Lund Institute of Technology
Lund University

Mitigating Procyclicality due to Minimum Capital Requirements in the Swedish Banking Sector

Master Thesis in Industrial Engineering and Management
Department of Mathematical Statistics
Lund Institute of Technology
Lund, Sweden

Christian Hultin &
Eirikur Arnljots
June 18, 2013

Abstract

This study explores methods for mitigating procyclicality due to calculations of *minimum capital requirements* to cover credit risk. The basis for calculations are provided by the Basel Committee in the Basel accords and the main concern is that they could strengthen the amplitude of economic cycle fluctuations. Our study constructs a portfolio that aims to replicate the *Swedish* market for corporate lending by using external Probability of Default data for Swedish companies in the span of 2005-2013. The data is used together with the Basel guidelines for calculations to compute the corresponding minimum capital requirements series, which in turn is used in testing four different options to prevent the apparent procyclical behaviour. The evaluation of the options is conducted by comparing the root-mean-square deviations of the adjusted series with respect to the Hodrick-Prescott trend of the unadjusted series. It turns out that adjusting the input with logistic regression or the output with a business multiplier are the best performing options, where the latter is favoured due to its simplicity in implementation.

Key Words: Credit Risk, Procyclicality, Regulatory Capital, Minimum Capital Requirements, Basel III, Economic Cycles, Probability of Default

Acknowledgements

This thesis has been a collaboration between Ernst & Young's (EY) Quantitative advisory services (QAS) in Copenhagen and the faculty of mathematics at Lund institute of technology. Jim Gustafsson (QAS) was the initiative force for the project but has also been our main coordinator and provided us with a lot of valuable insight. Our previous experience with credit risk was very limited when first arriving at EY and we have since then learnt a great deal for which we are very thankful.

Karin Gambe (QAS) and Anna Silén (QAS) has been our counsellors, without them this thesis would not have been possible since they have provided us with day-to-day guidance on technical and practical issues. We would also like to direct many thanks to the rest of the team at QAS for their support and friendly treatment during the entire process of our work.

Christian Hultin and Eirikur Arnljots

Copenhagen

Contents

1 Acronyms **10**

2 Introduction **11**
2.1 Background . . . 11
2.2 Research Questions . . . 12
2.3 Purpose . . . 12
2.4 Limitations . . . 13
2.5 Sources of Information . . . 13
2.6 Outline . . . 13

3 Theoretical Background **15**
3.1 Procyclicality . . . 15
3.2 Credit Risk . . . 16
3.3 Basel Committee on Banking Supervision . . . 17
3.3.1 Basel I . . . 17
3.3.2 Basel II . . . 18
3.3.3 Basel III . . . 19
3.4 Risk Weighted Assets (RWA) Calculations . . . 21
3.5 Minimum Capital Requirements (K) Calculations . . . 21
3.5.1 Probability of Default (PD) . . . 22
3.5.2 Loss given Default (LGD) . . . 25
3.5.3 Unexpected Losses: Final Equation for minimum capital requirements (K) . . . 25
3.5.4 Procyclical effects from minimum capital requirements calculations . . . 27

4 Mitigating Procyclicality from Minimum Capital Requirements **29**
4.1 Adjusting the input . . . 30
4.2 Adjusting the equation . . . 31

4.3 Adjusting the output 32

5 Method 33

6 Data 34
6.1 Probability of Default (PD) data 34
6.2 Company Specific data 35
6.3 Macroeconomic data 35
6.3.1 GDP - Gross Domestic Product 36
6.3.2 Unemployment rate 37
6.3.3 CPI - Consumer Price Index 37

7 Preparatory work 38
7.1 Replicating the Swedish market for Corporate Lending 38
7.1.1 Calculating Minimum Capital Requirements for the Portfolio 39
7.1.2 Unadjusted Minimum Capital Requirements for the Portfolio 40
7.2 Benchmark Series 41

8 Analysis 43
8.1 Adjusting the input: Logistic Regression 43
8.1.1 Mechanics of regression analysis 45
8.2 Adjusting the equation: Time varying confidence level 48
8.2.1 Mechanics of time varying confidence interval 49
8.3 Adjusting the output 50
8.3.1 Business cycle multiplier 50
8.3.2 Autoregressive filter 52

9 Results 54
9.1 Adjusting the input: Logistic Regression 55
9.2 Adjusting the equation: Time-varying confidence level 58
9.3 Adjusting the output 60
9.3.1 Business cycle multiplier 60
9.3.2 Autoregressive filter 62
9.4 Summary 63

10 Discussion and Conclusion 65

11 Appendix 72
11.1 Probability of Default (PD) estimation in Swedish Banks . . . 72
11.2 Statistical Concepts 73

11.2.1 Cubic Spline Interpolation 73
11.2.2 Root-mean-square Deviation 73
11.2.3 Hodrick-prescott filter 74
11.2.4 Maximum Likelihood estimation (MLE) 75
11.3 Company specific data and Portfolio weights 76
11.4 Detailed Results 79
11.4.1 Detailed Logistic Regression Results 79
11.4.2 Time-lags for Through-the-Cycle Probability of Default with Logistic Regression Analysis 81

List of Figures

3.1 *Amplified business cycles due to procyclical effect* 16
3.2 *Simple schematic over Basel I calculations and requirements.* . 18
3.3 *Credit-to-GDP ratio, its trend and the Credit-to-GDP gap for the United Kingdoms* 19
3.4 *Loss density function with expected and unexpected losses* . . . 22
3.5 *Through-the-Cycle and Point-in-Time measures* 23
3.6 *Minimum capital requirements (K) is a strictly increasing function of Probability of Default (PD)* 28
3.7 *GDP and minimum capital requirements (K) for a banks exposure towards Scania AB* 28

6.1 *Probability of Default data series ($PD_{i,t}$) for all 90 companies* 35
6.2 *GDP - Gross Domestic Product in Sweden (% change)* 36
6.3 *Unemployment rate in Sweden (%)* 37
6.4 *CPI - Consumer Price Index in Sweden (12 month % change)* 37

7.1 *Unadjusted minimum capital requirements for the portfolio ($K_{p,t}^{unadj}$)* 40
7.2 *GDP and unadjusted minimum capital requirements for the portfolio ($K_{p,t}^{unadj}$)* 41
7.3 *Cyclical and growth trend components* 41
7.4 *HP benchmark together with unadjusted minimum capital requirements for the portfolio ($K_{p,t}^{unadj}$)* 42

8.1 *Correlation between GDP and a random Probability of Default (PD) series* 47
8.2 *Illustration of 99,9% confidence level on the Loss density function* 48
8.3 *Time varying confidence interval with GDP as macroeconomic variable* 49

9.1 *Result example plot* 54

9.2 $K_{p,t}^{logit}$ *for different explanatory variables (**single**)* 55
9.3 $K_{p,t}^{logit}$ *for different explanatory variables (**multiple**)* 56
9.4 $K_{p,t}^{tvc}$ *for different macroeconomic variables* 58
9.5 $K_{p,t}^{mult}$ *for different macroeconomic variables* 60
9.6 $K_{p,t}^{AR}$ *optimal parameter variables* $i = 1$ *month and* $\phi = 0.0297$ 62
9.7 *The best performing options in terms of smallest RMSD* . . . 64

11.1 *Original series and smoothed series with HP filter* 75
11.2 *Time lags against different macroeconomic variables* 81

List of Tables

3.1 *Probability of Default (PD) estimation in Swedish banks summary* 24

9.1 *Detailed results for $K_{p,t}^{logit}$ with different explanatory variables **(single)*** 57
9.2 *Detailed results for $K_{p,t}^{logit}$ with different explanatory variables **(multiple)*** 57
9.3 *Detailed results for $K_{p,t}^{tvc}$ with different macroeconomic variables* 59
9.4 *Detailed result $K_{p,t}^{mult}$ with GDP, Unemployment rate or CPI as macroeconomic variables* 61
9.5 *Detailed result from $K_{p,t}^{AR}$ with optimal values of time-lag i and constant parameter ϕ* 63
9.6 *Summary of results. Rank is based on the overall smallest RMSD against the HP benchmark of the unadjusted series.* . 63
9.7 *RMSD in percent of unadjusted series (K^{unadj}) RMSD. 0% indicates 0 RMSD* 63

11.1 *Probability of Default (PD) estimation in Swedish banks summary* 73
11.3 *Example of logistic regression result, GDP as explanatory variable* 79
11.4 *Example of logistic regression result, CPI as explanatory variable* 79
11.5 *Example of logistic regression result, unemployment rate as explanatory variable* 79
11.6 *Example of logistic regression result, GDP and CPI as explanatory variable* 80
11.7 *Example of logistic regression result, GDP and unemployment rate as explanatory variable* 80
11.8 *Example of logistic regression result, CPI and unemployment rate as explanatory variable* 80

11.9 *Example of logistic regression result, GDP, CPI and unemployment rate as explanatory variable* 80

Chapter 1

Acronyms

BCBS - Basel Committee on Banking Supervision
CEBS - Committee of European Banking Supervisors
RWA - Risk Weighted Assets
IRB - Internal Rating-Based Approach
PIT - Point-in-time
TTC - Through-the-cycle
M - Maturity
LGD - Loss given default
EAD - Exposure at default
PD - Probability of default
RMSD - Root-mean-square deviation
CPI - Consumer price index
GDP - Gross Domestic Product
MLE - Maximum Likelihood Estimation

Chapter 2

Introduction

2.1 Background

As the financial market progresses and becomes more complex, so does the risk imposed on actors willing to take part in it. Banks and other large financial institutions are exposed to many types of risk that must be mitigated to avoid losses and bankruptcy in order to maintain stability in the economy. In recent times we have seen examples where this have failed, such as the latest sub-prime mortgage crisis preceding the global recession still in effect. There seems to be a will to learn from previous misjudgements but the learning process itself may not always be a smooth ride. Imposing guidelines, restrictions and regulations may prevent one problem but can in reality be the cause of multiple new ones.

The *Basel Committee on Banking Supervision* is a committee providing a forum in which matters of banking supervisory may be addressed between national boundaries. In the wake of the last financial crises the Basel Committee has published guidelines and standards for banking supervision (known as *the Basel Accords*) in order to prevent banks from repeating the same mistakes and avoid future financial distress. A main topic in the accord regards the amount of capital that banks are required to hold to be able to absorb losses in unfortunate times, also known as *regulatory capital.* These have been subjected to severe revisions in later versions of the accords. [1]

The latest accord, Basel III, was published recently and is to be introduced from 2013 and onwards. A very debated area of the previous accord, Basel II, was that of *procyclicality* i.e. that the regulations in fact could strengthen the amplitude of economic fluctuations. Many thought that this was to be revised in Basel III, and it was, but unfortunately the proposed changes have received mixed critique (e.g. [2][3]). Thus the question remains as how to optimally prevent procyclical behaviour due to calculations of the regulatory capital known as *minimum capital requirements*.

2.2 Research Questions

The Basel accords provides banks with equations and functions to calculate the regulatory capital needed, described in Chapter 3. This thesis will be centred around these equations and the phenomenon of procyclicality that arises as a consequence of them. Following questions will be answered:

- What is procyclicality and how does it relate to the Basel accords?
- How could procyclicality arising from calculations of the regulatory capital known as minimum capital requirements (as described in the Basel accords II and III) be prevented?
- Using Sweden as a case study, which method would prove most efficient to prevent procyclicality?

2.3 Purpose

The purpose of this thesis is to test methods for mitigating procyclicality on the Swedish market for corporate lending due to calculations of the regulatory capital known as minimum capital requirements. Methods considered will be alternatives to the changes proposed in Basel III (i.e. the *Countercyclical Buffers*).

We will investigate the problem from a regulatory point of view and hence focus on revising the Basel framework or its components - not bank specific implementation. Several methods will be evaluated in a mathematical sense and tested to ensure their validity. Finally the methods will be ranked based on quantitative and qualitative performance.

2.4 Limitations

This thesis is limited to assessing procyclicality arising from the calculations of the regulatory capital known as *minimum capital requirements* (due to credit risk) as stated in the Basel accords (II and III) with the Foundation Internal Rating Based approach (F-IRB). Extra buffers introduced in Basel III are discussed but not considered in the analysis, we will only look at the original 8% that constitutes the minimum capital requirements. Only banks corporate exposures on the Swedish market will be evaluated.

2.5 Sources of Information

The thesis has been based on research, articles and technical reports about credit risk and procyclicality. The Basel accords have been thoroughly reviewed together with literature on mathematical models combating procyclicality. To perform the quantitative analysis data collected from Thomson Reuters Datastream have been used.

2.6 Outline

The thesis starts with a theoretical background in Chapter 3 that aims to provide basic concepts to the subjects of procyclicality and credit risk. These are explained briefly together with the origin of regulatory capital calculations found in the Basel accords. The calculations are then examined closely to show how they produce procyclical behaviour.

The theoretical background is followed by Chapter 4 which describes three approaches for preventing the procyclical behaviour in regulatory capital calculations. Chapter 5 will briefly present how we intend to evaluate each approach.

In Chapter 6 a description of the data used in the thesis is provided, all of which are connected to the Swedish market. It is followed by Chapter 7 which will describe some preparatory work. Chapter 8 will describe in detail the analysis of the different approaches considered. The final results will be presented in Chapter 9.

Finally Chapter 10 will discuss and conclude our findings. There we will comment on the result of our different models used and discuss recommendations in further development of the Basel accords.

Chapter 3

Theoretical Background

3.1 Procyclicality

The term *economic cycle* is referring to large fluctuations in the macroeconomic environment such as trade, production and other general economic activity. It is often measured by growth in Gross Domestic Product (GDP) which is the market value of all goods and services produced in a year by a certain nation. The fluctuations alternate between periods of slow growth - *Recessions* - and rapid growth - *Booms*, which is why it is called a cycle. [4]

In essence procyclical is a term used to indicate when a quantitative measure is positively correlated with the economic cycle. However in economic policy making the terms *procyclical effects* and *procyclicality* are referring to behaviours leading to amplifications of the economic cycle fluctuations, i.e. recessions become deeper and booms become stronger. A simple example of this is banks approach to lending that tend to change with the economy. In an economic recession banks get more restrictive in their lending, as opposed to an economic boom when they are less restrictive. At the same time, an economic recession causes declining profits, which increases the demand for new credit. This means that the demand for credit is high while the supply is low, forcing market actors into failure or even bankruptcy. The result is deeper economic distress, or the opposite in a boom, thus amplifying the overall business cycle fluctuations as illustrated in Figure 3.1. [5]

In the last decade many academics, practitioners and policy makers have particularly pointed out this behaviour in regulatory standards imposed by

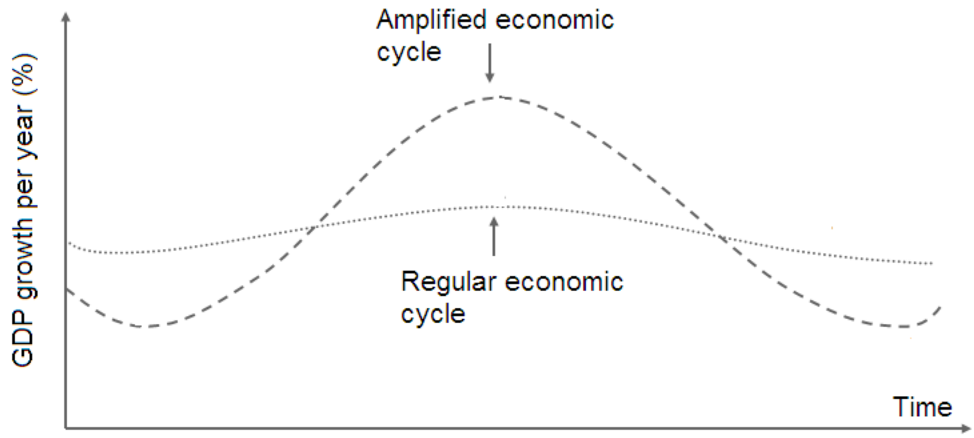


Figure 3.1: *Amplified business cycles due to procyclical effect*

the Basel Committee to tackle *credit risk* in the banking sector. During the sub-prime mortgage crisis with start in 2007 they gained strong recognition throughout the financial industry as being a major obstacle for turning the recession around [6]. Several studies have proved this concern, e.g. [7], others have come up with ways to reduce them [8]. In reality little has been done in practise. This states a major problem in all nations since the regulations affect the entire banking industry [9].

3.2 Credit Risk

The concept of financial risk in firms refers to future uncertain events potentially leading to monetary losses for the firm. Credit risk is the risk of losses due to a obligor's failure to fulfil its contractual obligations. When this event occurs the obligor is said to *default*. Simply put banks borrow money to an obligor which makes the loan an *asset* for the bank. The amount of money left to be paid to the bank at any given time (including interest) is known as the *exposure* which is what banks stand to loose in case the obligor defaults. For many institutions, in particular banks, credit risk is the main risk driver and the biggest source is often loans of different kinds. [10]

Historically we have seen that credit risk has been the dominant factor in the biggest banking failures, especially in the sub-prime mortgage crisis. Banks therefore have put much effort to identify, measure, monitor and control credit risk together with ensuring they have enough capital to cover the possible losses. However there is always a trade-off between cost of holding capital and amount of risk hedged, one must not forget that banks too are institutions aimed to maximise profit. [11]

Mitigating credit risk can be done by different methods such as diversification or derivative hedging, also banks often use collateral management (e.g. predefined property as security for the loan). These measures can be hard to quantify which is why regulations for banks have been imposed by the Basel Committee on Banking Supervision through the Basel accords. The accords cover several types of risk but for credit risk the aim is to make sure banks hold enough capital reserves as insurance against losses due to obligors default [12]. Later versions of these regulations is the major focus point of the critique regarding procyclicality.

3.3 Basel Committee on Banking Supervision

The Basel Committee was formed in 1974 with the purpose of being an institution for harmonising banking regulation and standards across its member states. The guidelines presented by the committee has no legal force, however they formulate directions for central banking institutions across member states on how to implement standards and best-practices, which are set to benefit banking activities on a global level. The conclusions reached by the Basel Committee are presented in the Basel Accords and since 1988 three accords have been developed. Each one is a revised version of its predecessor, once they are released they replace all previous versions. [1]

While Basel I only addressed credit risk, Basel II and III extended the scope to incorporate other types of risks (such as market- and operational risk). The main results of the accords with exclusive focus on credit risk and the corresponding regulatory capital is presented below.

3.3.1 Basel I

The first of the Basel accords was developed to address arising differences in nations regulatory capital regulations and was released in 1988. The Basel accord enabled implementation of a multinational framework for calculating regulatory capital known as *minimum capital requirements*, i.e. minimum capital reserves to cover losses due to credit risk. [1]

The framework builds upon a bank's *Risk Weighted Assets* (RWA). To calculate RWA, a bank multiplies its different exposures with a certain weight that represents its degree of risk. The accord defines 5 different asset classes (such as retail or corporate) to cover all assets on a banks balance sheet, each with a unique risk weight, in which the exposures are categorised in. It further states that a bank must hold equivalently 8% of its RWA in minimum capital requirements. [13]

These calculations are schematically shown in Figure 3.2.

Figure 3.2: *Simple schematic over Basel I calculations and requirements.*

3.3.2 Basel II

The Basel II accord greatly expanded the scope of credit risk from the first accord and was released in 2004. In Basel I banks were to hold 8% of its RWA, however RWA-calculations did not recognise different risk level within the asset classes. E.g. all exposures in the asset class residential mortgages were given a risk weight of 50%, deeming them as equally risky, despite major differences in the obligors ability to pay. This had the effect that Banks became prone to choose riskier investments since they required less capital in relation to the amount of risk, a phenomena known as *regulatory arbitrage*. [14]

Basel II maintains the 8% level but tries to address individual risk of exposures by expanding the previously limited RWA-calculations to eliminate regulatory arbitrage [14]. In the old regime of Basel I banks had stable minimum capital requirements. In Basel II they depend on risk measures such as Probability of Default (PD) and Loss Given Default (LGD) which are likely to increase in periods of recession leading to higher minimum capital requirements. Consequently when times are bad, the supply of credit is inhibited by the increase in minimum capital requirements (thus increasing the cost of lending for banks), which ultimately strengthens the business cycle fluctuations i.e. produces procyclical effects [15] [16].

3.3.3 Basel III

Basel III is primarily an attempt to apply the lessons learned form the recent financial crisis to the existing framework. In essence Basel III requires more regulatory capital. The 8% minimum capital requirements are still in effect, but two new buffers have been introduced. Capital conservation buffers to of at least 2.5% (to assure absorption of losses) together with a *counter-cyclical buffer* of 0-2.5% (depending on national regulators view of the economy). The latter is a way of combating procyclicality, which if assumed to be at maximum means that Basel III could require 5% of RWA in extra buffers. [17]

Countercyclical Buffers in Basel III

The countercyclical buffer was introduced in Basel III to reduce procyclicality arising from minimum capital requirements calculations. Its size differs in every nation (0-2,5%) but is determined through a measure known as a country's credit-to-GDP ratio. Here credit refers to all types of debt funds to the private sector and GDP to Gross Domestic Product growth of a nation. [18]

To calculate the size of the buffer the Basel Committee has decided one should look at deviations of the current credit-to-GDP ratio from it's long term trend, which is known as the *credit-to-GDP gap*.

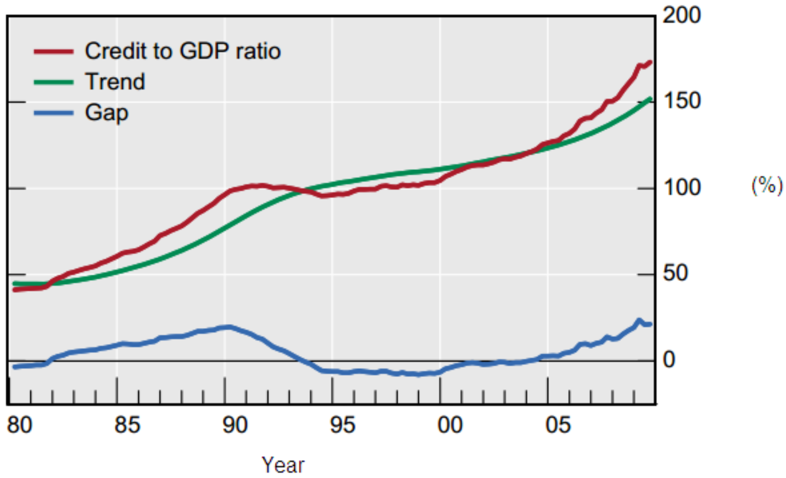


Figure 3.3: *Credit-to-GDP ratio, its trend and the Credit-to-GDP gap for the United Kingdoms*

The buffer then varies linearly towards the size of the gap with a lower and upper threshold, below the threshold the buffer is zero and above it is 2,5%. According to the Basel Committee the gap shows high predictive ability of a nations current position in the economic cycle by identifying when credit growth has become excessive. [18]

Although the buffers are planned to be implemented as of 2016 there has been a lack of consensus whether they are the right tool to tackle the issue of procyclicality in the minimum capital requirements calculations. Foremost the critique is directed towards the use of the credit-to-GDP gap as a measure and even the Basel Committee themselves says that *"while historically the credit-to-GDP gap would have been a useful guide in taking buffer decisions, it does not always work well in all jurisdictions at all times"* [18].

Looking at the academic side, in a critical assessment of the buffers Repullo and Saurina dismisses the credit-to-GDP gap's predictive power and comes to the conclusion that *"the credit-to-GDP 'common reference point' should be abandoned"* and that *"the countercyclical capital buffer of Basel III, in its current shape, will not help to dampen the pro-cyclicality of bank capital regulation and may even exacerbate it"* [2]. Another investigation by Edge and Meisenzahl at the Federal Reserve Board states that *"Because these gap measures are very unreliable in time, they provide a poor foundation for policymaking"* [3]. In their research they go on to look closely at few instances where the gap indicates a false prediction of the position in the economic cycle, and find that in these cases the impact of the buffers can be highly significant in the wrong direction.

Hence many argue that the countercyclical buffers does not seem to solve the problem at hand and that there is need for an alternative approach. Asian banks have even rejected the approach claiming that it is too focused on the needs of North America and Europe [19]. The root of the problem however, is still the risk sensitive RWA-calculations.

3.4 Risk Weighted Assets (RWA) Calculations

There are two different ways in which financial institutions can calculate its Risk Weighted Assets (RWA) from Basel II and onwards; either by the *Standardised Approach* built on external ratings, or with the more advanced *Internal Rating Based Approach (IRB)*. All four largest Swedish banks use the IRB approach [20][21][22][23]).

In the IRB approach banks use internal methodologies to determine the risk level of different exposures. RWA is calculated as [17]:

$$RWA = K * EAD * 12.5 \tag{3.1}$$

EAD stands for Exposure at Default and is defined as the outstanding debt payment at the time of the default of an obligor.

K is the original minimum capital requirements (8% of RWA) in percent of EAD since:

$$\frac{RWA}{EAD} * 8\% = \frac{K * EAD * 12.5}{EAD} * 8\% = K \tag{3.2}$$

Calculating RWA is standard procedure, however if one aims to look directly at the minimum capital requirements in percent it is sufficient to calculate K. The procedure of calculating K is what produces the criticised procyclical effects.

3.5 Minimum Capital Requirements (K) Calculations

Calculating the minimum capital requirements (K) for an exposure is based on the concept of expected and unexpected losses, Figure 3.4 provides a simple illustration of the two. Expected losses are losses that a bank expects to occur and thus considered a cost of doing business, they are covered by provisioning and pricing policies. Unexpected losses are considered unforeseeable and these are what K are meant to cover, thus the regulation states that *K should equal the unexpected losses.* The rightmost quantile in Figure 3.4 is deemed extremely unlikely losses and does not need to be accounted for. [24]

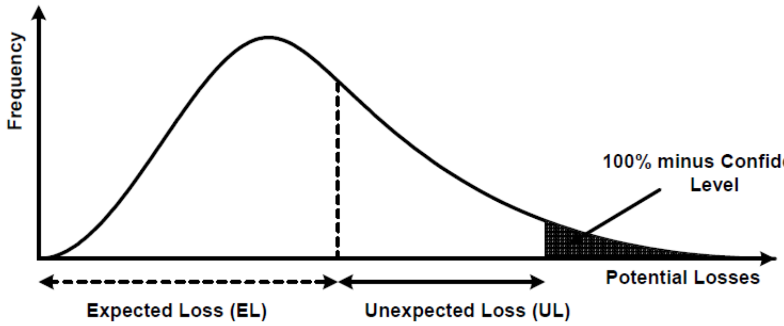


Figure 3.4: *Loss density function with expected and unexpected losses*

Expected losses can be calculated through the following formula [24]:

$$E[L] = PD * LGD * EAD \tag{3.3}$$

where PD stands for *Probability of Default* and LGD for *Loss Given Default*. Unexpected losses, i.e. K, are calculated with the same inputs but with a far more complex formula (Equation 3.4) which will be presented after definition of the loss parameters.

3.5.1 Probability of Default (PD)

Probability of default (PD) is the probability that an obligor will default over a predetermined time period. This is a measure of risk and tightly linked to an obligors external credit rating. PD is a very important factor in credit modelling and one's accuracy in predicting PD will often determine the quality of the whole model. [25]

We start by defining the meaning of a *default event*. In the Basel framework a default is considered to occur when either of the following two events have occurred in regard to a specific obligor (quote [14], paragraph 452):

- The bank considers that the obligor is unlikely to pay its credit obligations to the banking group in full, without recourse by the bank to actions such as realising security (if held).
- The obligor is past due more than 90 days on any material credit obligation to the banking group. Overdrafts will be considered as being past due once the customer has breached an advised limit or been advised of a limit smaller than current outstandings.

A common measure of PD is the 1-year PD which is used in the minimum capital requirements calculations provided by the Basel Committee (see Equation 3.4) [24]. PD is usually estimated for a single obligor or for segments of obligors with similar characteristics. There are many ways of estimating PD and the most simple approach rely on external ratings. One of the most popular ways is by using a regression model called logistic regression which we will expand on further in Section 8.1 [25]. The main problem in assessing the task is the lack of data since default events are rare (especially for high credit quality firms) and PD was not introduced until 2004 when Basel II was released. It is stated in Basel II that at least 5 years of data should be used in any attempt to estimate PD [14], which is also what the Swedish Financial Supervisory Authority (Finansinspektionen) has stipulated in their general guideline regarding regulatory capital [26] (exceptions can be made to permit the use of 2 years data until 5 years has been acquired).

Point-in-time and Through-the-cycle measures of Probability of Default (PD)

An important aspect of PD is its relation to the macroeconomic environment. This brings us on to the subject of "rating philosophy", a phrase coined by the British Financial Services Authority to describe whether a PD estimation model exhibits *Point-in-Time* (PIT) or *Through-the-Cycle* (TTC) behaviour. A simple illustration can be seen below in Figure 3.5.

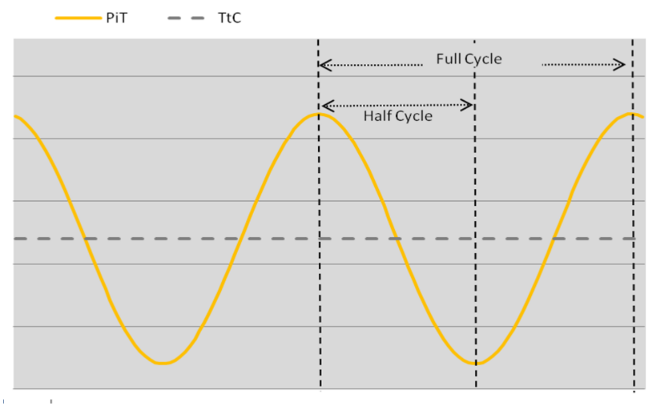


Figure 3.5: *Through-the-Cycle and Point-in-Time measures*

A PIT measure is the value of PD that capture all information available at a specific time. It is a measure calculated as the PD for the next 12 months (in the case of 1 year PD) that tends to be in opposite position of the economic cycles. The main advantage of PIT is that it is very responsive of external variables, however this also contributes to its greatest downside; high volatility. Banks tend to prefer PIT PD:s in pricing and management purposes due to its high sensitivity and simply because it requires less data to estimate. [25]

In contrast to PIT, TTC is a measure independent of the economic cycle. Here cycle is referring to a business cycle in the economy, thus whether the present state is exhibiting downturn or upturn behaviour is irrelevant in a perfect TTC measure. Not surprisingly its greatest pros and cons is the exact opposite of PIT; stable but low sensitivity. [25]

The concepts of PIT and TTC in PD modelling is closely related to the procyclical effects arising from minimum capital requirements calculation, we will expand further on this in Section 3.5.4. In reality pure TTC are rare and most models are considered hybrids, i.e. vary with the economic cycle to some extent but not fully. Table 3.1 shows the characteristics of Swedish banks in estimating PD for different obligors (see Appendix 11.1 for detailed description) [20] [21] [23] [22].

Bank	**Corporate PD type**
Nordea	Hybrid of PIT and TTC
Handelsbanken	Pure TTC
SEB	Aims toward TTC but some PIT behaviour
Swedbank	Aims towards TTC but some PIT behaviour

Table 3.1: *Probability of Default (PD) estimation in Swedish banks summary*

The main issue with producing a pure TTC measure is the lack of data, PD was first introduced in Basel II (2004) and therefore data only stretches back till this day. For a TTC measure the simplest approach is to use an average of PIT PD over a full business cycle which requires great amounts of data (often around 20 years) that most banks don't have. In a financial institution it is often valuable having both measures to get a broader view on both long- and short-term risk. [25]

3.5.2 Loss given Default (LGD)

Loss given default (LGD) is defined as the size of the loss, in percent of EAD (outstanding debt payment at the time of the default), that is incurred if an obligor defaults [14]:

$$LGD = \frac{incurred\ \ loss}{EAD}$$

As stated in the Basel accords a bank is obliged to have estimates of LGD for its corporate, sovereign and bank exposures. When producing the estimate there exists two approaches; a simple approach (Foundation-IRB) or a more advanced approach (Advanced-IRB). [14]

In the Advanced-IRB approach banks produce their own estimate of LGD. Under the simpler Foundation-IRB approach however, banks use a fixed estimate of LGD provided by the Basel Committee, for which the size depends on what type of claim the bank has. One usually separates between senior and subordinated claims respectively, where senior claims on a company's assets are prioritised before subordinate claims in the event of a default. For instance, funds provided by banks are characterised as senior claims. For senior claims the fixed estimate of LGD is given as 45%, whereas for subordinated claims this is given as 75%. [14]

In reality all four of the largest Swedish banks use both methods, but the Foundation-IRB to a much greater extent [20] [21] [22] [23]. The advantage of using the Advanced-IRB approach is mainly that risk can be assessed more accurately, potentially leading to less minimum capital requirements than the conservative Foundation-IRB. However it also requires a lot of data and work which could imply higher costs for the bank.

3.5.3 Unexpected Losses: Final Equation for minimum capital requirements (K)

The same inputs as in Equation 3.3 are used for the final equation to calculate unexpected losses for an exposure (which are to equal the minimum capital requirements), however the equation provided by the Basel Committee is far more complex. It is derived from an adaptation of Merton's single factor model, extended by Vasicek to fit credit portfolio modelling, which states that a company defaults if its own asset value fall below a certain threshold in a fixed time horizon [17]. Furthermore the model assumes that all systematic risk (like industry and regional risk) can be modelled by a single systematic risk factor, and that idiosyncratic risk factors cancel each other out in the context of large portfolios. It then calculates the unexpected loss as [27]:

$$E[UL] \quad = \quad Q_{0,999}[L] - E[L] \quad \approx \quad EAD * LGD * (f(PD) - PD) * \alpha$$

where $Q_{0,999}[X]$ denotes the 99,9% quantile of the stochastic variable X, L the loss, α an adjustment term, and f is a strictly increasing function of PD different for each type of exposure (i.e. the asset class it is categorized in). The point of f is that it creates a stressed PD in relation to the 99,9% quantile of the loss distribution by using the single factor, making sure losses are covered to a probability of 99,9%.

Asymptotic Single Risk Factor models have been shown to be portfolio invariant, i.e. capital requirements for an exposure will only depend on the risk of the exposure itself - not the portfolio it is added to. Hence it is possible to calculate the minimum capital requirement for individual exposures and then simply aggregate them together to get a portfolios minimum capital requirement. When developing the model this was an important requirement in order to fit supervisory needs. [24]

The final equation can be seen below for the corporate exposure class, where K is the minimum capital requirement (i.e. unexpected loss) in percent of EAD (the obligors outstanding debt at default) [14]:

$$K = LGD * \left(N \left[\frac{N^{-1}(PD) + \sqrt{R} * N^{-1}(0.999)}{\sqrt{1-R}} \right] - PD \right) * \frac{(1 + (M - 2.5)b)}{(1 - 1.5b)} \tag{3.4}$$

N represents the cumulative standard normal distribution and its inverse when -1 is in the superscript. The term $N^{-1}(PD)$ represents the default threshold and $N^{-1}(0.999)$ a conservative value of confidence (represented by the black quantile in Figure 3.4) making sure losses are covered with a probability of 99.9%. These are then weighted depending on the size of R.

R is the correlation to the single factor which describes the degree with which the exposure contributes systematic risk. In short it shows how the exposure is connected to other exposures.

M represents the effective maturity of the exposure and since long-term investments are considered riskier than short-term, capital requirements should increase with maturity. Standard maturity for corporate exposures in IRB is set to 2.5 years (M = 2.5) according to paragraph 318 in Basel II [14]. To incorporate the relationship between M and PD the maturity adjustment b has been introduced.

Both b and R are given as functions of PD in Basel II:

$$R = 0.12 * \frac{1 - e^{-50*PD}}{1 - e^{-50}} + 0.24 * [1 \; - \; \frac{(1 - e^{-50*PD})}{(1 - e^{-50})}] \tag{3.5}$$

$$b = [0.11852 - 0.05478 * ln(PD)]^2 \tag{3.6}$$

The function for R results in a value between 12% (when PD = 1) and 24% (when $PD = 0$). The factor of 50 is specifically set for corporate exposures, it determines how fast R decreases when PD increases (higher factor gives faster decline).

3.5.4 Procyclical effects from minimum capital requirements calculations

K in Equation 3.4 is a function of PD alone, all other variables are either constants or functions of PD under the Foundation-IRB approach. As previously stated K is also a *strictly increasing* function of PD as can be seen in Figure 3.6 on the next page.

This behaviour is relevant since higher PD means riskier exposures, however it is also what leads to the procyclical effects that strengthen the economic cycles. PIT PD tends to be in opposite relation to the economic cycle, thus banks using PD showing signs of PIT behaviour have higher PD for their exposures when the economy is in a recession and vice versa when in a boom. This does not necessarily mean that the exposure itself has gotten riskier in relation to other exposures, but that the overall economy has made all exposures riskier. Consequently minimum capital requirements become

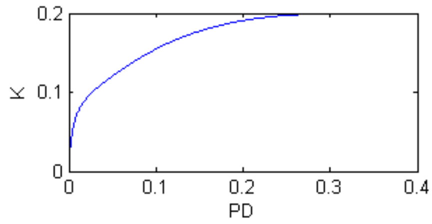


Figure 3.6: *Minimum capital requirements (K) is a strictly increasing function of Probability of Default (PD)*

higher in recessions which increases the cost of lending for banks. Being in a recession there is an overall difficulty in raising new credit, hence to manage the rise in costs bank will have to cut their lending leading to a contraction on the supply of credit on the market. The opposite is true during an boom which results in amplified fluctuations of the business cycles, i.e. procyclical effects are visible. [28]

As an illustrative example we have chosen the large Swedish company Scania AB, Figure 3.7 shows minimum capital requirements (K) for exposure towards Scania AB during a time period of 8 years with PIT PD as input. GDP is used to indicate state of the economy. In the figure we can clearly see that the minimum capital requirements increase drastically during the years 2008-2010 when Sweden experienced the greatest drop in GDP, implying a strong recession.

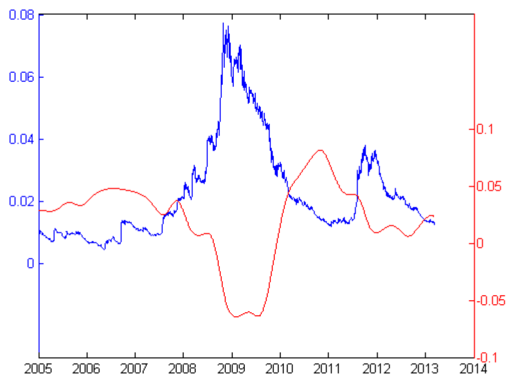


Figure 3.7: *GDP in **red** (right axis) and minimum capital requirements (K) for a banks exposure towards Scania AB in **blue** (left axis)*

Chapter 4

Mitigating Procyclicality from Minimum Capital Requirements

Theoretical proof that the increase (decrease) in minimum capital requirements (K) in recessions (booms) leads to procyclical effects on the economy is beyond the scope of this thesis, it has been addressed in several previous reports such as [7] and [8]. If instead this fact is assumed, focus can be directed on how to mitigate procyclicality by preventing the fluctuations. Optimally K would not be dependent on the state of the economy but still be sensitive to other factors increasing the risk of individual exposures considered.

The most obvious solution would be to force banks to use PD models producing pure TTC PD [27]. However as previously explained this is not always an easy task due to lack of data, also banks tend to prefer PIT PD in pricing and management purposes due to its risk sensitivity. Furthermore there seems to be some room for individual interpretation of the term TTC, the only consensus is that it should be independent of the economic cycle [8]. One view is that TTC is a PD where the business cycle has been filtered out, other state that it should be a long run average or a worst case scenario. This in turn could make it hard for regulators to make judgement on the quality of TTC PD since two different banks may have different views but both claim to use a TTC approach. Excluding the banks from the process of mitigating procyclicality would make the judgement process easier, leaving it up to be incorporated in the regulations of the Basel accords.

The countercyclical buffers introduced in the Basel III accord is one way of tackling this issue but as previously stated it has received mixed critique, an alternative is to instead look at the calculations of K directly. According to Gordy and Howells there are three main approaches to do this [8], naturally they are all centred round Equation 3.4 which is repeated here for convenience. We remind of the fact that K is a *function of PD only*, all other variables are either constants or functions of PD in the Foundation-IRB approach:

$$K(PD) = LGD * \left(N \left[\frac{N^{-1}(PD) + \sqrt{R} * N^{-1}(0.999)}{\sqrt{1-R}} \right] - PD \right) * \frac{(1 + (M - 2.5)b)}{(1 - 1.5b)} \tag{3.4}$$

The three approaches are stated below:

- **Adjusting the input**: Options to adjust the input of Equation 3.4, i.e. Probability of Default (PD).
- **Adjusting the equation itself**: Options to adjust Equation 3.4 itself and its inner components.
- **Adjusting the output**: Options to adjust the output of Equation 3.4 directly, i.e. the minimum capital requirements (K).

Different options are available for each approach but a general guideline is that of simplicity to incorporate with the existing framework. If options are too complex, many banks might have troubles understanding or incorporating them - especially smaller banks. Hence to achieve a widespread change the options are preferably intuitive and manageable for all types of banks.

4.1 Adjusting the input

The input of Equation 3.4 (i.e. PD) is provided as an estimate by banks themselves, this approach targets regulations for adjusting PIT PD to become a TTC estimate. As argued before, the goal is not to revise the banks' internal procedure of modelling PD, instead we focus on procedures for adjusting the output of existing PIT PD models to become more TTC.

At first glance a general smoothing procedure of PD might seem like a good idea, e.g. a simple smoothing average or more advanced procedures. The problem with these procedures are that they smooth out all variations and not only the part contributed by the fluctuations of the economic cycle. Hence K will be smoother but also less accurate in determining the individual risk. The point is not to make K more stable, but rather less dependent on the economic cycle.

Another option is to use a filter of sorts to filter out specific trends or frequencies related to the economic cycle. There are mainly two disadvantages in using such an approach: complexity and accuracy. To capture the behaviour of the economic cycle using a filter it requires a lot of ongoing tuning and multiple frequencies, a similar approach has been described by [29].

An intuitive option is to use regression analysis together with macroeconomic data to capture the relationship between the two. Here the macro-economic data will serve as a substitute to the economic cycle. Since PD is a probability measure (i.e. in the range of [0,1]) regular linear regression is not to be preferred, *logistic regression* solves this problem and will thus be considered in this thesis.

4.2 Adjusting the equation

Looking at the inner components of Equation 3.4 there are some room for adjustment, however the basic idea of the single factor model should remain intact.

The equation for R (the correlation coefficient, see Equation 3.5) is constructed to have negative correlation towards PD, which in turn leads to the entire equation being less sensitive towards PD. In an initial phase of this thesis test were performed as to quantify the magnitude of increasing the negative correlation, however it turned out to have little effect. Also it resulted a general smoothing of the entire series which is not what we are after.

The confident level however is of greater interest, i.e. the constant value of 0.999 representing a 99,9% probability of covering losses. By decreasing the confidence level the probability of covering losses are lowered which in turn decreases K (and vice versa by increasing). An option for utilising this feature is to make the confidence level time-varying, depending on where we are in the economic cycle. Reasoning behind this is that when the economy already is in a recession it is illogical for the bank to continue insuring itself against the worst 99.9 % that could happen - it has already happened and is reflected in the PD. The approach originated in [30] but has since been discussed in several other articles such as [9] and [7]. This thesis will test a *time-varying confidence interval* that varies linearly towards different macroeconomic variables.

4.3 Adjusting the output

In contrast to adjusting the input, which is done to PD, adjusting the output tampers with a finished value of K.

One simple option to incorporate with a finished K value would be a multiplier, which is considered in [31] and [32] amongst others. The multiplier could be provided by the regulators, meaning banks only have to multiply their existing K to adjust the output, i.e. :

$$K_t^{mult} = \mu_t * K_t^{orig} \tag{4.1}$$

where K_t^{mult} is the adjusted capital requirements series at time t, K_t^{orig} is the original capital requirements at time t, and μ_t is the business cycle multiplier at time t. There are different ways of determining how the value of multiplier μ_t should vary but it needs connection to the economic cycle which can be done through macroeconomic variables. This thesis will consider the *business multiplier* option and discuss different ways of implementing it.

Another option with ease of implementation is the *Autoregressive filter (AR-filter)* which weighs K_t^{orig} towards its previous values. The intuition behind this option is that shocks of the economic cycle will be distributed over a longer time rather than all at once, i.e. it is a type of smoother. We have previously stated that our goal is not to smooth the series, however this option is frequently mentioned in previous research, e.g. [31] [8] [9], thus we will consider it for comparative purposes. Its biggest advantage is that it requires very little amount of data .

Chapter 5

Method

To evaluate different options described in the previous chapter this thesis conducts an observational study with external data. First a portfolio is created that aims to represent the Swedish market for corporate lending. A number of companies will be included in the portfolio for which data has been collected, mainly Probability of Default (PD) data over a specific time period. In this way minimum capital requirements needed for holding the portfolio (K_p) can be calculated using the PD data and the portfolio weights, this represents the minimum capital requirements of the whole Swedish market for corporate lending.

The different options will then be tested *separately* on the portfolio to evaluate their performance:

- Options for adjusting the input will adjust each company's PD time series individually and then calculate K_p.
- Options for adjusting the equation will use the unadjusted PD time series but adjust inner parts of Equation 3.4 before calculating K_p.
- Options for adjusting the output will also use the unadjusted PD time series but calculates K_p directly and then adjusts the resulting K_p.

Evaluation on performance is done by constructing an optimal benchmark series of K_p and then calculating the root-mean-square deviation (RMSD) between the resulting K_p of the different options and the benchmark. Finally the options will be ranked according to lowest RMSD and qualitative judgements, the result will then be discussed and a conclusion will be stated.

Chapter 6

Data

The data used for this thesis are of three major characteristics; Probability of Default data, company specific data (market capitalisation and leverage ratio) and macroeconomic data. As previously mentioned our intentions are to focus on Sweden as a basis for the investigation, hence all data will be directly related to Sweden.

6.1 Probability of Default (PD) data

The Probability of Default data series ($PD_{i,t}$) have the following characteristics:

- 90 largest companies in Sweden, thus $i = 1, ..., 90$. Initially we choose 100 largest companies but after removing the banks (SEB, Nordea, Handelsbanken and Swedbank) and those who lacked appropriate amount of data it was narrowed down to 90. The list of these can be seen in the Appendix Section 11.3.
- For every company there are 99 data points, thus $t = 1, ..., 99$. These are monthly data points from 2005-01 till 2013-03 describing the 1 year Point-in-Time (PIT) PD (i.e. one year forward). The source of these are *Thomson Reuters Starmine Structural Credit Risk Model* . The model uses an approach of modelling a company's equity as a call option on its assets (introduced by Robert Merton) which is a common method to produce PIT measures of PD [33].

For illustrative purposes all $PD_{i,t}$ series have been plotted in the same plot in Figure 6.1 below:

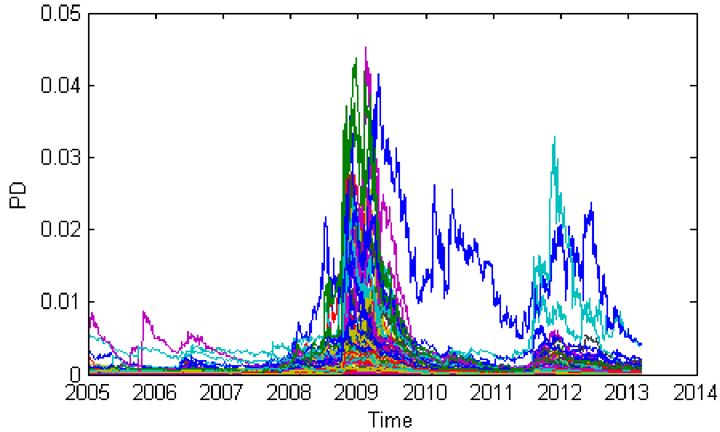


Figure 6.1: *Probability of Default data series ($PD_{i,t}$) for all 90 companies ($i = 1, ..., 90$) with different colouring for each company.*

6.2 Company Specific data

For all 90 companies on which PD data was gathered, information on the following was also gathered from Thomson Reuters database (the data can be seen in Appendix 11.3):

- **Market capitalisation**: Total value of all stocks issued (m_i)
- **Leverage ratio**: Debt in relation to market capitalisation (l_i)

These are the current values as of 2013-03-12.

6.3 Macroeconomic data

Macroeconomic data relating to Sweden has been collected to be used in various options described in the following chapters. Strong focus is on Gross Domestic Product (GDP) since the main ambition has been to provide a proxy for the general economy of Sweden and its location in the economic cycle. To further broaden the study Consumer Price Index (CPI) and unemployment rate have also been used which will be presented below.

Collected macroeconomic data is on a monthly or quarterly basis. In order to use all of the PD data mentioned above, which is on a monthly basis, all macroeconomic data on quarterly basis has been interpolated with cubic splines to be on a monthly basis from 2005-01 till 2013-03 (see Appendix Section 11.2.1 for cubic splines). The choice to use monthly data was simply to make the analysis as close to a real situation as possible.

6.3.1 GDP - Gross Domestic Product

GDP of Sweden has been extracted from Thomson Reuters database. The series is in percentage growth, seasonally adjusted without the effect of inflation and can be seen in Figure 6.2 below.

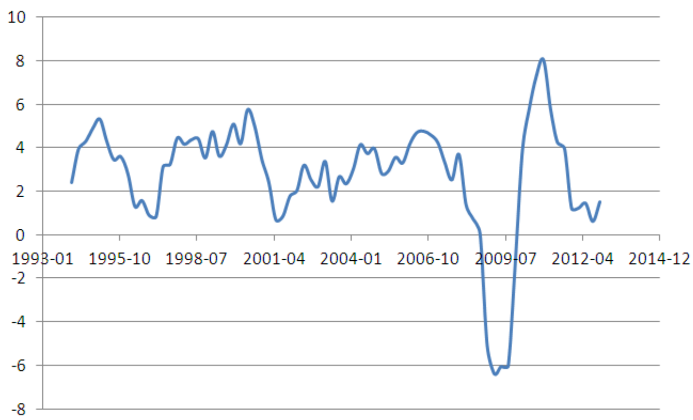


Figure 6.2: *GDP - Gross Domestic Product in Sweden (% change)*

6.3.2 Unemployment rate

Unemployment rate in Sweden has been extracted from OECD's database (Organisation for Economic Co-operation and Development). The series describes percentage unemployed in Sweden and can be seen in Figure 6.3.

Figure 6.3: *Unemployment rate in Sweden (%)*

6.3.3 CPI - Consumer Price Index

Consumer price index (CPI) has been extracted from Statics Sweden's database (SCB, Statistiska centralbyrån) and describes the 12-month percentage change.

According to SCB, CPI is one of the most widespread measures for price changes and is often used as a measure for inflation, it can be seen in Figure 6.4 below.

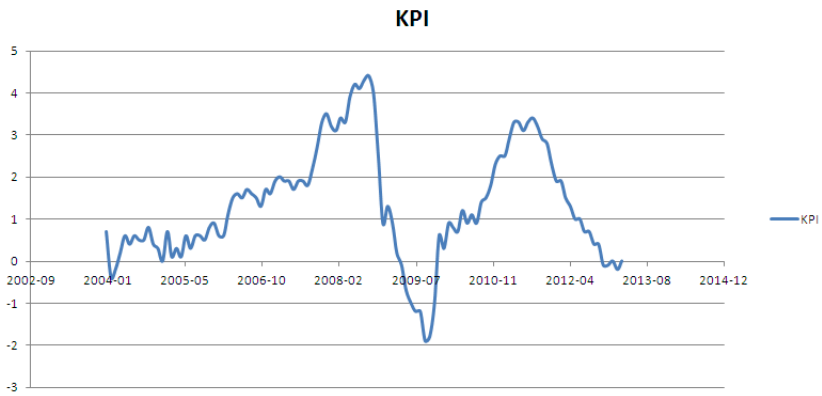


Figure 6.4: *CPI - Consumer Price Index in Sweden (12 month % change)*

Chapter 7

Preparatory work

7.1 Replicating the Swedish market for Corporate Lending

We will start to create a portfolio that aims to replicate the Swedish market for corporate lending which will be used in testing the different options.

The portfolio is constructed by specifying a set of weights (x_i). They are used to pool the individual minimum capital requirements of company i ($K_{i,t}$) to a portfolio minimum capital requirement ($K_{p,t}$) representing the minimum capital requirements of the Swedish market for corporate lending. As described in the previous chapter we have data on 90 of the largest companies on the Swedish stock market. The reasoning behind choosing these companies is simple: we want our portfolio to have the same features as the entire Swedish market for corporate lending. Since these companies undoubtedly constitute a large portion of the total debt on the Swedish market we consider it a reasonable assumption. Initially we considered to use more companies, however for computational efficiency a limit was set to 100 companies. Also there was a lack of data in many of the companies not included in the largest 90.

Every company was given a certain weight (x_i) in the portfolio that was proportional to their outstanding debt (d_i) in relation to the total outstanding debt of all companies:

$$x_i = \frac{d_i}{\sum_{j=1}^{90} d_i} \tag{7.1}$$

The actual weights can be observed in the Appendix Section 11.3. Furthermore the debt itself is calculated by multiplying the market-cap (m_i) of every company by its leverage ratio (l_i):

$$d_i = m_i * l_i \tag{7.2}$$

7.1.1 Calculating Minimum Capital Requirements for the Portfolio

Individual minimum capital requirements for company i at time t ($K_{i,t}$) are first considered, which are calculated through Equation 3.4 with each company's respective Probability of Default data ($PD_{i,t}$):

$$K_{i,t} = LGD * \left(N \left[\frac{N^{-1}(PD_{i,t}) + \sqrt{R} * N^{-1}(0.999)}{\sqrt{1-R}} \right] - PD_{i,t} \right) * \frac{(1 + (M - 2.5)b)}{(1 - 1.5b)} \tag{3.4}$$

$K_{i,t}$ is essentially a function of $PD_{i,t}$, but requires values for the constant parameters M and LGD. With the Foundation-IRB approach, LGD and M are set to 45% and 2.5 years respectively assuming exposures are senior claims (see Section 3.5.2 and 3.5.3).

All $K_{i,t}$ are then pooled together through the portfolio weights (x_i) to produce the minimum capital requirement for the portfolio ($K_{p,t}$):

$$K_{p,t} = \sum_{j=1}^{90} x_i * K_{i,t} \tag{7.3}$$

This pooling is possible due to the fact that the model upon which Equation 3.4 builds is portfolio invariant, as mentioned in Section 3.5.3. Hence regardless of whether the input, equation or output is adjusted, the pooling will occur after the individual $K_{i,t}$:s have been calculated.

7.1.2 Unadjusted Minimum Capital Requirements for the Portfolio

By using the $PD_{i,t}$ data described in the previous chapter, without executing any adjustment option, we calculate the unadjusted minimum capital requirements of the portfolio ($K_{p,t}^{unadj}$). The result is visible in Figure 7.1, as previously stated it aims to represent the minimum capital requirements of the Swedish market for corporate lending.

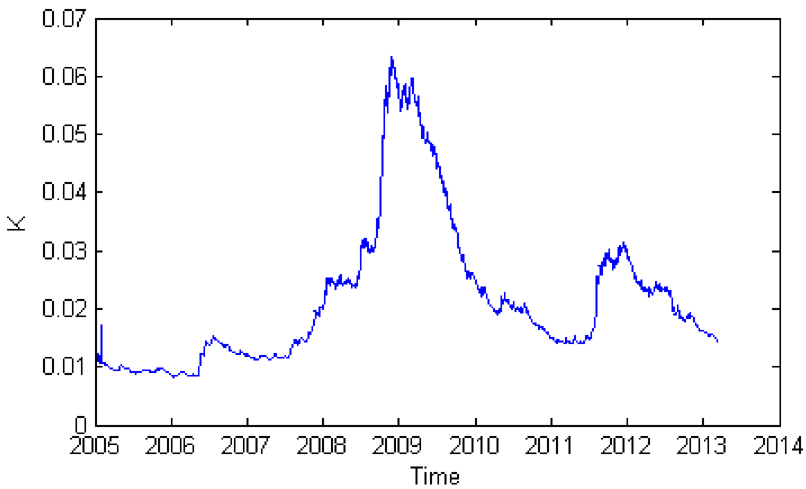


Figure 7.1: *Unadjusted minimum capital requirements for the portfolio* ($K_{p,t}^{unadj}$)

Looking at Figure 7.1 special note should be taken to the spike during 2008-2010, clearly dependent on the macroeconomic conditions at the time. The cyclical variation is confirmed by a maximum value of 6,3 % in 2009 (economic recession) and a minimum value of 0,83 % in 2006 (before the recession), indicating a ratio of approximately 7,6 between the maximum and the minimum in our data set.

To make this argument stronger we plot the series towards the Gross Domestic Product (GDP) of Sweden in Figure 7.2. The plot makes it very clear that $K_{p,t}^{unadj}$ is negatively correlated to the economic cycle.

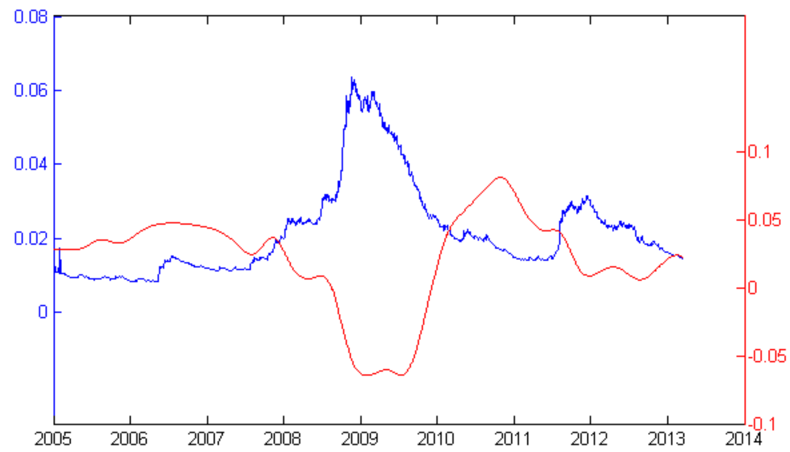


Figure 7.2: *GDP (red, right axis) and unadjusted minimum capital requirements for the portfolio ($K^{unadj}_{p,t}$) (blue, left axis)*

7.2 Benchmark Series

In order to evaluate each option in the different approaches on their performance we need a benchmark series to evaluate against. The evaluation is then done by comparing the root-mean-square deviation (RMSD) between the resulting minimum capital requirements series of the different adjustment options to our benchmark series (see Appendix Section 11.2.2 for RMSD).

To produce the benchmark we consider a common statistical method for macroeconomists studying time series: the *Hodrick Prescott filter* (HP filter). What the filter does is that it assumes a series to be a sum of two components; a cyclical trend and a growth trend (visible in Figure 7.3).

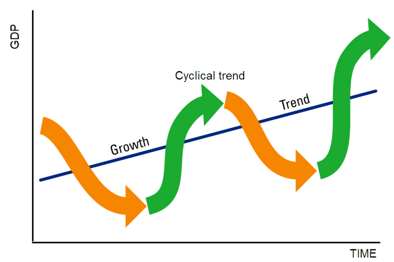


Figure 7.3: *Cyclical and growth trend components*

The cyclical trend represents the reoccurring pattern of the economic cycle and the growth trend part represents the long term growth. The HP filter makes it possible to extract the growth trend of the series and neglect the cyclical trend, since we want to minimise the influence of the economic cycle this will serve as a good benchmark (see Appendix Section 11.2.3 for statistical explanation of HP filter). [34]

Thus we apply the HP filter on the unadjusted minimum capital requirements series ($K_{p,t}^{unadj}$) to receive our benchmark series. First however there is a smoothness parameter λ to be chosen; the larger value of λ, the smoother the filter. We have chosen a quite large value which is based on a report by Banco de España [31], where they have annual values with $\lambda = 100$. Since we have monthly values we convert it by the standard conversion method [35]:

$$\lambda_{monthly} = \lambda_{monthly} * n^4 = 100 * 12^4 \approx 2,0736 * 10^6 \tag{7.4}$$

Here n represents the number of months in a year. The result is visible in Figure 7.4 as a solid red line.

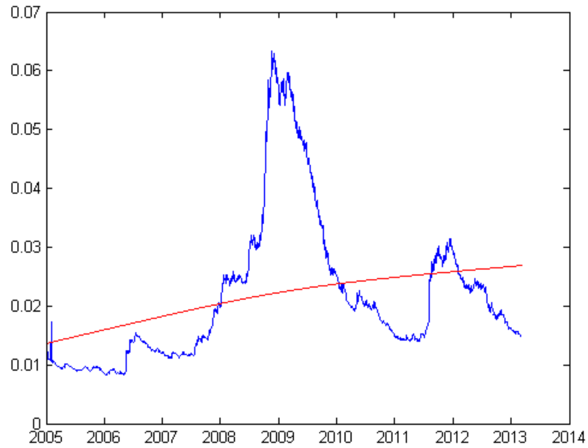


Figure 7.4: *HP benchmark in red together with unadjusted minimum capital requirements for the portfolio ($K_{p,t}^{unadj}$) in blue*

There are off course several alternatives to the HP filter, however it is by far the most common method used in macroeconomic research to decompose growth-cycle relationships [31]. For this reason we chose to use it for producing our benchmark series, in the final chapter of this thesis we will discuss the implications of this choice in detail.

Chapter 8

Analysis

8.1 Adjusting the input: Logistic Regression

By using logistic regression we aim to remove the dependence of the economic cycle on our Point-in-time (PIT) Probability of Default (PD) series, creating a Through-the-Cycle measure (TTC). In order to do this, we start by looking at a common internal model for estimating PIT PD through logistic regression. The dependent variable y_i is a binary (zero or one) variable, where one represents a default for firm i in one years time and 0 a non-default [31]:

$$PD_{i,t} = Pr(y_i = 1) = F(\beta_0 + \beta_1 X_{i,t}^1 + ... + \beta_{n-1} X_{i,t}^{n-1} + \beta_n Macro_t) \quad (8.1)$$

Here $PD_{i,t}$ is the PIT PD and F(x) describes the cumulative standard logistic function [36]:

$$F(\mathbf{x}) = \frac{e^{\mathbf{x}}}{1 + e^{\mathbf{x}}} = \frac{1}{1 + e^{-\mathbf{x}}} \quad (8.2)$$

The explanatory variables $X_{i,t}^j$ describe certain characteristics of the borrowing firm i that aims to describe its unique risk profile. E.g. size of loan, type of loan, previous defaults, age etc. The last explanatory variable $Macro_t$ describes the current macro economic condition through macroeconomic variables. To produce a TTC measure, $Macro_t$ can simply be replaced by its average over the sample period:

$$PD_{i,t}^{TTC} = Pr(y_i = 1) = F(\beta_0 + \beta_1 X_{i,t}^1 + ... + \beta_{n-1} X_{i,t}^{n-1} + \beta_n \bar{Macro_t}) \quad (8.3)$$

$$where \quad \bar{Macro} = \sum_{t=1}^{n} \frac{Macro_t}{n}$$

Since our $PD_{i,t}$ is externally given we do not have the β-values nor observations of $X_{i,t}^j$, thus we cannot reproduce the result in Equation 8.3. We can however perform a logistic regression analysis to get the variable β_n by using macro data:

$$PD_{i,t} = F(\hat{\beta}_n * Macro_t + \varepsilon_t) \quad (8.4)$$

were ε_t represents the residuals and $\hat{\beta}_n$ our estimate of β_n. There are two cases when our single regression gives the same result for β_n as the multiple regression in Equation 8.3, i.e. when $E[\hat{\beta}_n] = \beta_n$ [37]:

1. When the partial effect of $Macro_t$ is zero in the sample. That is $\beta_n = 0$
2. $Macro_t$ is uncorrelated to $X_{i,t}^1 + ... + X_{i,t}^{n-1}$

Since the $X_{i,t}^j$ represents individual risk factors these are by definition meant to be uncorrelated to the macro environment described by $Macro_t$, hence the estimate should be unbiased.

Furthermore we denote the estimated series from the regression as:

$$\hat{PD}_{i,t}(Macro_t) = F(\hat{\beta}_n * Macro_t) \quad (8.5)$$

By then executing the following calculations we try to remove the dependence of macro variables from the unadjusted PD series ($PD_{i,t}$) to estimate a TTC PD series ($\hat{PD}_{i,t}^{TTC}$):

$$(\hat{PD}_{i,t}^{TTC}) = F[F^{-1}(PD_{i,t}) - F^{-1}(\hat{PD}_{i,t}(Macro_t)) + F^{-1}(\hat{PD}_{i,t}(\bar{Macro})]$$

$\Leftrightarrow$

$(\hat{PD}_{i,t}^{TTC}) = F[\beta_0 + \beta_1 X_{i,t}^1 + ... + \beta_{n-1} X_{i,t}^{n-1} + \beta_n Macro_t - \hat{\beta}_n Macro_t + \hat{\beta}_n \bar{Macro}_t]$

$\Leftrightarrow$

$(\hat{PD}_{i,t}^{TTC}) = F[\beta_0 + \beta_1 X_{i,t}^1 + ... + \beta_{n-1} X_{i,t}^{n-1} + \beta_n * Macro_t + (\beta_n - \hat{\beta}_n)(Macro_t - \bar{Macro}_t)]$

$\Leftrightarrow$

$(\hat{PD}_{i,t}^{TTC}) = F[\beta_0 + \beta_1 X_{i,t}^1 + ... + \beta_{n-1} X_{i,t}^{n-1} + \beta_n * \bar{Macro} + \epsilon_t]$

$$where \qquad \epsilon_t = (\beta_n - \hat{\beta}_n)(Macro_t - \bar{Macro}_t)$$

Thus our $\hat{PD}_{i,t}^{TTC}$ will equal that of Equation 8.3 except for an error term ϵ_t that the depends on the accuracy of $\hat{\beta}_n$. If $\hat{\beta}_n = \beta_n$ the error will be zero.

Finally $\hat{PD}_{i,t}^{TTC}$ is used to calculate the adjusted minimum capital requirements for company i ($K_{i,t}^{logit}$) which are then pooled together through the portfolio weights to get the portfolio's adjusted minimum capital requirements ($K_{p,t}^{logit}$).

8.1.1 Mechanics of regression analysis

Performing the logistic regression in Equation 8.4 to estimate β_n could be done by using regular linear regression after the following transformation:

$$F^{-1}[PD_{i,t}] = F^{-1}[F(\hat{\beta}_n * Macro_t + \varepsilon_t)] = \hat{\beta}_n * Macro_t + \varepsilon_t$$

where $F(x)^{-1}$ is the inverse cumulative standard logistic distribution:

$$F(x)^{-1} = ln\left(\frac{x}{1-x}\right) \tag{8.6}$$

The linear regression model is defined as:

$$\mathbf{y} = \mathbf{X} * \beta + \varepsilon$$

where

$$\mathbf{y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}, \quad \mathbf{X} = \begin{pmatrix} x_{1,1} & \dots & x_{1,k} \\ x_{2,1} & \dots & x_{2,k} \\ \vdots & \ddots & \vdots \\ x_{n,1} & \dots & x_{n,k} \end{pmatrix}, \quad \beta = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{pmatrix}, \quad \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

and n represents the number of data points available. To estimate the parameters β we use Matlab's function *mvregress* which in turn is based on Maximum Likelihood Estimation (MLE) (see Appendix Section 11.2.4). The log-likelihood function for the regression is as follows [38]:

$$\begin{aligned} \log L(\beta, \Sigma | \mathbf{y}, \mathbf{X}) = \frac{1}{2} nd \log(2\pi) + \frac{1}{2} n \log(\det(\Sigma)) \\ + \frac{1}{2} \sum_{i=1}^{n} (\mathbf{y}_i - \mathbf{X}_i \beta)' \Sigma^{-1} (\mathbf{y}_i - \mathbf{X}_i \beta). \end{aligned}$$

Macro variables

We will consider all three macroeconomic variables described in the data chapter (GDP, unemployment rate and CPI) as explanatory variables when performing the linear regression on $F^{-1}[PD_{i,t}]$. These will be tested both together and separately. If more than one macro variable is incorporated we will get multiple β_n, hence if we have k number of macro variables:

$$\beta_n = \begin{pmatrix} \beta_{n,1} \\ \beta_{n,2} \\ \vdots \\ \beta_{n,k} \end{pmatrix}$$

Time-lag

Considering there might be a time-lag between when the change in PD is notable and the change in macro variables are notable, time-lags will be incorporated into the model. E.g. if a certain macro variable responds 3 months after PD, $Macro_{t+3}$ will be used when performing the regression:

$$F^{-1}[PD_{i,t}] = \hat{\beta}_n * Macro_{t+3} + \varepsilon_t$$

By investigating the correlation between data series of chosen macro variables and PD for different time-lags, we may choose the time-lag giving the highest absolute correlation between the series (and thus highest explaining power). Each company will have its own unique lag to each macro-variable. This is illustrated for GDP and a random company's PD series in Figure 8.1 below where a time-lag of 1 month was chosen (i.e. GDP 1 month later than PD) since it gave the highest absolute correlation.

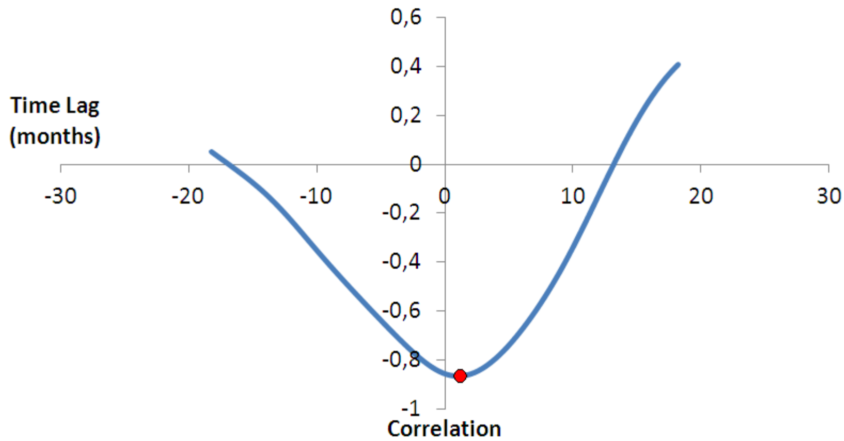


Figure 8.1: *Correlation between GDP and a random Probability of Default (PD) series*

8.2 Adjusting the equation: Time varying confidence level

Looking at Equation 3.4 we point out the fact that it contains a Normal distribution with fixed confidence level of 99.9%:

$$K_{i,t} = LGD*\left(N\left[\frac{N^{-1}(PD_{i,t}) + \sqrt{R} * N^{-1}(0.999)}{\sqrt{1-R}}\right] - PD_{i,t}\right)*\frac{(1+(M-2.5)b)}{(1-1.5b)} \tag{3.4}$$

This value is a conservative value of confidence (see Section 3.5), which imposes that the minimum capital requirement should make sure losses are covered with 99.9 % probability. In Figure 8.2 this is marked in red.

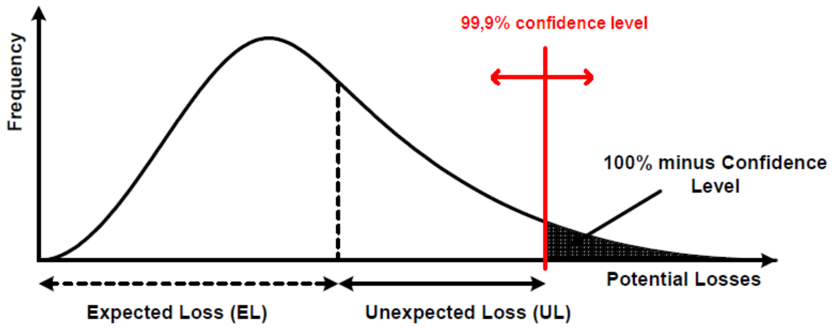


Figure 8.2: *Illustration of 99,9% confidence level (**red line**) on the Loss density function. Minimum capital requirements (K) are to equal unexpected losses*

Instead of using a fixed value (i.e. the 99.9% level), our intention is to make the confidence level time-varying depending on where we are in the economic cycle. Looking at Figure 8.2 it means we will shift the read line up and down, increasing and decreasing the unexpected loss (i.e. minimum capital requirements) depending on the current position in the economic cycle.

Thus the unadjusted $PD_{i,t}$ data for every company i will be used together with the time-varying confidence interval to produce the adjusted minimum capital requirement $K_{i,t}^{tvc}$, which are then pooled together through the portfolio weights to get the portfolio's adjusted minimum capital requirements ($K_{p,t}^{tvc}$).

8.2.1 Mechanics of time varying confidence interval

We will use a macroeconomic variable to represent the position in the economic cycle, all three mentioned in the data chapter will be tested separately (GDP, unemployment rate, CPI). A lower and upper limit will be determined for the confidence level which then varies linearly between these points depending on the macroeconomic variable:

$$C_t = \frac{Macro_t + min(Macro_t)}{max(Macro_t) - min(Macro_t)} * (C_{high} - C_{low}) - C_{low}$$

where C_t is the confidence level at time t, C_{low} and C_{high} are the lower and upper limits respectively. E.g. if Gross Domestic Product (GDP) and the limits [99.85% , 99.95%] are chosen, 99.85% will be applied when GDP reaches its minimum and 99.95% when GDP reaches its maximum. This example is illustrated in Figure 8.3 below.

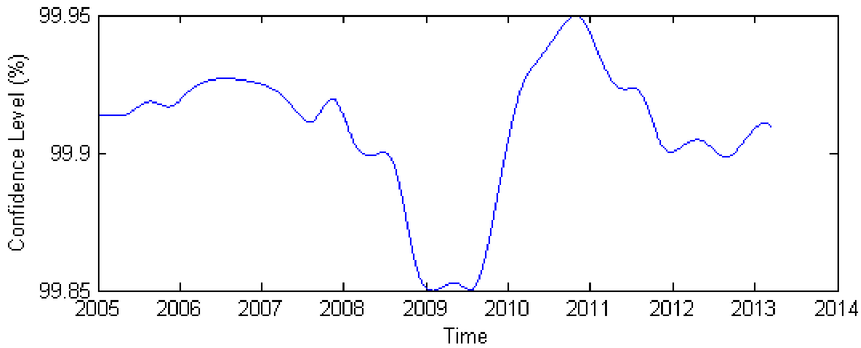


Figure 8.3: *Time varying confidence interval with GDP as macroeconomic variable*

To optimise the interval in which the confidence level can vary, the lower and upper limits will be chosen as to minimise the root mean square deviation (RMSD) in respect to the HP benchmark described in Section 7.2.

8.3 Adjusting the output

Adjusting the output are applied directly to the unadjusted minimal capital requirements ($K_{p,t}^{unadj}$). We will consider two different options; **Business cycle multiplier** and **Autoregressive (AR) filter**.

8.3.1 Business cycle multiplier

This model produces the adjusted minimum capital requirement for the portfolio by directly using a business cycle multiplier on the unadjusted series:

$$K_{p,t}^{mult} = \mu_t * K_{p,t}^{unadj} \tag{8.7}$$

where $K_{p,t}^{mult}$ is the adjusted minimum capital requirements series, $K_{p,t}^{unadj}$ is the original capital requirements, and μ_t is the business cycle multiplier at time t.

The mechanics of the multiplier

The multiplier is based on macro-economic information (e.g. GDP-growth rate), thus reducing the impact of the business cycles on K. This allows for the multiplier to adjust the minimum capital requirements in a counter-cyclical manner for every time point in our data, i.e. working as a counter-cyclical index.

There are several ways to derive a business multiplier, Gordy and Howell simulates their own PD data and uses an approach based on the exponential function when implementing the multiplier: [8]:

$$\mu_t = exp(\alpha * (w_1 * X_{t-1} + w_2 * X_{t-2} + ... + w_k * X_{t-k}) - \alpha^2/2) \tag{8.8}$$

where w_i are the lag weights and satisfy $w_1^2 + w_2^2 + ... + w_k^2 = 1$. Parameter α controls the degree of adjustment and is calibrated to achieve the desired variance of the multiplier. X_t is the random variable in the simulation relating to the macro economy at time t and is standard normally distributed. When performing the analysis they use $k = 1$ or $k = 2$ as time lags.

The key feature of the multiplier is that:

- It is continuous
- It Dampens K in bad times ($u_t < 1$) and increases K in good times ($u_t > 1$)
- $E[\mu_t] = 1$, which guarantees that over a long period (i.e. a full cycle) the adjustments cancel each other out.

These features are basically essential in any business multiplier, but can of course be done without the exponential distribution. Another particular multiplier used by Repullo et al is based on the normal distribution [31]:

$$\mu_t = \mu(X_t, \alpha) = 2 * N\left(\frac{\alpha * (X_t - \bar{X})}{\sigma_X}\right) \tag{8.9}$$

Here X_t is an *external* macroeconomic factor at time t, such as Gross Domestic Product Growth (GDP). The multiplier originates from a study with externally given data much like in our case. $\bar{X}$ and σ_X is the average and standard deviation of X_t over the sample period respectively. Parameter α again controls the degree of adjustment. μ_t will consequently have the following impact on the unadjusted minimum capital requirements ($K_{p,t}^{unadj}$):

- $\mu_t \ = 1 \ if \ X_t = \bar{X} \rightarrow$ No adjustment will be made at the average
- $\mu_t \ < 1 \ if \ X_t < \bar{X} \rightarrow$ Decrease in bad economic years
- $\mu_t \ > 1 \ if \ X_t > \bar{X} \rightarrow$ Increase in good economic years

The multiplier in Equation 8.9 has all the key features mentioned earlier. Unlike the exponential distribution however, it is bounded to the interval of [0,2] which is attractive since it implies K would not increase without bound. Furthermore it also allows us to intuitively interpret the adjustments of K in relation to the movements of X, expressed in standard deviation of X. E.g. if $\alpha = 0,1$ it implies that if X increase by one standard deviation (σ_X), the multiplier would increase K by $2 * N(0,01) - 1 = 0,08 = 8\%$.

Conclusively we will use the multiplier based on the normal distribution in our analysis, all three macroeconomic variables described in the data chapter (GDP, unemployment rate, CPI) will be considered for X_t separately. The parameter α will be optimally chosen as to minimise the root-mean-square-deviation (RMSD) of the portfolio's adjusted minimum capital requirements ($K_{p,t}^{mult}$) towards the HP benchmark.

8.3.2 Autoregressive filter

This option is based upon directly applying an AR filter to the portfolio's unadjusted minimum capital requirements ($K_{p,t}^{unadj}$):

$$K_{p,t}^{AR} = K_{p,t-i}^{AR} + \phi(K_{p,t}^{unadj} - K_{p,t-i}^{AR}) \tag{8.10}$$

where $K_{p,t}^{AR}$ denotes the adjusted minimum capital requirements, $K_{p,t}^{unadj}$ the unadjusted series at time t. The constant parameter ϕ controls the degree of adjustment, and i corresponds to the time-lag.

Mechanics of autoregressive filter

An autoregressive (AR) filter builds upon the AR process. Let X_t be a discrete time stochastic process $\{X_t : t \in Z\}$. An AR process expresses a time series as a linear function of its past values. The simplest AR process is the first-order, AR(1) process, model [39]:

$$X_t = \alpha X_{t-1} + \beta\epsilon_t \tag{8.11}$$

where X_t is the series at time t, X_{t-1} is the series at the previous time, α and β are coefficients, and ϵ_t is the residual (white noise process). Normally either α or β are set to 1.

The corresponding process of order p, AR(p), is:

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + ... + \alpha_p X_{t-p} + \beta\epsilon_t \tag{8.12}$$

where $\alpha_1, \alpha_2, ..., \alpha_p$ are p coefficients.

The idea behind the AR filter in Equation 8.11 is that the error term $\beta\epsilon_t$ is redefined as $\phi(X_t - \hat{X}_{t-i})$. This new error is the difference between the unadjusted series and the previous value of the adjusted series at time t, multiplied with the constant scaling factor ϕ. Using the AR(1) process in equation 8.11 and setting α to 1 we arrive at the following:

$$\hat{X}_t = \hat{X}_{t-i} + \phi(X_t - \hat{X}_{t-i}) \tag{8.13}$$

The right hand side of Equation 8.13 is the filter equation used to produce the adjusted minimum capital requirements $K_{p,t}^{AR}$ seen in Equation 8.10.

The AR filter adjusts the minimum capital requirements with respect to a time-lag, as opposed to the multiplier option (see Section 8.3.1) that uses macroeconomic variables. Consequently, the effect of the AR-filter is that economic shocks to $K_{p,t}^{unadj}$ are absorbed into the minimum capital over longer time, rather than all at once. This results in that $K_{p,t}^{AR}$ will react more slowly to current economic fluctuations and that the amplitude of the fluctuations will be smaller.

Practically we calculate the AR filter in Equation 8.10 for every time point t. Both ϕ and the length of time-lag i are chosen as to minimise the RMSD of the adjusted minimum capital requirements ($K_{p,t}^{AR}$) with respect to the HP benchmark described in the previous section. Practically we will vary both ϕ and the time-lag i simultaneously to find the optimal combination.

Chapter 9

Results

In this chapter we will present the result from the different procedures to mitigate procyclicality from minimum capital requirements calculations. As stated in Section 7.2 we will evaluate their performance by root-mean-square deviation (RMSD) against a HP benchmark. Each procedure will have their own respective section.

Graphical presentation of the result will all be done in the same manner to make interpretation easy, plots will be constructed consistently as visible in Figure 9.1 below (only an example). The unadjusted minimum capital requirements for the portfolio ($K_{p,t}^{unadj}$) will be printed in blue, the HP-benchmark in red and the adjusted minimum capital requirements series in green.

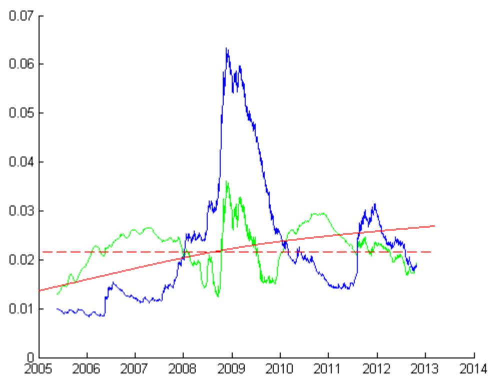
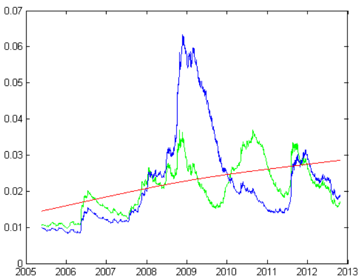


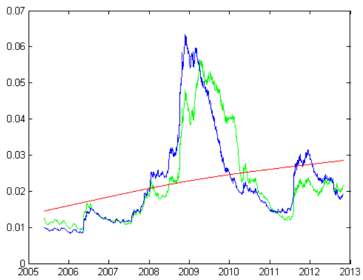
Figure 9.1: *Result example plot*

9.1 Adjusting the input: Logistic Regression

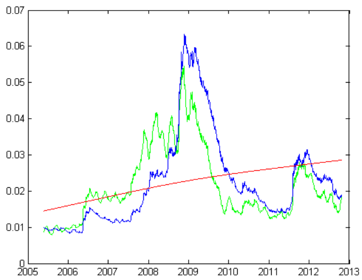
The logistic regression performed well in terms of trying to remove the dependence of the economic cycle on Probability of Default (PD). Seven tests were performed as all three macroeconomic variables (GDP, CPI and unemployment rate) were tested together and separately in all possible combinations. Different regressions were needed for each company's PD series (90 companies) in each test, thus we did a total of 90*7 = 630 logistic regressions. Here we will provide an overview of the results but a detailed example for a single company can be seen in Appendix Section 11.4.1. The final adjusted minimum capital requirements of the portfolio ($K_{p,t}^{logit}$) with different explanatory variables are visible in Figure 9.2 and Figure 9.3.



(a) GDP

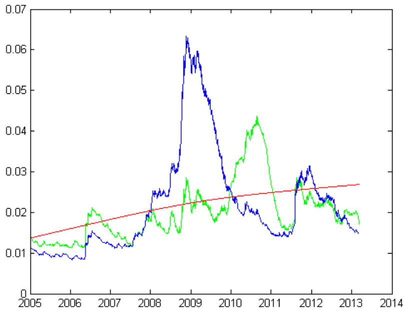


(b) CPI

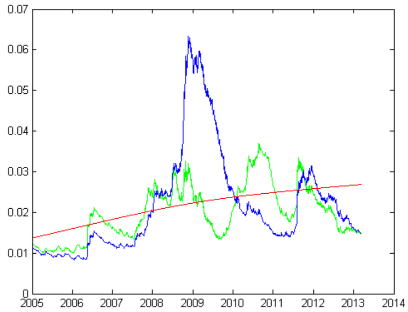


(c) Unemployment rate

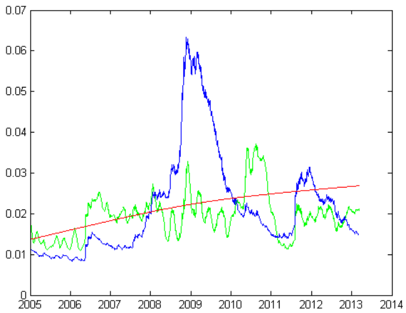
Figure 9.2: $K_{p,t}^{logit}$ *for different explanatory variables (**single**) printed in **green**. **Blue** line indicates the unadjusted series ($K_{p,t}^{unadj}$), **Red** line is the HP filter benchmark*



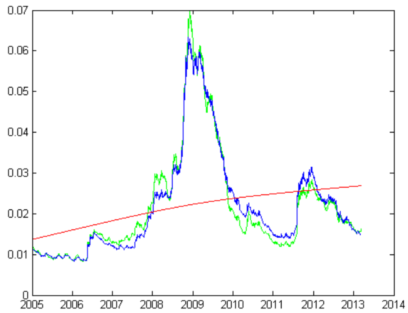
(a) GDP and CPI



(b) GDP and Unemployment rate



(c) GDP, CPI and Unemplyment rate



(d) CPI and Unemplyment rate

Figure 9.3: $K_{p,t}^{logit}$ *for different explanatory variables (**multiple**) printed in **green**. **Blue** line indicates the unadjusted series ($K_{p,t}^{unadj}$) and the **Red** line is the HP filter benchmark*

All three macroeconomic variables showed to be significant at the 5% level in all regressions, however Gross Domestic Product (GDP) was without doubt the variable able to remove most of the influence from economic cycles on PD. When testing GDP as a single explanatory variable it received an R-squared value of 40-50% while the other two only got 2-10% in the same tests.

In tests with a single macro variable all β:s were negative for GDP and CPI but positive for the unemployment rate. This is intuitively correct since it implies that PD increase when the macroeconomic variables indicate a recession (GDP and CPI goes down, unemployment rate goes up). However in tests with more than one macro variable GDP still had negative values but both CPI and unemployment rate got a mixture of positive and negative β:s for different companies, which is odd. Suspecting collinearity in the macro variables lead us to investigate correlation between the macroeconomic variables, however these proved to be less than 20% (most much lower) which is acceptable.

The time-lags showed different results for each macro-variable and company. For GDP the time-lag varied a lot but was in most cases not more than 5 months back or forth, often less. For CPI all time-lags were highly positive around 10 months (CPI responds before PD) and for unemployment rate they were extremely negative (unemployment rate responds after PD). We placed a limit of at most 15 months time-lag (back or forth) which we had to apply several times for the unemployment rate. Plots of time-lags are visible in the Appendix Section 11.2.

The different $K_{p,t}^{logit}$ were at last evaluated against the HP benchmark with RMSD. The result is visible in Table 9.1 and 9.2, mean and standard deviation were also calculated. Here we can conclude that the regression with only GDP as macroeconomic variable was the one achieving the best result, not surprisingly since the other variables experienced some problems mentioned above. Using all variables together generated a quite good result as well for the RMSD-value, but also when looking at the plot. The result looks like it is very independent of the large peaks in the unadjusted series, which is in line to what we are trying to achieve. However the amplitude of the lower frequencies is generally quite high, raising a concern for stability. This together with the varying signs of β mentioned above led us to discard it in favour of only GDP as macroeconomic variable.

	GDP	**CPI**	**unemp.**
RMSD	0,0055	0,0116	0,0103
σ	0,0069	0,0127	0,0101
Mean	0,0210	0,0221	0,0215

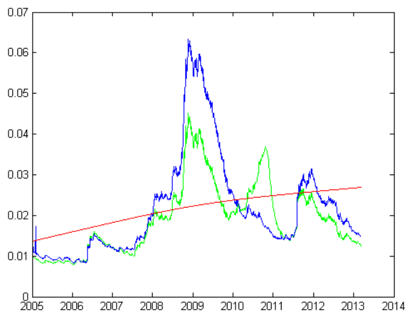
Table 9.1: *Detailed results for $K_{p,t}^{logit}$ with different explanatory variables **(single)***

	GDP and CPI	**GDP and unemp.**	**CPI and unemp.**	**GDP, CPI and unemp.**
RMSD	0,0057	0,0061	0,0125	0,0063
σ	0,0065	0,0073	0,0131	0,0059
Mean	0,0208	0,0208	0,0223	0,0202

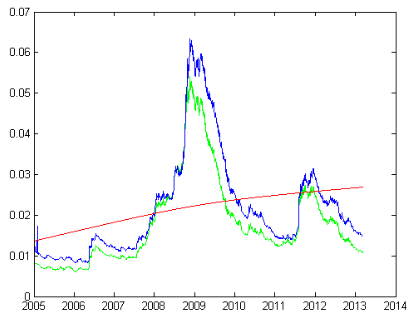
Table 9.2: *Detailed results for $K_{p,t}^{logit}$ with different explanatory variables **(multiple)***

9.2 Adjusting the equation: Time-varying confidence level

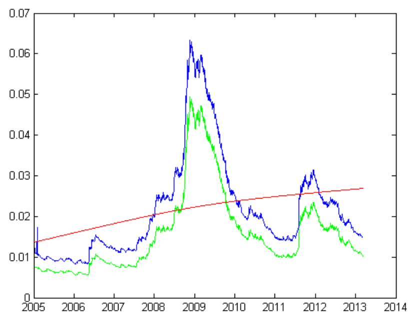
The time-varying confidence interval gave fairly good results. All macroeconomic variables (GDP, unemployment rate, CPI) were tested separately and optimised to find the best confidence limits that minimised the RMSD of the adjusted minimum capital requirements ($K_{p,t}^{tvc}$) against the HP benchmark. The resulting adjusted minimum capital requirements $K_{p,t}^{tvc}$ with different macro variables are plotted in Figure 9.4 and the detailed numerical results are presented in Table 9.3.



(a) GDP



(b) CPI



(c) Unemployment rate

Figure 9.4: $K_{p,t}^{tvc}$ *for different macroeconomic variables printed in* ***green****.* ***Blue*** *line indicates unadjusted series* ($K_{p,t}^{unadj}$) *and the* ***red*** *line is the HP filter benchmark*

	GDP	**CPI**	**unemp.**
RMSD	0,0080	0,0117	0,0107
σ	0,0087	0,0102	0,0108
Mean	0,0192	0,0158	0,0180
Confidence Limits	[99,66% - 99,99%]	[99,74% - 99,8%]	[99,74% - 99,91%]

Table 9.3: *Detailed results for* $K_{p,t}^{tvc}$ *with different macroeconomic variables*

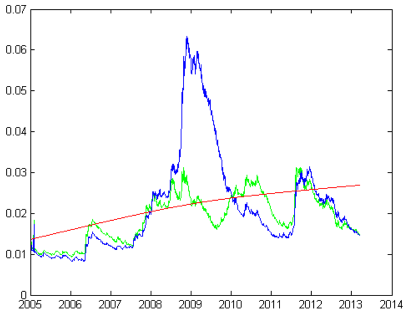
As in the approach for adjusting the input, using CPI or unemployment rate as macroeconomic variables gave poor results. The adjusted series were very similar to the unadjusted series and the trend from the economic cycle is still present. The main achievement was a general reduction of all data points in the unadjusted series, most likely due to their confidence limits being beneath (or just covering) the original 99,9% with a quite tight span. Changing the limits did not result in smaller values of RMSD.

When using GDP, there are some improvements visible. In particular, the greatest peak during 2008-2010 has been reduced, although we now see a new peak following the first one. The confidence limits constituted a wider span, but they also included the original 99,9% with some margin which is good since it goes in line with the Basel Committee's idea of covering losses to a probability of 99,9%. It also outperformed the other series in terms of the smaller RMSD towards the benchmark.

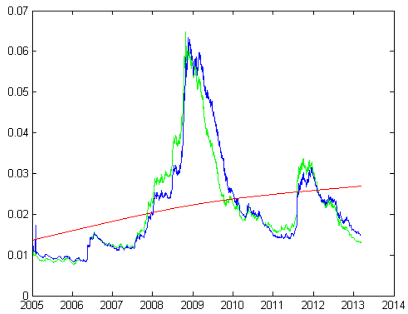
9.3 Adjusting the output

9.3.1 Business cycle multiplier

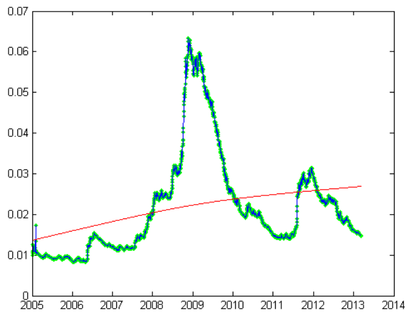
The business multiplier gave good results. All macroeconomic variables (GDP, unemployment rate, CPI) were tested but GDP resulted in the best performance. Once again the other two, CPI and unemployment rate, performed poorly. All of the adjusted minimum capital requirements $K_{p,t}^{mult}$ with different macroeconomic variables are visible in Figure 9.4 and 9.5 below.



(a) GDP



(b) CPI



(c) Unemployment rate

Figure 9.5: *$K_{p,t}^{mult}$ for different macroeconomic variables printed in* ***green***. ***Blue*** *line indicates unadjusted series ($K_{p,t}^{unadj}$) and the* ***red*** *line is the HP filter benchmark*

The constant parameter α was optimised for $K_{p,t}^{mult}$ to achieve the lowest RMSD against the HP benchmark. These are visible in Table 9.4 together with the RMSD, mean and standard deviation of $K_{p,t}^{mult}$.

The value of α describes the explaining power of the macroeconomic variable and obviously GDP excelled with $\alpha = 0,3518$. This implies that if GDP increases with one standard-deviation, K increase with approximately $2 * N(0,3518) - 1 \approx 27\%$. CPI had a relatively low α indicating low explaining power (11%), but more surprisingly α for the unemployment rate was zero. This means that the multiplier is constantly 1, i.e. it has no effect at all.

	GDP	Unemployment	CPI
RMSD	0,0050	0,0117	0,0112
σ	0,0058	0,0127	0,0121
Mean	0,0189	0,0216	0,0214
α	0,3518	0,0000	0,1457

Table 9.4: *Detailed result $K^{mult}_{p,t}$ with GDP, Unemployment rate or CPI as macroeconomic variables*

As for the RMSD towards the HP benchmark GDP achieved a great value. Looking at Figure 9.5 we can see that foremost the biggest peak has been avoided, not unlike when adjusting the input, and the general series is more centred around the HP benchmark. The CPI and unemployment rate resulted in very similar and identical series to the unadjusted one thus the RMSD was quite high.

9.3.2 Autoregressive filter

The autoregressive (AR) filter shows great quantitative results but less great qualitatively. The main problem with using the technique was deciding on values of the parameters, i.e. the time lag i and the weight ϕ.

By optimising the RMSD of the adjusted minimum capital requirements ($K_{p,t}^{AR}$) towards the HP Benchmark we arrived at $i = 1$ month and $\phi = 0,0297$ which is visible in Figure 9.6. With a low ϕ the series rely heavily on the previous value connected to the time lag (in our case 1 month before). The value of 0,0297 is very low which is a big concern since we incorporate little of the actual present variations. Thus the series is smoothed and not only the variations depending on the economic cycle fluctuations are dampened. By looking at the plot this is obvious, we see that the adjusted series have the same peaks as the unadjusted series but dampened. Essentially, these are the peaks we are trying to remove since they are results of the economic cycle.

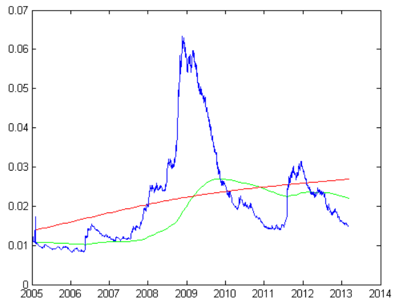


Figure 9.6: *$K_{p,t}^{AR}$ optimal parameter variables $i = 1$ month and $\phi = 0.0297$ printed in **green**. **Blue** line indicates unadjusted series ($K_{p,t}^{unadj}$) and the **red** line is the HP filter benchmark*

Attempts of tampering with the AR parameters did improve the result in some aspects qualitatively, but its very hard to decide which values to choose when not optimising. By only raising the time-lag i the result looks even smoother. By raising ϕ, the AR filter reacts faster to changes in the unadjusted series but also increases its dependence on cycle fluctuations. Conclusively, the results are hard to interpret qualitatively in respect to our goal of making K less dependent on the economic cycle.

Regarding the quantitative results they were very good, for the optimal series they are visible in Table 9.5.

	$i = 1$, $\phi = 0{,}0297$
RMSD	0,0051
σ	0,0065
Mean	0,0182

Table 9.5: *Detailed result from $K_{p,t}^{AR}$ with optimal values of time-lag i and constant parameter ϕ*

9.4 Summary

To summarise we have ranked the options in regard to their performance measured as the RMSD against the HP benchmark. This result is presented in Table 9.6.

	Optimal parameters	**RMSD**	**Rank**
Business Multiplier	GDP, $\alpha = 0{,}3518$	0,0050	1
AR filter	Time-lag 1; $\phi = 0,0297$	0,0051	2
Logistic Regression	GDP as explanatory variable	0,0055	3
Time-varying confidence	GDP, Limits: [99,66% - 99,99%]	0,0080	4

Table 9.6: *Summary of results. Rank is based on the overall smallest RMSD against the HP benchmark of the unadjusted series.*

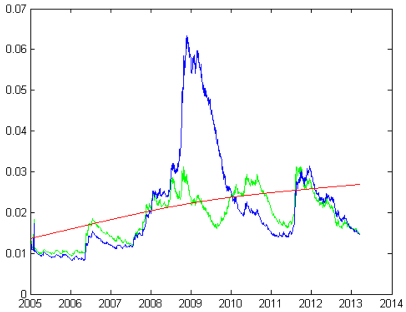
To get an indication of the amount of improvement we compare the resulting RMSD above with the RMSD of the unadjusted series (K^{unadj}). The result is visible in the Table 9.7 where 0% indicates a full improvement (i.e. 0 RMSD).

	RMSD	**Rank**
Business Multiplier	42,78%	1
AR filter	43,63%	2
Logistic Regression	47,06%	3
Time-varying confidence	68,45%	4

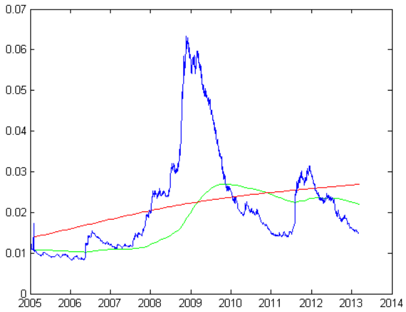
Table 9.7: *RMSD in percent of unadjusted series (K^{unadj}) RMSD. 0% indicates 0 RMSD*

Conclusively the best performing options were the business multiplier with GDP and the AR-filter, tightly followed by the Logistic regression with GDP.

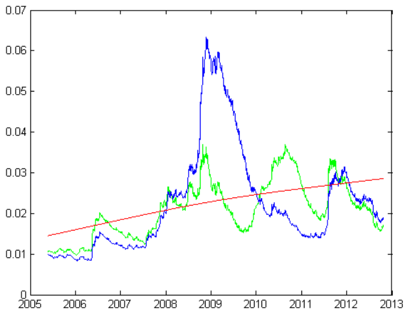
As mentioned above however, we experienced some qualitative issues with the AR-filter which lead us to discard this option in favour of the logistic regression. Time-varying confidence level with GDP showed potential but was significantly outperformed in terms of (RMSD). Figure 9.7 shows all four adjusted series.



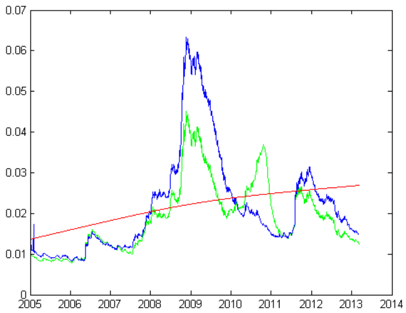
(a) Business Multiplier with indicator GDP ($K_{p,t}^{mult}$)



(b) AR-filter ($K_{p,t}^{AR}$)



(c) Logistic Regression with GDP ($K_{p,t}^{logit}$)



(d) Time-varying confidence level with GDP ($K_{p,t}^{tvc}$)

Figure 9.7: *The best performing options in terms of smallest RMSD.* ***Blue*** *line indicates unadjusted series,* ***green*** *is the modified.* ***Red*** *line is the HP filter benchmark*

Chapter 10

Discussion and Conclusion

This thesis has been built upon calculations for regulatory capital known as minimum capital requirements (K) provided by the Basel Committee and the phenomenon of procyclicality that arises as a consequence of them. Our main goal has been to evaluate methods for mitigating procyclicality on the Swedish market for corporate lending. Several options have been considered within three different approaches (adjusting the input, the equation or the output). The chosen options have then been evaluated by comparing the adjusted series of K against an optimal benchmark series constructed by using a HP-filter on the unadjusted series.

When choosing options to evaluate we have focused on prominent research and simplicity of incorporating them into the existing framework. The options showing the best results for mitigating procyclicality in the Basel minimum capital requirements calculations are either to adjust the output with a *business multiplier* or to adjust the input with *logistic regression*. Both options are based on macroeconomic variables and in this context *GDP growth* resulted in the best performance in both cases.

The logistic regression option removed the dependence on the economic cycle mainly through regressing Probability of Default (PD) on different macroeconomic variables. In essence the idea was to transform PD from PIT to TTC. The option is fairly simple and could hence be easy for the individual bank to implement. More importantly, even if the individual bank's initial PD already shows some TTC behaviour, the option could still be able to remove the remaining dependence. Looking at Sweden the largest banks (Handelsbanken, SEB, Nordea, Swedbank) already claim to show varying degree of TTC behaviour in their modelling of PD, thus in this context logistic regression would be an attractive option.

The problem with regression analysis is that it might be hard to control from a regulatory point of view (required amount of data for regression, accuracy, variables etc.). However the results indicate that creating a TTC PD is a good option for addressing the problem, whether this is achieved through regression or not is somewhat arbitrarily. Still, we strongly believe that change should not occur internally at the bank's PD model since this leaves room for interpreting the definition of a TTC measure.

Adjusting the output with a business cycle multiplier was executed fairly close to how it would be in a real situation. It is also a quite intuitive method with no need for extensive PD data, only data on the macroeconomic variable (in our case GDP) which often is easy to get hold of. Implementing the approach would be very easy since the multiplier value could be provided by the regulating authority in Sweden on e.g. a monthly basis for different exposures. Also banks could focus on using pure PIT PD measures, in fact they would have to since otherwise all banks would require different α:s.

When evaluating against the HP benchmark both options give similar results, conclusively we favour the use of a business multiplier due to its simplicity and transparency. In further research it would be interesting to thoroughly compare the multiplier in relation to the counter cyclical buffer proposal of Basel III, this thesis was rather aimed at investigating alternative ways of reducing procyclicality. In our view the advantage of the multiplier approach is its possibility to both increase and lower the regulatory capital (when the multiplier is less than 1) while the buffer can only increase it or at most leave it unadjusted (when the buffer is 0). The buffers also use a widely debated macroeconomic variable (credit-to-GDP gap) while the multiplier uses regular GDP growth.

Making a more qualitative judgement of the graphical result, the peaks and troughs of the adjusted series might seem to appear at random places. However for both the multiplier and the logistic regression we can see that they are often a counter-reaction to the peaks and troughs of the unadjusted series (although mathematically they only depend on the GDP growth). It would be desirable if they did not counter-react but removed the dependence as a whole, this however is rather a matter of tuning the models or replacing the macroeconomic variable than revising the framework of the models.

When using macroeconomic variables used as proxy for the economic cycle, Gross Domestic Product growth (GDP) gave the best result regardless of the options considered. This is not surprising since it generally is considered an important indicator for the economy, however it was more surprising that both Consumer Price Index (CPI) and unemployment rate gave very bad results. In futures studies it would be of interest to try other variables such as credit growth or the stock market return, but also look at the credit-to-GDP gap. We had difficulties in finding reliable data on these which is why we chose to limit our study to GDP, CPI and unemployment rate. Initially we also considered the stock index OMX30 but it was discarded since all 30 stocks in the index are companies we have PD data of. It described the individual performance of the companies rather than acting as a proxy for the economic cycle.

Regarding the constructed portfolio, it was an attempt to replicate the Swedish market for corporate lending by using the 90 largest corporations in Sweden. There is always a possibility of using more companies but for the scope of this thesis it was a reasonable assumption. As for the data one might consider not using external data of PD and instead simulating or modelling it, however since we wanted to link the results to the actual Swedish market using real data was a necessity. Furthermore the focus of this thesis was not about modelling PD but how to adjust the minimum capital requirements calculation.

Finally considering the benchmark used it was a growth trend produced by using a HP filter on the unadjusted K series. Many methods with this purpose, including the HP filter, has been recognized to suffer from so called "end-point problems". Basically this means that the procedure for producing the trend is optimal in the mid-points but not in the end-points, potentially leading an inaccurate trend in the beginning and at the end of the trend [40]. In our analysis this poses less of a problem though since λ (the smoothing factor) is quite high, thus limiting the potential deviation of the end-points from the rest of the series. Also the main behaviour we want to reduce is the increase of K occurring in the middle of the series, thus the end points are not as relevant as the middle points. There are however techniques in which to reduce the end-point problem which could be of interest in further research.

An alternative *flat benchmark* could be created by simple taking the average of the unadjusted series of K. Initially we used both benchmarks in this thesis but they actually produced the same ranking of options in the end, we chose the HP benchmark simply because it was better motivated through qualitative arguments. Both methods considered however was pure statistical concepts without any external data, in further research one might look beyond the numbers in the series to find a more accurate benchmark.

Bibliography

[1] Basel Committee on Banking Supervision. History of the basel committee and its membership. Technical report, Bank For International Settlements, 2009.

[2] Rafael Repullo and Jesus Saurina. The countercyclical capital buffer of basel iii - a critical assessment. Technical report, Centre for Economic Policy Research, 2011.

[3] Rochelle M. Edge and Ralf R. Meisenzahl. The unreliability of credit-to-gdp ratio gaps in real time: Implications for countercyclical capital buïňĂers. Technical report, OïňČce of Financial Stability Policy and Research, Federal Reserve Board, 2011.

[4] David E. O'Connor. *The basics of Economics*. Greenwood Publishing Group, first edition, 2004.

[5] Institute of international finance. Risk management across economic cycles. Technical report, Institute of international finance, 2009.

[6] Joel Clark. Regulators struggle to tackle pro-cyclicality. *Risk magazine*, 2010.

[7] Rafael Repullo and Javier Suarez. The procyclical effects of basel II. Technical report, International Monetary Fund, 2008.

[8] Michael B. Gordy and Bradley Howells. Procyclicality in basel II: Can we treat the disease without killing the patient? Technical report, Board of Governors of the Federal Reserve System, 2004.

[9] Committee of European Banking Supervisors. Position paper on a countercyclical capital buffer. Technical report, Committee of European Banking Supervisors, 2009.

[10] Philippe Jorion. *Financial Risk Manager Handbook.* John Wiley & Sons Inc., second edition, 2003.

[11] Florian Heider and Marie Hoerova. Interbank lending, credit risk premia and collateral. Technical report, European Central Bank, 2009.

[12] Joe Larson. The basel capital accords. Technical report, University of Iowa, 2011.

[13] Basel Committee on Banking Supervision. International convergence of capital measurement and capital standards. Technical report, Bank For International Settlements, 1988.

[14] Basel Committee on Banking Supervision. International convergence of capital measurement and capital standards - a revised framework comprehensive version. Technical report, Bank For International Settlements, 2006.

[15] Annamária Benyovszki, Eszter Bordás, László-Ádám Kürti, and Melinda Szodorai. Troubleshooting basel II: The issue of procyclicalityb. Technical report, University of Oradea, 2011.

[16] Frank Heid. The cyclical effects of the basel ii capital requirements. *Journal of Banking and Finance*, 2007.

[17] Basel Committee on Banking Supervision. Basel III: A global regulatory framework for more resilient banks and banking systems. Technical report, Bank For International Settlements, 2010 (rev June 2011).

[18] Basel Committee on Banking Supervision. Guidance for national authorities operating the countecyclical capital buffer. Technical report, Bank For International Settlements, 2010.

[19] Viren Vaghela. Asia bankers reject counter-cyclical capital buffer as effective tool for supervision, June 2012. Accessed 2013-06-04 from: `http://www.risk.net/asia-risk/feature/2183130/asia-bankers-reject-counter-cyclical-capital-buffer_effective-tool-supervision`.

[20] Nordea Group. Capital and risk management (pillar iii) report, 2012. Accessed 2013-04-10 from: `http://www.nordea.com/sitemod/upload/root/www.nordea.com%20-%20uk/Investorrelations/reports/risk/group/Nordea_Group_Capital_Risk_Management_Report_2012.pdf`.

[21] Handelsbanken. Risk and capital management - information according to pillar 3, 2012. Accessed 2013-04-10 from: `http://mb.cision.com/Main/3555/9371358/92924.pdf`.

[22] SEB Group. Capital adequacy and risk management report (pillar 3), 2012. Accessed 2013-04-10 from: `http://www.sebgroup.com/Documents/Investor_Relations/Capital_adequacy_reports/Cap_Adequacy_SEB_Pillar3_2012.pdf`.

[23] Swedbank Financial Companies Group. Risk and capital adequacy - 2012, 2012. Accessed 2013-04-10 from: `http://www.swedbank.com/idc/groups/public/@i/@sbg/@gs/@ir/documents/financial/cid_853323.pdf`.

[24] Basel Committee on Banking Supervision. An explanatory note on the basel II IRB risk weight functions. Technical report, Bank For International Settlements, 2005.

[25] Bernd Engelmann and Robert Rauhmeier. *The Basel II Risk Parameters*. Springer-Verlag Berlin Hedielberg, second edition, 2011.

[26] Finansinspektionen. Finansinspektionens föreskrifter och allmänna råd om kapitaltäckning och stora exponeringar - FFS 2007:1. Technical report, 2007.

[27] Magnus Carlehed and Alexander Petrov. A methodology for point-in-time-through-the-cycle probability of default decomposition in risk classification systems. *Journal of Risk Model Validation, Volume 6 / Number 3*, Fall 2012.

[28] Rafael Repullo, Jesús Saurina, and Carlos Trucharte. An assesment of basel II procyclicality in mortgage portfolios. Technical report, Banco de España, 2007.

[29] David T. Hamilton. An introduction to through-the-cycle public firm EDFTM credit measures, May 2011. `http://www.moodysanalytics.com/~/media/Insight/Quantitative-Research/Enterprise-Risk-Modeling/2011/2011-03-05-Introduction-to-Through-the-Cycle-Public-Firm_EDFTM-Credit-Measures.ashx`.

[30] Anil K Kashyap and Jeremy C. Stein. Cyclical implications of the basel II capital standards. Technical report, 2004.

[31] Rafael Repullo, Jesús Saurina, and Carlos Trucharte. Mitigating the pro-cyclicality of basel II. Technical report, Banco de España, 2010.

[32] D. Wilson Ervin and Tom Wilde. Pro-cyclicality in the new basel accord. Technical report, Risk Waters Group, 2001.

[33] Thomson Reuters. Starmine quantitative models, 2012. Accessed 2013-04-10 from url: `http://thomsonreuters.com/content/financial/pdf/i_and_a/starmine_quantitative_models.pdf`.

[34] Robert J. Hodrick and Edward C. Prescott. Postwar u.s. business cycles: An empirical investigation. *Journal of Money, Credit and Banking, Vol. 29, No. 1, pp. 1-16*, 1997.

[35] Morten O. Ravn. On adjusting the hp-filter for the frequency of observations. *University of Southampton, Universitat Pompeu Fabra,*, 1997.

[36] P. McCullagh and J.A. Nelder. *Generalized Linear Models*. Chapman & Hall, 1989.

[37] Jeffrey M. Woolridge. *Introductory Econometrics*. South-Western Cengage Learning, fourth edition, 2009.

[38] MathWorks. Estimation of multivariate regression models. Accessed 2013-04-10 from: `http://www.mathworks.nl/help/stats/estimation-of-multivariate-regression-models.html`.

[39] Henrik Madsen. *Time Series Analysis*. Chapman & Hall, first edition, 2008.

[40] Matthias Mohr. A trend-cycle(-season) filter. Technical report, European Central Bank, 2005.

[41] Gary D Knott. *Interpolating cubic splines*. Birkhauser Verlag GmbH, 2000.

[42] Gunnar Blom, Jan Enger, Gunnar Englund, Jan Grandell, and Lars Holst. *Sannolikhetsteori och statestikteori med tillämpningar*. Studentlitteratur in Lund, 5:5 edition, 2005.

Chapter 11

Appendix

11.1 Probability of Default (PD) estimation in Swedish Banks

We consider the largest Swedish banks Nordea, Handelsbanken, Swedbank and SEB.

Nordea expresses in a report form 2012 that they use a hybrid of both Through-the-Cycle (TTC) and Point-in-Time (PIT) for their corporate and institution exposures. For retail portfolios the measure is close to PIT [20].

Handelsbanken says in a similar report from 2012 that *"Handelsbanken's internal rating of a counterparty is so long-term that the PD at counterparty and portfolio level i expected to be stable during a normal business cycle"*, hence it may be regarded as pure TTC [21].

SEB does not state as clearly what their results are, they aim towards TTC but have seen some indication of PIT behaviour [22].

Finally Swedbank seems to be somewhat similar to SEB but only states that "Swedbank tries to take a through-the-cycle (TTC) perspective" [23]. They do however also calculate a PIT measure for predicting future expected losses (though not used for minimum capital requirements).

Bank	Corporate PD type
Nordea	Hybrid of PIT and TTC
Handelsbanken	Pure TTC
SEB	Aims toward TTC but some PIT behaviour
Swedbank	Aims towards TTC but some PIT behaviour

Table 11.1: *Probability of Default (PD) estimation in Swedish banks summary*

11.2 Statistical Concepts

11.2.1 Cubic Spline Interpolation

Cubic splines is one of the most common methods for interpolating data. There are multiple version of Spline interpolation but the cubic spline is the most popular, here cubic refers to the fact that interpolant is a piecewise polynomial of the third order [41]. The basic definition of a cubic spline is:

Definition: Let $U = \{x_0, ..., x_n\}$ be a set of knots with:

$$a = x_0 < \cdots < x_n = b$$

A function $f \in C^2[a, b]$ is called a cubic spline on the interval $[a, b]$ if f is a cubic polynomial in each sub-interval $[x_i, x_{i+1}]$. For given values y_i corresponding to the interval U, f is called an interpolating cubic spline if $f(x_i) = y_i$.

Splines are good for approximations for two general reasons; computationally light and good fit. We will not dwell further on the subject of cubic spline since it only has a minor role in this thesis, for further reading we refer to [41]. This thesis uses matlabs built in function *splines* to perform the cubic spline interpolation.

11.2.2 Root-mean-square Deviation

The root-mean-square deviation (RMSD) is a commonly used measure to describe accuracy of predicted variables, such as in a linear regression. The

RMSD, where $\hat{y}_t$ are the predicted value of variable y_t, can be calculated in a sample as:

$$RMSD = \sqrt{\frac{\sum_{t=1}^{n} (y_t - \hat{y}_t)^2}{n}}$$

The difference between predictor and real value, i.e. $(y_t - \hat{y}_t)$, are called residuals. The RMSD is not scalar invariant but it is independent of the size of the sample.

11.2.3 Hodrick-prescott filter

The Hodrick-prescot filter (HP filter) is a common tool used in macro economic theory to obtain a smoothed version of a time series, it is often used as a specialized filter for trend and business cycle estimation. [34]

What the filter does is that it assumes the series (y_t) to be a sum of two components; a trend component (g_t) and a cyclical component (c_t):

$$y_t = g_t + c_t \tag{11.1}$$

The trend part is recognized as a long term trend as opposed to the cyclical part (c_t) which is considered short term. By using the HP filter it is possible to extract the trend part of the series (g_t) and neglect the cyclical part by solving the following equation:

$$\min_{g_t}\{\sum_{t=1}^{T}(y_t - g_t)^2 + \lambda * \sum_{t=1}^{T}[(g_t - g_{t-1}) - (g_t - g_{t-1})]^2\}$$

The equation depends on a smoothing parameter λ which is set by the user and penalizes the variability in g_t. Thus a larger values of λ means a smoother series. When λ goes towards infinity, the solution of the equation goes towards the least square fit of a linear model. An example is provided in Figure 11.1 on the next page.

Most studies use a λ of 1600 when data is on a quarterly basis [35]. If data is on another basis, the standard conversion method is used:

$$\lambda_{daily} = \lambda_{annual} * n_{year}^4 = \lambda_{monthly} * n_{month}^4$$

where n_{month} and n_{year} is the number of days in a month and year respectively.

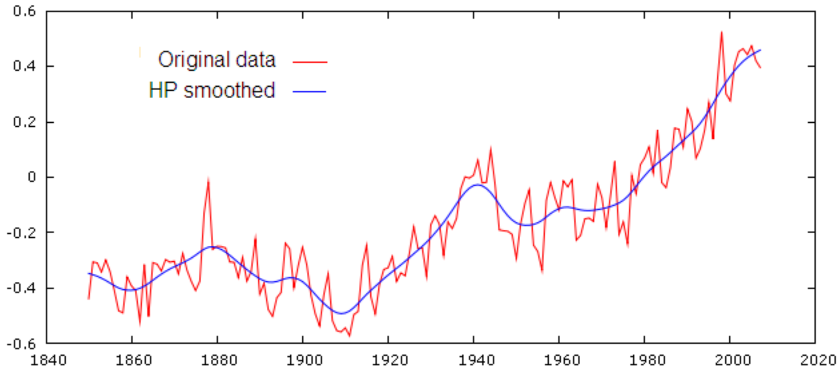


Figure 11.1: *Original series in red and smoothed series with HP filter in* ***blue***, $\lambda = 100$

11.2.4 Maximum Likelihood estimation (MLE)

Maximum Likelihood estimation is one of the most common used method to estimate parameters for a data set together with the Ordinary Least Square method (OLS). The following will describe the basics in executing the MLE. [42]

Let $\{x_1, x_2, ...x_n\}$ be the outcome of a series of stochastic variables $\{X_1, X_2, ...X_n\}$ that has a probability distribution dependent on an unknown variable θ (where θ could be a vector of variables). The Likelihood function is then defined as (direct quote from [42], page 254):

$$L(\theta) = P(X_1 = x_1, X_2 = x_2, ...X_n = x_n, \theta), \quad if\ discrete$$
$$L(\theta) = f_{X_1,X_2,...,X_n}(x_1, x_2, ..., x_n, \theta), \quad if\ continuous$$

The MLE estimation of the parameter (θ_{MLE}) is the value in which $L(\theta)$ reaches its maximum within the parameter space Ω_θ.

11.3 Company specific data and Portfolio weights

Following is a table containing the company specific data described in Section 6.2, the data is sorted on Market Capitalization (MCAP).

	Ratio Ratio	Mcap (M$)	Portfolio Weights
Hennes & Mauritz AB	0,28%	53500	0,00423
Ericsson	3,99%	42730	0,04800
Atlas Copco AB	3,36%	34700	0,03280
Volvo AB	13,41%	33050	0,12480
TeliaSonera AB	11,02%	30540	0,09476
Investor AB	4,87%	22660	0,03108
Sandvik AB	7,79%	20560	0,04510
Scania (publ) AB	8,98%	17200	0,04350
Svenska Cellulosa AB	8,67%	16800	0,04101
Assa Abloy AB	5,36%	14000	0,02112
SKF AB	9,88%	11800	0,03282
Alfa Laval AB	4,18%	9750	0,01149
Hexagon AB	6,12%	9640	0,01662
Electrolux AB	10,29%	7830	0,02270
Tele2 AB	7,57%	7440	0,01586
Industrivarden (AB)	5,12%	7320	0,01056
Skanska AB	9,11%	7260	0,01862
Lundin Petroleum AB	6,48%	7160	0,01306
Getinge AB	9,89%	6840	0,01906
Swedish Match AB	9,11%	6580	0,01688
Investment Kinnevik AB	3,91%	6520	0,00719
Elekta AB (publ)	4,45%	5400	0,00677
Melker Schorling AB	1,10%	5050	0,00156
Boliden AB	6,07%	4630	0,00792
Meda AB	13,96%	3510	0,01380
Trelleborg AB	6,36%	3500	0,00627
Husqvarna AB	9,63%	3480	0,00943
Investment Latour AB	0,87%	3350	0,00082
Ratos AB	12,07%	3320	0,01128
Securitas AB	16,98%	3310	0,01582
LE Lundbergforetagen AB	26,52%	3150	0,02353
Hufvudstaden AB	7,41%	2940	0,00613
Modern Times Group AB	3,73%	2900	0,00304
NCC AB	15,91%	2850	0,01277

Castellum AB	9,43%	2590	0,00688
SSAB Corporation	16,03%	2420	0,01093
Saab AB (publ)	6,20%	2360	0,00412
Axfood AB	2,59%	2200	0,00160
Hakon Invest AB	1,09%	2090	0,00064
Billerud AB	4,30%	2080	0,00252
JM AB	5,58%	2040	0,00321
Wallenstam AB	9,81%	2030	0,00561
Atrium Ljungberg AB	16,74%	1820	0,00858
Fabege AB	19,05%	1790	0,00960
Axis AB	0,75%	1760	0,00037
Nibe Industrier AB	10,49%	1730	0,00511
Hoganas AB	2,70%	1720	0,00131
PEAB AB	18,99%	1570	0,00840
Intrum Justitia AB	8,45%	1480	0,00352
Wihlborgs Fastigheter AB	29,64%	1290	0,01077
Mekonomen AB	6,88%	1280	0,00248
Betsson AB	1,80%	1240	0,00063
Sweco AB	4,26%	1120	0,00134
Fastighets Ab Balder	29,18%	1110	0,00912
AF AB	1,84%	1060	0,00055
Nobia AB	7,68%	966	0,00209
Kungsleden AB	11,93%	870	0,00292
Clas Ohlson AB	1,85%	842	0,00044
Systemair AB	4,20%	814	0,00096
Avanza Bank Holding AB	225,81%	786	0,04998
Klovern AB	46,41%	748	0,00977
G & L Beijer AB	5,40%	733	0,00111
Cloetta AB	15,76%	729	0,00324
SAS AB	25,76%	721	0,00523
Addtech AB	4,06%	718	0,00082
Rezidor Hotel Group AB	2,93%	716	0,00059
Active Biotech AB	1,64%	672	0,00031
Lindab International AB	12,63%	662	0,00235
Fast Partner AB	21,28%	627	0,00376
Beijer Alma AB	2,05%	621	0,00036
Nordnet AB	35,89%	573	0,00579
Net Entertainment NE AB	0,28%	507	0,00004
Biogaia AB	0,14%	505	0,00002
AB Sagax	39,44%	499	0,00554
IFS AB	1,74%	493	0,00024

Skistar AB	12,89%	493	0,00179
Concentric AB	3,22%	488	0,00044
Dios Fastigheter AB	44,62%	482	0,00606
Bilia AB	11,31%	467	0,00149
Duni AB	6,25%	438	0,00077
Medivir AB	0,61%	436	0,00008
Investment AB Oresund	0,11%	429	0,00001
Heba Fastighets AB	9,51%	416	0,00111
CDON Group AB	5,38%	408	0,00062
B&B Tools AB	12,63%	391	0,00139
Gunnebo AB	10,95%	370	0,00114
AB Fagerhult	11,24%	368	0,00116
Nolato AB	3,79%	367	0,00039
Byggmax Group AB	2,27%	363	0,00023
Fenix Outdoor AB	0,79%	348	0,00008

11.4 Detailed Results

11.4.1 Detailed Logistic Regression Results

This section provides detailed results from the logistic regression performed on the Probability of Default series ($PD_{i,t}$) of Scania AB as an example.

	β	**P-value (t-test)**	**95%-conf int.**
GDP	-0,1661	0,0000	[-0,174 ; -0,158]
constant	-6,3823	0,0000	[-6,414 ; -6,351]

Test Statistics	
P-value (F-test)	0,0000
R-squared	0,4604
Adj R-squared	0,4601
Root MSE	0,6419

Table 11.3: *Logistic regression with GDP as explanatory variable*

	β	**P-value (t-test)**	**95%-conf int.**
CPI	-0,1174	0,0000	[-0,144 ; -0,091]
constant	-6,5586	0,0000	[-6,612 ; -6,506]

Test Statistics	
P-value (F-test)	0,0000
R-squared	0,0347
Adj R-squared	0,0343
Root MSE	0,8585

Table 11.4: *Logistic regression with CPI as explanatory variable*

	β	**P-value (t-test)**	**95%-conf int.**
unemp	0,1966	0,0000	[0,158 ; 0,236]
constant	-8,2004	0,0000	[-8,493 ; -7,908]

Test Statistics	
P-value (F-test)	0,0000
R-squared	0,0441
Adj R-squared	0,0437
Root MSE	0,8544

Table 11.5: *Logistic regression with unemployment as explanatory variable*

	β	P-value (t-test)	95%-conf int.
GDP	-0,1704	0,0000	[-0,179 ; -0,162]
CPI	0,0324	0,0020	[0,011 ; 0,053]
constant	-6,4207	0,0000	[-6,461 ; -6,381]

Test Statistics	
P-value (F-test)	0,0000
R-squared	0,4627
Adj R-squared	0,4622
Root MSE	0,6407

Table 11.6: *Logistic regression with GDP and CPI as explanatory variable*

	β	P-value (t-test)	95%-conf int.
GDP	-0,1634	0,0000	[-0,171 ; -0,156]
unemp	0,1552	0,0000	[0,127 ; 0,184]
constant	-7,5482	0,0000	[-7,765 ; -7,332]

Test Statistics	
P-value (F-test)	0,0000
R-squared	0,4877
Adj R-squared	0,4872
Root MSE	0,6256

Table 11.7: *Logistic regression with GDP and unemployment rate as explanatory variable*

	β	P-value (t-test)	95%-conf int.
CPI	-0,0557	0,0010	[-0,09 ; -0,022]
unemp	0,1439	0,0000	[0,094 ; 0,194]
constant	-7,7243	0,0000	[-8,135 ; -7,313]

Test Statistics	
P-value (F-test)	0,0000
R-squared	0,0488
Adj R-squared	0,0479
Root MSE	0,8525

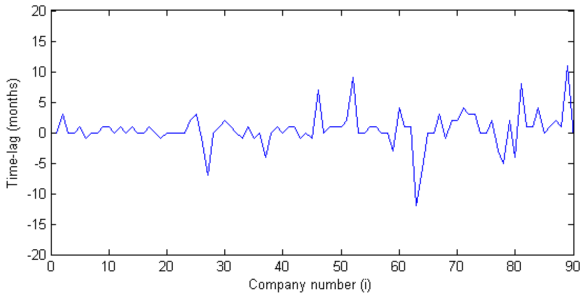
Table 11.8: *Logistic regression with CPI and unemployment rate as explanatory variable*

	β	P-value (t-test)	95%-conf int.
GDP	-0,1850	0,0000	[-0,193 ; -0,177]
CPI	0,1842	0,0000	[0,158 ; 0,21]
unemp	0,3242	0,0000	[0,288 ; 0,36]
constant	-9,0362	0,0000	[-9,33 ; -8,742]

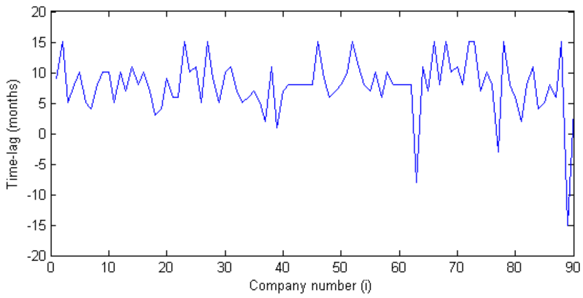
Test Statistics	
P-value (F-test)	0,0000
R-squared	0,5308
Adj R-squared	0,5301
Root MSE	0,5989

Table 11.9: *Logistic regression with GDP, CPI and unemployment rate as explanatory variable*

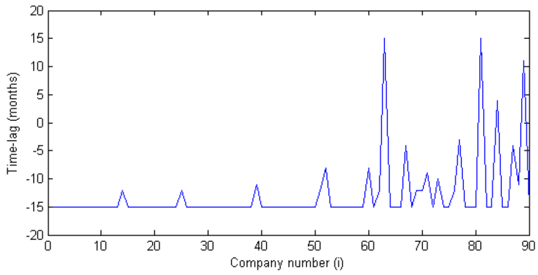
11.4.2 Time-lags for Through-the-Cycle Probability of Default with Logistic Regression Analysis



(a) GDP



(b) CPI



(c) Unemployment rate

Figure 11.2: *Time lags against different macroeconomic variables, x-axis indicate company number x*