the pool forced sales should affect the most, for non recovered loans varies wildly.

This volatility is caused by the lack of non recovered defaults; most quarters have less than 10 data points. This is because while residential mortgages are the largest pool measured by exposure, there are hardly any data points that have led to actual losses in this pool. Instead almost all observation that has led to actual losses is in the unsecured category, thus we have a significant mismatch. This means that we do not get a representative relationship between the variables and that the regression coefficients are extremely non robust.

For the reasons above, these variables have been left out of the regression model.

6.2 Linear Multifactor Model

While this model has some obvious disadvantages such as not being based on purely quantitative analysis, it is also the model that shows the best results. This is of course dependant on the fact that the lack of appropriate data disturbs the calibration of the other models, while this model depends on an economic theory, the legal situation, and expert opinions for calibration. This makes it possible to create a model that gives reasonable results that can be defended with economic reasonability and expert evaluations. Any numeric results for this model are not presented because of commercial confidentiality.

6.3 Latent Variable Single Factor Model

This model gives strange results, which may be because of two reasons, not enough calibration data/calibration data not representative or that the model does not work. Test with a larger simulated dataset give more reasonable results. The result however is not good enough to actually use. This because while the σ and q parameters are reasonable at least one of the μ 's are unreasonable, example of this is either negative, larger than 1. The LGD is not bounded at one

as there are observations with an LGD above one, however getting a μ above ones implies that in an average state of the economy the LGD is above 1. This is simply not the case. Neither Frye's original formulas nor the ones I arrived at, give any results that are usable.

While there are other latent variable models that could give better results, these were not tested since the chance of them working when the Frye model does not, probably due to data inadequacies, should be very low.

Chapter 7

Conclusion

As we have seen in the results above, most methods to calculate downturn LGD do produce results that are unreasonable in some way. The reason for this is obviously our lack of data and the fact that the period we have data from was an economic boom. This makes the data hard to use as a basis for a downturn scenario. To be able to produce some actually usable results, we choose methods based on economic knowledge and patterns in our data. While this method creates a model that feels more logical and consistent with common sense, it does not have the same quantitative backing but instead partly relies on experts.

To get data of sufficient quality we would have to experience a crisis like the property crisis in the nineties again. While the recent financial crisis was very severe in some senses, loan losses in the nordic countries did not increase that much. The period can thus not be used as a downturn period in our sense except for Denmark which had a more severe crisis.

While Nordea will get more data as the years go by, this also lessens the need for a downturn LGD model. When sufficient data has been amassed one might simply use the realized LGD value from an actual downturn scenario as downturn LGD. However there will always be an issue if the past can be used to predict the future so the modelling downturn LGD will always be of some interest.

The latent variable models might work if one have more data or use another specification. This category of models however has a big disadvantage, namely that the latent variable is inherently unobservable. This makes it impossible to determine how much you should stress the variable.

For example, if the latent variable is standard normal distributed as in Frye's model, how do one know which systematic risk factor value should be used to represent a crisis? There is no way to determine that but to assume that a crisis is equivalent to some quantile of the normal distribution. Such assumptions are impossible to justify since we have to base our model on facts and historical crises.

The model that is the most promising is the model based on microdata. This allows for a much more realistic modeling at the same time as it is both intuitive and mathematically simple. The biggest obstacle for this model is the data required, but as time goes, this kind of data will be collected and used. In fact, this kind of data already exists within every bank. This since no bank will lend money to private persons without knowing what they earn, what the collateral is worth and if the obligor has a bad credit record. The problem is that the processes and data systems have not been adapted to save this data in a way that makes it feasible to use for this kind of modeling. But, in the future I believe it will be available, which makes this kind of model possible.

The hypothesis in this paper was that $LGD \approx DLGD$. While we have not been able to support this with quantitative data, most aspects seem to point in that direction. Examples of this are the experience from the nineties crisis and that the pricefalls although severe was limited in the sense that it mostly hit the homeowners equity since the loan to value ratio was below 1 in most cases, seems to point in this direction.

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Appendix A

Table over macro data sources

The year the series starts in

Modeling Downturn LGD for a Retail Portfolio

Macro Variables	Denmark	Finland	Norway	Sweden
GDP	1990	1975	1978	1980
Consumer price index	1967	1960	1982	1900
Employment	1988	1988	1972	2001
Unemployment	1980	1959	1972	1991
Property prices	1992	1983	1989	1975
National Stock Index	1957	1957	1982	1987
Yield 10Y	1987	1991	1921	1918
Yield 5Y	1987	1948	1961	1986
Yield 2Y	1987	1992	1992	1960
Yield 3months	1972	1977	1971	1960
FX rate National Currency to EUR	1978	xxxx	1988	1978
LEAD	1968	1985		1970
Forced Sales	1984			
Bankruptcies	1979	1986	1980	1994
Debt to disposable income ratio				1970*
Interest rate payments to disposable income ratio				1980*
Household financial savings		1988		1994*
Disposable income	1990		2002	1993*

This table show the year the macro data series start in, cells marked with * means that the data only is available on a yearly basis instead of quarterly.

Collected from source

By: A. Wirehammar

Modeling Downturn LGD for a Retail Portfolio

Macro Variables	Denmark	Finland	Norway	Sweden
GDP	EW	EW	EW	SCB
Consumer price index	EW	EW	EW	SCB
Employment	EW	EW	EW	EW
Unemployment	EU	EU	EU+SSB	EU
Property prices	EW	EW	EW	EW
National Stock Index	EW	EW	EW	EW
Yield 10Y	EW	EW	EW	EW
Yield 5Y	EW	EW	EW	EW
Yield 2Y	EW	EW	EW	EW
Yield 3months	EW	EW	EW	EW
FX rate National Currency to EUR	EW		EW	EW
Forced Sales	EW			
Bankruptcies	EW	EW	EW	EW
Debt to disposable income ratio				SCB
Interest rate payments to disposable income ratio				SCB
Household financial savings		EW		SCB
Disposable income	EW		EW	SCB

EW=EcoWin EUR=EuroStat SSB\SCB=National Statistics Agency.

Appendix B

Plots of macro data

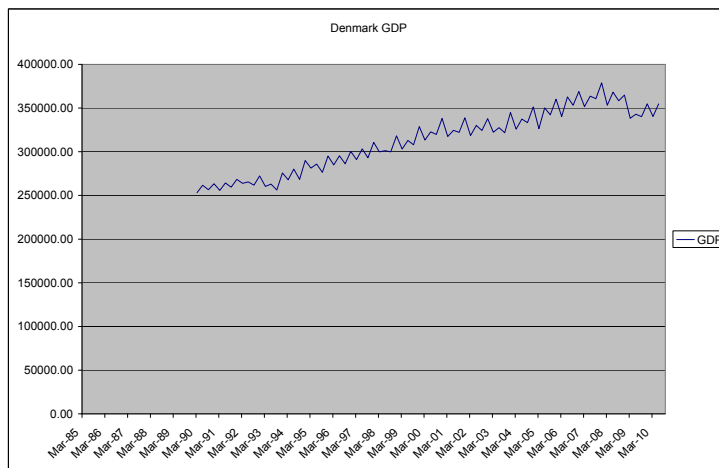


Figure B.9

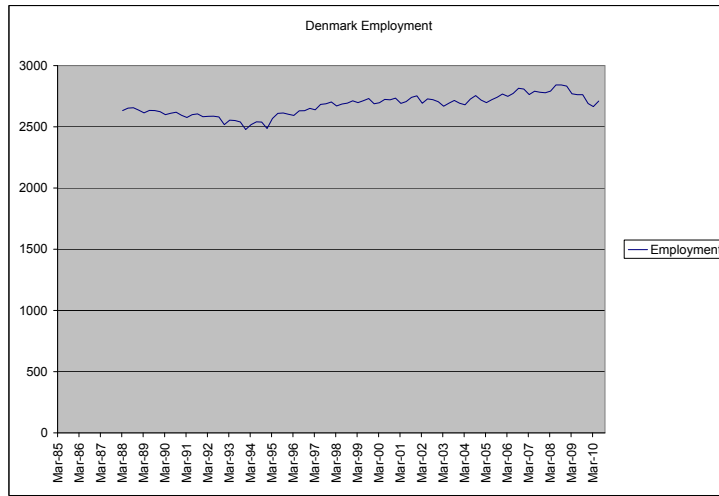


Figure B.1

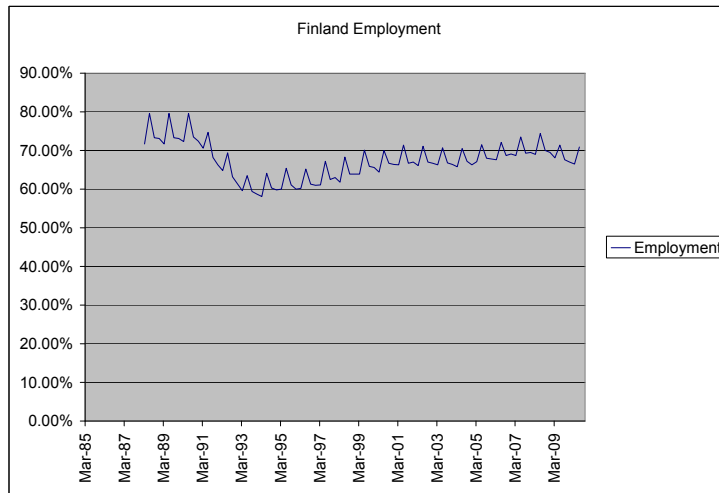


Figure B.2

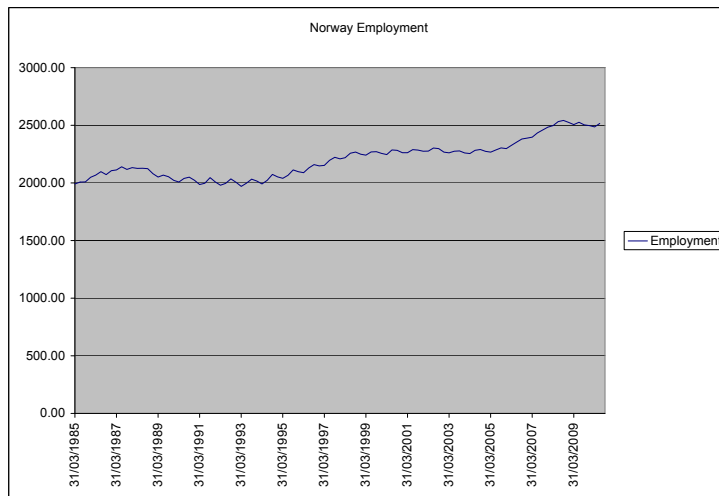


Figure B.3

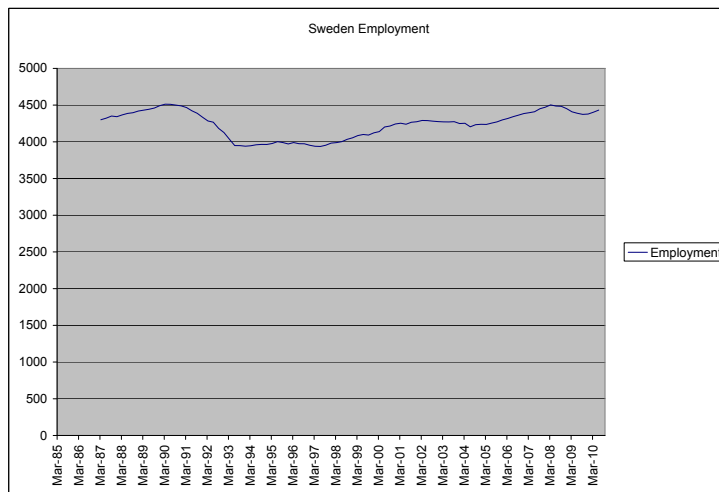


Figure B.4

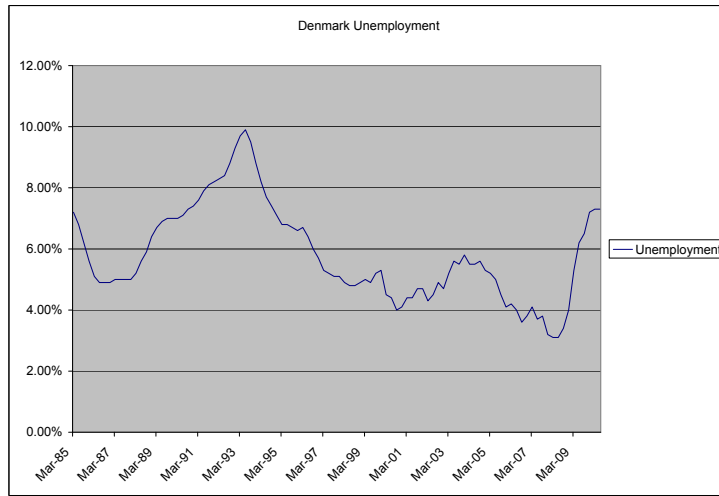


Figure B.5

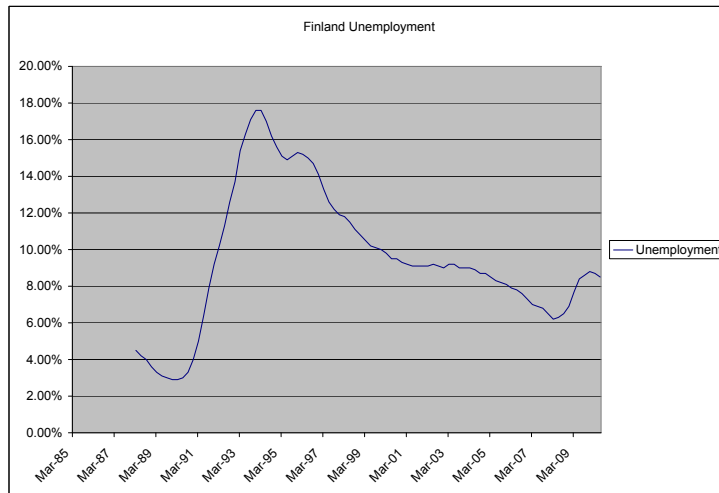


Figure B.6

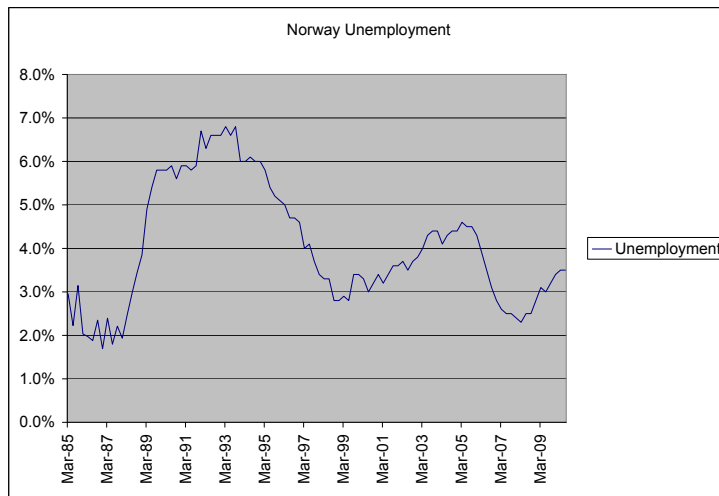


Figure B.7

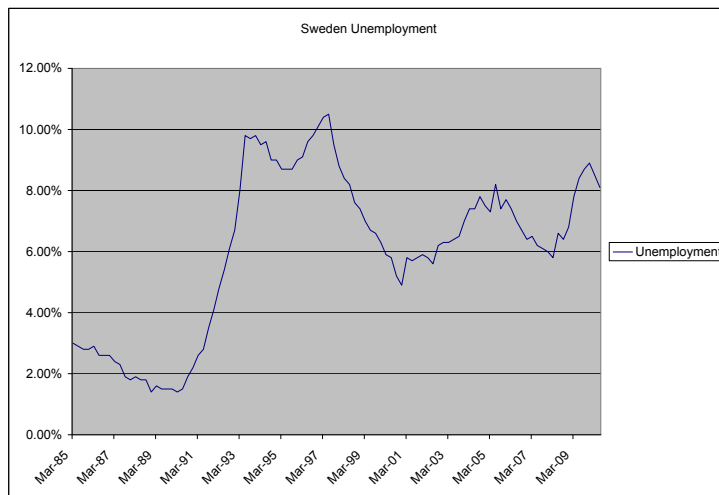


Figure B.8

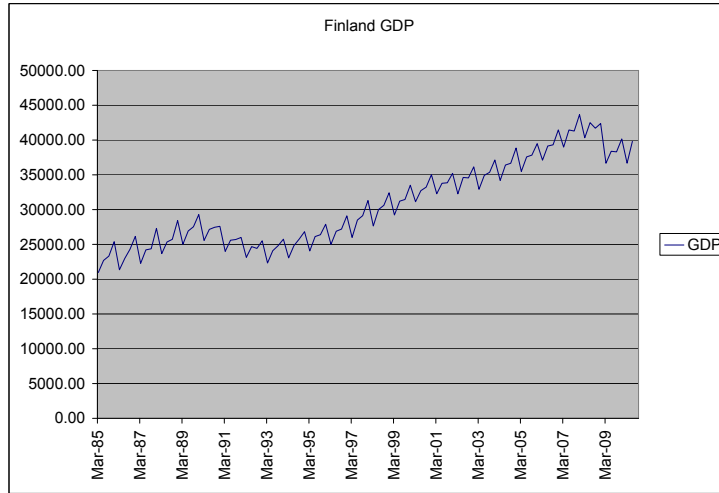


Figure B.10

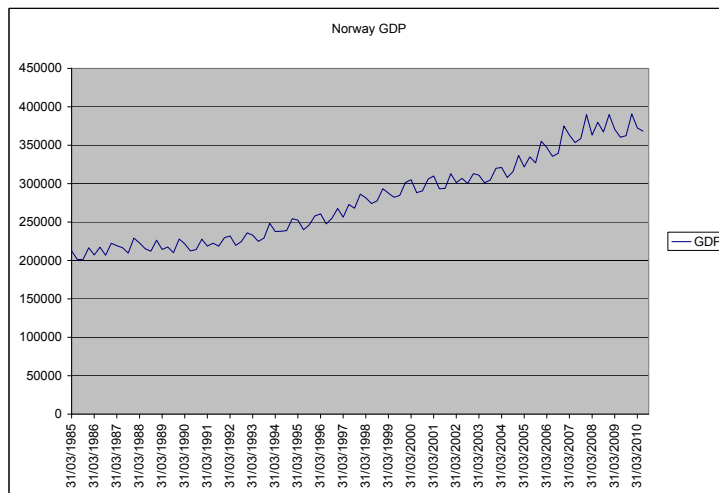


Figure B.11

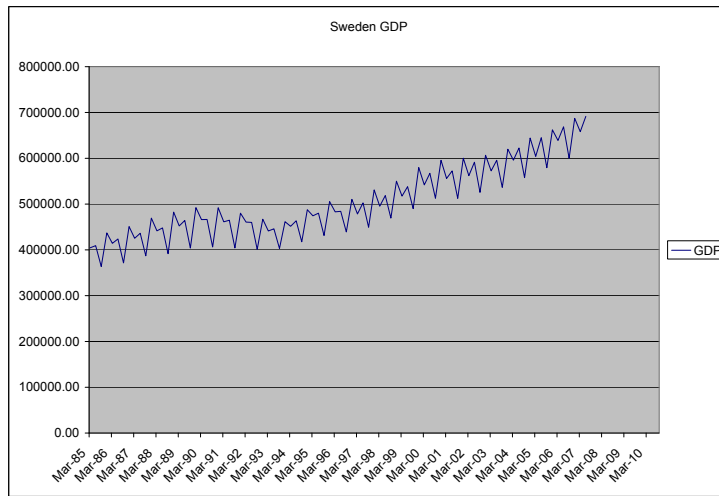


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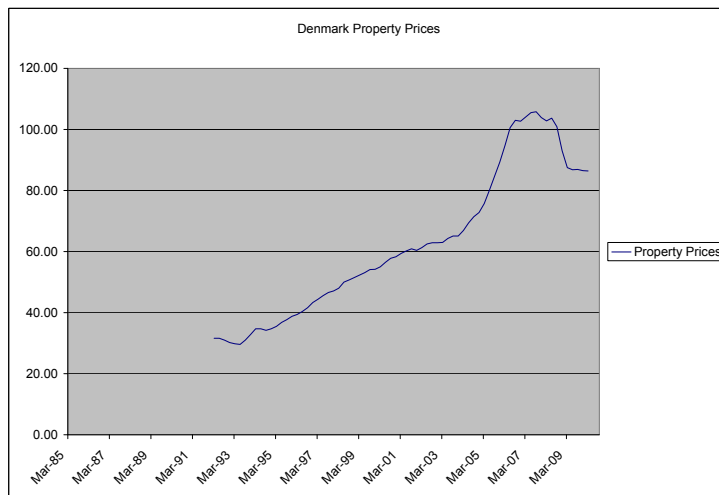


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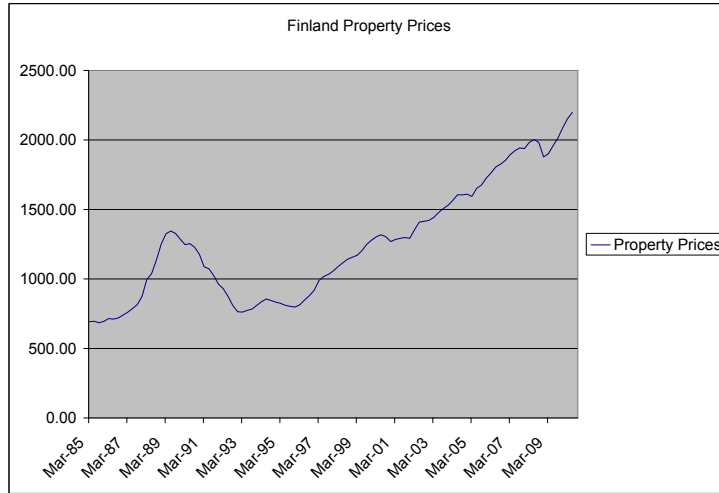


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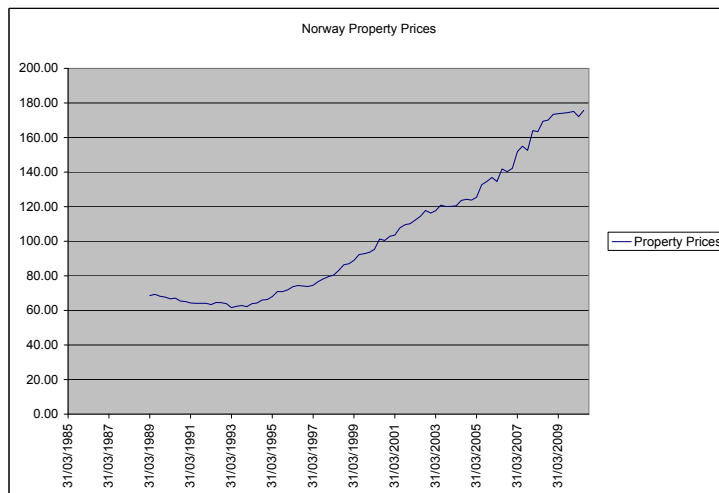


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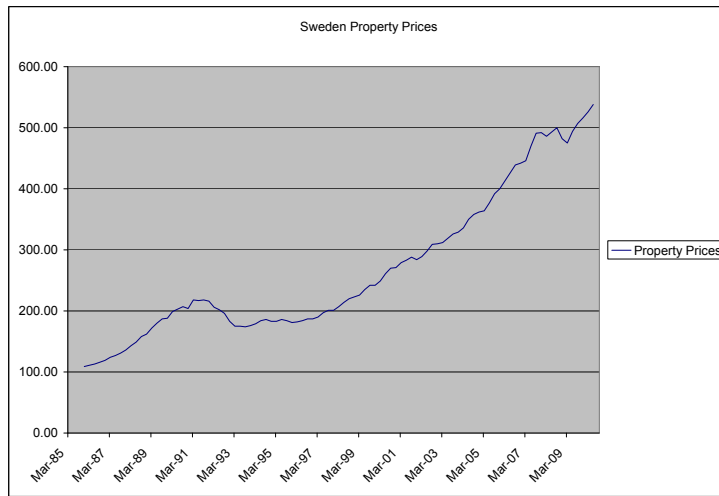


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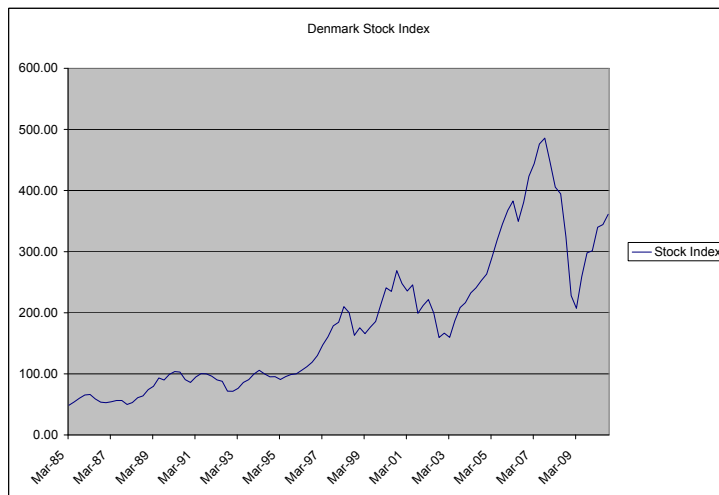


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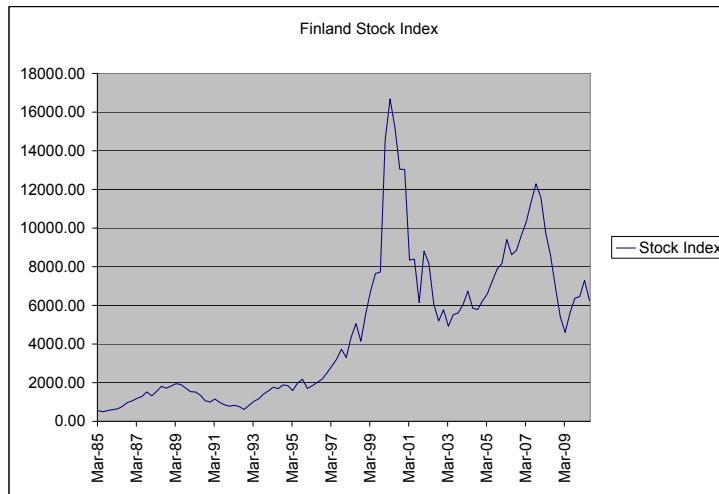


Figure B.18

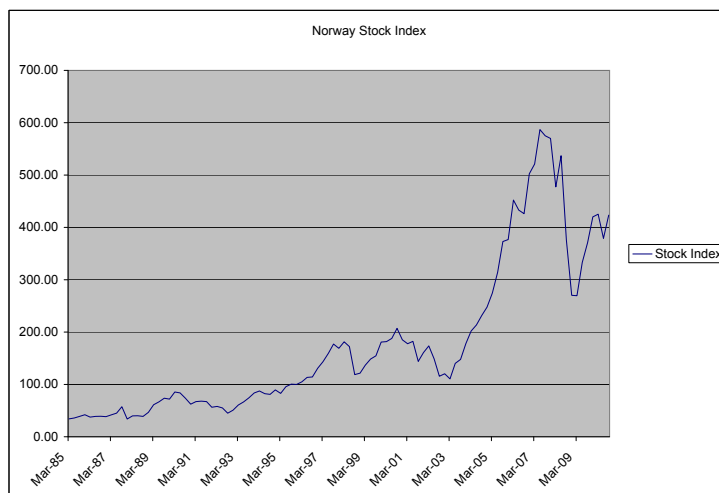


Figure B.19

Modeling Downturn LGD for a Retail Portfolio

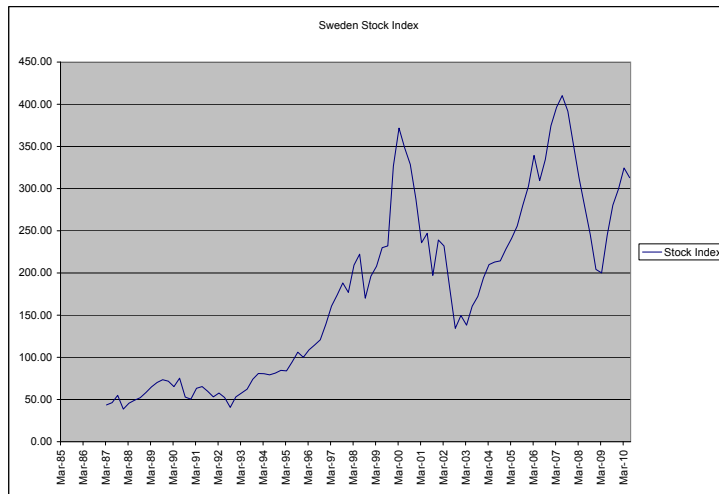


Figure B.20

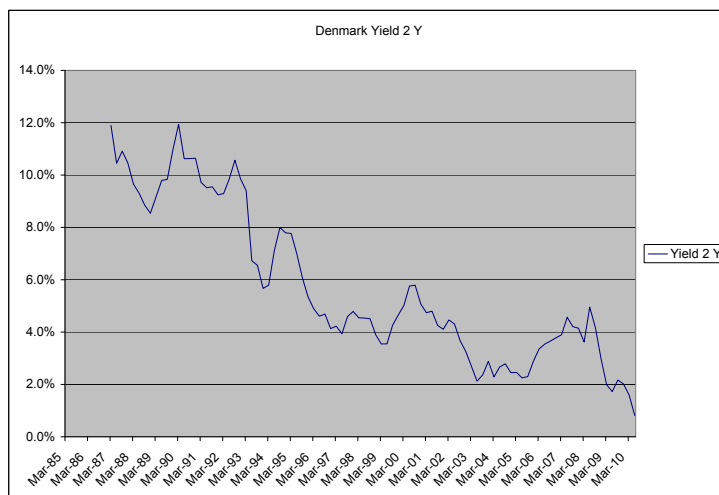


Figure B.21

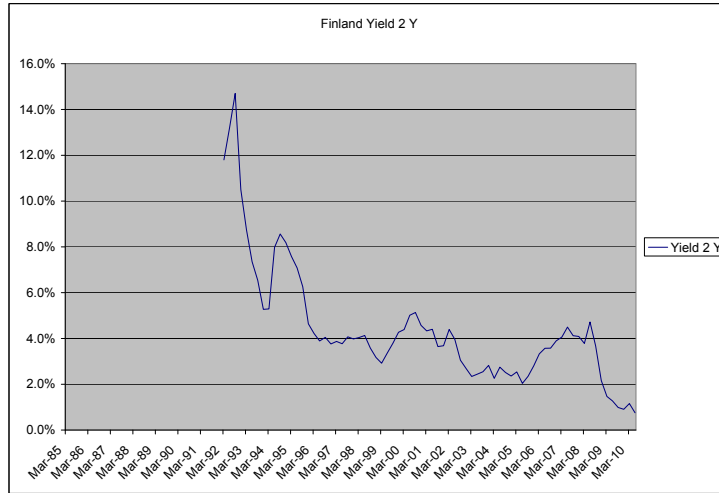


Figure B.22

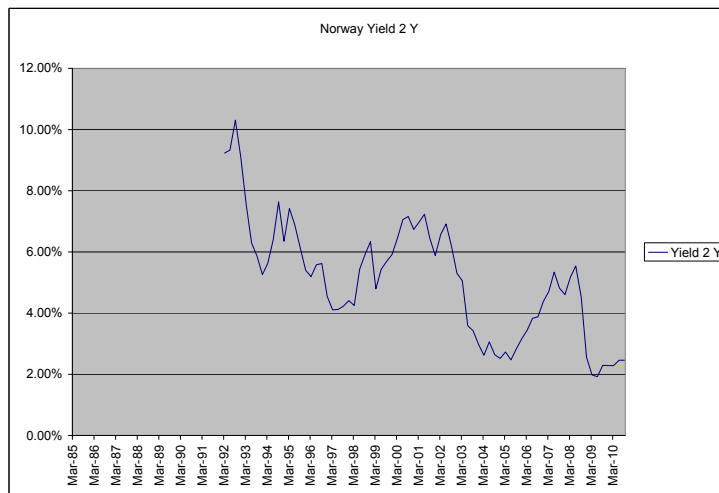


Figure B.23

Modeling Downturn LGD for a Retail Portfolio

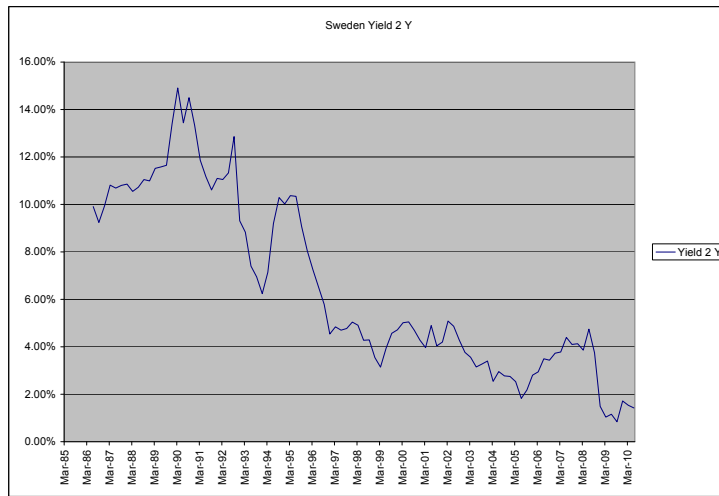


Figure B.24

Appendix C

Pool Specification

Country	Pool
Denmark	Residential
Denmark	Unsecured
Denmark	Other
Finland	Residential
Finland	Unsecured
Finland	Other
Norway	Residential
Norway	Unsecured
Norway	Other
Sweden	Residential
Sweden	Unsecured
Sweden	Other

Appendix D

Alternative Regressions

Country	Pool	Intercept	Unemployment	Property Prices
Denmark	Residential	0.xx	0.66	5.72
Finland	Residential	0.xx	-2.60	3.13
Norway	Residential	0.xx	0.05	0.15
Sweden	Residential	0.xx	0.18	-1.72