Macroeconomic factors in Probability of Default

A study applied to a Swedish credit portfolio

HERMINA ANTONSSON
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by

Hermina Antonsson
Makroekonomiska faktorer i Probability of Default
En studie tillämpad på en svensk kreditportfölj

av

Hermina Antonsson

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KTH Industriell teknik och management
Industriell ekonomi och organisation
SE-100 44 STOCKHOLM
Abstract

Macroeconomic conditions can impact the payment capacity of individual mortgage holders’ household loans. If the clients of a bank’s retail credit portfolio experience deteriorating payment capacity it will reflect on the probability of default of the overall portfolio. With IFRS 9, banks are expected to sophisticate their calculations of expected credit loss, demanding forward-looking estimates of probability of default by incorporation of macroeconomic forecasts. Finding what macroeconomic factors have a statistical significant relationship to the actual default frequency of a portfolio can aid banks in estimating probability of default with reference to current and forecasted macroeconomic conditions.

This study aims to explore the relationship between macroeconomic factors and the default frequency in a Swedish retail credit portfolio. The research is based on quantitative data analysis of historical default data, complemented by implications of the macroeconomic condition on the payment capacity of households from a theoretical perspective.

Macroeconomic factors studied are the Swedish gross domestic product, house price index, repo rate and unemployment rate. The supporting data consists of default data from Nordea’s Swedish retail credit portfolio. The time period covers 2008-2015 and provides basis for analysis of a time period with different conditions in the macroeconomy, including effects of the 2008 financial crisis. A multiple linear regression model is used as a method to suggest the relationship between the macroeconomic factors and the default frequency. The model coefficients are estimated with calculations of Ordinary Least Squares and the significance supported by statistical test.

Results show that gross domestic product and repo rate are statistically significant macroeconomic variables in explaining changes in the default frequency and thus probability of default of a Swedish retail credit portfolio.

Key-words Macroeconomic factors, Probability of Default, IFRS 9, credit risk, mortgage loans
Sammanfattning

Makroekonomiska omständigheter kan påverka hushållens betalningsförmåga och i sin tur återbetalningsförmågan hos bolånetsagare. Om flertalet låntagare inom en banks retailportfölj upplever en försämrad betalningsförmåga kommer det att avspeglas på sannolikheten för fallissemang (probability of default) i den totala portföljen. Med IFRS 9 förväntas banker förftina sina beräkningar av förväntade kreditförluster, vilket kräver framåtblickande beräkningar av probability of default med makroekonomiska prognoser i åtanke. Genom att identifiera vilka makroekonomiska faktorer som har statistisk signifikans för förändringar i historisk fallissemangsfrekvens i en portfölj förvändas banker kunna integrera dessa i, och därmed förbättra, sina beräkningar av probability of default.

Denna studie syftar till att utreda sambandet mellan makroekonomiska faktorer och fallissemangsfrekvensen i en svensk retailportfölj. Den kvantitativa analysen av data över historiska fallissemang och makroekonomiska faktorer kompletteras med teoretiska implikationer av makroekonomiska omständigheter för hushållens betalningsförmåga.


Resultaten visar att BNP och Reporäntan är statistiskt signifikanta makroekonomiska faktorer för påvisandet av förändringar i fallissemangsfrekvensen och följaktligen Probability of Default i en svensk retailkreditportfölj.

Nyckelord Makroekonomiska faktorer, Probability of Default, IFRS 9, kreditrisk, bolån
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ABBREVIATIONS

DEF | Actual default frequency (realized Probability of Default)
ECL | Expected Credit Loss
IFRS 9 | International Financial Reporting Standard
PD | Probability of Default
PIT | Point in time
SRC | Swedish Retail Credit
GDP | Gross domestic product
HPI | House price index
RR | Repo rate
UR | Unemployment rate

GLOSSARY

Covariate | Terms used interchangeably for Independent variable in regression
Explanatory variable

Basel I, II, III | Accords issued by Basel Committee of Banking Supervision as recommendations on banking laws and regulations.

Default | The Basel definition of default, as follows (BCBS, 2004):

“A default is considered to have occurred with regard to a particular obligor when either or both of the two following events have taken place.

- 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 realizing 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 out standings.”
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Hermina Antonsson

Disclaimer: Any assumptions, practices, adjustments, opinions, findings, and conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of Nordea.
1 INTRODUCTION

This chapter includes a background to the thesis and introduces the research problem. It further presents the research questions and the aim of the study. Assumptions and limitations are described, followed by an overview of the research disposition.

1.1 BACKGROUND

One of many lessons learned by banks as a result of the 2008 financial crisis was the importance of credit risk management and measurement. Credit risk arises whenever a bank exposes itself to the risk of obligors not meeting their payment obligations, where the worst-case-scenario is a client ending up in default. As providing loans is one of the key functions of a bank, credit risk is one of the most dominant sources of risk and it needs to be accurately modelled to ensure enough secured capital to cover potential credit losses. Modelling of credit risk is done in attempts to quantify, aggregate, forecast and manage it across different activities and product lines. The quantified credit risk, measured in terms of Expected Credit Loss (ECL), then serves as a determinant in setting provisioning levels and calculating reserves for expected and unexpected credit losses as part of fulfilling regulatory capital requirements. Provisioning levels then determine the risk-based pricing in interest rate mark-ups (BCBS, 2000).

During the 2008 financial crisis, the prevailing international financial reporting standard IAS 39 proved inadequate as it allowed for banks and financial institutions to fail in recognizing and balancing their credit risk and expected credit losses in time. The incurred loss model used in credit risk calculations under IAS 39 resulted in banks detecting many losses on financial instruments, including loans, too late. Also, to even report a defaulted exposure, firms first had to identify a credit loss event and suffer its losses. Provisioning for credit losses was done in a manner considered as “too little, too late” and the features in this reporting standard allowed for greater credit losses than they were intended to. All in all, the standard has been considered to have given an overly optimistic view on financial asset values and on estimated credit risk (Grant Thornton, 2016).

All credit risk models undergo validation through back-testing and stress-testing. The robustness, consistency, accuracy and overall performance under different micro- and macroeconomic circumstances is valued and compared with actual historical outcomes. The credit risk and thus ECL of a portfolio is estimated based on a number of other factors, including Probability of Default (PD). Accounting standards regulate how an asset, for example a loan, is to be accounted for if it induces a credit loss or defaults, why the risk models need to align with the requirements of the accounting standard in place. The model validation is done in line with accounting standards as well, and thus the standard currently in use becomes a vital part in assessing the model performance (Nordea, 2017d).

The new accounting standard, IFRS 9, became effective and replaced IAS 39 in January 2018 (IASB, 2014a). The transition from IAS 39 to IFRS 9 has induced a change in the level of provision for credit losses. Provisioning is done for both expected and unexpected credit losses, and seemingly the part that is modelled is the expected credit loss. Historically, these levels have been set based on actual and incurred losses, while IFRS 9 accounts for a more forward-looking
approach to ECL and thus provisioning levels (BCBS, 2000). In practice, this accounts for historical credit risk assessments solely. Wrongfully or inadequately assessed credit risk will not only impact provision levels and possibly interest rates, but also fabricate the PD for an exposure. As banks do not wish to carry defaulting loans, it is of great importance to accurately assess the credit risk and thus estimate the ECL.

One of the objectives with IFRS 9 is to have a more conservative approach to ECL calculations. Provisioning levels for loans need to reflect on their forward-looking ECL (de Groot and de Vries, 2016). The rather speculative PD factor is modelled based on some variables, and the model is then back-tested using historical and statistical data. By testing how well a model holds for a historical time period with a known macroeconomic scenario and default frequency outcome, the model can be said to be forward-looking if it aligns with estimated default frequencies for that time period. This allows for the model to incorporate macroeconomic forecasted variables and thus estimating PD as far ahead in time as the forecasts have covered.

With this great shift in regulatory environment as main driver, banks pursue the strive to refine their credit risk models integrating as much information as possible that is feasible and significant. All risk factors, and the extent to which they have statistical significance, are re-evaluated. These involve credit scores, macroeconomic factors, customer segment, demographic characteristics among others. All in all, all measures available at relative ease should be assessed in order to add predictive power to credit risk estimates (IASB, 2014a).

1.2 PROBLEM FORMULATION

Macroeconomic conditions are expected to impact the PD for exposures in all loan portfolios but which factors, and to which extent, remains a question at issue. While the PD of corporate clients will likely depend on industry related macroeconomic factors, the factors affecting clients in the retail segment are not necessarily as evident (Rosen and Saunders, 2009).

Under IFRS 9, banks have pursued the process of developing their credit risk models, and essentially all factors involved in calculating ECL are subject to their own models. As part of the guidance offered in IFRS 9, macroeconomic factors should be incorporated in the modelling of PD. Previous research associated with the link between credit risk and macroeconomic factors point to ambiguous results and is mostly focused on corporate credit risk (see section 3.1 for previous studies). With this in mind, there is a need to further evaluate what macroeconomic factors are relevant to incorporate in PD models. An interesting aspect of making PD calculations as forward-looking as possible is to back-test historical default frequencies (DEF) together with a number of macroeconomic factors.

The idea is that we could make use of information indicating how DEF fluctuates as macroeconomic factors fluctuate. If macroeconomic factors can be shown to be significant it would mean that more factors, and more forecasting parameters, can be integrated into PD models and used for back-testing and stress-testing of the them.
1.3 PURPOSE AND RESEARCH QUESTIONS

The purpose of this thesis is to investigate the relationship between macroeconomic factors and the default frequency in a Swedish Retail Credit (SRC) portfolio. We further aim to analyze how and why the information is useful in calculating PD.

To study the realized PD, we can make use of DEF data. As the inclusion of more macroeconomic factors could help add value to the predictive aspect of PD models, the investigation aims to identify which ones are most significant for the SRC portfolio.

The research has been set up to first target a main research question of more quantitative character, MQ, that addresses the nature of the relationship between macroeconomic factors and PD. We further aim to answer the sub-question, SQ, that has been derived as a means to provide more qualitative substance to the findings of MQ.

MQ: What macroeconomic factors are statistically significant for this default frequency?

SQ: How can changes in these macroeconomic factors help explain the default frequency in Nordea’s SRC portfolio?

1.4 DELIMITATIONS AND ASSUMPTIONS

In PD estimation and modelling, it is essential to differentiate segments from each other. As addressed in Basel II, the characteristics, performance and behavior of a retail portfolio will differ from that of a corporate portfolio (BCBS, 2004). Per recommendation from Nordea and considering that retail portfolios are less frequently present in previous research, the study will be limited to the retail portfolio.

The study is conducted in Sweden and is also limited to data from Nordea’s SRC portfolio as well as Swedish macroeconomic data. Market behaviors are expected to differ across countries, and so is the macroeconomy across countries.

An assumption made about the default data is that the Swedish retail portfolio consists of clients who are Swedish residents, and that their payment capacity thus can be modelled with reference to Swedish macroeconomic factors.

1.5 DISPOSITION

The chapters of the thesis are dispositioned as follows:

CHAPTER 2: Theory. This chapter presents material on topics treated in the study. The macroeconomic theoretical background and best practices in relation to the chosen topic is presented. Relevant concepts, theories, and models concerning credit risk and regulatory aspects are defined and evaluated to provide scientific justification for the study.

CHAPTER 3: Literature review. The literature review presents findings from previous research on the topic of credit risk modelling with macroeconomic factors.
CHAPTER 4: Method. Procedures for data collection, preparation and methods for statistical analysis are presented and the choice of methodological approach is justified. Reflections are made on the scientific quality in terms of validity and reliability of the research design.

CHAPTER 5: Econometric background. This chapter lists concepts and best practices for the statistical modelling.

CHAPTER 6: Empirical findings. The chapter lists descriptive statistics of the data used in the study and objective observations from the data analysis are presented through illustrative tables and text.

CHAPTER 7: Analysis. Findings from the previous chapter are connected to the literature material and framed by the theoretical background in order to provide observations made by the author. The results and the choice of methodological approach are discussed in a manner that suggests considerations to be made in future work on the topic. The methodology used, and assumptions made, are further discussed and motivated in a critical manner.

CHAPTER 8: Conclusion. Summarizing the previous chapter by concluding on key takeaways of the data analysis results, anchored by the theoretical background and literature review findings. The research questions are answered, and the chapter ends with recommendations for future research.

1.6 EXPECTED CONTRIBUTION

With IFRS 9 having just been implemented as of January 2018, there are many studies from the past decade on the topic of macroeconomic factors in relation to credit risk or PD of corporate portfolios. However, the focus on the macroeconomic impact on retail portfolio credit risk is found to be limited in previous studies. Especially, research concerning Swedish retail credit portfolios has not been identified by the author in scientific publications. Also, many studies use estimations of PD data or data based on credit losses rather than on actual defaults, meaning that their macroeconomic factor-incorporated models are based on another model in turn. Default frequency, in line with macroeconomic factors, is not modelled and thus provide sufficient historical ex post information.

The study is expected to provide empirical results to both existing research and to Nordea’s credit risk model validation teams. As the study is limited to a retail portfolio analysis, it aims to make use of relationships and theories concerning household economy in relation to the macroeconomy and apply it to a quantitative analysis on the default frequency of retail clients and the macroeconomy. In other words, the macroeconomic theoretical context of the study is framed by PD in a retail credit portfolio as a proxy for payment capacity of households.
2 Theory

This chapter aims to present how changes in a macroeconomic variable theoretically could impact each other, on the payment capacity of household and, in turn, on the default frequency of a SRC portfolio. Concepts, including fundamental credit risk factors, are presented in order to provide an understanding of the importance of PD calculations. Theoretical links between macroeconomic factors and credit risk are to be used as a basis for the model set up for the data analysis.

2.1 Credit Risk

This section defines credit risk, presents how and why it is calculated and how it relates to provisioning of credit losses. Credit risk is defined by the Basel Committee on Banking Supervision as “the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms” (BCBS, 2000). It arises whenever a business exposes itself to the risk of counterparties’ actions negatively affecting the business cash flow and refers both to late payments or part-payments, i.e. failing to pay interest on predetermined dates, as well as defaults, i.e. failing to fulfill the repayment of principal debt (Anderson, 2013; Yurdakul, 2014). While the probability of default of most counterparties is very low, the loss suffered in case of default can be much more significant. This is the fundamental principle to why credit risk needs to be measured, and it is most often quantified and represented in terms of four factors: Probability of Default (PD), Loss Given Default (LGD), Exposure at Default (EAD) and Expected Credit Loss (ECL). The following section introduces these factors and their place in the credit risk modelling framework.

2.1.1 General Modelling Framework

The total credit risk of a certain portfolio, segment or client is quantified by ECL, a product of three factors. The following is a general introduction to the factors that constitute ECL and their characteristics. In Credit risk modelling, each of these factors are subject to their own models and model validation processes, however a further analysis of these models is out of the scope of this research.

Expected credit loss (ECL)

The ECL estimation is complex and inherently judgmental. It is dependent on a wide range of data which may not be immediately available, including forward-looking estimates of key macro- and micro-economic factors and management’s assumptions about the relationship between these forecasts and the amounts and timing of recoveries from borrowers. Accordingly, it is important that ECLs are determined in a well governed environment, including accounting standards (IASB, 2014b). Expected credit loss (ECL) is calculated as following:

\[ ECL = \sum (PD \times LGD \times EAD \times \delta) \]  

(3.1)

Where \( \delta \) is an optional, fourth, discount factor included to consider the original effective interest rate in order to get the most accurate present value of expected credit losses (KPMG, 2017).
Probability of Default (PD)

Default risk is quantified by Probability of Default (PD), i.e. the likelihood that a default event occurs. It is, per definition, constrained to fall between 0 and 1 but is never equal to 0 as even strong counterparties have some, yet little, default risk (Altman and Saunders, 1997). For technicality, the definition of default adopted by Nordea can be found in the Glossary. Nordea uses different PD estimation models for different portfolios, and the purpose of the models are “to serve the accounting regulation IFRS9 as one of the parameters used for calculating the expected credit loss” (Nordea, 2017b).

Loss Given Default (LGD)

Loss risk is expressed by Loss Given Default (LGD) in terms of a fraction of the exposure in case of default.

Exposure at Default (EAD)

Exposure risk is quantified by Exposure at Default (EAD) and is the expected amount of loss the bank may be exposed to when a debtor defaults on a loan.

2.1.2 Risk Grading – Assessment of Payment Capacity

Assigning obligors with a risk grade is a way of assessing and labelling their credit worthiness and payment capacity. Risk grade is equivalent to the term credit scoring, and it can be seen as buckets where obligors with the same credit worthiness are put in the same risk grade bucket. Under the Internal Rating-Based (IRB) approach addressed in Basel II, the second of the accords issued by The Basel Committee of Banking Supervision, it is recommended that banks generate an average PD for each risk grade. Hence all obligors within the same risk grade are treated as having the same, average, PD (BCBS, 2004).

The risk grade is a numeric form for convenience and is assigned to clients after a two-step segmentation process (Nordea, 2017b). First, clients are divided after distinct exposure classes: Sovereign, Institutions, Corporate, Other assets and Retail. The Retail segment is further segmented by Nordic countries: Sweden, Denmark, Norway and Finland. Clients are distinguished by assigning them to a risk grade between 3 and 20, where 3 corresponds to the highest credit worthiness and 20 the lowest. The process of assigning clients to risk grades includes evaluating different characteristics that imply idiosyncratic risk including age, residential status and income status (BCBS, 2004).

The exponential relationship between PD and risk grade can be observed in Figure 1 and is motivated by the principle that the credit portfolio is risk-weighted, i.e. the majority of clients are represented by lower risk grades (better payment capacity). An increase in estimated 1 year-PD follows from an increase in risk grade. It should be noted that the PD-risk grade relationship depicts the specific estimates for the retail exposure class and can vary from other segment, so that the modelled PD for risk grade 3 of a retail client differs from that of a corporate client. Figure 1 illustrates the 1-year modelled PD estimated by Nordea for the SRC portfolio.
2.1.3 PROVISIONING

Additionally, ECL – and thus PD – is a key parameter in the calculation of provisioning levels. In line with the latest capital requirement framework put forth by the Basel Committee of Banking Supervision and known as Basel III, banks need to keep capital reserves to cover expected (and unexpected) credit losses and to pay its depositors in case of default (BCBS, 2011). The reserves known as regulatory capital are needed whenever credit loss events occur, and loan loss provisions work as a means of inflow to that account.

Essentially, banks issue loans to individuals and businesses and are consequently exposed to the risk of clients defaulting. If clients default, the value of their loans on the balance sheet decreases, meaning that some item on the liabilities and shareholder equity side must also decrease to level out the amounts. If there is no reserve to absorb the losses, the bank would need to use deposits or other funding i.e. other clients’ money to do the job. Estimating too high provisioning levels and building excessive reserves, however, would pose an opportunity cost. Hence, provisioning levels need to be sophistically calculated and demand well estimated ECL.

Before the 2008 financial crisis, the prevailing accounting standards allowed for insufficient provisioning for credit losses. Provisioning was calculated using historical, incurred losses. Essentially, credit loss recognition was delayed and is in retrospect regarded as “too little, too late” (Cohen and Edwards, 2017). The Incurred Loss model used in IAS 39 has been replaced by an Expected Credit Loss model in IFRS 9, which means that provisioning models now need to be based on forward-looking expected losses. Credit losses do no longer need to occur before impairment is recognized, which accelerates the ability to recognize impaired credit exposures (KPMG, 2016). Incurred loss-based models require that credit losses have been incurred as of the balance sheet date, while ECL provisioning model rather consider probable future losses, meaning...
that provisioning levels need to be calculated for all exposures where there is any expected credit loss (Cohen and Edwards, 2017). The need to incorporate forward-looking information means that application of the standard now requires considerable conservative judgement on how changes in macroeconomic factors will affect PD and hence ECL. The purpose of the new provisioning model is mainly that credit loss provisions should be made at an earlier stage but also to reduce the volatility in reported credit losses (ibid.). The provisioning levels will be calculated for either 12-month ECL or lifetime ECL, depending on which stage the exposure is considered to belong to in the concept known in IFRS 9 as staging (see section 2.3.3) (IASB, 2014b).

2.1.4 CATEGORIZATION OF RETAIL CREDIT

In accordance with Basel II (BCBS, 2004) an exposure is categorized as retail if its nature fulfills one of the following criteria: exposures to individuals e.g. credit cards and credit card overdrafts, residential mortgage loans, or loans to small businesses whose total exposure amount is less than €1 million. During 2017, the total retail portfolio covering all Nordic and non-Nordic countries, consisted 98% of residential mortgages (Nordea 2017a).

All credit portfolios are subject to both idiosyncratic risk, i.e. client or segment specific risk, and to systematic risk driven by changes in the macroeconomic market condition (IASB, 2014a). While IFRS 9 does not explicitly state what macroeconomic factors to include in the assessment of credit risk, it is expected that identifying some potential drivers of systematic risk will provide the calculations with predictive power (Burton et al., 2006).

2.2 MACROECONOMIC INDICATORS OF CREDIT RISK

Different macroeconomic variables represent different characteristics of the economic cycle. This section provides a description of the studied macroeconomic variables in a more general sense with the purpose to identify their role in the economic cycle and relationship to each other. Further, the theoretical link between macroeconomic factors and probability of retail default through household financial payment capacity is presented.

Finansinspektionen uses, among others, the following three factors to assess the financial stability and payment capacity of Swedish households in general: sensitivity to interest rate fluctuation, unemployment and house price fluctuations (FI, 2018). In addition, GDP is put in relation to the total mortgage debt as an indicator of debt-to-income and debt-to-consumption ratio. All these factors contribute to the payment capacity of mortgage holders (FI, 2015) and Finansinspektionen emphasizes the importance of payment capacity of households as an element of household resilience to changed macroeconomic conditions as well as of banks’ credit risk (FI, 2018).

2.2.1 MACROECONOMIC FACTORS

In line with findings from previous research (see section 3.1), this study covers four specific, Swedish macroeconomic variables. The intention is to provide a theoretical understanding for their interaction and potential impact on the credit risk in the banking industry.

**Gross Domestic Product (GDP)**
GDP is an indicator of the general state of a country’s economy and measures the value of final goods and services produced in a country in a given period of time (Callen, 2017; OECD, 2018). While GDP measures the output of a country, real GDP is the GDP adjusted for inflation, meaning that it tells the monetary value of the output while price changes are taken into account. This is done so that any changes can be traced to real changes in production output amounts and not be mistaken for changes derived from a constant production output amount only with increased or decreased price levels. GDP can also be expressed as the total of personal consumption, business investment, government spending and net exports because these components are equivalent to the amount spent in the national economy (OECD, 2018). In the event of a more severe economic downturn, the development of GDP can proceed as follows. When consumption decreases it indicates a reduced demand of final goods and services (Riksbank, 2017). Businesses will respond by reducing production volumes, leading to a decreased need for work (“human assets”) and downsizing as a result. Both companies and private individuals may experience difficulties meeting loan obligations such as amortization costs of mortgage loans. On a large scale, banks may see increased credit losses as a result (Hultkrantz, 2011).

**House price index**

The House price index, or Real estate price index, expresses the price level of one- and two-dwelling houses for households (SCB, 2017). Increasing house prices tend to increase the financial stability of households and reduce the risk of mortgage loan holders not being able to meet their loan obligations. In other words, the House price index can be interpreted to reflect on the financial wealth of mortgage holders. Westgaard and van der Wijst (2001) discuss the idea that a client’s credit risk is generally determined by two factors; repayment capacity and repayment willingness. If the client is a mortgage-loan holder and the value of his collateral, i.e. residential property, increases, the client has better chances of avoiding defaulting on loan obligations as he is then presented with the option of selling the property and make loan payments without making a loss.

The House price index may however act as an ambiguous variable in relation to household debt. If house prices increase, mortgage-loan holders who own residential properties may benefit from the upswing and have better chances of being able to fulfill their loan obligations towards their bank. First-time buyers, however, do not necessarily benefit from such an upswing, and may rather be exposed to the risk of not being able to meet obligations if house prices decrease again (FI, 2017).

**Repo rate**

The Repo rate is the interest rate at which the Riksbank lends money to commercial banks and is used as a means of inflation control (Riksbank, 2018a). The Riksbank makes assessments of the national and international inflation and economic situation and adjusts the Repo rate accordingly to control the inflation rate. If the Riksbank considers inflation rate as too low, it is likely to decide on the need for an expansionary monetary policy where the Repo rate will be decreased or remain unchanged if already at a low level (Riksbank, 2018b). The Repo rate can be interpreted as the cost of debt, and as the lending interest rates of commercial banks follow the Repo rate, a decreased rate tends to stimulate consumption and willingness to invest in financial instruments and residential property. Increased demand, in turn, tends to raise prices, debt levels (loan-to
value ratio), production levels and generally put pressure on the national inflation rate. If, on the other hand, the economy is experiencing a financial boom or anticipates an increased inflation rate, the Riksbank will identify a need for stabilization and slowed down economic activity and increase the Repo rate. The effect is subdued consumption, dropped stock prices and reduced willingness to invest as a consequence of risk aversion (Campbell and Viceira, 2002; Carlgren, 2018; Guiso and Paiell, 2008). Because a decreased Repo rate is also intended to stimulate an increase in production and employment, it may be positively related to banks’ credit risk.

As the Repo rate is adjusted as a means to account for forecasted changes in the macroeconomy, adjustments do not tend to impact the economy instantaneously but takes up to 12-24 months to take full effect (Riksbank, 2018a).

Unemployment rate

Statistiska centralbyrån presents official numbers on the Unemployment rate for the Swedish population aged 15-74 years on a monthly basis. SCB emphasizes that the Unemployment rate still has not recovered from the increase that was seen after the 2008 financial crisis (SCB, 2018).

William Phillips (1958) developed the Phillips curve to conceptualize the relationship between inflation and unemployment, shown in Figure 2.

![Phillips Curve](image)

The Phillips curve is commonly used to explain the correlation of the two factors and is useful in forecasts. Phillips conclusion, accepted as a universal theory due to its tenability over decades, is that the rate of change of money (i.e. the inflation rate) can be explained by the inversed rate of change of unemployment, “(...) except in or immediately after those years in which there is a sufficiently rapid rise in import prices to offset the tendency for increasing productivity to reduce the cost of living” (Phillips, 1958).

During a financial boom, for example, the demand for labor increases and wages increase due to the bargain power of workers. With increasing wages comes increased cost of production, followed by increased prices of goods and services. Eventually, the Riksbank will identify the need to stabilize the economy back to an unemployment-inflation equilibrium level, and an increased Repo rate will force the economy to return to stable levels. In a similar manner as GDP,
the Unemployment rate can be thought of as reflection on the general state of the economy, as well as on the debt-to-income ratio households. Hultkrantz and Tson (2011) point out that increased unemployment directly reflects on a deterioration of the payment capacity of household borrowers and especially mortgage holders.

2.2.2 **INDICATORS OF HOUSEHOLD PAYMENT CAPACITY**

The complex and codependent interplay of monetary policies, macroeconomic conditions and stability in the financial sector can be exemplified with a summary of the progress of the financial deregulation implemented in Sweden in 1985. This refers to the Swedish central bank, Sveriges Riksbank, decision to deregulate the credit market. The deregulation comprised of several resolutions, among which the most central ones are the abolishment of banks’ penalty lending rates and the lending ceiling controlled by the Riksbank (Svensson, 1996; Berg, 1994). The penalty lending rates meant a fixed rate that constrained the households’ ability to take on loans, and the prevailing lending ceiling allowed banks and financial institutions to have a maximum increase of 2% of their outstanding credits on a yearly basis which largely limited their lending. With the deregulation came a stair-step rate rise that increased progressively with the debt-to-asset ratio, and the lifting of the lending ceiling allowed banks to offer lending in a more optimistic manner. The changes in the monetary policy landscape triggered a vigorous a lending expansion to both businesses and households (Finocchiaro et al., 2011).

Lower interest rates meant lower cost of debt, and a rapid increase in house prices was a fact. The house price increase was enhanced by beneficial macroeconomic conditions that turned mortgage holders optimistic both in terms of future expected income and in terms of current financial wealth. In the mid 1980’s, before the deregulation, Swedish household’s debt-to-income ratio was stable at around 100 percent, and at the peak of the house market boom it rose to 140 percent while households reduced their savings (Finocchiaro et al., 2011).

In the early 1990’s the monetary policy was tightened as a response to an overly expansive macroeconomy, and interest rates increased while inflation decreased. With higher cost of debt, house prices deteriorated and so did mortgage holders’ payment capacity. Households tend to reduce consumption rather that go into default on their mortgages, which instead lead to severely increased corporate loan losses for banks as production decreased. This culminated in the banking crisis that lasted 1990-1993. After finally reduced borrowing levels, the economy stabilized and once again the debt-to-income ratio increased (Englund, 2011). In 2017, the debt-to-income ratio was up again at 411 (FI, 2018). If high debt-to-income ratios in fact make households more sensitive to macroeconomic shocks, it would be of interest to identify the interplay of the stability in terms of default frequency on a more general basis, together with interest rates, unemployment and house prices, as these factors reflect on changes in each other.
2.3 **REGULATORY BACKGROUND**

A general remark on the regulatory change from IAS 39 to IFRS 9 is that the new accounting standard does not define the term *default* but instead requires each individual entity to do so. The guidance in IFRS 9.B5.5.37, as cited by GPPC (2016, pp. 26-28), does not go much further than to say that whatever definition used, and any qualitative indicators related to the definition used, should be consistent with the definition used within all of the bank’s internal credit risk management. A presumption can hence be made that the definitions differ across banks, and that the differences in the way “default” is defined is counterbalanced by the credit losses that arise in each entity as a result of that very definition (as cited by Ernst & Young, 2015). Regardless, the main objective of the new ECL model is to ensure financial statements of banks contain more useful information about the ECL of financial assets. The amount of ECL is to be updated and recognized at each reporting date to reflect changes in credit risk during the time represented. Timelier ECL information is required as a result of this, which puts pressure on the PD vector to be more forward-looking (IASB, 2014a).

2.3.1 **POINT IN TIME**

There are mainly two different approaches to describe the behavior and evolution of the PD over time: point-in-time (PIT) and through the cycle (TTC). In general, a PIT PD is described as a rating system that follows the business cycle and changes over time, while the TTC PD approach is normally not affected by macro-economic conditions and remains constant. If the historical PD perfectly follows the DEF for the same time period, the PD is PIT. A TTC PD is a mean of the historical default frequency for the time period (Gobeljic, 2012). Calculating PD with a PIT approach is a requirement under IFRS 9.

Macroeconomic factors would be expected to affect the default rates and provisioning levels of banks, as both cyclic and non-cyclic trends affect a borrower’s financial condition and capacity to pay (BCBS, 2006). Nordea’s newest PD model includes one macroeconomic factor and fulfills the requirement to be PIT thanks to its term structure of estimates for each point in time (Nordea, 2017b). Nordea found one (confidential) macroeconomic factor to be significant as indicator of PD for the new model.

The point in time-ness in Nordea’s PD calculation are considered to be on a yearly prediction level, meaning that a customer’s risk grade and thus PI can change on a yearly basis. A perfect PIT PD would mean that, looking at historical values, DEF exactly corresponds to the calculated PD on a portfolio level, while a TTC PD relies on average economic business cycle conditions.

2.3.2 **EXPECTED CREDIT LOSS (ECL) MODEL**

The ECL estimates need to be accurate, requiring the PD factor to be PIT and forward-looking. It is difficult to predict and model client specific scenarios that affect their PD and credit risk imposed on the lender. Mapping historical changes in macroeconomic and financial market conditions to historical PD and DEF as a means of back-testing is however possible. IFRS9 states that credit risk calculations, probability of default included, should use supporting information that is “available without undue cost or effort” and includes “historical, current and forecast
information” (GPPC, 2016). The regulation does not explicitly state requirements on number of factors, or which factors, to include.

Credit risk models should capture both systematic and idiosyncratic risk sources in order to calculate conservative credit risk estimates. Idiosyncratic risk, i.e. client or segment specific risk is accounted for using the risk grade segmentation of clients. It can be diversified away, which is also the case with the segmentation. The systematic risk, however, is driven by the macroeconomy and should be accounted for using macroeconomic factors in a forward-looking approach (IASB, 2014a).

2.3.3 Staging

The new ECL model is to be used as input for the concept known in IFRS 9 as staging. This three-stage model refers to if the ECL of an exposure should be calculated for a one-year horizon or a lifetime horizon. The decision is based on both initial credit quality and on any increases in credit risk during the maturity of the financial asset (IASB, 2014a). Staging is an accounting related method to classify loans on the basis of their potential credit risk, and they are provisioned for with regards to their staging as follows:

- In stage 1: An expected credit loss during a 12-month period.
- In stage 2: An expected credit loss some time over the remaining life of the asset.
- In stage 3: Incurred loss.

A loan is moved from stage 1 to stage 2 if it underperforms its expected loss and exhibits a significant increase in credit risk. Defining what exactly is a significant increase is out of scope but one clear example could be a downgrading of the borrowers risk grade. Table 1 illustrates the staging model in IFRS 9. For a loan to be classified as a stage 3 loan, it needs to have defaulted, and once it enters stage 3 it cannot be reversed back to stage 1 or 2.

Table 1. IFRS 9 staging model.

<table>
<thead>
<tr>
<th>Stage</th>
<th>Stage 1 (Performing)</th>
<th>Stage 2 (Under-performing)</th>
<th>Stage 3 (Non-performing)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit risk</td>
<td>Low credit risk or no significant increase in credit risk since initial recognition</td>
<td>Significant increase in credit risk since initial recognition</td>
<td>Default</td>
</tr>
<tr>
<td>Performance</td>
<td>&lt; 30 days past due and not deteriorated</td>
<td>30 days past due backstop</td>
<td>90 days past due backstop</td>
</tr>
<tr>
<td>ECL calculation</td>
<td>12-month ECL</td>
<td>Lifetime ECL</td>
<td>Lifetime ECL</td>
</tr>
</tbody>
</table>
CHAPTER 3

LITERATURE REVIEW

This chapter presents relevant literature aided to deepen the knowledge on the topics treated in the thesis. Previous studies within the field of credit risk related to the macroeconomy are summarized, followed by a review of key aspects regarding the regulatory background of the research topic.

3.1 PREVIOUS STUDIES

This section presents extracts from prior research regarding the relationship between default cycles and macroeconomic factors. Most previous studies on the macroeconomic determinants of default rates concern corporate sectors on corporate specific or industry specific levels. The sets of explanatory variables studied typically involve GDP and different interest rates. The need to optimize credit risk models has been explored before IFRS 9 was on the map, but pre-IFRS 9 studies most often examine idiosyncratic risk factors rather than systematic ones. While the loss amount in case of default in retail portfolios will tend to be smaller than in corporate portfolios due to the exposure size, there is still a need to identify risk determinants, in order to meet regulatory capital requirements and make accurate provision level calculations.

Despite the existence of an extensive literature base within the research area concerning macroeconomic factors relationship to PD, different methods, models and sets of explanatory variables are used. The results across studies are ambiguous, pointing to different relationships and levels of significance. The disparity might be explained by the variation in data quality and number of parameters or sample size. Another explanation might be the variety of countries in the research, ranging from large economies; the UK (Bellotti and Crook, 2009) and the US (Rösch and Scheule, 2004) to smaller such as the Czech Republic (Vaněk, 2016). The different methods of analysis is another explanation.

Survival analysis, also called time-to-event analysis, is frequently used in research related to the modelling of time to default with macroeconomic variables used as time-caring covariates (Hua et al., 2015). Bellotti and Crook (2009) applied survival analysis to model PD and time to default of credit card account data in the UK. Macroeconomic variables were incorporated in the analysis and it was found that the inclusion of national production index and interest rate (certain selected retail banks’ base rates) as indicators improved PD model fit. They show that the inclusion of bank interest rates and an earnings index had the expected effects: increased interest rates tend to raise the PD while increased earnings tend to lower the PD. Increased interest rates and increased aggregate unemployment rates were also found to increase the LGD (Bellotti and Crook, 2012). In 2014 Bellotti and Crook modeled credit risk for retail credits using survival analysis. They developed a model that includes macroeconomic conditions to be able to stress test credit losses during economic downturn, i.e. estimate an extreme quantile of a loss distribution.

Many studies related to the topic on macroeconomic factors as determinants of credit risk are limited to country-specific data and cover different portfolio sizes. Summaries of the methodologies and findings of a number of these studies are presented below.

In 2004, Rösch and Scheule aimed to forecast retail portfolio credit risk by calibrating PD calculations with macroeconomic variables, using a CreditMetrics™ model (for more details see
which is based on the probability of moving from one credit rating class to another. They used charge-off rates (the percentage of customers who have entered default in credit card accounts, residential real estate and other consumer loans) for all commercial U.S. banks as an estimation for real default rates to compare their calculations with. As a first step in the modelling of historical probability of default levels, they estimated it as an average long-term default rate, i.e. as constant, over the years 1991-2001. They then calibrated the calculations by adding a number of macroeconomic variables with a one-year time lag: change of consumer prices, deposit interest rate, GDP and industrial production. The conclusion was that they were statistically significant at a level of 6%, so the inclusions of these variables decreased the difference between real historical default rates and the estimated probability of default for the time period 1991-2001. Rösch and Scheule (2004) concluded that the macroeconomic risk factors allow for a better forecast of PD.

Bonfim (2009) used a dataset of 30,000 Portuguese firms with information on liabilities another detailed accounting information for the time period 1996-2002. With a Cox proportional hazard model, Bonfim aimed to describe the impact of firm-specific information versus macroeconomic variables on default and credit risk. His research addressed a commonly posed question for corporate firms: whether credit risk is driven mostly by idiosyncratic risk, i.e. firm-specific factors, or systematic risk, i.e. macroeconomic factors. The purpose was to determine how the PD depends on the macroeconomy and more specifically in which stage of the macroeconomic cycle that PD increases. Bonfim showed that, while firm-specific information has explanatory power on PD for the firms evaluated in the study, the inclusion of macroeconomic factors substantially and independently improved the results of back-testing Probability of Default in relation to actual historical default rates. It was further found that periods of economic expansion, as a rule, are followed by increased default frequency and thus PD. The theory behind Bonfim’s (2009) conclusion is that the risks behind default probability are built up during periods of economic growth, when the credit growth is higher due to consumption overconfidence. More sources for increased credit risk are given space and the built-up risk materialize firstly in economic downturn, thus increasing the default frequency during this period. The macroeconomic factor found most significant was GDP growth rate, with a negative impact on Probability of Default. Other Portuguese macroeconomic factors investigated, but found not to be statistically significant, include exports, private consumption, employment, an exchange rate index, 10-year bond yields and stock market prices variation.

Chaibi and Fititi (2015) investigated the banking sector on a larger scale. They examined which macroeconomic credit risk determinants have overlapping significance for non-performing loans of commercial banks across two different euro currency countries: Germany and France. They discuss the role of non-performing loans in the 2008 financial crisis and the importance of academics examining credit risk drivers by emphasizing the theory that a banking crisis primarily is caused by banks’ incapacity to fulfill their payment obligations, and essentially triggered by impaired loans on their balance sheets. They looked at impaired loans data from 147 French banks and 133 German banks, covering the period 2005-2011 and used a Gauissan mixture model. They concluded that GDP growth as a macroeconomic variable is highly significant and negatively correlated with the number of non-performing loans, while unemployment rate and exchange rate have a significant positive correlation to non-performing loans. This would indicate that on a
general credit risk portfolio level in banks, these macroeconomic variables would be of interest when modelling credit risk and its determinants.

The household debt of a retail portfolio client is part of the assessment of its credit risk grade. As risk grade is linked to the modelled PD, the size and performance of the household debt is linked to probability of default imposed on the bank having an outstanding loan to such a retail client. Schularick and Taylor (2012) argue that credit booms are a valuable predictor for financial crises, i.e. that a downturn is to be expected when there has been a rapid expansion of lending by banks or other financial institutions, to both retail and other customer segments. Intuitively, it is interesting to investigate the relationship between household debt and macroeconomic conditions. Nomatye and Phiri (2018) investigate macroeconomic determinants of South African household debt over the years 2002-2016 through the use of quantile regression analysis and find that inflation and consumption are variables of statistical insignificance. They find that GDP and house prices are of moderate to high significance in predicting household debt levels, whereas interest rates and domestic investments are the only macroeconomic variables highly correlated to the debt levels.

Bofondi and Ropele (2011) examined macroeconomic determinants for Italian banks’ bad household loans, a ratio defined as the flow of bad loans to the stock of performing loans in the previous quarter. Using single-equation time series regression they found that the loan quality of the stock of loans was related to the GDP, unemployment rate, 3-month Euribor rate and the loan to disposable income-ratio.

Ali and Daly (2010) examined the impact of adverse macroeconomic shocks on default rates in the U.S. – the country considered by the authors to be most affected by the 2008 financial crisis, and Australia – a country considered practically immune to it. Using logistic regression, they found that GDP for the two respective countries was a significant factor in explaining default risk in both.

Virolainen (2004) tied corporate credit losses to macroeconomic factors using industry-specific corporate sector bankruptcy data over 18 years of time (1986-2003) including an early 1990s recession. Virolainen used Monte Carlo simulation to analyze corporate credit risk conditional on current macroeconomic conditions with the purpose of being able to stress test expected credit losses in different points of time in the economic cycle. The study’s result suggests that there is a significant relationship between Finnish corporate sector default rates and the country’s GDP as well as 12-month interest rates\(^1\).

With the lifetime ECL calculation concept in IFRS 9 in mind, Vaněk (2016) proposed a regression model that allows for economic adjustment of default probabilities, meaning that probability of default estimates can be modified by adding macroeconomic adjustment factors. The data used is on a yearly basis during the time period 2002-2015 and is described as “the share of non-performing loans (NPL) – the share of residents’ and non-residents’ non-performing loans to gross loans”, limited to the Czech Republic. No further segmentation was done. Vaněk included GDP, unemployment rate, 3-month interest rate and an inflation index in his model and concluded that GDP was the only one found significant.

\(^1\) Helsinki interbank offered rate (Helibor) up till end-1998, and Euribor from 1999 onwards.
Leow et al., (2014) examined UK retail lending data to relate macroeconomic factors with predictions of LGD for two sub-portfolios: residential mortgage loans and unsecured personal loans. Their results from logistic regression analysis differed between the two sub-portfolios as the mortgage loan LGD estimates proved to be improved by incorporation of mortgage interest rate, while the unsecured personal loan LGD estimates was only improved by involving an index of national net lending growth, meaning that LGD increases with increased lending levels.
4 Method

In this chapter of the thesis the methodology and research design are described. The research process is outlined, followed by a presentation of input data, adjustment steps and methods of data analysis applied in SAS and Python. Finally, the scientific quality of the study and the research design is discussed.

4.1 Research Design

This section describes how the problem was approached and analyzed in order to best answer the research questions. The methodological approach of the research determines the association between theoretical framework and research work. Lewis et al. (2009) state that the research process is generally conducted in one of two manners: either through a deductive or an inductive approach. Figure 3 illustrates a schematic overview of the two research approaches, based on the methodology of Bell and Bryman (2011). It displays the concept that the deduction-based approach requires a hypothesis to be formed based on theory. Data and literary information is used to confirm or reject the hypothesis in order to resolve an issue. In the induction-based approach, however, the research rather starts with data and information collection that is observed and tested to construct a theory.

As previously presented, this thesis aims to study how and what macroeconomic factors impact the default frequency of an SRC portfolio. Based on theoretical background and results of previous research and regulatory implications, research questions were formed with the intent of identifying and filling a knowledge gap. Based on the research questions, a deductive approach was followed where a model fitting the research questions was constructed, data was collected and analyzed, and the objective results were presented. Main findings were put in relation to the theoretical background and critically discussed and evaluated against the background of the study’s assumptions and delimitations.
The two research questions outlined in Chapter 1 require different methodological approaches. Hence, the following paragraphs present how the study was framed to answer the different research questions.

4.1.1 ANSWERING RESEARCH QUESTIONS

The research conducted was set out to first answer SQ, and then MQ. To answer MQ and investigate whether Nordea’s SRC portfolio default frequency can be explained through macroeconomic factors, the quantitative analysis was carried out using regression analysis between aggregated default frequencies and four chosen macroeconomic variables. Collis and Hussey (2013) emphasize that quantitative research cater for generally applicable and reproducible results, which is desirable in this study. The statistical model used for estimation of the unknown regression model parameters was Ordinary Least Squares.

Answering SQ required a more qualitative approach to the study of macroeconomic factors in relation to credit risk and PD. Theories on macroeconomic behavior were studied to understand the dynamic relationship, and regulatory aspects were taken into consideration when assessing whether macroeconomy can help explain default frequencies and thus PD.

More specifically, answering SQ required identifying what macroeconomic factors to study, which was first done based on a review of the results of previous studies on the topic. Macroeconomic theories and relationships were reflected on in order to hypothesize their interaction and theoretical influence on the credit risk of retail portfolios.

4.2 RESEARCH PROCESS

A summary of the research process is described below. It is presented in chronological order, however most of the phases are overlapping as re-evaluation of new input throughout the research contributed to narrowing down on subjects and rewriting of some of the literature review.

- **Pre-study** – The pre-study phase was initiated by literature review in parallel with informal meetings and interviews. Short semi-structured meetings were held with Nordea Credit risk model validation team to gain knowledge of the thesis topic. They simply served to lead the thesis in a direction that adds the most value contribution to Nordea and are hence not included as references themselves. In other words, these were conducted in order to get an understanding of the subject and of obstacles recognized in the work done on it so far, rather than to be used as empirical data. This phase also included formulating the introducing section of the thesis.

- **Literature review** – The literature review continued as the subject and problem formulation were narrowed down. Relevant studies and theoretical concepts were analyzed to be applied to the topic in question.

- **Data collection** – The data consists of historical exposure performance i.e. defaulted and non-defaulted exposures as well as macroeconomic variables. The data was collected by and received from Nordea, where the default data stems from their internal client database and the macroeconomic variables are collected from three large database sources: Statistiska Centralbyrån, Valueguard and Sveriges Riksbank.
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METHOD

- **Quantitative data analysis** – This phase included data preparation where we identified descriptive statistical information and segmented the data as needed. The regression models were tested and adjusted.

- **Analysis** – In this phase the mathematical analysis was done, i.e. the diagnostic testing of the regression analysis. Simultaneously, the theoretical background and literature review findings were put into comparison with our own empirical findings.

- **Conclusion** – This phase included summarizing the results together with descriptive analysis and answering of the research questions put forth.

4.2.1 LITERATURE REVIEW

Much of the literature and sources collected for the research was searched for in the pre-study and then used or reused throughout the process. It was used in parallel with the data preparation and analysis in order to gain an increased understanding both of the state of the regulatory development, and of other relevant research studies within the topic. The literature and theory review aim to summarize gaps of knowledge or lacking results identified in previous research and to lay the foundation for the choice of statistical model used in the analysis (Collis and Hussey, 2009).

Also, confidential information has been provided by Nordea concerning internal documentation on local processes, data preparation standards and internal credit risk models.

The literature was collected through databases including KTH Primo, Google Scholar, university libraries, Science Direct, Google Books and the DiVA portal (a search engine and open archive for research publications and student theses). Key words used in the search for previous studies for the literature review and theoretical background include, but are not limited to, the following words and combinations of words:

*Risk management, Credit risk, Financial crisis, Macroeconomic factors, Default, Actual default frequency, Expected Credit Loss, IFRS 9, Accounting standards, Provisioning levels, Probability of Default, Credit rating, Capital requirements, Impairment, Time series analysis, Household debt, Household payment capacity, Staging, Loan portfolio, Credit risk drivers, Credit risk determinants, Economic cycle, etcetera.*
4.3 DATA

In order for the research to be replicable and repeatable, this section presents the sampling method and describes the procedures used to collect data, followed by techniques applied to the selection, processing and analysis of the data collected.

4.3.1 DATA COLLECTION

The data included in this study consists of 1) historical default data and 2) historical macroeconomic factor data, as outlined in the following paragraphs.

4.3.1.1 DEFAULT DATA

The default data is characteristic for this study as it is limited to Nordea’s SRC portfolio. The data is comprised of a SAS dataset, provided by Nordea, with just over 83 million observations of individual exposures and their default status (default or non-default) on a monthly basis over the years 2008-2016. The data time period is limited but was considered to be of interest as it contains a period of both lower and higher economic activity and is considered to contain enough observations to provide for a good sample analysis.

While the microdata set does not present exposure type, it was observed that during 2017 Nordea’s total retail credit portfolio covering all Nordic and non-Nordic countries, consisted 98% of residential mortgages (Nordea 2017a, p. 166). A summarized description of the data is presented in Table 2, including the covered time period, data frequency, number of observations, number of unique data periods and available parameters.

Table 2. Summary of raw default data

<table>
<thead>
<tr>
<th>Description</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time period</td>
<td>Jan 2008 – Dec 2016</td>
</tr>
<tr>
<td>Frequency</td>
<td>Monthly</td>
</tr>
<tr>
<td>Number of observations (microdata)</td>
<td>83,037,283</td>
</tr>
<tr>
<td>Number of data periods</td>
<td>108</td>
</tr>
<tr>
<td>Parameters</td>
<td>Client ID - Risk grade - Exposure size - Default status</td>
</tr>
</tbody>
</table>

Source: Author’s observations

Table 3 presents characteristics of the aggregated data. For reference on the parameter Risk class, see section 4.3.2.1.

Table 3. Summary of aggregated default data

<table>
<thead>
<tr>
<th>Description</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time period</td>
<td>Jan 2008 – Dec 2015</td>
</tr>
<tr>
<td>Frequency</td>
<td>Monthly</td>
</tr>
<tr>
<td>Number of observations (per risk class)</td>
<td>96</td>
</tr>
<tr>
<td>Number of data periods</td>
<td>96</td>
</tr>
<tr>
<td>Parameters</td>
<td>Risk class - Default status</td>
</tr>
</tbody>
</table>

Source: Author’s observations
Figure 4 displays the historical default frequency for the whole Nordea SRC portfolio on a monthly basis over the time period 2008-2015. In the beginning of the period, the aggregated default frequency was relatively high. This may be explained by the prevailing financial crisis that negatively impacted the financial wealth and payment capacity of many households. After January 2009, the default frequency declined until June 2010, when it increased again, leading up to a maximum in May 2011. The default frequency then steadily declined until the end of the time period.

![Figure 4](image)

**Figure 4. Historical development of Nordea SRC portfolio default frequency, 2008-2015**

Note: For confidentiality, the magnitude of the default frequencies is censored. The vertical axis is linear.

### 4.3.1.2 MACROECONOMIC DATA

Time series on Swedish macroeconomic variables are public data and can be retrieved from databases of different public sources. Table 4 lists an overview of the raw data on the four macroeconomic factors used further in the analysis, including a short description, unit in which the data is reported, source from where the data is retrieved and reporting frequency of the data.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Unit</th>
<th>Source</th>
<th>Data frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>(GDP) Gross Domestic Product</td>
<td>Measure of the national economic performance.</td>
<td>bn.SEK</td>
<td>SCB</td>
<td>Quarterly</td>
</tr>
<tr>
<td>(HPI) House Price Index</td>
<td>Measure of real estate prices where year 1981 is = 100.</td>
<td>Index</td>
<td>Valueguard</td>
<td>Monthly</td>
</tr>
<tr>
<td>(RR) Repo rate</td>
<td>The interest rate set by the Swedish central bank.</td>
<td>%</td>
<td>Sveriges Riksbank</td>
<td>Monthly</td>
</tr>
<tr>
<td>(UR) Unemployment rate</td>
<td>Measured as $Unemployment/Labor supply \cdot 100$</td>
<td>%</td>
<td>SCB</td>
<td>Monthly</td>
</tr>
</tbody>
</table>

Table 4. Overview of the set of macroeconomic variables
CHAPTER 4

METHOD

Time series data consisting of the four macroeconomic factors is retrieved from three large databases: Statistiska Centralbyrån (SCB), Valueguard and Sveriges Riksbank. The data retrieved covers \textit{ex post} observations of Swedish macroeconomic factors during the years 2006-2015, on a monthly basis (GDP on a quarterly basis, linearly interpolated to obtain corresponding monthly data). Older data is available but not of relevance for this study with respect to the limited default data period. Figure 7 through Figure 10 in Appendix I illustrate the historical development of the macroeconomic factors over the time period 2008-2015.

4.3.2 QUANTITATIVE DATA ANALYSIS

Figure 5 illustrates an overview of the procedures carried out in the quantitative data analysis of this study. Each procedure is further described in the continuation of this section (for data collection procedure, see previous section, 4.3.1).

![Data analysis methodology used in the study.](image)

4.3.2.1 DEFAULT DATA PREPARATION

Evaluation and screening of the data proceeded by removal of some observations that were considered to lack of quality or in any other way as described below deemed to fulfil the requirements of removal.
For the default dataset the following conditions were assumed:

- A cured client, i.e. a client that defaults, pays of its debts and then returns to the bank, is treated as a new client.
- Risk grade is updated once every month by Nordea. The risk grade of a client can change.
- Data is summarized by Nordea end-of-month, meaning that an observation of a default in Jan. 2008 may have been observed at any point during that month.

In preparing the default dataset for analysis, using statistical software SAS:

- Observations after December 2015 were removed due to poor data quality and lacking consistency in the number of observations over time.
- Observations not assigned with risk grades (3 to 20) were removed as they were not able to model based on risk grade.
- Observations with exposure size < 1,000 EUR were removed because they were assumed to consist of minor credit cards overdrafts, which in turn were not assumed to reflect on household payment capacity in the same sense as larger exposures.

From the prepared default panel data, the default frequency (DEF) was evaluated so that:

\[
DEF_{c,d} = \frac{\text{# of default observations in risk class } c \text{ during data period } d}{\text{Total # of observations in risk class } c \text{ during data period } d}
\]  

The aggregated DEF in this research was investigated in a manner where the SRC portfolio is segmented into three classes based on risk grades (see section 2.1.2), and one for the whole portfolio. Each DEF class and its representative risk grades are illustrated in Figure 6. This enables us to assess the relationship between macroeconomic factors and DEF on a low risk, medium risk, high risk and total aggregated risk level. All four classes are represented by 96 data points each, given the time period and monthly data frequency.

![Figure 6. Aggregated risk classes, author’s computation](image)

Finally, the aggregated default data was checked for stationarity using the Augmented Dickey-Fuller (ADF) test and for normality using the Anderson-Darling test. The data was transformed for stationarity.
4.3.2.2 MACROECONOMIC DATA PREPARATION
In the macroeconomic dataset, no observations were removed, but only the time period needed to match the aggregated default data in the regression analysis was used. The time series data was checked for stationarity using ADF test and for normality using Anderson-Darling test. The data was then transformed for stationarity.

4.3.2.3 DESCRIPTIVE STATISTICS
Table 5 illustrates some descriptive statistics of the DEF data before transformation. For confidentiality, non-stationary values are presented with reference to the top left value, denoted x. Table 8 in Chapter 6 illustrates the corresponding descriptive statistics of the dependent variables used in the regression models after transformation for stationarity. The non-stationary variables are not used in the analysis but are presented for convenience and clarity of what happens when the data is transformed in accordance with (5.3). As expected, considering that the risk grades and thus risk classes reflect the credit risk, the data tells us there is a large difference in default frequency across the three risk classes. The total default frequency, however, is much closer in magnitude to the low and medium risk class. This is explained by the fact that the SRC portfolio is largely represented by clients in the low risk class. A high share of low risk clients with low default frequency is groped with a smaller share of high risk clients with high default frequency.

Table 5. Descriptive statistics of non-transformed default frequency data

<table>
<thead>
<tr>
<th>Non-stationary variables</th>
<th>Unit</th>
<th>Mean</th>
<th>Min.</th>
<th>Max.</th>
<th>Std. dev.</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEF&lt;sub&gt;low&lt;/sub&gt;</td>
<td>%</td>
<td>x</td>
<td>x - 0.50</td>
<td>x + 0.80</td>
<td>x - 0.11</td>
<td>96</td>
</tr>
<tr>
<td>DEF&lt;sub&gt;med&lt;/sub&gt;</td>
<td>%</td>
<td>x + 1.57</td>
<td>x + 1.13</td>
<td>x + 2.13</td>
<td>x + 0.18</td>
<td>96</td>
</tr>
<tr>
<td>DEF&lt;sub&gt;high&lt;/sub&gt;</td>
<td>%</td>
<td>x + 8.13</td>
<td>x + 6.02</td>
<td>x + 10.53</td>
<td>x + 1.10</td>
<td>96</td>
</tr>
<tr>
<td>DEF&lt;sub&gt;total&lt;/sub&gt;</td>
<td>%</td>
<td>x + 0.43</td>
<td>x + 0.26</td>
<td>x + 0.64</td>
<td>x - 0.06</td>
<td>96</td>
</tr>
</tbody>
</table>

Source: Author’s computations

Table 6 illustrates descriptive statistics of the macroeconomic variables before transformation, with time period corresponding to the period limited by the default data.

Table 6. Descriptive statistics of non-transformed macroeconomic data

<table>
<thead>
<tr>
<th>Non-stationary variables</th>
<th>Unit</th>
<th>Mean</th>
<th>Min.</th>
<th>Max.</th>
<th>Std. dev.</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP</td>
<td>bn. SEK</td>
<td>3272</td>
<td>301.3</td>
<td>360.9</td>
<td>14.6</td>
<td>96</td>
</tr>
<tr>
<td>HPI</td>
<td>Index</td>
<td>155.9</td>
<td>122.3</td>
<td>210.7</td>
<td>20.7</td>
<td>96</td>
</tr>
<tr>
<td>RR</td>
<td>%</td>
<td>1.21</td>
<td>-0.35</td>
<td>4.67</td>
<td>1.29</td>
<td>96</td>
</tr>
<tr>
<td>UR</td>
<td>%</td>
<td>7.7</td>
<td>5.2</td>
<td>9.8</td>
<td>1.0</td>
<td>96</td>
</tr>
</tbody>
</table>

Source: Author’s computations
4.3.2.4  MODEL FITTING, ADJUSTMENTS AND ANALYSIS

Based on indications from theoretical background and previous studies from the literature review, Table 7 illustrates the transformed variables (without lags) used as covariates in the regression model, along with a short description of them and each expected effect on the dependent variable based on theory and findings from previous research.

Table 7. Regression covariates

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
<th>Expected effect on dependent variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\Delta DEF_c)</td>
<td>Default frequency</td>
<td>Dependent variable</td>
</tr>
<tr>
<td>(\Delta GDP)</td>
<td>Real GDP</td>
<td>-</td>
</tr>
<tr>
<td>(\Delta^2 \ln HPI)</td>
<td>House Price Index</td>
<td>+/-</td>
</tr>
<tr>
<td>(\Delta RR)</td>
<td>Repo Rate</td>
<td>+</td>
</tr>
<tr>
<td>(UR)</td>
<td>Unemployment Rate</td>
<td>+</td>
</tr>
</tbody>
</table>

Thus, three different proposed multiple linear regression models were set up as follows, where \(c\) represents the risk classes low, medium, high and total, respectively. One with no lags:

\[
DEF_c = \beta_0 + \beta_2 \Delta GDP + \beta_3 \Delta^2 \ln HPI + \beta_4 \Delta RR + \beta_5 UR \quad (Model 1)
\]

And another one, using multiple lag lengths \(l\) for each macroeconomic variable, with regards to the 90 day long overdue definitions of default (see Glossary):

\[
DEF_c = \beta_0 + \beta_2 \sum_{l=0}^{4} \Delta GDP_{t-l} + \beta_3 \sum_{l=0}^{4} \Delta^2 \ln HPI_{t-l} + \beta_4 \sum_{l=0}^{4} \Delta RR_{t-l} + \beta_5 \sum_{l=0}^{4} UR_{t-l} \quad (Model 2)
\]

Based on results from previous studies and from theory, it is expected that RR will take effect after up to approximately 12 months after a rate change, why we also chose to test for a third proposed model:

\[
DEF_c = \beta_0 + \beta_2 \Delta GDP + \beta_3 \Delta^2 \ln HPI + \beta_4 \sum_{l=0}^{12} \Delta RR_{t-l} + \beta_5 UR \quad (Model 3)
\]

Ordinary Least Squares (OLS) was used for estimating the unknown coefficients of the regression models. The interpretation of the OLS results are summarized in the following steps:

- Model performance assessment: adjusted \(R^2\) was analyzed as a measure of the model performance.
- Explanatory variables assessment: The coefficient, \(p\)-value and variance inflation factor (VIF) of each explanatory variable was used to explain strength and nature of the relationship with the dependent variable.
• Model significance assessment: The F-statistic and its \( p \)-value quantifies the overall statistical significance of the regression model.

• Model bias assessment: Diagnostic tests are used to test for autocorrelation (Breusch-Godfrey), heteroscedasticity (Breusch-Pagan), non-normality (Jarque-Bera and Anderson-Darling).

Depending on the outcome of the statistical tests, the covariates were either kept or excluded from the final regression model. The final regression model was diagnostically tested with validity and stability tests in accordance with Chapter 4 so that robust results could be presented. The quantitative data analysis results in combination with the theoretical background and findings from previous studies in the literature review, were used as support for making concluding remarks on the analysis results.

4.4 SCIENTIFIC QUALITY

When conducting scientific work, Blomkvist and Hallin (2015) claim that the search of knowledge should be done in a systematic, independent and critical manner with the problematization as a starting point. Validity and reliability are two terms associated both with the very foundation of a scientific work, and the scientific quality of it. The logic behind the terms is that relevant results in scientific works should be repeatable and statistically significant, not just coincidental one-off findings (Collis and Hussey, 2009).

4.4.1 VALIDITY

The validity of scientific work requires that it studies the relevant subject field and topic (Collis and Hussey, 2009). This means an experimental design that enables the topic of the problematization to be analyzed as intended, for example through the choice of data collection method and the relevance of the literature review subject field. Also, the research method should be followed so that the posed research questions are answered (Blomkvist and Hallin, 2015).

The validity of the default data and macroeconomic data relies on that it is a representative sample that can be statistically analyzed as intended, that the focus group of all the datasets are tallied and that the correct units are used. The study is focused on Nordea’s default data although their retail portfolio could be considered a retail banking sample group of the Swedish population random enough to generalize the results for other banks’ corresponding portfolios.

The validity of the research method relates to how valid of a method regression analysis is when studying the relationship between multiple variables. The decision to reject or not reject certain macroeconomic factors rely on that hypothesis testing is a valid mathematical statistical test. Both of these are assessed to have a sound basis in logic and thus being valid and relevant for this study.

4.4.2 RELIABILITY

The reliability of scientific work essentially requires that the topic being studied is done so in a correct and relevant manner. The same experiment under the same conditions should generate the same results if performed again (Collis and Hussey, 2009). The literature review is assessed to compose of relatively high reliability as all necessary sources are referenced in the list of
references. Classified information may pose a threat to the reliability of the study as seen by others as all microdata cannot seamlessly be accessed, but this is not considered to reflect on the scientific quality as such. The data preparations – together with the subjective decisions made in connection with these – as well as mathematical tests are thoroughly documented. This contributes to the assessment that the analysis of empirical results is reliable and reproducible.
5 ECONOMETRIC BACKGROUND

This chapter presents the econometric background for the statistical models used on collected data. It includes elaborations on coefficient estimation and diagnostic tests carried out to check the robustness of the regression model and on the results of the data analysis. The statistical tests described are carried out in Python for this study.

5.1 TIME SERIES ANALYSIS

When modelling a time series process, it is of importance whether it is stationary or not, and in this study, we opt for stationarity in our sets of time series. Stationarity implies that the variable distribution does not depend upon time: essentially that the time series has statistical properties that do not change over time, does not exhibit trends or periodic fluctuations, but has constant variance over time and a constant autocorrelation structure over time (Brooks, 2014; Dickey and Fuller, 1979; Verbeek, 2004). While non-stationarity of a time series process often can be visually identified from a plot, there is a more useful test method. The Augmented Dickey-Fuller (ADF) test investigates the presence of a unit-root in data, and so shows that a time series is stationary if a unit-root is not present (Dickey and Fuller, 1979).

5.1.1 AUGMENTED Dickey-Fuller TEST

The ADF test is based on regression analysis and is applied to:

\[ \Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \epsilon_t \]  

(5.1)

where \( \alpha \) is a constant, \( \beta \) is the coefficient for a time trend, \( p \) is the chosen order of lag of the autoregressive process. There are three main versions of the test depending on the constraints for \( \alpha \) and \( \beta \) (\( \alpha = 0, \alpha = \beta = 0 \), or neither).

The unit root test is conducted by testing the following null hypothesis test:

\[ H_0 : \gamma = 0, \quad \text{unit root present (non-stationary time series)} \]

\[ H_1 : \gamma < 0, \quad \text{unit root present (stationary time series)} \]

specified in terms of the test statistic:

\[ DF_t = \frac{\hat{\gamma}}{SE(\hat{\gamma})} \]  

(5.2)

where \( \hat{\gamma} \) is an estimate from equation (5.1) and \( SE(\hat{\gamma}) \) is the standard error of that estimate.

The decision rule of hypothesis testing of the test statistic \( DF_\alpha \) at significance level \( \alpha \) is denoted:

\[ DF_t \geq DF_\alpha \Rightarrow \text{Do not reject } H_0 \text{ (unit root present)} \]

\[ DF_t < DF_\alpha \Rightarrow \text{Reject } H_0 \text{ (unit root not present)}, \]
where $DF_t$ is the critical value for the distribution (found in Fuller, 1976, p. 373; Cheung and Lai, 1995). For this research, the ADF test will be conducted in Python, where the results include a p-value. The p-value or probability value denotes the probability to find a test statistic $DF_t$ that (in absolute value) exceeds the test statistic value. If the p-value is smaller than the significance level $\alpha$, the null hypothesis $H_0$ is rejected. If the p-value is greater than the significance level $\alpha$, the null hypothesis $H_0$ cannot be rejected (Verbeek, 2004, p. 31). It specifies the risk of being wrong when rejecting $H_0$ and thus the risk of being wrong when stating that the time series is stationary.

If a time series does not exhibit stationarity, it can yield stationarity by being differenced using first-order differencing or second-order differencing as following. First order of difference, the change in $y$, $\Delta y$ is calculated so that

$$\Delta y_t = y_t - y_{t-1}, \quad \text{for data point } t = 2, ..., n$$

(5.3)

and the second order of difference so that

$$\Delta^2 y_t = \Delta y_t - \Delta y_{t-1} = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2}), \quad \text{for data point } t = 3, ..., n$$

(5.4)

A time series is denoted I(d) where the order of integration d is the minimum number of times that the time series need to be differenced to yield stationarity. I.e. a series that is stationary is denoted I(0), while a time series that yields stationarity after first-order differencing is said to have an order of integration of one, denoted I(1). If the series needs to be differenced using second-order differencing to be stationary, it is said to be integrated of order two, denoted I(2) (Verbeek, 2004, p.267). A third option is to use a logarithmic transformation of the first-order differencing as following:

$$\Delta \ln y_t = \ln y_t - \ln y_{t-1}, \quad \text{for data point } t = 2, ..., n$$

(5.5)

and a forth is to use a logarithmic transformation of the second-order differencing as following:

$$\Delta^2 \ln y_t = (\ln y_t - \ln y_{t-1}) - (\ln y_{t-1} - \ln y_{t-2}), \quad \text{for data point } t = 3, ..., n$$

(5.6)

Seemingly, the first observation is lost so that a regression of the first- or second order differenced variable of $y$ would have a starting point at one or two time periods after the first observed data point, as noted next to each equation (Brooks, 2014, Chapter 4).

### 5.1.2 Lag Lengths

The delay between an economic event or change and a consequence is known as time lag. As Figlewski et al., (2012) remark, macroeconomic factors like interest rates are unlikely to have immediate effect on a population and thus there is expected to be some lag length before, for example, an interest rate change, takes effect. It is reasonable to test for up to a 4 month (one quarter) lag length for monthly time series data.

To decide on optimal lag length of covariates in a regression model, the autocorrelations of the variables can be studied. The magnitude of Pearson’s correlation coefficient (-1 to 1) indicates the strength of linear relationship between two variables. By identifying what lag length exhibits the largest value of Pearson’s correlation coefficient an optimal lag length can be derived.
5.2 MULTIPLE LINEAR REGRESSION

Regression analysis is used to generate predictions and for testing economic hypotheses regarding the relationship between a dependent variable and one or multiple independent variables (Verbeek, 2004). It is a useful tool when there is the need to not just present coincidental historical relationships between variables, but to draw conclusions about what changes can be expected if one of the variables actually changes in one way or another. When studying a well-defined population, a regression model can be used to investigate and possibly present a fundamental relationship between variables in that very population.

The general multiple regression model takes the form:

\[ y_i = \sum_{j=0}^{k} x_{ij} \beta_j + \varepsilon_i, \quad i = 1, \ldots, n \] (5.7)

where \( n \) = number of observations and \( k \) = number of covariates

Where \( y_i \) represents observations that depend on the stochastic covariates \( x_{ij} \). \( \varepsilon_i \) denotes the error or residual term, which represents the part of the model that can explain deviations in modelled observations from reality. \( \beta_j \) are unknown coefficients to be estimated (see section 0). In matrix form the model is expressed as:

\[ Y = X\beta + \varepsilon \] (5.8)

with parameters

\[
Y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}, \quad X = \begin{pmatrix} 1 & x_{1,1} & \cdots & x_{1,k} \\ 1 & x_{2,1} & \cdots & x_{2,k} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n,1} & \cdots & x_{n,k} \end{pmatrix}, \quad \beta = \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{pmatrix}, \quad \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}
\]

where it is assumed that:

\[ E(\varepsilon_i|X) = 0, \quad i = 1,2, \ldots, n \] (5.9)

so that for all \( i \) the expected mean value of the residual term is 0.

There are mainly two advantages of using a regression analysis approach in this research. Firstly, it is relatively easy to interpret. Secondly, the estimated coefficients can be relatively easily employed to predict future default probabilities by using forecasted projections of the explanatory variables. Covariates that are not linearly related to the dependent variable can be transformed (see discussion in Brooks, 2014, on transformations including division, squaring, log-transformation, exponential transformation). The model fit of the explanatory variables will be tested and, where necessary, transformations and lags of variables will be adjusted for.
5.2.1 **Ordinary Least Square (OLS)**

To estimate the unknown coefficients, the most common method is Ordinary Least Squares (OLS) where the sample \((y_i, x_i), i = 1, ..., n\) can be used. Translating a sample into an approximate value for \(\beta\) gives us an estimate, which is a vector of numbers that respond to the principle that the sample may change. One of the most common methods used for estimating \(\beta\)-coefficients and residual terms \(\epsilon\) is the OLS estimator (Brooks, 2014; Verbeek, 2004). The OLS estimate \(\hat{Y}\) of the dependent variable \(Y\) is expressed in matrix form as:

\[
Y = X\hat{\beta} + \hat{\epsilon}
\]

where \(\hat{\beta}\) is the estimate of \(\beta\) and \(\hat{\epsilon}\) equals the residual terms of the OLS estimation.

OLS minimizes the sum of squared error terms, i.e. \(|\hat{\epsilon}|^2\) is minimized to find the best fit of the estimates and fulfill the normal equation:

\[
X^T \hat{\epsilon} = 0
\]

5.3 **Diagnostic Testing Methods**

This section describes the measures and tests that can be adopted to test the robustness of both the initial regression model and of adjustments made to improve its fit along with the analysis.

5.3.1 **Measures of Fit**

\(R^2\) is known as the coefficient of determination, an expression of the explanatory power or as the goodness of fit of a model (Stock and Watson, 2003). Essentially, the statistical measure of how close the data are to the fitted regression line, i.e. the fraction of the measurement variance that is explained by the linear model. In turn, \(1 - R^2\) is the fraction of the measurement that is not explained by the covariates, why a value of \(R^2\) close to 1 is to prefer. \(R^2\), however, always increases with added covariates, which is why we look for the adjusted \(R^2\), denoted \(R^2_{adj}\) or \(\bar{R}^2\), that penalizes the addition of new covariates by reducing \(R^2\) with some factor. \(R^2\) is written as

\[
R^2 = 1 - \frac{SSR}{SST}
\]

where

\[
SSR = \text{Sum of Squares Residual} = \sum_{i=1}^{n} |\hat{\epsilon}_i|^2
\]

\[
SST = \text{Sum of Squares Total} = \sum_{i=1}^{n} (Y_i - \bar{Y})^2
\]

The adjusted \(R^2\) is written as:

\[
\bar{R}^2 = R^2_{adj} = 1 - \frac{n - 1}{n - k - 1} \times \frac{SSR}{SST}
\]
From this follows that

\[ R^2_{adj} < R^2 \]

but for larger number of observations \( n \) the two terms will be very close (Stock and Watson, 2003).

Alternative criteria that provide a measure of the trade-off between goodness-of-fit and the number of explanatory variables in the chosen regression model includes Akaike’s Information Criterion (AIC) (Akaike, 1973) and Bayesian Information Criterion (BIC) (Schwarz, 1978). AIC and BIC, respectively, are given by

\[
AIC = \log \frac{1}{n} \sum_{i=1}^{n} e_i^2 + \frac{2k}{n} \tag{5.14}
\]

\[
BIC = \log \frac{1}{n} \sum_{i=1}^{n} e_i^2 + \frac{k}{n} \log n \tag{5.15}
\]

and we look for a lower value of AIC or BIC (Verbeek, 2004, Chapter 3). Further, while \( R^2 \) provides an estimate of the goodness-of-fit of the regression model, it does not provide a formal hypothesis test for the relationship. The F-test can be used to determine whether the relationship between the regression model and the dependent variable is statistically significant. The p-value in the F-test can be used so that if it is less than the significance level, \( R^2 \) can be concluded to be statistically significant.

### 5.3.2 P-VALUE

As introduced in the Dickey-Fuller test description, in hypothesis testing, the p-value specifies the risk of being wrong when rejecting the null hypothesis \( H_0 \) and thus the risk of being wrong when declaring the alternate hypothesis \( H_1 \) to be true (Studenmund, 2014). The OLS estimators of \( \beta \) are interpreted and tested using hypothesis testing. To test the hypothesis that a covariate is or is not significant in the regression model, the p-value for each covariate is calculated. In our multiple regression model the hypotheses are to be posed as:

\[ H_0 : \text{the covariate } x_i \text{ does not have explanatory power on the dependent variable } y_i \]

\[ H_1 : \text{the covariate } x_i \text{ has explanatory power on the dependent variable } y_i \]

It is then used as a means of a decision rule for which covariates to include or not in the final regression model. A common limit level is a p-value of 0.05 i.e. 5% risk of being wrong when rejecting the null hypothesis and thus stating that a covariate has significance in a regression model.
5.4 REGRESSION ASSUMPTIONS AND PITFALLS

In the setup of a regression model we make assumptions about the data, its behavior, and about the residual terms $\varepsilon_i$ in the model. This section lists some common pitfalls to be aware of, accompanied by tests to identify them and measures that can be taken to adjust for them, to ensure that the model is both valid and stable.

5.4.1 MULTICOLLINEARITY

In regression analysis, the term multicollinearity refers to the issue at risk when there is an approximate linear relationship amongst the explanatory variables and the regression estimates may exhibit unreliable behavior (Verbeek, 2004, Chapter 2). When using the OLS estimation method, the explanatory variables are assumed not to be correlated. In a completely zero-correlation context between explanatory variables, adding or removing one or more of the variables would not affect the coefficients on the other variables. Any practical context will exhibit non-zero correlation, and hence real-life observation data is not expected to have zero-correlation (Brooks, 2014). For two covariates $x_1$ and $x_2$ the following applies:

$$
\text{corr}(x_1, x_2) = 1, \quad \text{perfect multicollinearity}
$$

$$
\text{corr}(x_1, x_2) \to 1, \quad \text{imperfect multicollinearity}
$$

which can be studied using a Pearson correlation matrix. In the case of multicollinearity, the covariate coefficient for $x_1$ implies the impact of $x_1$ with all other things equal, which is contradicted if the change in $x_1$ depends on the change in $x_2$ (Wooldridge, 2013, Chapter 3).

If the variables exhibit multicollinearity, one solution is to neglect the issue if the model is otherwise deemed to be adequate in terms of statistically significant coefficients. If this is not the case, one of the collinear variables can either be dropped, transformed or the collinear variables can be transformed into a ratio of each other and used as a new explanatory variable. In forecasting, multicollinearity is deemed less fateful if the relationship between the explanatory variables is expected to continue over the forecasted time period and sample (Brooks, 2014).

We can test for multicollinearity by calculating the Variance Inflation Factor ($VIF$) that quantifies the severity of the multicollinearity in the regression analysis. We calculate $k$ different $VIF$s, one for each covariate in the regression model. An OLS regression analysis is then estimated for each covariate $X_i$ on the other explanatory variables in the original regression model. For each regression, $R_i^2$ is computed and used to calculate $VIF_i$, given by:

$$
VIF_i = \frac{1}{1 - R_i^2} \quad (5.16)
$$

The cutoff value for $VIF$ is usually set to 10. That is, for $VIF > 10$ we conclude multicollinearity is an issue for estimating the regression model coefficients $\beta$ (Wooldridge, 2013).
5.4.2 AUTOCORRELATION

Autocorrelation occurs when the residuals are not independent from each other. To detect and avoid it, we can look at residual scatter plots or test for linear autocorrelation with the Breusch-Godfrey test (Verbeek, 2004, Chapter 4). The Breusch-Godfrey test tests the null hypothesis that residuals in the regression are not linearly autocorrelated so that:

\[ H_0 : \text{Residuals independent from each other (No autocorrelation)} \]
\[ H_1 : \text{Residuals not independent from each other (Autocorrelation)} \]

5.4.3 NON-NORMALITY OF ERROR DISTRIBUTION

In linear regression, we assume normality of the error distribution. Normality is estimated based on the minimization of the squared error terms and if the error distribution exhibits significant non-normality, the confidence intervals of the regression coefficients may be too wide or too narrow.

Normality can be graphically identified through a normal quantile plot of the residual terms, where normality is assumed if the points in the normal quantile plot fall close to a diagonal reference line (Verbeek, 2004, Chapter 6). For statistical testing, the Jarque-Bera test is often used, where the following hypotheses are tested:

\[ H_0 : \text{Error terms are normally distributed} \]
\[ H_1 : \text{Error terms are not normally distributed} \]

If the error distribution does not exhibit normality, it may depend on that the sample data is originally not from a normal distribution. Testing the original sample data can be statistically done using the Anderson-Darling test that tests the following hypotheses:

\[ H_0 : \text{Normal distribution well describes the data sample} \]
\[ H_1 : \text{Normal distribution does not describe the data sample} \]

If the null hypothesis is rejected at a 5% level \( (p < 0.05) \) the data can be transformed through, for example, log transformations, to make the data normally distributed.

5.4.4 HETEROSCEDASTICITY

Another assumption in regression analysis is that all residual terms \( \varepsilon_i \) of the explanatory variables have the same standard deviation \( \sigma \) for all values of \( i \) so that:

\[ \sigma^2 = Var(\varepsilon_i), \quad i = 1, ..., n \quad (5.17) \]

and hence \( \varepsilon \) is normally distributed so that:

\[ \varepsilon_i \sim N(0, \sigma^2), \quad i = 1, ..., n \quad (5.18) \]
and hence exhibit homoscedasticity (Brooks, 2014; Verbeek, 2004). To the contrary, heteroscedasticity, where the residual terms’ standard deviation is not the same, is generally the case for real life sampled data, so that:

\[ E(\varepsilon_i | X) = 0 \quad \text{and} \quad E(\varepsilon_i^T \varepsilon_i | X) = \sigma_i^2 \]  

(5.19)

To identify whether data points are equally distributed across all values of the explanatory variables, the standardized values of residual terms can be plotted against the predicted covariate values. Regressing with heteroscedastic residuals without taking it into consideration may lead to inconsistent hypothesis testing results and inconsistency in the calculated standard deviations for the residual terms, and hence mismatched estimates (Wooldridge, 2013, Chapter 8-12). A statistical test for heteroscedasticity is the Breusch-Pagan test, which tests the following hypotheses:

\[ H_0 : \text{Constant variance (Homoscedasticity)} \]

\[ H_1 : \text{Not constant variance (Heteroscedasticity)} \]

Thus, if the test statistic has a \( p \)-value above the chosen significance level, 0.05, the null hypothesis of homoscedasticity is not rejected, and homoscedasticity can be assumed.

A non-linear data transformation may fix the presence of heteroscedasticity. A preferred method, however, is to adjust for the presence of heteroscedasticity with White’s robust errors (Verbeek, 2004, Chapter 4). The method is used to calculate residual terms that exhibit homoscedasticity when the observed residual terms in fact exhibit heteroscedasticity. With White’s robust error we estimate a standard deviation, i.e. standard error, for \( \beta_1 \), denoted SE as follows:

\[ SE(\hat{\beta}_1) = \sqrt{\frac{\sum(\hat{u}_i \varepsilon_i)^2}{\sum \hat{u}_i^2}}, \quad i = 1, \ldots, n \]  

(5.20)

Where the term \( \varepsilon_i \) is derived from (5.7) and the error term \( u_i \) is derived from regressing \( X_1 \) (because we are estimating for \( \beta_1 \)) on the other covariates so that the estimate for \( u_i \) is calculated as:

\[ \hat{u}_i = X_{i1} - (\hat{\beta}_0 + \hat{\beta}_2 X_{i2} + \hat{\beta}_3 X_{i3} + \cdots + \hat{\beta}_k X_{ik}) \]  

(5.21)
CHAPTER 6

EMPIRICAL FINDINGS

This chapter compiles empirical results of the data analysis, the multiple linear regression model and the diagnostic testing procedures. The final models are presented with the covariate coefficients that are deemed to have explanatory power of significance for the dependent variable.

6.1 DESCRIPTIVE STATISTICS

The ADF test of the aggregated default data demonstrated non-stationarity, and thus the data was transformed in accordance with (5.3) so that:

\[ DEF_c \rightarrow \Delta DEF_c \]

For all risk classes \( c \) (low, medium, high, total), meaning that the first data point in each risk class was lost. Descriptive statistics of the transformed aggregated default data are presented in Table 8 to provide an oversight of the data used.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean (%)</th>
<th>Min. (%)</th>
<th>Max. (%)</th>
<th>Std. dev. (%)</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta DEF_{\text{low}} )</td>
<td>0.00</td>
<td>-0.06</td>
<td>0.08</td>
<td>0.01</td>
<td>95</td>
</tr>
<tr>
<td>( \Delta DEF_{\text{med}} )</td>
<td>-0.01</td>
<td>-0.63</td>
<td>0.48</td>
<td>0.13</td>
<td>95</td>
</tr>
<tr>
<td>( \Delta DEF_{\text{high}} )</td>
<td>-0.02</td>
<td>-2.82</td>
<td>1.45</td>
<td>0.52</td>
<td>95</td>
</tr>
<tr>
<td>( \Delta DEF_{\text{total}} )</td>
<td>0.00</td>
<td>-0.16</td>
<td>0.18</td>
<td>0.04</td>
<td>95</td>
</tr>
</tbody>
</table>

Source: Author’s computations

The macroeconomic data was transformed for stationarity and normality in accordance with (5.3), (5.4), (5.5) and (5.6). Table 9 illustrates some descriptive statistics of the transformed macroeconomic variables.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Unit</th>
<th>Mean</th>
<th>Min.</th>
<th>Max.</th>
<th>Std. dev.</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta GDP )</td>
<td>bn. SEK</td>
<td>0.373</td>
<td>-3.989</td>
<td>2.400</td>
<td>1.352</td>
<td>95</td>
</tr>
<tr>
<td>( \Delta^2 \ln HPI )</td>
<td>%</td>
<td>0.001</td>
<td>-0.075</td>
<td>0.080</td>
<td>0.026</td>
<td>95</td>
</tr>
<tr>
<td>( \Delta R )</td>
<td>%</td>
<td>-0.046</td>
<td>-1.105</td>
<td>0.214</td>
<td>0.191</td>
<td>95</td>
</tr>
<tr>
<td>( UR )</td>
<td>%</td>
<td>7.778</td>
<td>0.214</td>
<td>9.800</td>
<td>0.985</td>
<td>95</td>
</tr>
</tbody>
</table>

Source: Author’s computations
6.2 Regression Models

To assess whether it is viable to assume the same general regression model for the low, medium, high and total risk classification, a correlation matrix was constructed. The results are shown in Table 10.

<table>
<thead>
<tr>
<th></th>
<th>(\Delta DEF_{low} )</th>
<th>(\Delta DEF_{med} )</th>
<th>(\Delta DEF_{high} )</th>
<th>(\Delta DEF_{tot} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\Delta DEF_{low} )</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\Delta DEF_{med} )</td>
<td>0.71</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\Delta DEF_{high} )</td>
<td>0.51</td>
<td>0.75</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>(\Delta DEF_{tot} )</td>
<td>0.79</td>
<td>0.73</td>
<td>0.71</td>
<td>1</td>
</tr>
</tbody>
</table>

*Source: Author’s computations*

As all variables are highly correlated, it is considered viable to first model only \(\Delta DEF_{tot} \) against the macroeconomic variables, and then apply that same model construction onto \(\Delta DEF_{low}, \Delta DEF_{med} \) and \(\Delta DEF_{high} \). Hence, for each model fit and test, \(\Delta DEF_{tot} \) was used as the dependent variable. After the revised regression model was decided on, it was applied to the remaining variables \(\Delta DEF_{low}, \Delta DEF_{med} \) and \(\Delta DEF_{high} \) respectively, so that all risk classes were modelled against the same macroeconomic covariates.

All four macroeconomic variables were included in the regression models 1, 2 and 3 to begin with, as they were expected to be of significance based on previous studies and as the inclusion of lagged variables may improve the statistics for autocorrelation in residual terms. Hence the proposed models had a large number of covariates that were then reduced in order to identify the best model fit for different combinations of macroeconomic variables and time lags.

As can be seen in Table 15-Table 17 in Appendix II, all \(R^2_{adj} \) values are small, and thus the models have low overall explanatory power. 0.4\% of the changes in the first-order differenced default frequency of the total portfolio are explained by Model 1, 14.5\% by Model 2 and 2.8\% by Model 3. A few of the covariates are significant at a 10\% level \((p < 0.1)\) and a few at a 5\% level \((p < 0.05)\) meaning that there is a significant relationship between those independent variables and the dependent variable. The Breusch-Pagan test detected no heteroscedasticity in any of the three proposed models, why White’s robust standard errors were not needed and hence not presented. The Jarque-Bera test results indicate non-normal distribution of the residuals \((p \ll 0.05)\) which is another reason to consider the proposed models to be misspecified.

As macroeconomic theory and previous studies point to different lag lengths being significant, the testing was extended so that \(\Delta DEF_{tot} \) was regressed against 0 to 13 lag lengths of each macroeconomic variable at a time. The few lagged variables that, when combined, systematically showed high significance \((p < 0.05)\) were kept. The variables that showed individual significance in any of the three proposed models and in the 0-to-13 lag regressions were then kept for fitting and testing of a revised model, while the non-significant were excluded one by one. After also
considering the exclusion of variables with $VIF > 10$ from the same models, the most statistically significant combination of variables was kept and concluded on as the final revised model.

The results of the revised multiple linear regression model, analyzed through OLS, applied to all risk classes (low, medium, high, total) and hence referred to as Model 4a, 4b, 4c, 4d, can be seen in Table 11. Standard errors are presented in parenthesis and notations *, **, *** represent a significance level of 10%, 5% and 1% respectively. For interpretation, an example follows. The $GDP_{t-6}$ variable is first differenced, and its coefficient for $\Delta DEF_{tot}$ is 0.0180. A month-to-month change of 1 bn. SEK would cause a change in the default frequency of 0.0180, i.e. 0.0180%, six months later.

$R^2_{adj}$ is overall low, meaning that the highest explanatory power of 24.3% and 23.2% are seen in Model 4a and Model 4b respectively. The F-statistic $p$-value for Model 4a and Model 4b, however, are also low, indicating statistically significant models.

The coefficient signs for the different lagged variables alternate from positive to negative, which might indicate instability in the models. However, our significance levels indicate that we should reject the hypothesis that the coefficients are zero, and thus we consider the alternating signs across different lag lengths not to be an issue.

Table 11. Regression results of revised models

<table>
<thead>
<tr>
<th></th>
<th>OLS Regression coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 4a: $\Delta DEF_{tot}$</td>
</tr>
<tr>
<td>$\Delta GDP_{t-6}$</td>
<td>0.0180***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
</tr>
<tr>
<td>$\Delta GDP_{t-7}$</td>
<td>-0.0172***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
</tr>
<tr>
<td>$\Delta GDP_{t-9}$</td>
<td>0.0175***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
</tr>
<tr>
<td>$\Delta GDP_{t-10}$</td>
<td>-0.0254***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
</tr>
<tr>
<td>$\Delta GDP_{t-12}$</td>
<td>0.0209***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
</tr>
<tr>
<td>$\Delta GDP_{t-13}$</td>
<td>-0.0189***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
</tr>
<tr>
<td>$\Delta RR_{t-2}$</td>
<td>0.0786***</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
</tr>
<tr>
<td>$\Delta RR_{t-3}$</td>
<td>-0.0771***</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
</tr>
<tr>
<td>Observations</td>
<td>95</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.307</td>
</tr>
<tr>
<td>$R^2_{adj}$</td>
<td>0.243</td>
</tr>
<tr>
<td>F-statistic</td>
<td>4.811</td>
</tr>
<tr>
<td>F-statistic $p$-value</td>
<td>6.36e-05</td>
</tr>
</tbody>
</table>

Source: Author’s computations
6.3 REVISED MODEL ASSESSMENT

Diagnostic tests were used in assessing the biasedness of the revised regression model. The following section refers to the diagnostic test results, numerically presented in Table 12. Breusch-Godfrey tests the null hypothesis that residuals in the regression are not linearly autocorrelated. The results do not show evidence of autocorrelation for $\Delta DEF_{tot}$, $\Delta DEF_{low}$ and $\Delta DEF_{med}$, as $p > 0.05$, while $\Delta DEF_{high}$ is shown to have autocorrelation.

The Breusch-Pagan results, ran for heteroscedasticity testing, show high p-values ($p > 0.05$). Hence, the null hypothesis assuming homoscedasticity is not rejected, and we assume homoscedasticity in all of the models.

Considering the small p-values of the Jarque-Bera test, the residual terms are not likely normally distributed. Attempts of performing log-transformations of the regression variables were made without improved results. The test for normal distribution in the residuals is extended through observations of the quantile-quantile (Q-Q) plots in Figure 11 through Figure 14, Appendix III. The Q-Q plots point to a near-normal distribution in Model 4a, with the exception of a few outliers, while Model 4b, 4c and 4d exhibit more deviation from a theoretical normal distribution.

Figure 15-Figure 18 in Appendix IV illustrate prediction plots of the revised models on our sample data, to graphically present the regression models’ fit. In late 2010 for the total portfolio, it can be seen in Figure 15 that the increase in the differenced default frequency is not accurately modelled, as the model underestimates the decreased default effect for the total portfolio. The same principle of underestimated effects at the point of decrease in default frequency in mid-2011. Specifically, in Figure 17 of the medium risk class and Figure 18 of the high risk class, it is clear that the models do not follow the patterns of changes in the default data well.

<table>
<thead>
<tr>
<th>Diagnostic test results</th>
<th>Model 4a: $\Delta DEF_{tot}$</th>
<th>Model 4b: $\Delta DEF_{low}$</th>
<th>Model 4c: $\Delta DEF_{med}$</th>
<th>Model 4d: $\Delta DEF_{high}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIC</td>
<td>-376.5</td>
<td>-572.1</td>
<td>-112.8</td>
<td>150.3</td>
</tr>
<tr>
<td>BIC</td>
<td>-356.0</td>
<td>-551.7</td>
<td>-92.41</td>
<td>170.8</td>
</tr>
<tr>
<td>Durbin-Watson</td>
<td>2.301</td>
<td>1.938</td>
<td>2.296</td>
<td>2.780</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>149.933</td>
<td>683.348</td>
<td>253.103</td>
<td>361.576</td>
</tr>
<tr>
<td>Jarque-Bera p-value</td>
<td>2.77e-33</td>
<td>4.10e-149</td>
<td>1.10e-55</td>
<td>3.05e-79</td>
</tr>
<tr>
<td>Anderson-Darling p-value</td>
<td>0.000588</td>
<td>0.000000</td>
<td>0.000000</td>
<td>0.001036</td>
</tr>
<tr>
<td>Breusch-Godfrey LM p-value</td>
<td>0.299501</td>
<td>0.785500</td>
<td>0.099518</td>
<td>0.000965</td>
</tr>
<tr>
<td>Breusch-Godfrey F p-value</td>
<td>0.420900</td>
<td>0.862409</td>
<td>0.145514</td>
<td>0.000897</td>
</tr>
<tr>
<td>Breusch-Pagan LM p-value</td>
<td>0.233474</td>
<td>0.703043</td>
<td>0.309995</td>
<td>0.155227</td>
</tr>
<tr>
<td>Breusch-Pagan F p-value</td>
<td>0.322376</td>
<td>0.808335</td>
<td>0.415627</td>
<td>0.220429</td>
</tr>
</tbody>
</table>

Source: Author’s computations

(LM is the Lagrange multiplier statistic, F is the F statistic.)
7 ANALYSIS

This chapter presents an analysis of the empirical findings of the research in the light of findings from the literature review and theoretical background. The empirical findings are further analyzed and discussed, with respect to both significant and insignificant macroeconomic variables.

The research was conducted to investigate the significance of macroeconomic variables on the default frequency of an SRC portfolio, and to identify the nature of their relationship. GDP, House price index, Repo rate and Unemployment rate, with respect to macroeconomic theory and previous research, was expected to explain changes in the default frequency as a proxy for households’ payment capacity. Our results exhibit mixed variable significance, and do not identify these four macroeconomic variables as sole explanatory variables.

7.1 INITIALLY PROPOSED MODELS

The initially proposed models exhibit low predictive power on observed values. Simultaneously, the coefficients of the non-lagged and lagged macroeconomic variables have high p-values as a sign of weak dependence between the combination of macroeconomic variables and the default frequency, which is shown in Table 15, Table 16 and Table 17 in Appendix II. As seen in Table 13 below, only 0.4% of the changes in the $\Delta DEF_{tot}$ are explained by Model 1, 14.5% by Model 2 and 2.8% by Model 3.

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>0.046</td>
<td>0.327</td>
<td>0.193</td>
</tr>
<tr>
<td>$R^2_{adj}$</td>
<td>0.004</td>
<td>0.145</td>
<td>0.028</td>
</tr>
</tbody>
</table>

Model 1 is the model whose construction has most similarities to those suggested in previous research, characterized by few lags and few regression covariates. Ali and Daly (2010) found non-lagged GDP and 1-quarter lagged Interest rates (6-month Treasury bill) to be inversely related to default rates in their dataset, where their multiple linear regression model showed high significance and 90% predictive power. Bellotti and Crook (2009) found that decreases in non-lagged Interest rate and Unemployment rate increased the LGD in their dataset, and that these macroeconomic variables added explanatory power to an LGD model with otherwise only idiosyncratic risk variables. However, our test results deviate from those of previous research concerning significant lag lengths, significant macroeconomic variables and coefficient signs of macroeconomic covariates in the regressions.

While Model 2 still has low predictive power, it is the best model fit out of the three, seen to the magnitude of $R^2_{adj}$. A reason to this might be the large number of variables used, which tends to produce a higher predictive power of regression models.

Unlike the other previous studies discussed, Chaibi and Ftiti (2015) clearly comment on the importance of stationarity in time series data and demonstrate stationarity of their data once differenced. This is in line with our research where stationarity in regression data is presumed,
and the reason for multiple transformations of the dependent and independent variables. Chaibi and Fiti (2015) find GDP growth, interest rate and unemployment rate to influence non-performing loans frequency, while inflation rate does not. Where stationarity is not discussed or postulated, it is justified to question the accuracy of regression results and emphasize it as a possible reason for deviating results in model fit and variable significance.

Vaněk (2016) does not mention stationarity as a reason, but argues that changes, i.e. differenced values, in macroeconomic variables are of greater interest than level values. He concludes that GDP is the only significant macroeconomic variable out of GDP, unemployment rate, 3-month interest rate and consumer price index. This conclusion combined with a low predictive power ($R^2_{adj} = 0.36$) makes his multiple linear regression model and results the ones most similar to those of our research.

One explanation for our deviating results might be the geographical aspect, as previous studies covered, among others, the U.S. (Ali and Daly, 2010; Rösch and Scheule, 2004), the U.K. (Bellotti and Crook, 2009) and the Czech Republic (Vaněk, 2016). Monetary policies, inflation rate targets, political state, household living standards, employments contracts, banking supervision and banking best practices will differ among countries. These are reasons to hypothesize that credit risk portfolios in different countries react differently to macroeconomic factors, and that sensitivity to macroeconomic changes are country-specific. Further, macroeconomic modelling of corporate credit risk is believed to be more predictive than retail credit risk, given that large corporate segments are subject to larger systematic risks. For example, one would expect high explanatory power of house prices in the modelling of PD of real estate investing companies. Retail credit clients are not necessarily exposed to such systematic risk.

### 7.2 Revised Models

Our final revised regression model suggests that the change in GDP is significant for the change in the total portfolio default frequency for a lag length of 6, 7, 9, 10, 12 and 13 months, as presented in detail in Table 11. Exceptions of significance for different lag lengths are identified in the three risk classes low, medium and high. Changes in Repo Rate, with 2 and 3 lag lengths, are significant for the change in the total portfolio default frequency. The low predictive power indices, seen in Table 14, of the model applied to the low, medium and high risk class default frequency, however, suggest that the model is even less predictive for the PD in segmented risk classes than in the SRC portfolio as a whole. The low explanatory power of our models suggests that, while GDP and Repo rate are significant macroeconomic variables with various lag lengths, we are missing other explanatory variables. Hence, these macroeconomic variables do not predict the default frequency in Nordea’s SRC portfolio alone.

<table>
<thead>
<tr>
<th></th>
<th>Model 4a</th>
<th>Model 4b</th>
<th>Model 4c</th>
<th>Model 4d</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>0.307</td>
<td>0.297</td>
<td>0.126</td>
<td>0.107</td>
</tr>
<tr>
<td>$R^2_{adj}$</td>
<td>0.243</td>
<td>0.232</td>
<td>0.045</td>
<td>0.025</td>
</tr>
</tbody>
</table>
Macroeconomic theory suggests that GDP reflects on the general state of an economy and the Repo Rate on the cost of debt. Model 4a, 4b, 4c and 4d suggest that changes in these macroeconomic factors are significant for changes in default frequency of Nordea’s SRC portfolio, but that they do not single-handedly explain these changes. More variables would need to be added to the regression, either idiosyncratic risk factors or other macroeconomic factors than those investigated in this study, to establish explanatory significance of the model fit.

7.2.1 STATISTICAL SIGNIFICANCE

Based on macroeconomic theory, our macroeconomic variables are in different aspects related to each other. The Repo rate is adjusted to control inflation rate and stimulate GDP, which in turn reflects on the Unemployment rate and House prices index. However, any variable that indicated multicollinearity with another (VIF > 10) throughout the data analysis were not kept in the same model. Hence, none of the variables in the revised model exhibit multicollinearity.

Diagnostic testing of autocorrelation shows that it is present in \( \Delta DEF_{high} \) but not in the other risk classes or in the total portfolio. No measures are taken to adjust for the autocorrelation in this model as it is technically a back-test of model 4a, applied to another risk class.

While heteroscedasticity can oppose a threat to the reliability of a regression model, the null hypothesis of homoscedasticity is not rejected for any of the Models 4a, 4b, 4c and 4d, and hence we assume homoscedasticity in all of the models.

The diagnostic test results indicate that our regression models’ residual terms are not normally distributed. This is a reason to declare misspecification in the models, or lacking quality of data. In the Q-Q plots in Figure 11 through Figure 14 in Appendix III, we identify outliers in the tails. Also, the prediction plots of our models support this suggestion, considering that the models inaccurately predict small fluctuations in default frequency with the selected lag lengths. Larger default frequency changes are also not well-modelled, as can be specifically seen in the spikes of the sample data in the medium and high risk class in Figure 17 and Figure 18 in Appendix IV. The back-testing of the model in Figure 15 through Figure 18 has data-mining bias as it is applied to in-sample data, but is considered of interest as it provides for a graphical interpretation of the model fit of Model 4a, 4b, 4c and 4d.

7.2.2 EXCLUDED VARIABLES

The House price index and Unemployment rate exhibit insignificance as covariates in our initially proposed models and throughout the model development and are thus excluded from the final revised model.

The House price index was investigated as a reflection on the financial wealth of mortgage holders. Based on macroeconomic theory, the House price index was expected to exhibit some ambiguity as a regression covariate, as presented in section Error! Reference source not found., why the insignificance on the default frequency in Nordea’s SRC portfolio is not unexpected, albeit contradictory to previous research results (Bofondi and Ropele, 2011).
The *Unemployment rate* was included in the study as a proxy for the general state on the economy and the payment capacity of households. It was expected to be a directly related macroeconomic factor for explaining the SRC default frequency. One explanation for the insignificance may be the concept of self-selection, i.e. that the bank does not offer large credit to unemployed household clients to begin with. (Bellotti and Crook, 2012; Bofondi and Ropele, 2011; Chaibi and Fititi 2015)

### 7.2.3 Significant variables

The *GDP* is included in the study as an indicator of the general state of the economy. As presented in Table 11, changes in *GDP* with 6, 7, 9, 10, 12 and 13 month lags appear to be significant for the changes in the default frequency of the *total* portfolio, 6, 7, 9, 10 lags for the *low* risk class, 6, 7, 10, 12, 13 for the *medium* risk class and 9, 10, 12, 13 for the *high* risk class.

Specifically, for changes in *GDP* with lags 6, 9 and 12 in Model 4a, the coefficients are negative and thus these covariates are inversely related to changes in the default frequency. For ∆*GDP* lagged 7, 10, 12 and 13 months in Model 4a, the coefficients are positive and indicate a positive relationship to changes in the default frequency. This alternation in coefficient sign among variable lags indicate, for example, that there is a positive relationship between ∆*GDP*\(_{t-6}\) and ∆*DEF*\(_{tot}\), while here is a negative relationship between ∆*GDP*\(_{t-7}\) and ∆*DEF*\(_{tot}\). This combination of lags on variables produce the best explanatory variable significance combined with the best model fit (highest \(R^2_{adj}\)), but theoretically the lag lengths appear random, why it must be noted that the results are problematic to interpret.

*Repo rate* is motivated as a macroeconomic factor of interest as it reflects on the cost of debt. The change in *Repo rate* with 2 and 3-month lags are significant for changes in the default frequency of the *total* portfolio and the *low* risk class. Based on macroeconomic theory, *Repo rate* was expected to take effect after up to 12 months, why the results of significance in only 2 and 3-month lags may be questioned.

The *Repo rate* has no significance on the change in default frequency in the *medium* and *high* risk classes, which may be explained by clients in these risk classes being more exposed and sensitive to idiosyncratic risk factors. Clients in these risk classes, i.e. assigned with risk grades 9-14 and 14-20 respectively, may be more exposed to PD because of e.g. large exposure sizes and number of loans within the bank or unexpected unemployment within the household as a result of unstable working conditions; predictor variables used in the assessment of risk grades to begin with.

### 7.3 Practical implications

PD of retail credit clients was used as a proxy for the payment capacity of households, which allowed the study to use macroeconomic theory to explain expected credit risk movements. To utilize the results showing significance of *GDP* and the *Repo rate*, these macroeconomic factors are recommended to be included in the modelling of the PD of the SRC portfolio. While they do not single-handedly explain changes in the default frequency, they are considered valuable variables to include in models estimating the PD of mortgage loans as they are significant default indicators and can hence add stability to predictions of PD.
Including \textit{GDP} and \textit{Repo rate} in the modelling of retail PD is considered to add point-in-time value as it is available on monthly or quarterly basis. The forward-looking condition of Expected credit loss calculations in IFRS 9 is perhaps not fulfilled as forecasts in \textit{GDP} and \textit{Repo rate} will not alone predict 1-year PD. However, as IFRS 9 does not precise on the amount of macroeconomic factors to include in order to produce forward-looking estimates, any factors found to add significance in predictive power are deemed valuable.

7.4 \textbf{LIMITATIONS OF THE STUDY}

Other researchers (Bofondi and Ropele, 201; Bellotti and Crook, 2010; Chaibi and Fiti, 2015) have found high significance of both house prices and unemployment in credit risk modelling, using different models. The deviations in our results from theirs may indicate multiple linear regression to be a less well-fitted choice of model for our specific dataset. Also, the low explanatory power of all models may stem from biases in the default data as a result of assumptions. For example, risk grade mitigation is not investigated, meaning that the default frequency of a specific risk grade and, in turn, risk class, is not necessarily statistically accurate. Any one client may mitigate from its origin risk grade because of either deterioration or improvement in relative payment capacity – a change not captured in our modelling. Complexity is, however, added to an approach including the risk grade mitigation as soon as risk grading criteria changes.

Segmenting the 18 risk grades (ranging from 3 to 20) into three risk classes (\textit{low, medium, high}) is a simplification interpretation made by the author and not motivated through specific risk-weighing. However, as the results for the total portfolio does not exhibit satisfactory explanatory power in the models either, the risk classification is not considered a crucial shortcoming.

Modelling the default not only with risk grade, but with respect to exposure types, may further improve the significance of the excluded macroeconomic covariates in our regression models. However, as the majority of the SRC portfolio is known to cover mortgage loans, the exposure types are not expected to provide for much better segmentation of results but could be of interest for statistical purposes.

While Probability of Default is generally estimated on a yearly basis, a monthly default frequency was selected for this research to make the best use of our sample size. Also, as IFRS 9 demands PIT PD calculations, the aim was to identify a relationship between the macroeconomic variables and default frequency with as much activity as possible, in order to identify correlated fluctuations in the time series. However, a credit portfolio’s behavior might be difficult to study with such fine granularity, especially with respect to the 90-days past due that it takes for a default to be recognized (see Glossary).
8 CONCLUSION AND RECOMMENDATIONS

In this chapter the conclusions and key takeaways of the study are presented. The research questions are answered with respect to the analysis on theoretical background and empirical findings.

8.1 MACROECONOMIC FACTORS STATISTICALLY SIGNIFICANT FOR PROBABILITY OF DEFAULT

The main question, MQ, asks: What macroeconomic factors are statistically significant for the default frequency in Nordea’s SRC Portfolio?

The aim of investigating MQ was to help identify what factors were of interest in the macroeconomic-based model of default frequency, and by doing so providing more specific substance to SQ. Specifically, using multiple linear regression analysis, we find that the changes in historical default frequency in the whole portfolio during the years 2008-2015 is influenced by GDP and the Repo rate with a number of lag months. Changes in GDP with 6, 7, 9, 10, 12 and 13-month lags are statistically significant for the default frequency, while the Repo rate with 2 and 3-month lags are correspondingly significant. The regression coefficient sign alternates between different lag lengths on GDP and the Repo rate, and hence it is difficult to interpret the immediate effect on the default frequency.

IFRS 9 demands forward-looking macroeconomic factors to be incorporated in PD models. Also, previous research (Bofondi and Ropele, 2011; Bellotti and Crook, 2010; Chaibi and Ftiti, 2015) emphasize the significance of both GDP, interest rates, house prices and unemployment as significant macroeconomic drivers of credit risk. This study identifies both House price index and Unemployment rate as redundant variables in explaining changes in default frequency in Nordea’s SRC portfolio.

An explanation for the deviating results is believed to be caused by the fact that Sweden is not studied in any of the previous research, and that differences in monetary policies, inflation rate targets, political state, household living standards, employments contracts, banking supervision and banking best practices will cause different PD patterns in different countries.

8.2 MACROECONOMIC FACTORS AS INDICATORS OF PROBABILITY OF DEFAULT

The sub question, SQ, asks: How can changes in macroeconomic factors help explain this default frequency?

The aim was to first investigate what macroeconomic factors would theoretically be of interest, and then to investigate the nature of the relationship between those factors and changes in the default frequency. A statistically significant relationship is found between two macroeconomic factors and the default frequency, as outlined in section 8.1. Macroeconomic factors alone, however, do not explain changes in default frequency but should be included in PD models based on idiosyncratic risk factors for added predictive power.
Our results show that changes in macroeconomic factors can help explain changes in the default frequency to some extent. Quantitively analyzed through multiple linear regression analysis, 24.3% of the changes in historical default frequency in the whole SRC portfolio are found to be explained by GDP and the Repo rate with a number of lag months.

The sensitivity to changes in GDP and the Repo rate varies among different risk classes, where a low risk class and the total portfolio responds to changes in these variables well, while a medium and high risk class respond less to such changes and exhibit a weaker model fit through the macroeconomic-based model.

The study’s results are partly supported by previous research. Impacts of macroeconomic factors on PD have been identified (e.g. in Ali and Daly, 2010; Bofondi and Ropele, 2011; Bellotti and Crook, 2010; Chaibi and Ftiti, 2015), but with ambiguous results. It is evident that the choice of statistical model, client segment, portfolio characteristics and quality and parameters of default data, impact what factors are found to impact the PD.

As literature on macroeconomic factors in credit risk modelling has been identified to mainly address corporate, industrial or institutional credit portfolios, this study contributes to the field of research by investigating a retail portfolio. While the LGD of retail clients tends to be smaller than for corporate clients, any expected credit loss in the bank’s credit portfolio needs to be addressed and modelled under IFRS 9, which emphasizes the need to understand credit risk drivers in retail portfolios as well.

### 8.3 Suggestions for Further Research

Modelling retail credit risk with macroeconomic factors could benefit from dividing the data analysis into different data periods, so that it is based on time series with economic downturns and upswings separately, to better model the movements in default frequency with the macroeconomy.

The research could be expanded by applying another statistical model, e.g. survival analysis or logistic regression, to the same sample data. This would provide the field of research with further proof or disproof for the nature of the relationship between macroeconomic variables and retail credit risk.

Using more client-specific covariates in the statistical modelling could also help improve the explanatory power of a similar regression model. Examples include employment industry, hypothesized to relate to changes in industry-specific macroeconomic variables, and city of residence, hypothesized to relate to changes in local unemployment rates and house prices.

If more parameters for a similar historical default dataset are available, the default frequency can be modelled not only based on risk grade or risk class, but also on exposure type. For example, more specific data on client income could be used to differentiate the default frequency between low income and high-income households.
9  REFERENCES

Data sources


Bibliography


GPPC - Global Public Policy Committee of representatives of the six largest accounting networks (GPPC) (2016). The implementation of IFRS 9 impairment requirements by banks: Considerations for those charged with governance of systemically important banks. Availavle at:


10 APPENDIX I

Figure 7 to Figure 10 below illustrates the historical development of the four, macroeconomic variables used in the study, before stationarity transformations, during 2008-2015 (Sources: SCB, Sveriges Riksbank, Valueguard). We see a reduced GDP during the time period Jan 2008-Jan 2010 as a result of the 2008 financial crisis. The House price index is generally increasing throughout the whole time period, indicating a stable demand for housing. In September 2008 the Repo rate was reduced in order to stimulate the economy after the financial crisis, and it has since been kept on record-low levels in order to reach Sweden’s inflation target. Unemployment is clearly seasonally dependent and in October 2008 the Unemployment rate increased and remained high after the financial crisis. Since early 2010, the levels have remained relatively stable.

![Figure 7. Historical development of GDP, 2008-2015](image1)

![Figure 8. Historical development of House Price Index, 2008-2015](image2)
Figure 9. Historical development of Repo rate, 2008-2015

Figure 10. Historical development of Unemployment rate, 2008-2015
11 APPENDIX II

Table 15, Table 16 and Table 17 present results of OLS regression on the initially proposed models (Model 1, Model 2, Model 3 respectively).

Table 15. Regression results of initially proposed Model 1

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<thead>
<tr>
<th>Model 1 OLS Regression on $\Delta DEF_{tot}$</th>
<th>$\beta$</th>
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<th>t-statistic</th>
<th>p-value</th>
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<td>1.401</td>
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<td>$\Delta GDP$</td>
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<td>$\Delta^2 \ln HPI$</td>
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<td>0.893</td>
<td>0.374</td>
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<td>$\Delta RR$</td>
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<td>$UR$</td>
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<td>1.168</td>
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Model 2 summary

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<tr>
<td>$R^2_{adj}$</td>
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<td>BIC</td>
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<td>Durbin-Watson</td>
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<td>Jarque-Bera</td>
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<td>Prob(Jarque-Bera)</td>
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<td>Anderson-Darling p-value</td>
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<td>Breusch-Godfrey LM p-value</td>
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<td>Breusch-Godfrey F p-value</td>
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<td>Breusch-Pagan F p-value</td>
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Source: Author’s computations

(LM is the Lagrange multiplier statistic, F is the F statistic.)
### Table 16. Regression results of initially proposed Model 2

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<td>0.665</td>
<td>0.508</td>
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<td>( \Delta GDP_{t-1} )</td>
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<td>0.007</td>
<td>-1.011</td>
<td>0.315</td>
<td>6.855</td>
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<td>( \Delta GDP_{t-2} )</td>
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<td>0.007</td>
<td>0.624</td>
<td>0.534</td>
<td>6.367</td>
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<tr>
<td>( \Delta GDP_{t-3} )</td>
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<td>0.329</td>
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<tr>
<td>( \Delta GDP_{t-4} )</td>
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<td>1.021</td>
<td>0.311</td>
<td>3.900</td>
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<td>( \Delta^2 \ln HPI_{t-1} )</td>
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<td>0.348</td>
<td>-1.204</td>
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<td>5.459</td>
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<td>0.574</td>
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<td>0.034</td>
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<td>-0.452</td>
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**Model 2 summary**

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*Source: Author’s computations*

*(LM is the Lagrange multiplier statistic, F is the F statistic.)*
Table 17. Regression results of initially proposed Model 3

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Model 3 summary

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<td>Prob(F-statistic)</td>
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</tr>
<tr>
<td>BIC</td>
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<td>Jarque-Bera</td>
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<td>Prob(Jarque-Bera)</td>
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<td>Breusch-Pagan F p-value</td>
<td>0.950598</td>
</tr>
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</table>

Source: Author’s computations

(LM is the Lagrange multiplier statistic, F is the F statistic.)
12 Appendix III

Figure 11. Q-Q plot of Model 4a

Figure 12. Q-Q plot of Model 4b
Figure 13. Q-Q plot of Model 4c

Figure 14. Q-Q plot of Model 4d
13 APPENDIX IV

Figure 15. Model 4a fit on sample data

Figure 16. Model 4b fit on sample data
Figure 17. Model 4c fit on sample data

Figure 18. Model 4d fit on sample data