MASTER THESIS QUANTITATIVE FINANCE

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ERASMUS SCHOOL OF ECONOMICS

# Modelling the interaction between market and credit risk for different economic environments under Basel III

*Author:*
**Annick van der Wal**
*Student number:*
**380344**

*Supervisor EUR:*
**dr. A. Pick**
*Supervisor Zanders:*
**Robbert-Jan Milané**
*Second Assessor:*
**dr. A.M. Schnucker**

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**Abstract**

This paper aims to model the interconnectedness of market risk and credit risks through different macroeconomic environments. From literature, we know that there is a complex intrinsic relation between the two risks and that they are related to the business cycle (Jarrow & Turnbull (2000)). As in practice, they are often modelled separately, this paper adds to existing literature by capturing the joint movements. The relation is established by estimating parameters for different risk variables conditional on three macroeconomic states. The combined effects on a hypothetical European retail bank balance sheet are measured using performance measures, among which the capital adequacy and liquidity ratios from the Basel III accords. We show that in a Recession state, lower interest rates and higher probabilities of loan defaults lead to the expected performance of the retail bank to be worse than in the other two states. In neither state, the regulatory minima for the capital adequacy and liquidity ratios are expected to be exceeded within three years. However, when 95% confidence intervals of risk variables are taken into account, we observe that there are scenarios prevalent in each state, in which the bank goes in default. In addition, we show that incorporating the conjunction of both risks in the model gives a more exhaustive picture of the total risk the bank is exposed to.

## Contents

# 1 Introduction

For banks, it is crucial to optimise their asset and liability structure such that there is an efficient balance between profitability and the cost of regulation. The 2008 financial crisis uncovered flaws in the supervision and regulation of the banking sector as it was highly leveraged with insufficient liquidity buffers under the Basel II accords. This, in combination with other factors such as hazardous incentive structures, lead to the mispricing of risks and induced a global crisis (BCBS (2009)). After this, stricter and more complex regulations were introduced (Anginer et al. (2019)) through the Basel III accords. In these accords, constraints on capital and liquidity buffers are defined which banks need to meet to increase their ability to absorb financial shocks (BCBS (2010a,c)). However, the recent economic downturn caused by the worldwide outbreak of the coronavirus shows to have large impact on banks (Rooijers (2020)). Following this, the European Central Bank (ECB) temporarily relaxed regulatory constraints on, amongst others, the capital buffers to provide capital relief for banks (European Central Bank (2020)). This suggests that the risk exposure that banks are subject to, varies through different macroeconomic environments, and raises the question whether these differences in risk exposure should be accounted for. And if so, how do these differences in risk exposure, through different macroeconomic environments, affect banks and their regulatory capital buffers?

In this paper, we consider the two most important risks for retail banks, credit risk and market risk (Kuritzkes & Schuermann (2010)). We investigate the effects of these two risks on the asset and liability structure of a bank through different macroeconomic environments. As the effects depend on the type, size, operating area and other characteristics of a bank, we restrict our research by investigating the effects on a hypothetical average-sized European retail bank. The area of choice is made for convenience, as banks in Europe all need to comply to the same guidelines and regulations. Due to fundamental differences in value propositions and balance sheet structures of different bank types, we limit the research to the effects on retail banks only, hence excluding other types, such as investment banks. And although we realise that these restrictions still leave us with a heterogeneous sample of banks in terms of size, we believe that investigating the effects on an average-sized bank delivers interesting insights for retail banks on both sides of the spectrum.

From literature and theory, we know that there is an intrinsic relation between credit risk and market risk and that they are related to the business cycle (Alessandrini (1999), Fridson et al. (1997), Jarrow & Turnbull (2000), Barnhill Jr & Maxwell (2002), Drehmann et al. (2010), Liang et al.

(2013)). If they are modelled separately, complex interactions between the two are lost which are crucial when measuring the total risk that banks are exposed to (Alessandri & Drehmann (2010)). Therefore, to obtain a complete overview of the effects of risks on the balance sheet of a bank, besides investigating the effects of credit risk and market risk separately, it is crucial to model the joint effects of the risks as well. However, because the correlation between the two risks is very hard to measure, Jarrow & Turnbull (2000) argue that in practice, the risk measures are often calculated separately and then added, hence assuming perfect correlation. This simplistic approach delivers conservative estimates for the total risk and "inappropriately" large capital buffers (Jarrow & Turnbull (2000)). Incorporating the dependency of the risks on the macroeconomic environment potentially improves the accuracy of the estimated total risk (Alessandrini (1999)).

To incorporate this dependency, we define three macroeconomic states $S_t$ based on changes in historical unemployment rates in the Euro Area. Subsequently, we obtain conditional risk variables for each state that reflect credit risk and market risk by estimating model parameters using the observations of either of the three states. This way, we obtain co-movements of these risk variables through the business cycle. For credit risk, we model annual probabilities of default (PD) for corporate and consumer loans using a distributed lag regression model with mixed data sampling, following Ghysels et al. (2004). We consider interest rates and securities portfolios to reflect market risk, where conditional movements of the short-rate are modelled using two discrete-time short-rate models, introduced by Vasicek (1977) and Merton (1974). To get insight in the added value of incorporating the conjunction of the two risks, we also model the effects while the intrinsic relation to the business cycle is ignored.

Using forecasting and Monte Carlo simulation, we obtain expected future values of the risk variables conditional on the macroeconomic states. The effects of these risk variables are modelled on an hypothetical European retail bank balance sheet. The impact of the risks is measured using different risk and return performance measures, among which capital adequacy and liquidity constraints from the Basel III accords. Using these methods, a broader picture of the total risk that banks are exposed to is obtained. For banks, as well as for regulators, this is of interest as it gives more insight in the combined impact of the two risks.

Alessandri & Drehmann (2010) report another shortcoming of methods to investigate the effects of credit and market risk used in existing literature. They argue that often, the effects of the intersection of credit risk and market risks are investigated on assets only, hence excluding the liabilities. This way, a very important source of interest rate risk for banks is forgotten: the imbalance between rate-sensitive assets and liabilities of banks. By including the entire asset and liability structure of a retail bank in our research, this important source of market risk is included. Drehmann et al. (2010) investigate the combined effects of credit and market risks in the banking books. If the effects are decomposed in the impact of credit risk and market risk separately and the impact of the interaction of both risks, they find that "the interaction term is a significant driver of net-profitability and capital adequacy". We apply their methods to model the effects of interest rate risk in the banking book and credit risk combined. As their method restricts itself to the effects of the risks on the banking book, we extend their work by including a simplified trading book in our analysis as well. To do so, we model the prices of stock portfolios using a discrete-time log-normal diffusion process following the basic assumption for the evolution of stock prices introduced by Black & Scholes (1973). We also extend their research by investigating the effects using a more sophisticated stochastic simulation model for the term structure.

The remainder of this paper is structured as follows: the data used to model the risk variables and to construct a balance sheet of a retail bank will be discussed in Section 2. The methods used to define the macroeconomic environments and to investigate the effects of credit risk and market risk on the balance sheet, conditional on these environments will be discussed in Section 3. The results are presented in Section 4 and Section 5 concludes.

# 2 Data

This section specifies the data used to define the macroeconomic states, to model the risk variables and to construct a hypothetical balance sheet of a European retail bank.

## 2.1 Macroeconomic states data

To model the risk variables through different macroeconomic environments, we define three macroeconomic states $S_t$. We base these states on changes in the monthly Euro Area unemployment rates obtained from Eurostat, as this economic variable reflects the macroeconomic condition in Europe. As the data is only available from January 1995, we extend the monthly unemployment rate in the time period from 1983 until 1994 to include more observations in our analysis.

We construct the extended unemployment rates using available economic and demographic data from individual Euro Area countries, obtained from Eurostat as well. Euro Area countries are included for which there is data available on the total number of unemployed people in the active labour population, the unemployment rate and the size of the total population in (part of) the months from January 1983 until December 1994. From the data, we calculate that the size of the active labour population in the Euro Area in the years 1995 until 1997 is stable around 60.0% of total population. Assuming that from January 1983, until December 1994 this number remains stable as well, the total size of the active labour population of the included countries can be obtained from the total population. The extended unemployment rate follows from the ratio of the amount of unemployed people and the amount of people in the active labour population. Table 1 shows the descriptive statistics of the extended unemployment rates.

### 2.2 Risk variables data

To model credit and market risk, we use historical data on different risk variables that reflect these risks. We model interest rates and bond yields using the model specifications from Vasicek (1977) and Merton (1974), using monthly data on German Bund yields obtained from Bloomberg.

To model credit risk, we use annual PD rates on consumer and corporate loans, obtained from Standard and Poor's (S&P), from 1984 until 2019. For both client types, we distinguish PD rates for both investment grade and speculative grade loans to reflect the differences in default risk among the different credit ratings. These two ratings include loans with credit ratings respectively from AAA to BBB, and BB and lower. As the PD rates are published annually, we model the PD rates using a distributed lag regression model with mixed data sampling. This way, we can use quarterly provided exogenous variables to model the annual PD rates. Following literature (Wilson (1997), Bunn et al. (2005)), we include quarterly exogenous variables on interest rates, market returns, industrial production growth and housing prices in the model. Therefore, we consider again the data on German Bund yields, as well as respectively changes in the S&P500 Stock Index obtained from CRSP, changes in the Euro Area Industrial Production Index and changes in the Euro Area Housing Prices Index. The latter two are obtained from OECD (2020b) and OECD (2020a).

Lastly, to model the stock portfolio returns, we assume that the portfolio the bank holds follows the market return. We therefore again use monthly returns on the S&P500 index to model stock returns. Table 1 shows the descriptive statistics for each time series. For each variable, we choose the starting date equivalent or later than the starting date of the extended unemployment rate, i.e. January 1983. As this variable defines the macroeconomic states, and model parameters are estimated conditionally on these states, this time series indicates the starting point of our analysis.

Table 1: Descriptive statistics

| | Start date | End date | Frequency | Obs. | Avg. | Std. dev. | Min. | Max. |
|---|---|---|---|---|---|---|---|---|
| Unemployment rate Euro Area | Jan/83 | Apr/20 | Monthly | 448 | 9.7% | 0.011 | 7.1% | 12.1% |
| German Bunds 3-month yields | Nov/02 | Apr/20 | Monthly | 210 | 0.9% | 0.016 | -1.0% | 4.3% |
| Consumer PD Investment Grade | 1984 | 2019 | Annually | 36 | 0.1% | 0.004 | 0.0% | 2.0% |
| Consumer PD Speculative Grade | 1984 | 2019 | Annually | 36 | 7.5% | 0.109 | 0.0% | 43.5% |
| Corporate PD Investment Grade | 1984 | 2019 | Annually | 36 | 0.1% | 0.001 | 0.0% | 0.4% |
| Corporate PD Speculative Grade | 1984 | 2019 | Annually | 36 | 4.1% | 0.027 | 0.9% | 11.1% |
| S&P 500 stock index returns | Jan/83 | Apr/20 | Monthly | 448 | 0.8% | 0.043 | -21.7% | 13.2% |
| Euro Area Housing Prices Index | 1984Q1 | 2019Q4 | Quarterly | 144 | 1.0% | 0.009 | -1.4% | 3.1% |
| Euro Area Industrial Production Index | 1984Q1 | 2019Q4 | Quarterly | 144 | 0.4% | 0.016 | -10.3% | 4.4% |

*Note: The table shows start- and ending dates, frequencies, number of observations (Obs.), average values (Avg.), standard deviations (Std. dev.) and minimum and maximum values for the data used in this paper. PD = Probability of Default.*

### 2.3 Balance sheet data

To model the effect of credit risk and market risk on an average-sized European retail bank, we construct a hypothetical but realistic simplified balance sheet. We take averages of different balance sheet components of a sample of retail banks obtained from the BankFocus database following the methods in Alessandri & Drehmann (2010).

Table 2 shows the simplified balance sheet components and their maturities. For each component, we construct buckets based on characteristics and maturity. For loans and residential mortgages, we distinguish between investment grade and speculative grade credit ratings. For loans, residential mortgages and term deposits, we distinguish between maturities, varying from 3 months up until 30 years, as well as between fixed and floating interest rates. Furthermore, we define two levels of riskiness for mortgages, namely residential mortgages that are guaranteed by the Dutch National Mortgage Guarantee ('Nationale Hypotheek Garantie' (NHG)), and mortgages that are not. All loans considered are assumed to be in bullet payment form. Furthermore, the current and savings deposits are assumed to be non-maturing. We model the client rate and outflow behaviour of the non-maturing current and savings deposits separately using a savings model developed by Zanders. Based on real client data, we obtain parameter estimates for a client rate model and savings volume outflow model. The model specifications for this are included in Section 3.3.2.

Table 2: Simplified balance sheet of a retail bank

| **Assets** | **Maturity** | **Liabilities** | **Maturity** |
|---|---|---|---|
| Reserves and Cash | | Consumer Deposits | |
| Residential Mortgages | 3M - 30Y | Current Deposits | - |
| Loans | | Savings Deposits | - |
| Consumer Loans | 3M - 10Y | Term Deposits | 3M - 10Y |
| Corporate Loans | 3M - 10Y | Interbank Loans | 3M - 10Y |
| Traded assets | | Other Liabilities | |
| Stock portfolios | | Equity | |
| Bond portfolios | | | |
| Other Assets | | | |

*Note: The table shows the simplified balance sheet used in this paper. Other assets and liabilities include e.g. physical capital, real estate. M = month, Y = year.*

To obtain a selection of European retail banks from BankFocus, all companies that are currently active and located in Western Europe and that have available accounting data in 2018, 2019 or 2020 are selected. From this subset, commercial banks are selected using two industry classifications, namely the NACE Rev. 2 classification and the North American Industry Classification System (NAICS) 2017. The former is a statistical classification of economic activities in the European Community, which is used to select companies that fall in the category "64 - Financial Service activities, except insurance and pension funding". In addition to this, banks are also required to have the NAICS classification code "52211 - Commercial Banking" to be selected. This leaves us with 4,792 Western European commercial banks, from which the retail banks are selected using the balance sheet descriptive statistics for banking business models from Ayadi et al. (2016). They define three types of commercial banks, namely retail, wholesale and investment banks, which can be distinguished using the balance sheet descriptive statistics in Table 3.

Table 3: Balance sheet descriptive statistics of different bank types from Ayadi et al. (2016)

| Bank Type | | Bank Loans (in % of Assets) | Customer Loans (in % of Assets) | Trading Assets (in % of Assets) | Bank Liabilities (in % of Assets) | Customer Deposits (in % of Assets) | Debt Liabilities (in % of Assets) |
|---|---|---|---|---|---|---|---|
| Retail | Mean | 7.0% | 78.5% | 11.8% | 12.3% | 69.5% | 10.1% |
| | Std. dev. | 0.057*** | 0.079*** | 0.071*** | 0.141** | 0.153*** | 0.078*** |
| Wholesale | Mean | 52.2% | 20.7% | 17.1% | 22.4% | 51.8% | 10.4% |
| | Std. dev. | 0.201*** | 0.151*** | 0.126*** | 0.265** | 0.321*** | 0.193*** |
| Investment | Mean | 11.4% | 23.5% | 60.2% | 14.9% | 49.3% | 19.9% |
| | Std. dev. | 0.092*** | 0.133*** | 0.158*** | 0.189** | 0.311*** | 0.214*** |

*Note: Ayadi et al. (2016) tested the independence of balance sheet clusters using a non-parametric Wilcoxon-Mann-Witney two-sample test. The number of asterisks (*, **, ***, and ****) shows the significance of these tests, namely if the given cluster is statistically different from any other cluster: "Two asterisks (**) implies that the cluster is statistically different from two other clusters but not the third and fourth (closest) ones."*

We compare the balance sheet statistics of our 4,792 commercial banks with the confidence intervals constructed using the means and standard deviations for balance sheet ratios from Ayadi et al. (2016),

$$\text{Confidence Interval} = \min\{1, \max\{0, \text{Mean} \pm 2 \cdot \text{Std. dev.}\}\}, \tag{1}$$

which gives us the results in Table 4. As data is missing for some banks and descriptive statistics, the total amount of available observations for each statistic is included in the table as well. As we observe that there are relatively little observations for the statistic Debt Liabilities (in % of Assets), we exclude this statistic from the analysis. We include all banks in our research from which all five remaining balance sheet statistics fall in the confidence intervals. Especially the amount of customer loans as a percentage of assets is restrictive for a large part of the sample, as this is one of the statistics that is fundamentally different for investment banks. This leaves us with 438 retail banks for our balance sheet analysis.

Table 4: Comparison balance sheet data with statistics of bank types from Ayadi et al. (2016)

| | Bank Loans (in % of Assets) | Customer Loans (in % of Assets) | Trading Assets (in % of Assets) | Bank Liabilities (in % of Assets) | Customer Deposits (in % of Assets) | Debt Liabilities (in % of Assets) |
|---|---|---|---|---|---|---|
| Mean Ayadi et al. (2016) | 7.0% | 78.5% | 11.8% | 12.3% | 69.5% | 10.1% |
| Std. dev. Ayadi et al. (2016) | 0.057 | 0.079 | 0.070 | 0.141 | 0.153 | 0.078 |
| CI lower bound | 0.0% | 62.7% | 0.0% | 0.0% | 38.9% | 0.0% |
| CI upper bound | 18.4% | 94.3% | 26.0% | 40.5% | 100.0% | 25.7% |
| Observations falling in CI | 1021 | 625 | 1089 | 1114 | 1065 | 288 |
| Observations total | 1383 | 1374 | 1304 | 1257 | 1318 | 400 |

*Note: Following the balance sheets statistics from Ayadi et al. (2016), Confidence Intervals (CI) are constructed using the mean and standard deviation of the balance sheet components, $CI = min\{1, max\{0, Mean \pm 2 \cdot Std.\ dev.\}\}$. The table shows the CI bounds, the amount of banks in our sample that have balance sheet data falling in the CI's, and the amount of banks that have data available on these balance sheet components.*

We investigate the sizes of the separate balance components in the empirical data to obtain a hypothetical but realistic balance sheet. For the total size of the balance sheet, we take the average value of the total assets, which is €60.5 billion. We assume that the proportion of loans, traded assets, reserves and cash, consumer deposits, interbank loans and equity are equal to the average proportions in the data. Because there is no distinction between consumer and corporate deposits in the data, we assume that consumer deposits take up 90% of total deposits. This gives us the balance sheet in Table 5. As the data does not distinguish between the buckets based on maturities and characteristics, we base the proportions between the buckets on assumptions. We assume that 50% of loans, residential mortgages and term deposits have floating rates, and while to the other half fixed rates apply. Furthermore, we assume that 75% of residential mortgages have investment grade credit rating (hence, 25% speculative grade) and use equivalent proportions for respectively NHG backed and Non-NHG mortgages. For the different time to maturity buckets, we assume that the notional amount is distributed over time to maturity buckets such that a total duration of equity of the balance sheet is obtained that reflects realistic value sensitivities to fluctuations in interest rates. This is calculated by taking the difference between the value-weighted effective duration of assets and liabilities, and dividing this by the total amount of equity. In practice, retail bank balance sheets have a duration of equity of around 3, which is obtained by actively applying asset-liability management. In our balance sheet composition, we assume that the notional amount of term deposits and interbank loans is distributed equally over the time to maturity buckets. For the residential mortgages, the notional amount of the buckets with a time to maturity less than ten years is twice the amount in buckets with a remaining maturity of more than ten years. For consumer- and corporate loans, the notional amount in buckets with a remaining maturity of five years is 1.5 times the amount in buckets with longer time to maturities. These distribution weights leave us with a total duration of equity of 3.38.

Table 5: Hypothetical balance sheet retail bank constructed from BankScope data

| **Assets** | **of which** | **Proportion (%)** | **of which** | **Total (x bn)** | **of which (x bn)** |
|---|---|---|---|---|---|
| Reserves and Cash | | 8.6% | | €5.2 | |
| Residential Mortgages | | 42.4% | | €25.7 | |
| Loans | | 39.2% | | €23.7 | |
| | *Consumer Loans* | | *15.6%* | | *€9.4* |
| | *Corporate Loans* | | *23.7%* | | *€14.3* |
| Traded Assets | | 9.1% | | €5.5 | |
| | *Stocks* | | *1.7%* | | *€1.0* |
| | *Bonds* | | *6.6%* | | *€4.0* |
| Other Assets | | 1.5% | | €0.9 | |
| Total Assets | | 100% | | €60.5 | |

| **Liabilities** | **of which** | **Proportion (%)** | **of which** | **Total (x bn)** | **of which (x bn)** |
|---|---|---|---|---|---|
| Consumer Deposits | | 60.4% | | €36.6 | |
| | *Current Deposits* | | *24.0%* | | *€14.5* |
| | *Savings Deposits* | | *19.3%* | | *€11.7* |
| | *Term Deposits* | | *17.2%* | | *€10.4* |
| Interbank Loans | | 8.9% | | €5.4 | |
| Other Liabilities | | 23.5% | | €14.2 | |
| Equity | | 7.2% | | €4.3 | |
| Total Liabilities | | 100% | | €60.5 | |

*Note: The table shows the simplified balance sheet with proportions and nominal values of balance sheet components. The size of the components are obtained by taking averages of European retail bank balance sheet data from BankScope. bn = billion.*

## 3 Methodology

In Section 3.1, we discuss the methods to define the macroeconomic states $S_t$. Section 3.2 describes the construction of the risk variables. The methods to obtain the effects of the combined risks on the balance sheet of an average-sized retail bank will be discussed in Section 3.3 and lastly, the performance measures will be introduced in Section 3.4. Figure 1 shows a summarised overview of the methodology.

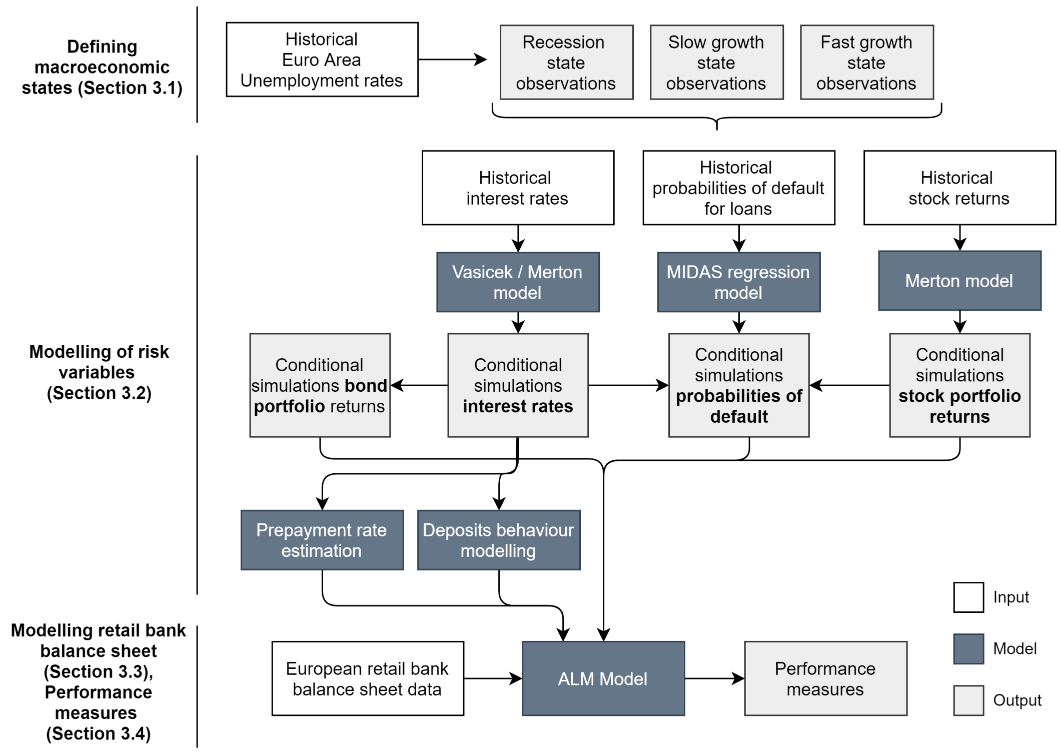



Figure 1: Summarised overview of methodology structure.

*Note: The methodology consists of three parts, where the first part considers the construction of the macroeconomic states. The second part describes the modelling of risk variables, where the states obtained from the first part are used to model the risk conditional on the macroeconomic states. In the last part combines the risk variables from the second part in an Asset-Liability Management model of a retail bank. The effects of the risks variables are expressed using performance measures.*

## 3.1 Defining macroeconomic states

As credit and market risk are both related to the macroeconomic environment, we model the risk variables conditional on the macroeconomic state $S_t$ to capture interdependencies of the risk variables through these relations. Despite the existence of research that distinguish only two regimes to model regime-dependent behaviour of macroeconomic variables, i.e. recession and expansion states, other evidence suggests that differentiating between three state is more suitable to characterise such behaviour, due to the existence of significant behavioural changes in the macroeconomic tendency within the expansion state (Emery & Koenig (1992), Sichel (1994), Van Dijk & Franses (1999)). Within this state, periods of slow growth and fast growth can be distinguished with their own distinctive nature, which might indicate different risk effects within these periods. Therefore, including only two states might not satisfy our objective. Although some research suggests the existence of four states, often two of these states are considered to be rather economic turning points (peaks and troughs) in between recessions and expansions, rather that economic states with a longer duration (Stock & Watson (2014)). Therefore, we define three macroeconomic states, $S_t \in \{R, SG, FG\}$, respectively for Recessions ($R$), Slow Growth ($SG$) and Fast Growth ($FG$) environments. Following a method inspired by Ilmanen et al. (2014), we appoint historical observations to either one of these states when the change in unemployment rate, used as a proxy for the state of the economy, is above or below some threshold value. We specifically base the economic state at time $t$ on the six month change, $\Delta Unemployment_t = Unemployment_{t+6} - Unemployment_t$, as a parsimonious method to find the right balance between neglecting minor changes in the unemployment rate, while capturing only larger tendencies and predominant movements of the business cycle. While the choice of a six-month change specifically is partially selected for convenience, this method proves to be able to make clear distinctions between the akin Slow Growth and Fast Growth states especially. We adopt threshold values $a_1$ and $a_2$, such that $S_t$ corresponds to some state when the six-month change in unemployment rate is respectively above or below the thresholds at a certain point in time, as shown in Equation 2.

$$S_t = \begin{cases} R & \text{if} \quad a_2 \leq \quad \Delta Unemployment_t \\ SG & \text{if} \quad a_1 \leq \quad \Delta Unemployment_t < a_2 \\ FG & \text{if} \qquad\quad \Delta Unemployment_t < a_1. \end{cases} \tag{2}$$

As the Slow Growth state should reflect a more prevalent macroeconomic environment than the Recession and Fast Growth states, we opt to assign a larger amount of observations to this state. However, modelling the risk variables conditional on the states demands for a sufficient amount of observations in each state to be able to obtain reliable parameter estimates. Therefore, the threshold values $a_1$ and $a_2$ are chosen such that $Pr[S_t = R] \approx 0.25, Pr[S_t = FG] \approx 0.25$, and $Pr[S_t = SG] \approx 0.5$ for some $t$, that is, the probability of the macroeconomic state being a Recession or a Fast Growth environment is approximately 25%, and the probability of the state being a Slow Growth environment is approximately 50%. This way, we obtain Recession and Fast Growth states with a smaller amount but more extreme observations than the more common Slow Growth state. The specific probabilities are, however, selected for convenience. We verify the obtained states with true recessions and expansions to ensure that our method provides a viable proxy of different states of the macroeconomic environment.

### 3.2 Modelling financial risk variables

This section concerns the methods to model the risk variables. The aim of these models is to obtain quarterly future expected values of the risk variables conditional on the state $S_t$ for three year ahead, i.e. for the quarters $t + k$, $k = 1, \ldots, 12$. We use PD rates, interest rates, stock portfolio returns and bond yields as variables that reflect credit and market risk. We use the historical observations from the different macroeconomic states $S_t$, as described in Section 3.1, to obtain parameter estimates for the risk variable models for each macroeconomic state. Using these parameter sets to obtain future expected values of the risk variables enables us to investigate the behaviour of the risks in the different macroeconomic environments. Besides the future expected values, we also include the 2.5th and 97.5th percentiles of expected risk variables in our analysis as "worst case" and "best case" scenarios, given a certain state. This allows us to investigate the conditional future expected values as well as a confidence interval around these expectations.

To get further insight into the effects of the risks when the relation between the credit risk and market risk is not included, we also investigate the effects using unconditional estimates for either credit risk or market risk. This way, we are able to investigate the combination of the two risks when their intrinsic relation is neglected. As the expected values of the risk variables in the Slow Growth state are the averages of the values in the most moderate scenario, we adopt this scenario to model the unconditional estimates for either the credit risk variable or the market risk variables. This way, we can investigate how the effects differ when more extreme values of one of the risks, is combined with moderate behaviour of the other risk and hence, extreme joint movements are eliminated.

#### 3.2.1 Modelling interest rates

To obtain the interest rates that apply to the different asset and liability classes, we model market interest rates for different maturities using short-rate models. In literature, many short-rate models are suggested that attempt to capture the empirical movements of interest rates. Modelling the short-rate conditionally on the macroeconomic state $S_t$ not only allows us to estimate different parameters among the states, but also allows us to define different model specifications for each state. As we expect the behaviour of the short-rate to vary among the macroeconomic states, caused by monetary policy of central banks, different short-rate models might be appropriate to capture these behavioural differences. Whereas in one state, a model that is able to capture mean-reverting properties of the short-rate might be optimal, short-rates in other states might be characterised by falling or rising interest rates which might make a model that includes a drift more suitable. In this paper, we explore two of these models.

A first model that we use is the one-factor short-rate Vasicek model as pioneered by Vasicek (1977). The advantage of this model is that it allows for negative interest rates, in contrast to, for example, the popular Cox-Ingersoll-Ross short-rate model introduced by Cox et al. (1985). In the current low interest rate environment, this is a crucial characteristic of a short-rate model. Another characteristic of interest rates that is reflected in the Vasicek model is mean-reversion, which makes it a suitable model specification to capture long-term equilibrium levels of interest rates. Lastly, as we require a unique parameter set to be estimated for each macroeconomic state, a model specification is preferred in which the amount of parameters to be estimated is modest. Therefore, we disregard more sophisticated models, such as multi-factor short-rate models, and explore the one-factor Vasicek model specification in our analysis.

The discrete-time stochastic differential equation of the Vasicek model follows a Ornstein-Uhlenbeck process and is obtained by applying the Euler method to the continuous process. This gives us the following discrete-time process:

$$\begin{aligned} \Delta r_{t+\Delta t} &= r_{t+\Delta t} - r_t && (3) \\ &= \kappa(\mu - r_t)\Delta t + \sigma\sqrt{\Delta t}\,\varepsilon_{t+1}, && (4) \end{aligned}$$

where $\Delta r_{t+\Delta t}$ is the instantaneous change in the short-rate, $\mu$ is the long term average of the short-rate and $\kappa$ is the speed of mean-reverting. Furthermore, $\sigma$ is the volatility of the process and $\varepsilon_t \sim N(0, 1)$. From this short-rate process, the complete term structure can be derived through the definition of the zero-coupon bond price $P(t, T)$ with a contingent claim of 1 at maturity date $T$:

$$\begin{aligned} P(t, T) &= \mathbb{E}_t^{Q}\left[exp\{-\tau y_t(\tau)\}|\mathcal{I}_t\right] && (5) \\ &= exp\{A(t, T) + B(t, T)r_t\}, && (6) \end{aligned}$$

where $\mathcal{I}_t$ is the information set at time $t$. Closed form solutions for $A(t, T)$ and $B(t, T)$ in Equation 6 can be derived by applying the definition of the expectation of a log-normally distributed variable to the expectation in Equation 5. We define the yield at time $t$ for a zero-coupon bond maturing at $t + T$ as

$$y_t(\tau) = \frac{-lnP(t, T)}{\tau} = -\frac{A(t, T)}{\tau} - \frac{B(t, T)}{\tau} r_t, \tag{7}$$

where $\tau$ is the time to maturity. The complete term structure at time $t$ is then obtained by plotting the yields $y_t(\tau)$ against the time to maturity $\tau$.

Since 2009, interest rates have been persistently exceptionally low. Furthermore, following monetary policy of central banks, in theory, interest rates fall in recessions and rise in expansions. As we model interest rates conditionally on the state of the economy $S_t$, we consider a second short-rate model that might capture these characteristics of monetary policy, as well as the current persistency in low interest rates, conditionally on $S_t$. In the parsimonious arithmetic Brownian motion model as introduced by Merton (1974), the short-rate follows a log-normal diffusion process with a drift instead of a mean-reverting process like the Vasicek model. The discrete-time stochastic differential equation for this model is obtained from the continuous process using the Euler discretisation, and defined as follows:

$$\Delta r_{t+\Delta t} = r_{t+\Delta t} - r_t \tag{8}$$

$$= \alpha \Delta t + \sigma \sqrt{\Delta t}\, \varepsilon_{t+1}, \tag{9}$$

where $\alpha$ is the drift parameter, $\sigma$ is the volatility and $\varepsilon_t \sim N(0,1)$. Using this model specification as an alternative to the Vasicek model allows us to investigate a second approach to capture the short-rate behaviour in specific states.

To reflect the differences in behaviour of interest rates through different macroeconomic environments like recession and expansion cycles (Kenc et al. (2003)), we estimate the parameters for both models conditionally on the macroeconomic state $S_t \in \{R, SG, FG\}$ for $\mu_{S_t}$, $\kappa_{S_t}$, $\sigma_{S_t}$ and $\alpha_{S_t}$. This way, we allow the short-rate to have both a different model specification and a different mean, speed of mean-reversion, volatility and drift in the three macroeconomic states.

Despite the conditional modelling of the short-rate, the model performance proves to suffer from the rapid drop in interest rates and subsequent low interest rate environment since the 2008 global crisis, as shown in the short-rate in Figure 4. Besides estimating the parameters conditionally, it turns out that incorporating a structural break at the beginning of 2009 in the $\mu_{S_t}$ and $\kappa_{S_t}$ parameters for the Vasicek model, and in the $\alpha_{S_t}$ parameters for the Merton model, is beneficial to obtain sensible parameter estimates. We therefore distinguish between parameter estimates before and after January 2009 for the $\mu_{S_t}$, $\kappa_{S_t}$ and $\alpha_{S_t}$.

The parameters for both models are estimated using maximum likelihood. We define a parameter set $\theta$ for each state, which consists of $\theta_{S_t} = \{\kappa_{S_t}, \mu_{S_t}, \sigma_{S_t}\}$ for the Vasicek model and $\theta_{S_t} = \{\alpha_{S_t}, \sigma_{S_t}\}$ for the Merton model. As the transition probabilities of the short-rate process

$f(r_{t+\Delta t}|r_t, \theta_{S_t})$ are normally distributed for both model specifications, we define the total likelihood function for both model specifications as follows:

$$\mathcal{L}(\theta_R, \theta_{SG}, \theta_{FG}; r_0, \ldots, r_T) = \sum_{t=1}^{T} ln\left[\sum_{S_t} f(r_t|r_{t-1}, \theta_{S_t}) \cdot \mathrm{I}[r_t \in S_t]\right] \tag{10}$$

where $f(r_t|r_{t-1}, \theta_{S_t})$ is the probability density function of the normal distribution and $\mathrm{I}[S_t = R]$, $\mathrm{I}[S_t = SG]$ and $\mathrm{I}[S_t = FG]$ are indicator functions which equal one when the process is in a certain state $S_t$ at time $t$, and zero otherwise. From this likelihood function, partial likelihood functions can be defined for each state, in which only the observations for that single state are included in the likelihood function. This way, we obtain the maximised likelihood value and parameter estimates for one of the models for a single state:

$$\mathcal{L}(\theta_{S_t}; r_0, \ldots, r_T) = \sum_{r_t \in S_t} ln\left[f(r_t|r_{t-1}, \theta_{S_t})\right]. \tag{11}$$

As for each of the three states, two model specifications are possible, we maximise eight partial likelihood functions from which the optimal model specification is chosen using the Likelihood Ratio Test:

$$LR = -2 \cdot \left[\mathcal{L}(\theta_0; \mathcal{I}_t) - \mathcal{L}(\hat{\theta}; \mathcal{I}_t)\right], \tag{12}$$

where $\mathcal{L}(\theta_0; \mathcal{I}_t)$ is the likelihood value of the model with the highest likelihood, which we want to compare the likelihood value of some other model with, which is given by $\mathcal{L}(\hat{\theta}; \mathcal{I}_t)$. The test statistic of the likelihood ratio test converges to a $\chi^2$ distribution. This way, we explore what the optimal model specification is for the three states combined.

When the model specifications and parameters for the states are defined, future expected values and the 2.5th and 97.5th percentiles of short-rate paths and term structures conditional on the macroeconomic state $S_{t+k}$ for each quarter $t + k$, $k = 1, \ldots, 12$, are found using Monte Carlo simulation.

As interest rates that apply to asset and liability classes are composed of multiple components (risk free rate, market duration spread, market liquidity spread, general market credit spread and idiosyncratic credit spread), there is a spread in interest rates between individual asset and liability classes, depending on the characteristics. Therefore, we adjust the interest rate for each balance sheet class by adding a constant spread, which accounts for these differences in interest rate components following Alessandri & Drehmann (2010). The downside of this method is that in practice, when PD's rise, e.g. caused by an increase in credit risk, spreads on newly issued loans and residential mortgages, or those with a floating rate, would increase as well to reflect increasing losses. As modelling the separate interest rate components is outside of the scope of this paper, we neglect this effect for the sake of simplicity.

We count a higher spread for assets than for liabilities, and a higher spread for balance sheet classes with a lower credit rating, or in case of a residential mortgage, a higher spread for mortgages without NHG insurance than those with. This way, we include heterogeneity of interest rate levels on different balance sheet classes through a fixed spread, however, changes in interest rates are homogeneous among balance sheet classes. The spreads for each asset class in percentage points are shown in Table 6. The client rates for the current and savings deposits will be modelled separately using a savings model developed by Zanders. The model specification for this will be discussed in Section 3.3.2.

Table 6: Interest rate spreads on bank products in percentage points

| Assets | | | Liabilities | |
|---|---|---|---|---|
| Type | Riskiness | Spread (% pnt.) | Type | Spread (% pnt.) |
| Residential Mortgage | NHG | + 2.15% | Interbank Loan | + 0.50% |
| Residential Mortgage | Non-NHG | + 2.25% | Term Deposit | + 1.00% |
| Consumer Loan | IG | + 4.50% | | |
| Consumer Loan | SG | + 6.00% | | |
| Corporate Loan | IG | + 3.50% | | |
| Corporate Loan | SG | + 5.00% | | |

*Note: The table show interest rate spreads for all relevant asset- and liability classes that will be added to the market interest rate to obtain the client rate. NHG = "Nederlandse Hypotheek Garantie" (Dutch National Mortgage Guarantee), IG = Investment Grade, SG = Speculative Grade*

### 3.2.2 Modelling probabilities of default

As a risk variable that reflects credit risk, we use annual PD rates obtained from S&P, where we make a distinction between PD rates for consumer and corporate loans, as well as between investment grade and speculative grade credit ratings. The annual historical one-year default rate for each category is shown in Figure 2. It stands out that there are large differences in PD rates between the categories as well as through time.

Following the methods from Westgaard & Van der Wijst (2001), instead of modelling the PD rates, we model the log-odds ratio of the PD rates for each client type and credit rating at time $t$, Log-Odds $\text{PD}_t = ln\left(\frac{\text{PD}_t}{1-\text{PD}_t}\right)$, to ensure that the PD is bounded between zero and one. Due to few decimal places present in the data, a zero percent change of default is prevalent in the PD rates time series, especially for the investment grade credit rating. However, as the log-odds ratio is not

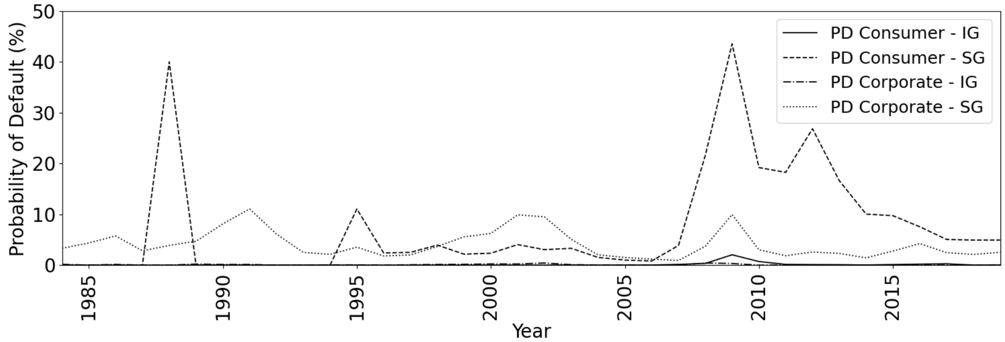


Figure 2: Historical probabilities of default for consumer and corporate loans

*Note: PR = Probability of Default, IG = Investment Grade, SG = Speculative Grade.*

defined if $\text{PD}_t = 0$, the probability is set to 0.001% in case of a PD rate of zero for convenience as a probability of default for a loan will never be exactly zero in practice, as it is never entirely risk free.

We model the Log-Odds $\text{PD}_t$ as a function of output growth, market return and the interest rate, following Wilson (1997). As a measure for output growth, we use changes in the Euro Area Industrial Production Index. For the market return, we use returns on the S&P500 index and for interest rates, we use 3-month German Bund yields. Also, following Wilson (1997) and Bunn et al. (2005), we include changes in housing prices by including changes in the Euro Area Housing Prices Index in the model as well. This leaves us with a model for the Log-Odds PD rate with four exogenous variables.

As there are only few observations available in the historical PD rates, caused by the annual frequency of the data, we model the four PD rates using a distributed lag regression model with mixed data sampling, following Ghysels et al. (2004). This way, we can include the exogenous variables in the model in a quarterly frequency while keeping the PD rates annualised. As literature shows evidence of the existence of multiple discrete regimes in PD rates (Bangia et al. (2002), Pederzoli & Torricelli (2005)), we expect the PD rates to behave differently during the different macroeconomic states. We therefore again model them conditionally on $S_t$ through the regression coefficients. Following the notation from Foroni & Marcellino (2013) and including the states, the model specification is defined as follows:

$$\text{Log-Odds PD}_{t+4h}(S_t) = \sum_{S_t} \beta_{0,S_t} \mathrm{I}[PD_{t+4h} \in S_t] + \sum_{i=1}^{4} \beta_i b(L_m;\theta) x^{(4)}_{i,t_4+w} + \varepsilon_{t_4+h_4}, \tag{13}$$

where $x_{i,t_m+w}$, $i \in \{1,\ldots,4\}$ are the four quarterly explanatory variables. The regression coefficients $\beta_{0,S_t}$ are the constants of the model that are estimated conditionally on the state $S_t$ using the indicator function $\mathrm{I}[PD_{t+mh} \in S_t]$. As there are limited PD rate observations available, we include only a conditional constant in the model to limit the amount of parameters to be estimated. We therefore assume that the effects of the four exogenous variables (market returns, interest rates and changes in output growth and housing prices), reflected in the coefficients $\beta_i$, $i \in \{1, \ldots, 4\}$, are similar among the different states. Furthermore, for the lag distribution $b(L_m; \theta) = \sum_{k=0}^{K} c(k; \theta) L_m^k$, we use the restricted Beta lag specification, which is able to provide different weighting shapes while there is just one parameters $\theta$ to be estimated. Therefore, this lag specification allows for flexibility without the burden of many more parameters to be estimated. Following Ferrara & Marsilli (2019), the lag function is defined as $c(k; \theta) = \theta(1-k)^{1-\theta}$, where we assume $k = 4$, corresponding to exogenous variables being incorporated in the model using four quarter lags. The parameter $\theta$ and therefore the distribution function of the mixed data sampling is assumed to be equivalent for the four exogenous variables. Non-linear least squares is used to obtain model parameters estimates.

To obtain the future expected PD rates, we use the parameter estimates to calculate expected annual future log-odds ratio of PD rates, Log-Odds $\text{PD}_{t+k}$, conditionally on the future state $S_{t+k}$, for three years ahead. To do so, we need the expected values of the exogenous variables as well. The expected values for interest rates and market returns are obtained from the simulations performed in Sections 3.2.1 and 3.2.3. For the expected future values of the other two exogenous variables used in the model, the Industrial Production Index and the Housing Prices Index, we construct a conditional autoregressive model specification with order $p$, AR($p$), $p = 1, \ldots, 3$, where we select the optimal $p$ using the Akaike (AIC) and Bayesian Information Criterion (BIC). The AR($p$) model is specified as follows:

$$X_t = \phi_0 + \sum_{j=1}^{p} \left[ \sum_{S_t} \phi_{j,S_t} \mathrm{I}[X_t \in S_t] X_{t-j} + \varepsilon_t \right], \tag{14}$$

where the coefficients $\phi_j$ are estimated conditionally on the macroeconomic state $S_t$. The constant is represented by $\phi_0$ and is assumed to be equivalent for each state, to limit the amount of parameters to be estimated. The parameters are estimated using linear regression. To do so, we convert the monthly specified macroeconomic state as constructed in Section 3.1, to quarterly by defining a Recession or Fast Growth quarter if that quarter contains two or more months which were respectively Recessions or Fast Growth states. All other quarters are considered being Slow Growth quarters. Using this method, the conditionality of the modelled PD rates on the macroeconomic state is incorporated in the model twofold: on the one hand through the constants in the mixed data sampling regression model in Equation 13, and on the other hand through the (parsimonious) conditional modelling of the exogenous variables.

### 3.2.3 Modelling stock portfolio returns

Similar to the interest rates, the returns of a stock portfolio will be obtained using the discrete-time stochastic process introduced by Merton (1974). A basic assumption as first suggested by Black & Scholes (1973), is that the value of a stock evolves according to a log-normal diffusion process $dY_t = \mu dt + \sigma dW_t$, where $dY_t$ is the instantaneous change in the stock price $Y_t$, $\mu$ is the drift term, $\sigma$ is the volatility and $W_t$ is a standard Brownian motion. We again use the Euler discretisation to obtain the discrete-time process:

$$
\begin{aligned}
\Delta Y_{t+\Delta t} &= Y_{t+\Delta t} - Y_t && (15)\\
&= \mu_{S_t}\Delta t + \sigma_{S_t}\sqrt{\Delta t}\,\varepsilon_t, && (16)
\end{aligned}
$$

where $\varepsilon_t \sim N(0,1)$. As stock returns show differences in mean $\mu_{S_t}$ and volatility $\sigma_{S_t}$ among regimes (Schaller & Norden (1997)), we again estimate the model conditionally on $S_t$. The parameters $\mu_{S_t}$ and $\sigma_{S_t}$ are estimated using Maximum Likelihood using historical data of the S&P 500 Index, where we assume that the stock portfolio that is held by the bank follows the market return. Also, the bank is assumed to keep the current position of the portfolio in each scenario. Monte Carlo simulation is used to obtain expected values and the 2.5th and 97.5th percentiles of stock portfolio returns for the quarters $t+k$, $k = 1, \ldots, 12$.

### 3.2.4 Modelling bond portfolio returns

To obtain a realistic bond portfolio, we investigate yields of zero-coupon bonds with different maturities and credit ratings. We derive the change in bond prices using term structure processes from Vasicek (1977) as described in Section 3.2.1. As the Vasicek model is an exponential affine term structure model, we can describe the price of a zero-coupon bond at time $t$ as $P(t,T) = exp\{A(t,T)+B(t,T)r_t\}$, with closed form solutions for $A(t,T)$ and $B(t,T)$ (Zhou & Mamon (2012)). Using the results from a Monte Carlo simulation for the term structures conditional on the macroeconomic state $S_{t+k}$ for each quarter $t+k$, $k = 1, \ldots, 12$, expected values and the 2.5th and 97.5th percentiles for bond yields are obtained.

## 3.3 Modelling effects risk variables on balance sheet

To investigate the effects of the risk variables on the balance sheet of a retail bank, we use the expected future values and the 2.5th and 97.5th percentile confidence interval bounds of the risk variables conditional on the macroeconomic states $S_t \in \{R, SG, FG\}$, as obtained using the methods in Section 3.2. This section describes methods to model the effects of the risk variables on the hypothetical balance sheet as constructed in Section 2.3. Section 3.3.1 outlines the effects on the banking book. For the deposits modellings, a model developed by Zanders is used, which is briefly described in Section 3.3.2. Lastly, Section 3.3.3 describes the effects on the trading book.

### 3.3.1 Effect of risks on the banking book

To investigate the effects of the risks on the banking book, we use the dynamic methods from Alessandri & Drehmann (2010). We assume that, at time $t$, the bank holds a portfolio of respectively $N$ assets, hence $A_t = [A_{1,t}, \ldots, A_{N,t}]$. Each asset $A_{i,t}$ can be seen as a basket of products with its own characteristics such as size, maturity, time-to-repricing, PD, loss given default, coupon rate, (fixed or floating) interest rate and insurance. Similarly, we assume that, at time $t$, the bank has $M$ liabilities in the banking book, hence $L_t = [L_{1,t}, \ldots, L_{M,t}]$ with $L_{j,t}$ being the basket of liability products with similar characteristics at time $t$.

We assume that the bank shows passive behaviour: the portfolio composition is not actively optimised by the bank during the analysis. This means that if an asset matures or gets prepayed, the same amount is reinvested in equivalent assets with the same characteristics, even if this would not be optimal in practice. To the new assets, new interest rates conditional on the macroeconomic state $S_t$ apply. Concerning client behaviour, we assume that clients show passive behaviour concerning deposits and interbank loans and that, once these products mature, the same amount is rolled over to an equivalent liability and the same repricing characteristics hold.

For the principal payments of fixed-rate residential mortgages however, we do assume that a proportion of these baskets will be prepayed before it actually matures. Despite an often present prepayment penalty, the incentive for consumers to refinance their fixed-rate mortgage rises if interest rates drop. Therefore, usually banks incorporate a prepayment rate in their model conditional on the current interest rates. In our model, we incorporate a prepayment rate that is a function of changes in the interest rate and a constant prepayment rate from BCBS (2010b). The constant prepayment rate is set to 7.5% based on expert knowledge. The prepayment rate is specified as follows:

$$\text{Prepayment rate}_t = min(1, \gamma_t * \text{Constant prepayment rate}), \tag{17}$$

where $\gamma_t$ is a multiplier, which is set at $\gamma_t = 0.8$ in a 200 basis points short-rate upward shock and $\gamma_t = 1.2$ in a 200 basis points short-rate downward shock, following BCBS (2010b). As we do not model discrete interest rate shock scenarios but rather continuous interest rate scenarios, we interpolate the $\gamma_t$ multiplier based on differences between the current interest rate and future predicted interest rates.

Following Alessandri & Drehmann (2010), we define the total loss function for asset $i$ in a certain period $t$ conditional on the expected risk variables in macroeconomic state $S_t$ as

$$Loss_{i,t}(S_t) = \sum_{i}^{N} \delta_i(S_t) \cdot A_{i,t} \cdot LGD_i, \tag{18}$$

where we define $\delta_i(S_t)$ as the default indicator conditional on the macroeconomic state $S_t$, which takes the value 1 with probability $PD_{i,t}(S_t)$ and 0 with probability $(1 - PD_{i,t}(S_t))$. We assume that the PD's for different assets are independent. The exposure at default is reflected in the asset buckets $A_{i,t}$. Furthermore, we assume that the loss given default ($LGD$) for asset $i$ is a constant independent of the macroeconomic state. As in general, loss given defaults are substantially higher for uncollateralised loans than for residential mortgages, we follow Alessandri & Drehmann (2010) and use a loss given default of 30% for residential mortgage loans, 100% for other retail loans and 80% for corporate loans.

Using an algorithm, we model the effects of the financial risks conditional on $S_t$ on the banking book. We start with the initial banking book with $A_0 = \sum_i A_{i,t}$ and $L_0 = \sum_j L_{j,t}$. For each quarter $t + k$, $k = 1, \ldots, 12$, we repeat the following steps:

1. We move to the next quarter $t+k$, where the expected values of risk variables at $t+k$ conditional on $S_{t+k}$ hold and the bank reprices all assets and liabilities with a time to maturity smaller than one quarter according to the new asset characteristics.

2. Following this, credit losses are calculated for each asset $A_{i,t+k}$ using $PD_{i,t+k}(S_{t+k})$ and the total loss function from Equation 18.

3. After incorporating losses from credit risk, interest on assets and liabilities is paid, and principal payments and prepayments on loans are carried out.

4. Returns on the traded asset portfolios are incorporated.

5. Performance measures are calculated.

6. All matured and prepayed assets and matured liabilities are reinvested using the expected

values of risk variables from $S_{t+k}$. Also, in this step an annual growth of 4% of loans and deposits is incorporated.

7. Positive or negative returns are respectively added or subtracted from the "Cash and reserves" balance sheet component. Following this, the balance sheet is rebalanced such that the nominal values of assets and liabilities are equal, by increasing or decreasing the nominal value of equity.

Through these iterations, we obtain the performance measures for each quarter $t$ in each scenario. In this analysis, taxes and operating expenses are neglected.

### 3.3.2 Effect of risks on deposits

The client rates for current and savings deposits and outflow behaviour are modelled using the *Savings Modelling Solution* developed by Zanders. The model assumes that the client rate and the outflow behaviour are interest rate dependent, as would be expected. The client rate model assumes that the client rate is an autoregressive model where the client rate at time $t$ is a linear function of a constant, the lagged client rate, and a 3-month moving average of 3-year maturity market yields. As the model is not specifically built to deal with the currently visible effects of a low interest rate environment, the model allows for client rates to fall below zero. As in practice, we currently notice that banks have capped their deposits client rates at zero (for deposits with a value less than €100.000), we impose this restriction as well. This is a simplistic way to incorporate interest rate dependency in the client rate, although we are aware of the fact that this restriction violates the conceptual soundness of the linear regression model.

For the performance measures, it is necessary to obtain an accurate calculation of the present value of deposits. To do so, we need the volume outflow of current and savings deposits. In practice, the amount of deposits that gets withdrawn from the current and savings deposits by clients shows interest rate dependent behaviour. Therefore, to model the outflow, we use the *Savings Modelling Solution* developed by Zanders as well. The model assumes that the outflow of deposits at time $t$ is an autoregressive linear regression function. It incorporates a constant, the lagged outflow, a 12-month outflow lag (to incorporate a seasonality effect) and the difference between the client rate and the market rate as exogenous variables. In this formula, the difference between the client rate and the market rate represents the incentive of the client to withdraw their money from their deposits account. If the difference between the client rate and the market rate becomes smaller, the incentive to withdraw grows as the client is more likely to move their money to investments that retrieve a higher return.

As we have no historical data to estimate the parameters for the *Savings Modelling Solution*, we use the parameters estimated using historical client data from a bank. Therefore, we assume that the outflow patterns of our hypothetical retail bank are equivalent to the bank from which we have obtained the data.

#### 3.3.3 Effect of risks on the trading book

The expected future values and the 2.5th and 97.5 percentile confidence interval bounds of the stock returns and bond yields conditional on $S_t$ are used to obtain the effects of market risk on the trading book. The traded asset portfolio is simplified and is assumed to only consist of bonds and stocks. Derivatives and other more complex instruments are neglected. Often, the traded assets of a retail bank are not specifically held to make profit, however, devaluation of these assets might influence the banks performance. The return on the traded assets at time $t + k$ conditional on $S_{t+k}$, $k = 1, \ldots, 12$, is calculated by multiplying the return on the assets by the size of the asset portfolio.

### 3.4 Performance measures

The combined effects of the risks at the different balance sheet components can be quantified using performance measures. We define risk as well as return performance measures, discussed respectively in Section 3.4.1 and Section 3.4.2.

#### 3.4.1 Risk performance measures

We define two performance measures from the Basel III accords that are introduced to provide capital adequacy: the Total Capital Ratio and the Leverage Ratio. The capital that is preserved through these requirements serves as a buffer to absorb unexpected losses and to secure the survival of the bank. Banks should hold a minimum amount of core (Tier 1) and supplementary (Tier 2) capital of 10.5% of their risk weighted assets to account for the exposure of risk that follows from risky assets. This is captured in the Total Capital Ratio. In our simplified balance sheet, no distinction is made between Tier 1 and Tier 2 capital, such that we define the numerator of the Total Capital Ratio simply as the total amount of equity. The risk weighted assets are calculated following the weight factors obtained from BCBS (2010a).

Furthermore, the Leverage Ratio is a risk based requirement that serves to cap the leveraged activities of banks which appeared problematic in the 2008 global crisis (BCBS (2010a)). Under Basel III, the minimum proportion of Tier 1 capital to the amount of assets is restricted at 3.0%. In practice, banks often preserve higher amounts of Tier 1 and Tier 2 capital than the Total Capital Ratio and Leverage Ratio prescribe. This way, banks are able to absorb unexpected losses without their capital ratios falling below the central bank regulatory minimum. The two ratios are defined as follows:

$$\text{Total Capital Ratio} = \frac{\text{Tier 1} + \text{Tier 2}}{\text{Risk Weighted Assets}} \geq 10.5\%, \tag{19}$$

$$\text{Leverage Ratio} = \frac{\text{Tier 1}}{\text{Total consolidated assets}} \geq 3.0\%. \tag{20}$$

Furthermore, we also include the Liquidity Coverage Ratio and the Net Stable Funding Ratio from the Basel III accords as liquidity risk performance measures. The objective of the Liquidity Coverage Ratio is to ensure that banks hold a sufficient amount of high-quality liquid assets to meet a 30-day stress period cash outflow demand. The stressed outflow is calculated using the in- and outflow factors obtained from BCBS (2010d).

The Net Stable Funding Ratio ensures that banks hold sufficient stable funding with medium and long-term maturity to prevent large maturity mismatches between assets and liabilities. The required amount of stable funding is calculated using liquidity characteristics of assets for the coming year (BCBS (2010c)), combined with the available stable funding and required stable funding factors from BCBS (2014).

In practice, banks often hold additional amounts of high quality liquid assets and available stable funding, on top of the amount prescribed. The Liquidity Coverage Ratio can be quite volatile in practice such that the Liquidity Coverage Ratio swings between 120% and 150%. The Net Stable Funding Ratio is less volatile, most banks aim to hold a Net Stable Funding Ratio around 130%. The formulas for the two ratios are defined as follows:

$$\text{Liquidity Coverage Ratio} = \frac{\text{High Quality Liquid Assets}}{\text{30-day stress-period Liquidity Outflow}} \geq 100\%, \tag{21}$$

$$\text{Net Stable Funding Ratio} = \frac{\text{Available Amount of Stable Funding}}{\text{Required Amount of Stable Funding}} \geq 100\%. \tag{22}$$

Violation of the capital adequacy and liquidity ratios is undesirable as it can lead to increased supervision, lower investor confidence and an increase in difficulty to raise capital on the capital markets.

To get insight in the interest rate risk that the bank is exposed to, we define the Economic Value of Equity, which is the present value of the difference between positive and negative cash flows that follow from assets and liabilities (BCBS (2010b)):

$$\text{Economic Value of Equity} = \sum_{k}^{K} CF(k) \cdot DF(t_k), \tag{23}$$

where $CF_t$ is the time bucket midpoint of cash flows at time $t$ and $DF(t_k) = exp(-R(t_k) \cdot t_k)$ is the continuously compounded discount factor. The difference between the Economic Value of Equity and the net present value of the cash flows, is that for the Economic Value of Equity, the zero curve is used for discounting. The zero curve is obtained from the simulated yield curve from Section 3.2.1 using the bootstrapping methods in de Barbanson & van Grootheest (2011). To assure that the difference in Economic Value of Equity among the different scenario's is caused by differences in future cash flows, we use the expected yield curve in the Slow Growth state to construct the zero curve. The volume of outflowing cash flows for deposits are obtained using the *Savings Modelling Solution* developed by Zanders. The model specification for this is discussed in Section 3.3.2.

Using this measure, we define a related measure to get insight in the effect of interest rate shocks following BCBS (2010b). First, the difference in the Economic Value of Equity ($EVE$) between a benchmark scenario $EVE_0$ and some scenario $i$, $EVE_i$, as caused by a change in interest rates is reflected in the $\Delta EVE = EVE_0 - EVE_i$. As a benchmark scenario, we use the expected value of the yield curve in the Slow Growth state, such that we use the most moderate scenario as benchmark. To get more insight in the Economic Value of Equity-at-Risk, we perform two of the regulatory Supervisory Outlier Tests, for which we choose the most simplistic but penalising scenarios. The test statistic is obtained by calculating the Economic Value of Equity in the cases of parallel instantaneous yield curve shocks with respective magnitudes of 200 basis points up and down (European Banking Authority (2018)). Besides the cash flows, also the discount curve is adjusted in these scenarios. Using these measures, we can investigate the differences in interest rate sensitivity among the different states.

### 3.4.2 Return performance measures

The Net Interest Income at time $t$ is the difference between income and expenses of interest at time $t$ and is also used by Alessandri & Drehmann (2010). It measures the impact of changes in net cash flows generated by the banking book portfolio through changes interest rates:

$$\text{Net Interest Income}_t = \text{Interest Income}_t - \text{Interest Expenses}_t. \tag{24}$$

For banks, there exists a trade-off between the stability of the Net Interest Income and the Economic Value of Equity. The first is a return measure that reflects earnings, where the second is a value measure. As it is impossible to improve both measures simultaneously (BCBS (2010b)), the objective is to find the right balance between the two. Banks often ignore credit risk in Net Interest Income computations, however, because we are specifically interested in the conjunction between market risk and credit risk, we incorporate both risks.

Besides the Net Interest Income, we also define the performance measures Return on Equity and Return on Assets, both measures of bank profitability. The Return on Equity, the net profit per dollar of equity is a good measure for the shareholders to see how much is earned on their investment. In our analysis, we assume that profit and losses made by the bank are reflected in the value of the bank through rising or falling equity. We assume that no dividend payouts are done. The Return on Assets is slightly more general, and provides information on how much is earned per dollar of assets, and hence, how efficiently the bank is run. The formulas for the two ratios are as follows:

$$\text{Return on Equity} = \frac{\text{Net Return}}{\text{Total Equity}}, \tag{25}$$

$$\text{Return on Assets} = \frac{\text{Net Return}}{\text{Total Assets}}. \tag{26}$$

# 4 Results

In this section, the results are discussed. Section 4.1 elaborates on the definition of the macroeconomic states. Section 4.2 discusses the results of the risk variables estimated conditionally on these macroeconomic states. Finally, in Section 4.3, the effects of the risk variables on the retail bank balance sheet are considered in terms of the performance measures.

## 4.1 Macroeconomic states

Figure 3 displays the unemployment rate in the Euro Area, together with the Recession, Slow Growth and Fast Growth states coloured respectively red, blue and green. Table 7 shows the threshold values that mark the 25th and 75th percentiles of six month changes in unemployment rate, used to appoint observations to each state. In this table, also the amount of observations falling in each state is given.

Table 7: Thresholds (left) and observations (right) in different economic states $S_t$

| Thresholds | Value | Percentile |
|---|---|---|
| $a_1$ | -0.30 | 25th |
| $a_2$ | 0.20 | 75th |

| State $S_t$ | Percentage | Observations |
|---|---|---|
| Recession | 23.6 % | 106 |
| Slow Growth | 50.0 % | 224 |
| Fast Growth | 26.3 % | 118 |
| Total sample | 100 % | 448 |

*Note: The left table show the threshold values $a_1$ and $a_1$ for the 25th and 75th percentiles of observations of changes in six month unemployment rates in the Euro Area. The right table shows the percentage and amount of observations falling above or below the threshold, which corresponds to the three macroeconomic Recession, Slow Growth and Fast Growth states.*

We observe that the periods around 1983, from 1990 until 1993, around 2001, from 2008 until 2009 and from 2011 until 2012 are marked as Recession states. These states roughly correspond to respectively the tightening of monetary policy in the US from 1980, the oil price shock and the US savings- and loan crisis in 1992, the dotcom bubble, the 2008 global crisis and the European sovereign debt crisis around 2011. Except the latter one, all recession periods fall in line with recessions from the US business cycle indicator provided by the National Bureau of Economic Research (NBER (2020)). The Fast Growth states appear to be more difficult to distinct using the current method as Fast Growth and Slow Growth states alternate often in some periods. We observe Fast Growth states in the years 1987 until 1990, 1998 until 2000, 2007 and 2014 until 2018. It stands out that overall, Recessions and Fast Growth states roughly seem to alternate every few years with Slow Growth states in between, which corresponds to what we would expect of the business cycle.

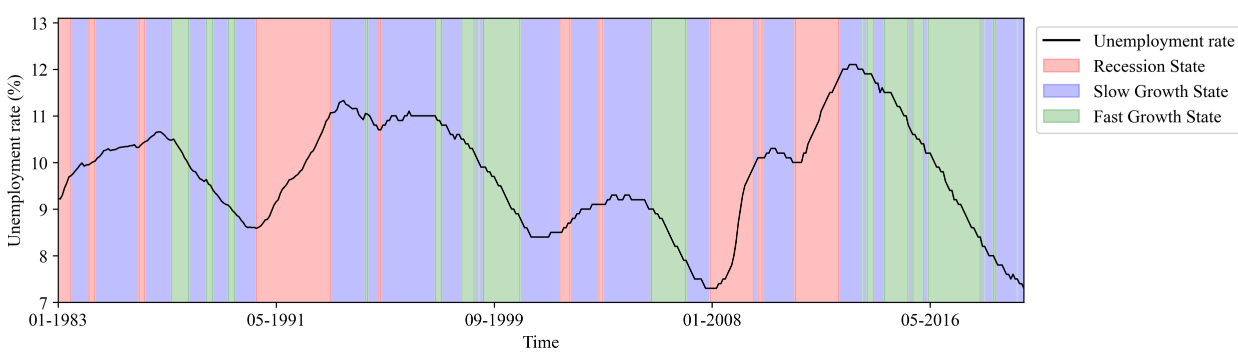



Figure 3: Unemployment rate Euro Area with three macroeconomic states

### 4.2 Financial risk variables

This section describes the model parameters from the risk variables, estimated conditionally on the observations from the macroeconomic states.

#### 4.2.1 Interest rates

Table 8 shows the parameter estimates for both the Vasicek and Merton models, for the three macroeconomic states. Also, for both models, the partial log likelihood values that are obtained by including the observations for a single state in the likelihood function are included for each state. From these values, we conclude that for each state, the Vasicek model is the optimal model and that the mean reverting property is a better fit than the Merton model specification with drift.

Table 8: Interest rate parameter estimates and log likelihoods for Vasicek and Merton

| | Vasicek | | | | | | Merton | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\kappa_{S_t,<2009}$ | $\kappa_{S_t,>2009}$ | $\mu_{S_t,<2009}$ | $\mu_{S_t,>2009}$ | $\sigma_{S_t}$ | Partial LogL | $\alpha_{S_t,<2009}$ | $\alpha_{S_t,>2009}$ | $\sigma_{S_t}$ | Partial LogL |
| Recession | 0.03 | 0.16 | 0.95 | -0.21 | 1.15 | **-10.36** | -1.63 | -0.76 | 1.16 | -15.52 |
| t-stat | 0.011 | 0.079 | 0.261 | -0.432 | 0.909 | | -0.052 | 0.131 | 0.012 | |
| Slow Growth | 0.04 | 0.07 | 0.31 | 0.12 | 0.29 | **96.32** | -0.22 | 0.08 | 0.29 | 96.06 |
| t-stat | 0.007 | -0.033 | 0.022 | 0.029 | 0.594 | | 0.003 | 0.123 | 0.132 | |
| Fast Growth | -0.46 | -0.14 | 0.27 | 0.11 | 0.29 | **76.99** | 1.11 | -0.16 | 0.28 | 76.89 |
| t-stat | -0.027 | 0.031 | 0.013 | 0.033 | 0.712 | | 0.004 | 0.023 | 0.923 | |

*Note: The table shows parameter estimates and log likelihood values for two short-rate model specifications (Vasicek and Merton), for three macroeconomic states (Recession, Slow Growth and Fast Growth states). Highest log likelihood values per state are in bold.*

As for each of the three states, two model specifications are defined, we construct eight possible combinations of model specifications. Table 9 shows the log likelihood value for each specification. We test each total log likelihood value against the log likelihood of model specification 1, with has the highest log likelihood value, using the Likelihood Ratio test from Equation 12. We observe that model specification 1 has a significantly better fit than all specifications that have a Merton specification for the Recession state. However, for the models that use the Vasicek specification for the recession states, a particular model choice for the other states does not deliver more significant improvements in terms of log likelihood. As model specification 1 has the highest log likelihood, we adopt this specification to obtain our interest rate future expected values and 2.5th and 97.5th percentile confidence interval bounds.

Table 9: Results Likelihood Ratio test for different interest rate model specifications

| | Recession | Slow Growth | Fast Growth | Total LogL | LR test stat. |
|---|---|---|---|---|---|
| Model specification 1 | Vasicek | Vasicek | Vasicek | 162.95 | 0 |
| Model specification 2 | Vasicek | Vasicek | Merton | 162.85 | 0.20 |
| Model specification 3 | Vasicek | Merton | Vasicek | 162.69 | 0.52 |
| Model specification 4 | Merton | Vasicek | Vasicek | 157.79 | 10.32** |
| Model specification 5 | Vasicek | Merton | Merton | 162.59 | 0.72 |
| Model specification 6 | Merton | Vasicek | Merton | 157.69 | 10.52** |
| Model specification 7 | Merton | Merton | Vasicek | 157.53 | 10.84** |
| Model specification 8 | Merton | Merton | Merton | 157.43 | 11.04*** |

*Note: Results likelihood ratio test for the Vasicek and Merton models for Recession, Slow Growth and Fast Growth states. The results are tested against model specification 1, which has the highest likelihood test statistic. Asterix indicate significance, where * indicates* $\alpha = 0.01$, ** *indicates* $\alpha = 0.05$ *and * indicates* $\alpha = 0.10$.

The historical short-rate, and future expected values and confidence interval bounds for the short-rate for the next three years, conditionally on the macroeconomic states, can be found in Figure 4. We observe that the expected pattern for interest rates in a Recession state is much more volatile than in the other two states, which corresponds to what we would expect. Especially in the Recession state around 2008, it is visible that interest rates changed more drastically than they did in the economic growth states. Furthermore, interest rates in the Recession and Slow Growth state follow a mean-reverting process from the Vasicek model which causes their forecasts to remain stable around their mean value. The short-rate in the Fast Growth state however, moves slightly up towards its mean.

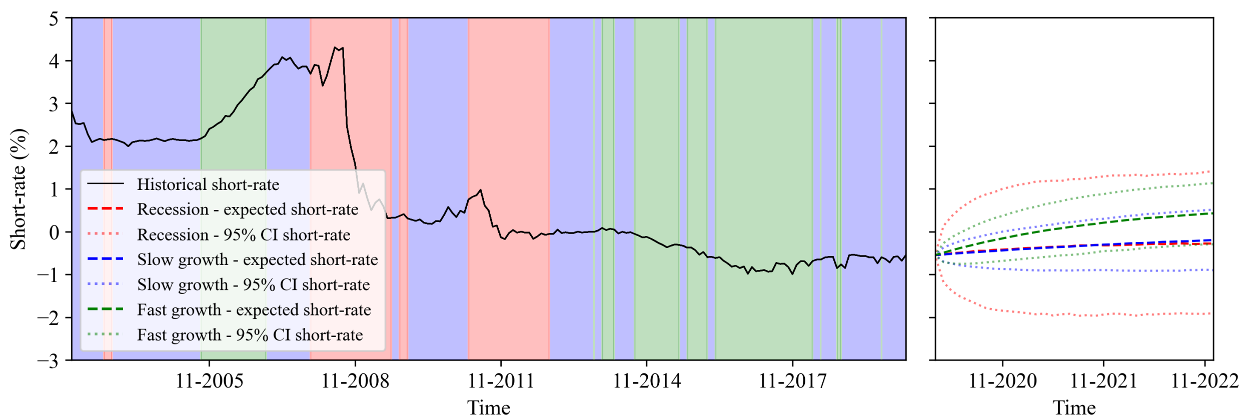


Figure 4: Short-rate historical values and Monte Carlo simulation results

#### 4.2.2 Probabilities of default

Table 10 shows the regression results for the AR($p$) models for the exogenous variables for the distributed lag model, the Euro Area Industrial Production Index and the Euro Area Housing

Prices Index. For both variables, the AR(1) model has a higher log likelihood, AIC and BIC value than the AR(2) model specification. Also, most of the parameter estimates in the AR(1) model specification are significantly different from zero. Therefore, we adopt the AR(1) model specification for the forecasting of the exogenous variables. The forecasting results of the AR(1) model conditional on the macroeconomic states for the Euro Area Industrial Production Index are shown in Figure 5, and for the Euro Area Housing Prices Index in Figure 6. It stands out that in the Recession state, both housing prices and industrial production drop, whereas in the other two states, both indicators are expected to rise.

Table 10: Estimates for AR(p) models for Output Growth Index and Housing Prices Index

| Industrial Production Index | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| p = 1 | $\phi_0$ | $\phi_{1,R}$ | $\phi_{1,SG}$ | $\phi_{1,FG}$ | | | | LogL | 241.02 |
| Parameter | 2.51 | 0.96 | 0.98 | 0.98 | | | | AIC | 490.04 |
| t-stat | 0.209 | 4.165 | 6.757 | 53.405 | | | | BIC | 501.92 |
| p = 2 | $\phi_0$ | $\phi_{1,R}$ | $\phi_{1,SG}$ | $\phi_{1,FG}$ | $\phi_{2,R}$ | $\phi_{2,SG}$ | $\phi_{2,FG}$ | LogL | 226.38 |
| Parameter | 2.30 | 1.52 | 1.20 | 0.97 | -0.55 | -0.22 | 0.01 | AIC | 466.77 |
| t-stat | 0.015 | 0.081 | 0.078 | 0.015 | -0.032 | -0.013 | 0.000 | BIC | 487.56 |

| Housing Prices Index | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| p = 1 | $\phi_0$ | $\phi_{1,R}$ | $\phi_{1,SG}$ | $\phi_{1,FG}$ | | | | LogL | 110.27 |
| Parameter | 0.68 | 0.99 | 1.00 | 1.00 | | | | AIC | 228.54 |
| t-stat | 0.039 | 2.189 | 3.431 | 2.918 | | | | BIC | 240.42 |
| p = 2 | $\phi_0$ | $\phi_{1,R}$ | $\phi_{1,SG}$ | $\phi_{1,FG}$ | $\phi_{2,R}$ | $\phi_{2,SG}$ | $\phi_{2,FG}$ | LogL | 54.33 |
| Parameter | 0.24 | 1.73 | 1.85 | 1.55 | -0.74 | -0.86 | -0.55 | AIC | 122.66 |
| t-stat | 0.004 | 0.062 | 0.039 | 0.035 | -0.027 | -0.018 | -0.012 | BIC | 143.45 |

*Note: The table shows regression results for the autoregressive model of order $p$, $p = \{1, 2\}$ for both the Industrial Production Index and the Housing Prices Index. The model considers a constant $\phi_0$, and autoregressive coefficients conditional on the macroeconomic state $S_t$, $\phi_{j,S_t}$, $j \in \{1, 2\}$. Three macroeconomic states are defined: Recession, Slow Growth and Fast Growth states, such that $S_t \in \{R, SG, FG\}$.*

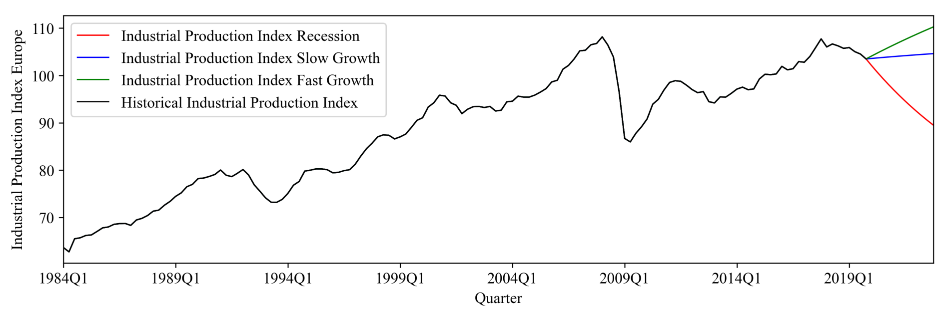



Figure 5: AR(1) forecasts of Industrial Production Index conditional on three macroeconomic states

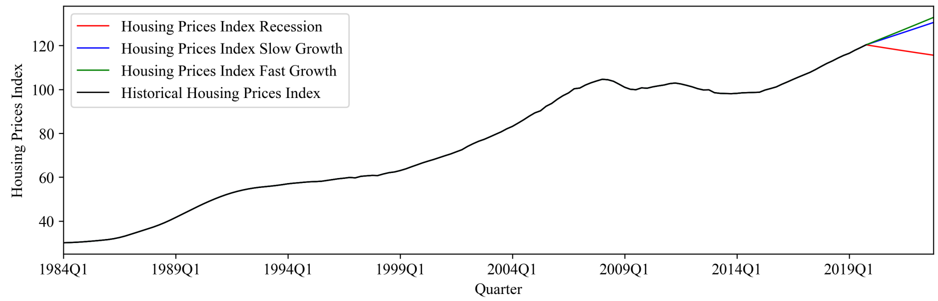



Figure 6: AR(1) forecasts of Housing Prices Index conditional on three macroeconomic states

When we estimate the conditional constants, exogenous variable coefficients and the distributed lag variable $\theta$ for the PD rate models, we find that many of the parameter estimates for the coefficients are not significantly different from zero. Therefore, we test whether the models where all exogenous variables are included perform significantly better than the nested models that only include the conditional constants, and no exogenous variables, using an F-test. With the degrees of freedom of respectively 4 and 9 for the nested and the full model specifications, we have a critical value for $\alpha = 0.05$ of 3.63. We observe that for both corporate PD rates, the critical value is not exceeded. Hence, for these PD rates, the full model specifications do not perform better than the simple nested models. Therefore, we model the corporate PD rates using only the conditional constants. The PD rate models for the consumer PD rates however, despite not all coefficients being significantly different from zero, do perform better than the simple nested models, hence we adopt these specifications.

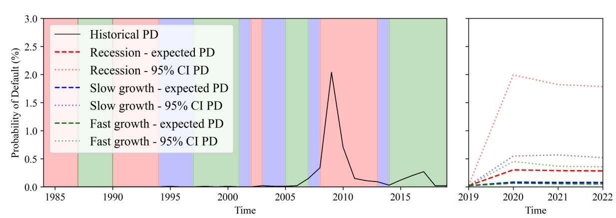
Table 11: Parameter estimates for Distributed Lag MIDAS model for PD rates

| Consumer - IG | $\beta_{0,R}$ | $\beta_{0,SG}$ | $\beta_{0,FG}$ | $\beta_1$ | $\beta_2$ | $\beta_3$ | $\beta_4$ | $\theta$ | $\sigma$ | $R^2$ | F-stat |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Parameter | -6.08 | -6.99 | -7.15 | -3.97 | -1.82 | -0.32 | -31.06 | 55.13 | 0.96 | 0.578 | 19.918 |
| t-stat | -5.397 | -6.181 | -12.989 | -1.048 | -0.068 | -1.978 | -0.430 | 0.488 | 0.747 | | |
| Consumer - SG | $\beta_{0,R}$ | $\beta_{0,SG}$ | $\beta_{0,FG}$ | $\beta_1$ | $\beta_2$ | $\beta_3$ | $\beta_4$ | $\theta$ | $\sigma$ | $R^2$ | F-stat |
| Parameter | -1.28 | -1.15 | -1.41 | -8.99 | 9.66 | -0.80 | -41.39 | 81.92 | 1.76 | 0.674 | 29.212 |
| t-stat | -1.558 | -1.518 | -0.985 | -1.354 | 0.383 | -2.752 | -0.370 | 0.462 | 7.354 | | |
| Corporate - IG | $\beta_{0,R}$ | $\beta_{0,SG}$ | $\beta_{0,FG}$ | | | | | | $\sigma$ | $R^2$ | F-stat |
| Parameter | -7.67 | -8.25 | -8.96 | | | | | | 2.02 | 0.212 | 1.879 |
| t-stat | -5.878 | -12.365 | -7.811 | | | | | | 5.011 | | |
| Corporate - SG | $\beta_{0,R}$ | $\beta_{0,SG}$ | $\beta_{0,FG}$ | | | | | | $\sigma$ | $R^2$ | F-stat |
| Parameter | -2.91 | -3.49 | -3.98 | | | | | | 1.41 | 0.269 | 0.597 |
| t-stat | -1.993 | -3.603 | -2.998 | | | | | | 1.452 | | |

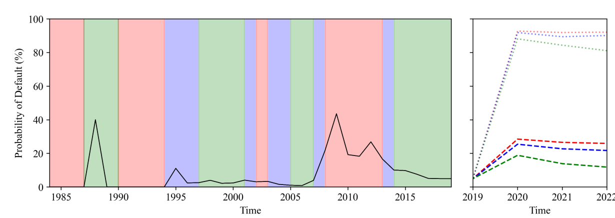
*Note: The table shows parameter estimates, t-statistics, $R^2$ and F-statistics for the distributed lag model for four types of Probability of Default (PD) rates. The parameters $\beta_i$, $i = 1, \dots, 4$, correspond respectively to coefficients for the exogenous variables market return, industrial production growth, interest rates and changes in housing price. The $\theta$ is the parameter of the lag function $c(k, \theta)$. IG = Investment Grade, SG = Speculative Grade.*

This gives the results in Table 11, where the parameter estimates for the distributed lag model for the PD log-odds ratios are shown. It stands out that most conditional estimates of the constants and the volatility parameters are significantly different from zero. The $R^2$, that reflects the amount of variation that is explained by the model, differs among the PD types, with higher explaining power for the consumer PD rates than for the corporate PD rates.

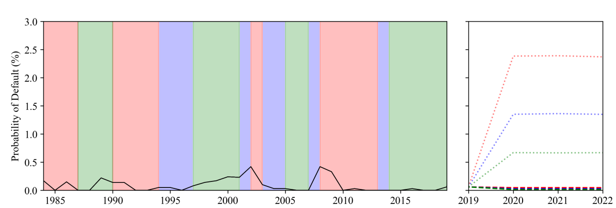
When we use the model specification to forecast the PD rates three years ahead, we obtain the results in Figure 7. The expected PD rates as well as the upper bounds of the 95% confidence intervals show different patterns among the four categories. It stands out that the expected values of the PD rates are approximately equivalent to the average values of the historical PD rates. The 97.5th percentile of PD rates are relatively high, as they reflect rather extreme scenarios for the risk variable. However, for both the investment grade types, even the upper bounds are no higher than 2%, as could be expected since this is approximately the historical maximum for this PD. Although differences in the historical PD rate patterns among the three states are less obvious that for the other macroeconomic variables, the PD rate forecasts show some interesting characteristics among the sates. It stands out that the upper confidence interval bounds in Recession states are visibly higher than in the other states, indicating higher PD rates in the more extreme scenarios of these states. The expected PD rates are higher for Recession states as well, although this difference is less obvious. Similarly, PD rates for the Fast Growth state are, for the upper bounds as well as for the expected values, lower that the equivalent PD rates in the other two states. All together, the expected values and 97.5th percentiles of PD rates correspond to what could be expected.



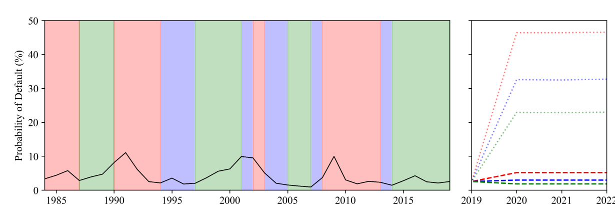

(a) Consumer Investment Grade




(b) Consumer Speculative Grade




(c) Corporate Investment Grade




(d) Corporate Speculative Grade

Figure 7: Historical values and forecasts of probability of default rates

### 4.2.3 Stock portfolio returns

Table 12 shows the parameter estimates for the stock index returns. We observe that the average return is higher for the two Growth states than for the Recession state. Also, the Growth states show less volatile stock returns than the Recession state, which is exactly what could be expected. Figure 8 shows the historical time series of the S&P500 stock index, with expected values and 2.5th and 97.5th confidence interval bounds for the index. These forecasts reflect the results in Table 12.

Table 12: Stock index parameter estimates and log likelihoods Merton

| | $\alpha_{S_t}$ | $\sigma_{S_t}$ |
|---|---|---|
| Recession | 0.016 | 0.048 |
| t-statistic | 0.006 | 1.087 |
| Slow Growth | 0.108 | 0.041 |
| t-statistic | 0.013 | 0.274 |
| Fast Growth | 0.084 | 0.044 |
| t-statistic | 0.023 | 0.120 |

*Note: The table shows (annualised) parameter estimates and t-statistics for the mean and variance of the Merton model, for three macroeconomic states (Recession, Slow Growth and Fast Growth states).*

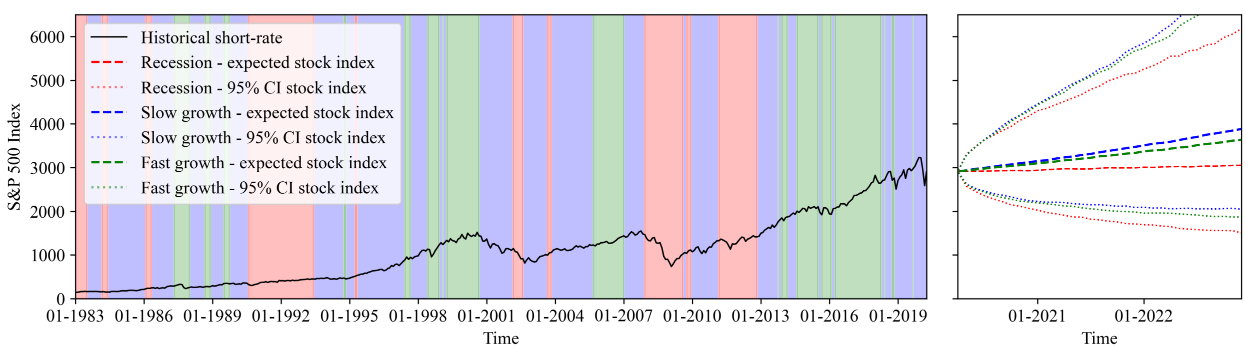



Figure 8: S&P500 historical values and Monte Carlo simulation results

## 4.3 Effects of risks variables on balance sheet

In this section, the effects of the conditional risk variables on the balance sheet of the hypothetical retail bank are discussed. In Section 4.3.1, the results of the risk performance measures are discussed, and in Section 4.3.2 the performance measures on return.

### 4.3.1 Results risk performance measures

Table 15 in Appendix A.1 and Figure 9 show the results for the Total Capital Ratio. We observe that in each macroeconomic state, the Total Capital Ratio is expected to grow and thus stay above the regulatory minimum. More specifically, the Total Capital Ratio is highest for the Fast Growth state, followed by the Slow Growth state. The Recession state has the lowest expected Total Capital Ratio. In the lower percentile scenarios, which reflect the confidence interval bounds of the risk variables, the Total Capital Ratio regulatory minimum is exceeded within a few quarters in each macroeconomic state. From the results, it follows that in the "worst case" scenarios in each macroeconomic state, the Total Capital Ratio of the retail bank potentially falls below the regulatory minimum. As we ignore taxes and operating expenses, in practice, the Total Capital Ratio will not rise as fast as the results show.

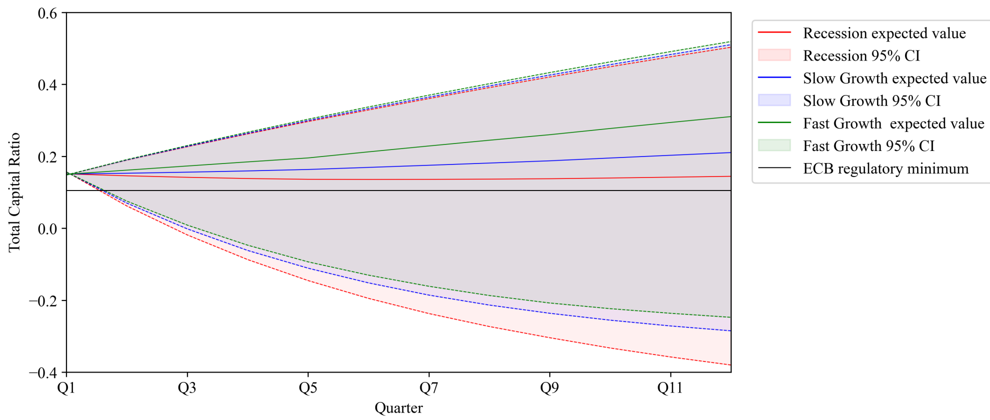



Figure 9: Total Capital Ratio expected values and confidence intervals in three economic states

The results for the Leverage Ratio are shown in Table 16 in Appendix A.1 and Figure 10. The results show that, equivalent to the results for the Total Capital Ratio, in each macroeconomic state, the Leverage Ratio is expected to stay above the regulatory minimum. But again, in the lower percentile scenarios in each macroeconomic state, the Leverage Ratio potentially falls below the regulatory minimum within just a few quarters. Also, the expected performance in terms of Leverage Ratio is worse for the Recession state than for the Growth states. Similar to the results of the Total Capital Ratio, the expected Leverage Ratios are higher than they would be in practice, because taxes and operating expenses are ignored.

In Table 17 in Appendix A.1 and Figure 11, the results for the Liquidity Coverage Ratio are given. In practice, this measure is often volatile and therefore, banks keep enough liquid assets such that the Liquidity Coverage Ratio remains above the regulatory minimum. Our results show that indeed, the Liquidity Coverage Ratio is expected to stay far above the regulatory minimum, however, because we only use forecasts in a quarterly frequency, we do not observe the high volatility of the Liquidity Coverage Ratio that is present in practice. In the lower percentile scenarios, the

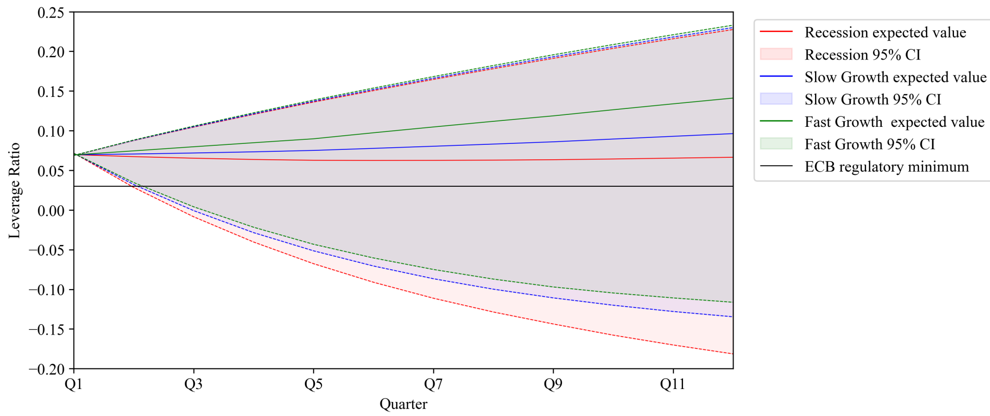



Figure 10: Leverage Ratio expected values and confidence intervals in three economic states

Liquidity Coverage Ratio is potentially violated in each state.

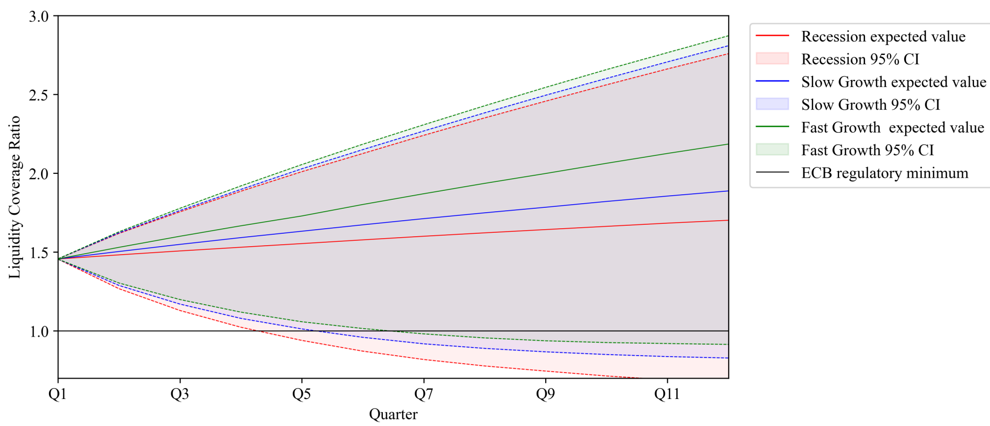



Figure 11: Liquidity Coverage Ratio expected values and confidence intervals in three states

The Net Stable Funding Ratio, displayed in Table 18 in Appendix A.1 and in Figure 12, shows a similar image as the Liquidity Coverage Ratio. The Net Stable Funding Ratio is expected to grow in each state, with the growth being larger in the Slow Growth and Fast Growth states. None of our scenarios shows a violation of the Net Stable Funding Ratio regulatory minimum set by the ECB, not even the lower percentile scenarios. Again, banks tend to hold sufficient amounts of required stable funding such that they meet up to the liquidity requirements.

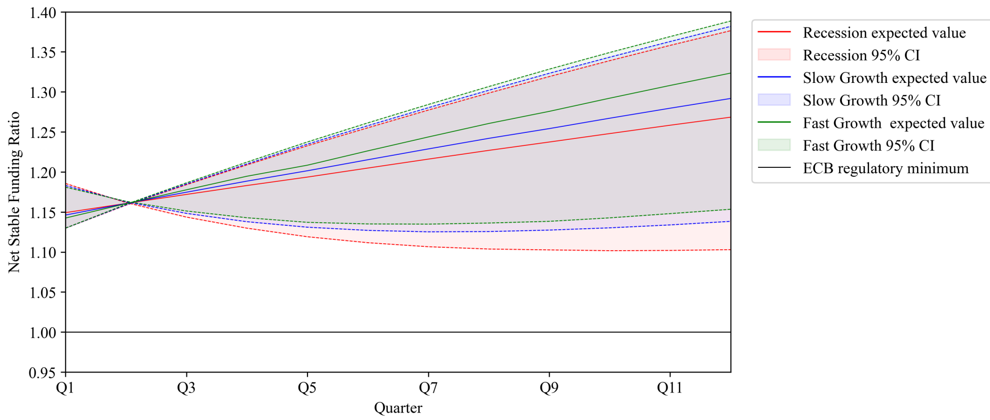



Figure 12: Net Stable Funding Ratio expected values and confidence intervals in three states

Table 13 shows the results for the (Δ)Economic Value of Equity. We observe that the values for the Recession states are lower than those of the Growth states, which is caused by the future cash flows being higher for states with higher interest rates. To get more insight in the effects of interest rate shocks in the different states, Table 14 shows the results of the two Supervisory Outlier Tests. It stands out for both a 200 basis point down- and upward shock, the interest rate exposure is larger in the Growth states than in the Recession state. This is caused by the Economic Value of Equity of the assets being larger with lower discounting factors following the lower interest rates. As the effect is smaller for the liabilities, that have a shorter maturity, the total effect is larger for Growth states.

Table 13: Results (Δ) Economic Value of Equity (x bn)

| State | Recession | | | Slow Growth | | | Fast Growth | | |
|---|---|---|---|---|---|---|---|---|---|
| Scenario | 2.5 pctl | 50 pctl | 97.5 pctl | 2.5 pctl | 50 pctl | 97.5 pctl | 2.5 pctl | 50 pctl | 97.5 pctl |
| Economic Value of Equity | 85.0 | 85.7 | 86.2 | 85.7 | 86.2 | 86.6 | 86.3 | 86.6 | 86.8 |
| Δ Economic Value of Equity | 1.2 | 0.5 | -0.1 | 0.5 | 0.0 | -0.4 | -0.2 | -0.4 | -0.6 |

*Note: The table shows the results of the Economic Value of Equity (EVE) and the ΔEVE in three macroeconomic states (Recession, Slow Growth and Fast Growth states). For each state, upper and lower bounds for the confidence interval are given, which is constructed by taking the 2.5th and 97.5th percentile expected values of the risk variables. The ΔEVE is calculated by subtracting the EVE from the EVE in the Slow Growth scenario, the most basic scenario.*

These results show that most of the risk performance measures are potentially violated in the lower percentile scenarios. Despite the interest rate risk exposure being larger in the Growth states, the overall performance in terms of risk measures is worse in the Recession state. As could be expected, for each of the capital adequacy and liquidity ratios from the Basel III accords, the expected value for the Recession state lies below the expected values of the other two states.

Table 14: Results Supervisory Outlier Test

| | Recession | Slow Growth | Fast Growth |
|---|---|---|---|
| Regular EVE | 85.7 | 86.2 | 86.6 |
| SOT -200 BP | 93.2 | 156.4 | 131.3 |
| Difference from EVE | 8.7% | 81.4% | 51.6% |
| SOT +200 BP | 52.4 | 46.1 | 38.3 |
| Difference from EVE | -38.8% | -46.5% | -55.8% |

*Note: The table shows the results of the 200 basis points up- and downward parallel yield curve shift test of the Supervisory Outlier Test for a retail bank in three macroeconomic states (Recession, Slow Growth and Fast Growth states). EVE = Economic Value of Equity, SOT = Supervisory Outlier Test, BP = basis points.*

### 4.3.2 Results return performance measures

In this section, we will discuss the results for the return performance measures. To get some grasp on the effects on the performance of the bank in terms of return, in Figure 13, the total amount of Equity is given in each scenario. It stands out that in each macroeconomic state, in the 2.5th percentile scenarios, where the "worst" 2.5th percentile of risk variables is used, the amount of equity reaches zero and the bank potentially goes in default after three quarters due to higher PD rates, lower net interest incomes and a lower returns on traded assets. However, in each state, the expected scenario is that the amount of equity remains positive, with higher equity in the Growth states than in the Recession state, as could be expected. Again, as taxes and operating expenses are ignored, in practice, the amount of equity would not rise as fast as the results show.

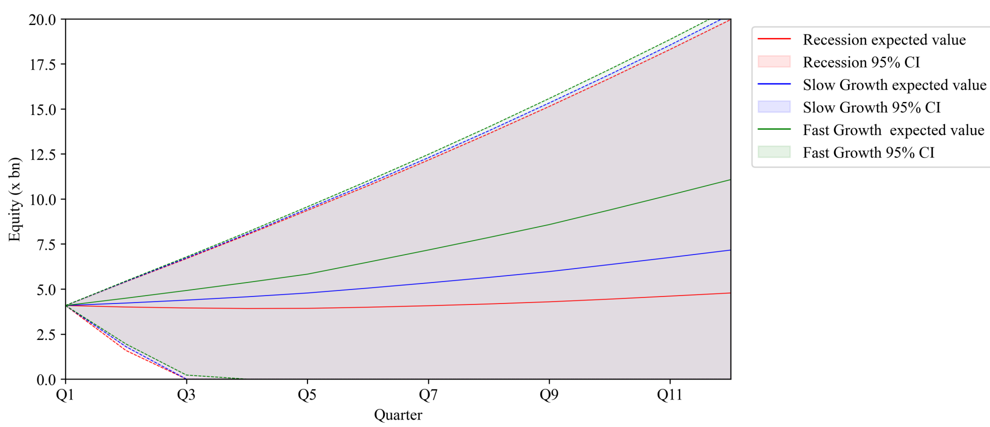



Figure 13: Equity expected values and confidence intervals in three economic states

in Table 19 in Appendix A.1 and Figure 14, the results of the Net Interest Income are given. As could be expected, the Net Interest Income is lower if the interest rates are lower. This results in lower Net Interest Income in the Recession states, which is one of the reasons the total return of the bank is lower in this state. Also, we included the expected future values of PD rates in the Net

Interest Income in the projections. As no interest is paid on defaulted loans, the higher PD rates in the Recession state also lead to a lower Net Interest Income.

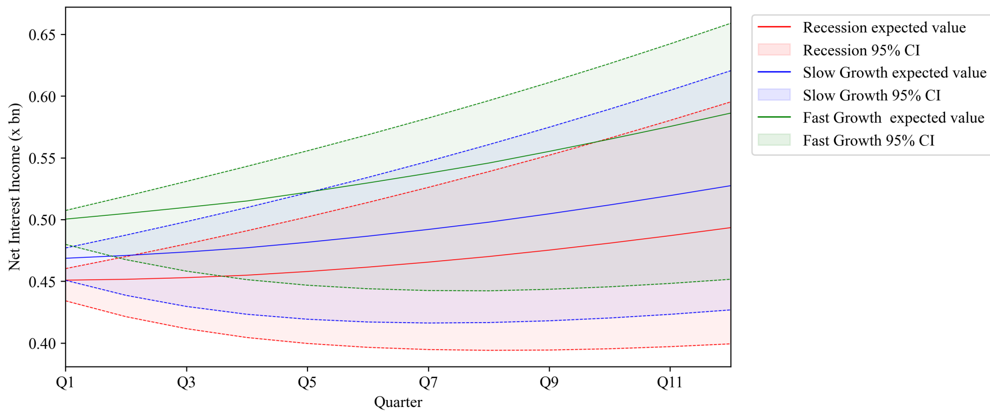



Figure 14: Net Interest Income expected values and confidence intervals in three states

In Table 20 in Appendix A.1 and Figure 15, the results for the Return on Equity are given. Within the first quarters, in the "worst case" scenarios of all states, the bank goes in default. Therefore, the lower percentiles are not shown, as these are not defined when the amount of equity reaches zero. We observe that overall, the Return on Equity is fairly low in each state, and in each scenario. This can be explained by the equity rising fast when high returns are obtained, of which the effect is larger than it would be in practice because taxes and operating expenses are ignored. Because of the rising equity, the Return on Equity drops rapidly. This also leads to the Return on Equity being higher in the expected scenarios than in the upper bounds of the confidence intervals of the risk variables: the amount of Equity rises fast in these scenarios, which leads to a decreasing Return on Equity as the denominator of the return performance measure increases fast.

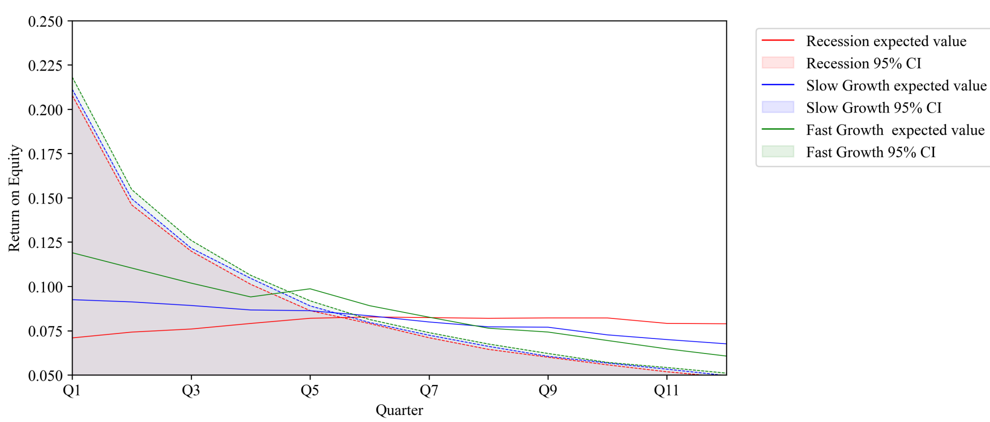



Figure 15: Return on Equity expected values and confidence intervals in three economic states

Lastly, Table 21 in Appendix A.1 and Figure 16 show the results for the Return on Assets. We observe that for each scenario, the Return on Assets moves to some average value around one percent. This can again be explained by the design choices of the methods. As a positive return causes the amount of assets to grow through a growth in cash and reserves, the Return on Assets shows a decreasing decay. Similarly, negative returns cause the amount of assets to drop, causing the Return on Assets to grow, but at a decreasing rate. More interesting are the expected scenarios: again, caused by the higher PD rates, the lower interest rates and the lower returns on traded assets portfolios, the Return on Assets is lower for in the Recession state than in the other states. Overall, the performance of the bank in the Recession state in terms of return measures is worse than the performance in the growth states.

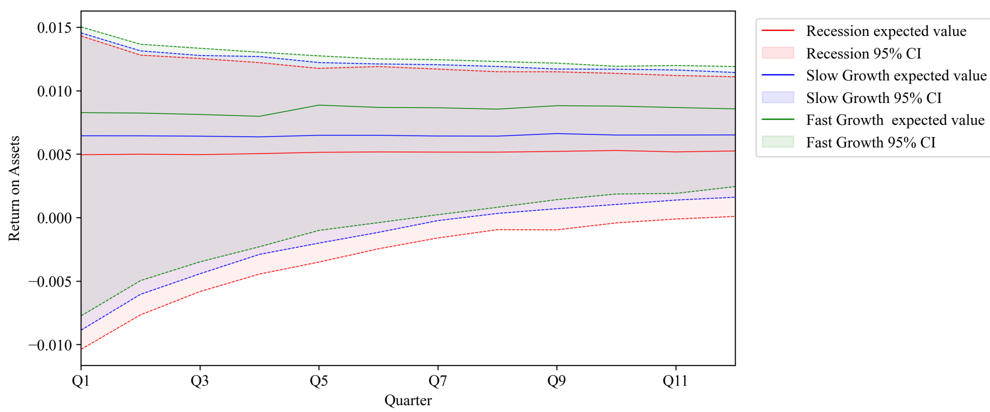
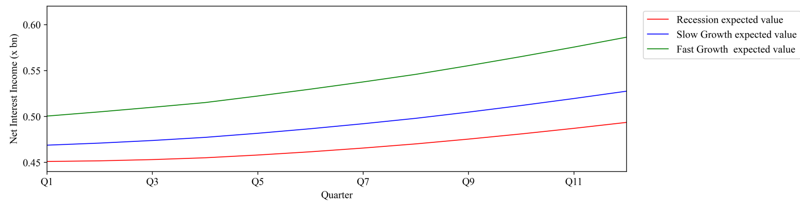
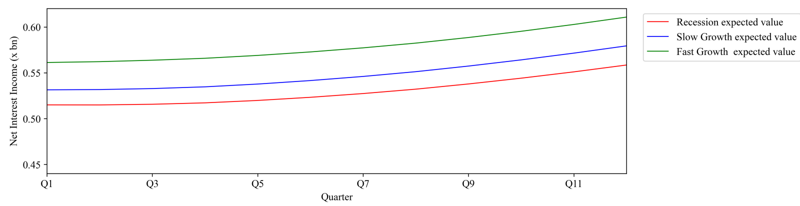



Figure 16: Return on Assets expected values and confidence intervals in three economic states

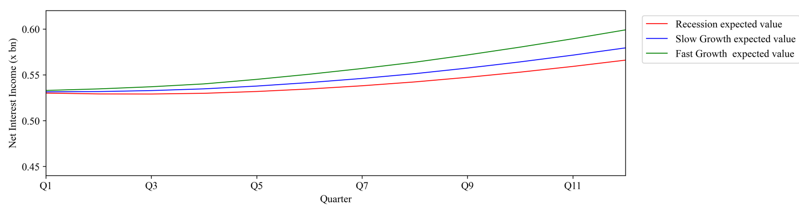
Lastly, we investigate the effects on the performance measures when the relation between the two risks through the business cycle is ignored. For this, we use the expected risk variables in the three macroeconomic states. Figure 17a shows the expected Net Interest Income when the relation between the two risks is incorporated, which is the equivalent of the results in Figure 14. Figure 17b shows the Net Interest Income when only the market risk variables are modelled conditionally on the business cycle. For the PD rates, for each state, the expected values in the Slow Growth state are used. Hence, the relation between the market risk variables and the credit risk variable that is established through the business cycle is ignored. Figure 17c shows the effects of the risks, while the relation is ignored by assuming the market risk variables follow the expected values in the Slow Growth state. In both cases, when the conjunction between the two risks is ignored, the Net Interest Income shows different and less extreme patterns. Especially for the Net Interest Income in the Recession state, the expected value is lower when the relation between both risks through their dependence on the business cycle is incorporated. Figures 18 until 21 in Appendix A.2 show equivalent graphs for the other performance measure. These results indicate the importance of including the intrinsic relation between the two risks as well. From these figures, we observe that for a complete overview of the effects of the combined risks, it is best if the relation between credit risk and market risk is incorporated.




(a) With conditional market risk and conditional credit risk




(b) With conditional market risk only




(c) With conditional credit risk only

Figure 17: Net Interest Income of a retail bank

*Note: The Net Interest Income is given for three macroeconomic states (Recession, Slow Growth and Fast Growth state) when both market risk and credit risk (a), only market risk (b) and only credit risk (c) are modelled conditional on the macroeconomic state.*

# 5 Conclusion

This paper provides a comprehensive method to investigate the combined effects of credit and market risk through their dependence on the business cycle. It aims to identify the complex effects of risk variables on the balance sheet of an average European retail bank. We show that in a Slow Growth and Recession state, interest rates are expected to be lower compared to a Fast Growth state. At the same time, PD rates are expected to be higher in a Recession state. Combined with a worse performance of the traded asset portfolio in this state, the expected performance of the retail bank in a Recession state is therefore worse than the in the other two states, which is reflected in the risk as well as return performance measures. In neither state, the regulatory minima of the capital adequacy and liquidity ratios from the Basel accords are expected to be exceeded within three years. However, when 95% confidence interval bounds of risk variables are taken into account, we observe that there are scenarios prevalent in each state, in which the bank goes into default. This is caused by the prevalence of extreme rises in loan defaults, falling net interest income and low returns on traded assets portfolios in each state given the current model specifications of risk variables. When we investigate the effects of both risks on the performance measures when the relation between the two risks is ignored, we observe that the total effect of both risks is less extreme, especially in the Recession state. This indicates that for a complete overview of the risks, the conjunction between the two risks that is established through the business cycle should be incorporated, otherwise, an important part of risk is neglected.

Although we have aimed to incorporate as many of the pathways through which credit risk and market risk affect a retail bank into the framework as possible, there are some limitations to our paper. First of all, the results are limited in the sense that they depend highly on the design choices made in this paper. First of all, we investigate the effects of risks on an average retail bank, however, the spectrum of retail banks in terms of client types and balance sheet compositions and asset-liability management strategies is much broader than the hypothetical retail bank used in this research. The magnitude of potential differences in effects of the risks depend on the client portfolio, balance sheet structure and strategy of the bank. Besides this, the construction of scenarios and thus, the risk variables used, also depend on choices and assumptions made throughout the paper. As the parameters of each risk variable model are estimated conditionally on the macroeconomic state, the construction of these states influences the risks in the different scenarios. The assumption is made that the macroeconomic states contain 25%, 50% and 25% of observations respectively for the Recession, Slow Growth and Fast Growth states. This distribution is constructed such that the amount of observations in the moderate Slow Growth scenario is larger than the other two scenarios, however, the specific distribution is arbitrary and might influence the outcomes. Another consequence following the design choice of the three macroeconomic states is that the total amount of parameters to be estimated grows, which, combined with the use of monthly, quarterly and even annual data frequencies, delivers less significant results. As the obtained results indicate different effects among the three macroeconomic states, we do have to note that many of the estimated parameters in the risk variable models are not significant.

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# A Appendix

## A.1 Tables

This Appendix shows Tables containing the results of the performance measures.

Table 15: Results Total Capital Ratio

| State | Recession | | | Slow Growth | | | Fast Growth | | |
|---|---|---|---|---|---|---|---|---|---|
| Scenario | 2.5 pctl | 50 pctl | 97.5 pctl | 2.5 pctl | 50 pctl | 97.5 pctl | 2.5 pctl | 50 pctl | 97.5 pctl |
| Q1 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 |
| Q2 | 0.10 | 0.16 | 0.19 | 0.11 | 0.17 | 0.19 | 0.11 | 0.17 | 0.19 |
| Q3 | 0.06 | 0.17 | 0.23 | 0.08 | 0.18 | 0.23 | 0.08 | 0.19 | 0.24 |
| Q4 | 0.02 | 0.18 | 0.27 | 0.05 | 0.20 | 0.27 | 0.06 | 0.21 | 0.27 |
| Q5 | -0.01 | 0.19 | 0.30 | 0.03 | 0.21 | 0.31 | 0.04 | 0.23 | 0.31 |
| Q6 | -0.03 | 0.20 | 0.34 | 0.01 | 0.22 | 0.34 | 0.03 | 0.26 | 0.35 |
| Q7 | -0.05 | 0.21 | 0.37 | 0.00 | 0.24 | 0.37 | 0.02 | 0.28 | 0.38 |
| Q8 | -0.07 | 0.22 | 0.40 | -0.01 | 0.25 | 0.41 | 0.01 | 0.30 | 0.41 |
| Q9 | -0.08 | 0.23 | 0.43 | -0.01 | 0.27 | 0.44 | 0.01 | 0.32 | 0.44 |
| Q10 | -0.09 | 0.24 | 0.46 | -0.02 | 0.28 | 0.47 | 0.01 | 0.34 | 0.47 |
| Q11 | -0.10 | 0.25 | 0.49 | -0.02 | 0.29 | 0.49 | 0.01 | 0.36 | 0.50 |
| Q12 | -0.11 | 0.26 | 0.52 | -0.02 | 0.31 | 0.52 | 0.01 | 0.38 | 0.53 |

*Note: Note: The table shows the results of the expected Total Capital Ratio in three macroeconomic states (Recession, Slow Growth and Fast Growth states), for twelve quarters ahead. For each state, upper and lower bounds for the confidence interval are given, which is constructed by taking the 2.5th and 97.5th percentile expected values of the risk variables.*

Table 16: Results Leverage Ratio

| State | Recession | | | Slow Growth | | | Fast Growth | | |
|---|---|---|---|---|---|---|---|---|---|
| Scenario | 2.5 pctl | 50 pctl | 97.5 pctl | 2.5 pctl | 50 pctl | 97.5 pctl | 2.5 pctl | 50 pctl | 97.5 pctl |
| Q1 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 |
| Q2 | 0.05 | 0.07 | 0.09 | 0.05 | 0.08 | 0.09 | 0.05 | 0.08 | 0.09 |
| Q3 | 0.03 | 0.08 | 0.11 | 0.04 | 0.08 | 0.11 | 0.04 | 0.09 | 0.11 |
| Q4 | 0.01 | 0.08 | 0.12 | 0.02 | 0.09 | 0.12 | 0.03 | 0.10 | 0.13 |
| Q5 | 0.00 | 0.09 | 0.14 | 0.01 | 0.10 | 0.14 | 0.02 | 0.11 | 0.14 |
| Q6 | -0.01 | 0.09 | 0.15 | 0.01 | 0.10 | 0.16 | 0.01 | 0.12 | 0.16 |
| Q7 | -0.02 | 0.10 | 0.17 | 0.00 | 0.11 | 0.17 | 0.01 | 0.13 | 0.17 |
| Q8 | -0.03 | 0.10 | 0.18 | 0.00 | 0.12 | 0.18 | 0.01 | 0.14 | 0.19 |
| Q9 | -0.04 | 0.11 | 0.20 | -0.01 | 0.12 | 0.20 | 0.00 | 0.15 | 0.20 |
| Q10 | -0.04 | 0.11 | 0.21 | -0.01 | 0.13 | 0.21 | 0.00 | 0.15 | 0.21 |
| Q11 | -0.05 | 0.11 | 0.22 | -0.01 | 0.14 | 0.22 | 0.00 | 0.16 | 0.23 |
| Q12 | -0.05 | 0.12 | 0.23 | -0.01 | 0.14 | 0.24 | 0.00 | 0.17 | 0.24 |

*Note: Note: The table shows the results of the expected Leverage Ratio in three macroeconomic states (Recession, Slow Growth and Fast Growth states), for twelve quarters ahead. For each state, upper and lower bounds for the confidence interval are given, which is constructed by taking the 2.5th and 97.5th percentile expected values of the risk variables.*

Table 17: Results Liquidity Coverage Ratio

| State | Recession | | | Slow Growth | | | Fast Growth | | |
|---|---|---|---|---|---|---|---|---|---|
| Scenario | 2.5 pctl | 50 pctl | 97.5 pctl | 2.5 pctl | 50 pctl | 97.5 pctl | 2.5 pctl | 50 pctl | 97.5 pctl |
| Q1 | 1.48 | 1.49 | 1.49 | 1.48 | 1.49 | 1.49 | 1.48 | 1.49 | 1.49 |
| Q2 | 1.42 | 1.56 | 1.66 | 1.44 | 1.58 | 1.67 | 1.45 | 1.60 | 1.67 |
| Q3 | 1.37 | 1.64 | 1.81 | 1.42 | 1.67 | 1.82 | 1.45 | 1.71 | 1.84 |
| Q4 | 1.34 | 1.70 | 1.95 | 1.41 | 1.75 | 1.97 | 1.45 | 1.81 | 1.99 |
| Q5 | 1.32 | 1.77 | 2.09 | 1.41 | 1.83 | 2.11 | 1.45 | 1.90 | 2.13 |
| Q6 | 1.30 | 1.82 | 2.21 | 1.41 | 1.90 | 2.24 | 1.46 | 2.00 | 2.27 |
| Q7 | 1.29 | 1.88 | 2.33 | 1.41 | 1.97 | 2.36 | 1.47 | 2.09 | 2.40 |
| Q8 | 1.28 | 1.93 | 2.45 | 1.42 | 2.04 | 2.48 | 1.48 | 2.17 | 2.53 |
| Q9 | 1.28 | 1.98 | 2.56 | 1.43 | 2.10 | 2.60 | 1.50 | 2.25 | 2.65 |
| Q10 | 1.27 | 2.02 | 2.67 | 1.44 | 2.16 | 2.71 | 1.51 | 2.33 | 2.77 |
| Q11 | 1.26 | 2.06 | 2.78 | 1.45 | 2.21 | 2.82 | 1.53 | 2.41 | 2.88 |
| Q12 | 1.26 | 2.10 | 2.88 | 1.46 | 2.26 | 2.93 | 1.54 | 2.48 | 2.99 |

*Note: Note: The table shows the results of the expected Liquidity Coverage Ratio in three macroeconomic states (Recession, Slow Growth and Fast Growth states), for twelve quarters ahead. For each state, upper and lower bounds for the confidence interval are given, which is constructed by taking the 2.5th and 97.5th percentile expected values of the risk variables.*

Table 18: Results Net Stable Funding Ratio

| State | Recession | | | Slow Growth | | | Fast Growth | | |
|---|---|---|---|---|---|---|---|---|---|
| Scenario | 2.5 pctl | 50 pctl | 97.5 pctl | 2.5 pctl | 50 pctl | 97.5 pctl | 2.5 pctl | 50 pctl | 97.5 pctl |
| Q1 | 1.03 | 1.01 | 1.00 | 1.03 | 1.01 | 1.00 | 1.03 | 1.01 | 1.00 |
| Q2 | 1.03 | 1.04 | 1.04 | 1.03 | 1.04 | 1.04 | 1.03 | 1.04 | 1.04 |
| Q3 | 1.03 | 1.06 | 1.07 | 1.03 | 1.06 | 1.07 | 1.04 | 1.06 | 1.07 |
| Q4 | 1.03 | 1.07 | 1.10 | 1.04 | 1.08 | 1.10 | 1.04 | 1.09 | 1.10 |
| Q5 | 1.03 | 1.09 | 1.13 | 1.04 | 1.10 | 1.13 | 1.05 | 1.11 | 1.13 |
| Q6 | 1.04 | 1.11 | 1.16 | 1.05 | 1.12 | 1.16 | 1.06 | 1.13 | 1.16 |
| Q7 | 1.04 | 1.13 | 1.18 | 1.06 | 1.14 | 1.19 | 1.07 | 1.15 | 1.19 |
| Q8 | 1.05 | 1.15 | 1.21 | 1.07 | 1.16 | 1.21 | 1.07 | 1.18 | 1.22 |
| Q9 | 1.05 | 1.16 | 1.24 | 1.07 | 1.18 | 1.24 | 1.08 | 1.20 | 1.25 |
| Q10 | 1.06 | 1.18 | 1.26 | 1.08 | 1.20 | 1.27 | 1.09 | 1.22 | 1.27 |
| Q11 | 1.06 | 1.19 | 1.29 | 1.09 | 1.21 | 1.29 | 1.10 | 1.24 | 1.30 |
| Q12 | 1.07 | 1.21 | 1.31 | 1.10 | 1.23 | 1.32 | 1.11 | 1.26 | 1.32 |

*Note: Note: The table shows the results of the expected Net Stable Funding Ratio in three macroeconomic states (Recession, Slow Growth and Fast Growth states), for twelve quarters ahead. For each state, upper and lower bounds for the confidence interval are given, which is constructed by taking the 2.5th and 97.5th percentile expected values of the risk variables.*

Table 19: Results Net Interest Income (x bn)

| State | Recession | | | Slow Growth | | | Fast Growth | | |
|---|---|---|---|---|---|---|---|---|---|
| Scenario | 2.5 pctl | 50 pctl | 97.5 pctl | 2.5 pctl | 50 pctl | 97.5 pctl | 2.5 pctl | 50 pctl | 97.5 pctl |
| Q1 | 0.50 | 0.51 | 0.52 | 0.52 | 0.53 | 0.54 | 0.55 | 0.56 | 0.57 |
| Q2 | 0.49 | 0.51 | 0.53 | 0.51 | 0.53 | 0.55 | 0.54 | 0.57 | 0.58 |
| Q3 | 0.48 | 0.51 | 0.53 | 0.50 | 0.53 | 0.55 | 0.53 | 0.57 | 0.59 |
| Q4 | 0.47 | 0.51 | 0.54 | 0.49 | 0.53 | 0.56 | 0.52 | 0.57 | 0.59 |
| Q5 | 0.46 | 0.51 | 0.55 | 0.49 | 0.54 | 0.57 | 0.52 | 0.58 | 0.60 |
| Q6 | 0.46 | 0.52 | 0.56 | 0.49 | 0.54 | 0.58 | 0.51 | 0.58 | 0.61 |
| Q7 | 0.46 | 0.52 | 0.57 | 0.48 | 0.55 | 0.59 | 0.51 | 0.59 | 0.62 |
| Q8 | 0.46 | 0.52 | 0.58 | 0.49 | 0.55 | 0.60 | 0.51 | 0.60 | 0.64 |
| Q9 | 0.46 | 0.53 | 0.59 | 0.49 | 0.56 | 0.61 | 0.52 | 0.60 | 0.65 |
| Q10 | 0.46 | 0.53 | 0.60 | 0.49 | 0.56 | 0.62 | 0.52 | 0.61 | 0.66 |
| Q11 | 0.46 | 0.54 | 0.61 | 0.49 | 0.57 | 0.64 | 0.52 | 0.62 | 0.68 |
| Q12 | 0.46 | 0.55 | 0.63 | 0.50 | 0.58 | 0.65 | 0.53 | 0.63 | 0.69 |

*Note: Note: The table shows the results of the expected Net Interest Income in three macroeconomic states (Recession, Slow Growth and Fast Growth states), for twelve quarters ahead. For each state, upper and lower bounds for the confidence interval are given, which is constructed by taking the 2.5th and 97.5th percentile expected values of the risk variables.*

Table 20: Results Return on Equity

| State | Recession | | | Slow Growth | | | Fast Growth | | |
|---|---|---|---|---|---|---|---|---|---|
| Scenario | 2.5 pctl | 50 pctl | 97.5 pctl | 2.5 pctl | 50 pctl | 97.5 pctl | 2.5 pctl | 50 pctl | 97.5 pctl |
| Q1 | -0.14 | 0.07 | 0.21 | -0.12 | 0.09 | 0.21 | -0.11 | 0.12 | 0.22 |
| Q2 | -0.27 | 0.07 | 0.15 | -0.19 | 0.09 | 0.15 | -0.14 | 0.11 | 0.15 |
| Q3 | - | 0.08 | 0.12 | - | 0.09 | 0.12 | -0.87 | 0.10 | 0.13 |
| Q4 | - | 0.08 | 0.10 | - | 0.09 | 0.10 | - | 0.09 | 0.11 |
| Q5 | - | 0.08 | 0.09 | - | 0.09 | 0.09 | - | 0.10 | 0.09 |
| Q6 | - | 0.08 | 0.08 | - | 0.08 | 0.08 | - | 0.09 | 0.08 |
| Q7 | - | 0.08 | 0.07 | - | 0.08 | 0.07 | - | 0.08 | 0.07 |
| Q8 | - | 0.08 | 0.06 | - | 0.08 | 0.07 | - | 0.08 | 0.07 |
| Q9 | - | 0.08 | 0.06 | - | 0.08 | 0.06 | - | 0.07 | 0.06 |
| Q10 | - | 0.08 | 0.06 | - | 0.07 | 0.06 | - | 0.07 | 0.06 |
| Q11 | - | 0.08 | 0.05 | - | 0.07 | 0.05 | - | 0.06 | 0.05 |
| Q12 | - | 0.08 | 0.05 | - | 0.07 | 0.05 | - | 0.06 | 0.05 |

*Note: Note: The table shows the results of the expected Return on Equity in three macroeconomic states (Recession, Slow Growth and Fast Growth states), for twelve quarters ahead. For each state, upper and lower bounds for the confidence interval are given, which is constructed by taking the 2.5th and 97.5th percentile expected values of the risk variables.*

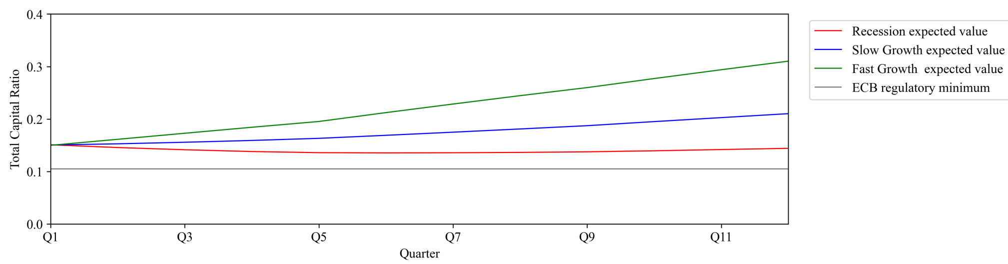
Table 21: Results Return on Assets

| State | Recession | | | Slow Growth | | | Fast Growth | | |
|---|---|---|---|---|---|---|---|---|---|
| Scenario | 2.5 pctl | 50 pctl | 97.5 pctl | 2.5 pctl | 50 pctl | 97.5 pctl | 2.5 pctl | 50 pctl | 97.5 pctl |
| Q1 | -0.001 | 0.009 | 0.015 | 0.000 | 0.010 | 0.016 | 0.001 | 0.011 | 0.016 |
| Q2 | 0.000 | 0.009 | 0.014 | 0.002 | 0.010 | 0.014 | 0.003 | 0.011 | 0.015 |
| Q3 | 0.001 | 0.008 | 0.013 | 0.003 | 0.010 | 0.014 | 0.003 | 0.011 | 0.014 |
| Q4 | 0.002 | 0.008 | 0.013 | 0.003 | 0.009 | 0.014 | 0.004 | 0.010 | 0.014 |
| Q5 | 0.002 | 0.008 | 0.013 | 0.003 | 0.009 | 0.013 | 0.004 | 0.011 | 0.014 |
| Q6 | 0.002 | 0.008 | 0.013 | 0.004 | 0.009 | 0.013 | 0.004 | 0.010 | 0.013 |
| Q7 | 0.002 | 0.008 | 0.012 | 0.004 | 0.009 | 0.013 | 0.004 | 0.010 | 0.013 |
| Q8 | 0.003 | 0.008 | 0.012 | 0.004 | 0.009 | 0.012 | 0.005 | 0.010 | 0.013 |
| Q9 | 0.002 | 0.007 | 0.012 | 0.004 | 0.009 | 0.012 | 0.005 | 0.010 | 0.013 |
| Q10 | 0.003 | 0.007 | 0.012 | 0.004 | 0.008 | 0.012 | 0.005 | 0.010 | 0.012 |
| Q11 | 0.003 | 0.007 | 0.012 | 0.004 | 0.008 | 0.012 | 0.005 | 0.010 | 0.012 |
| Q12 | 0.003 | 0.007 | 0.011 | 0.004 | 0.008 | 0.012 | 0.005 | 0.010 | 0.012 |

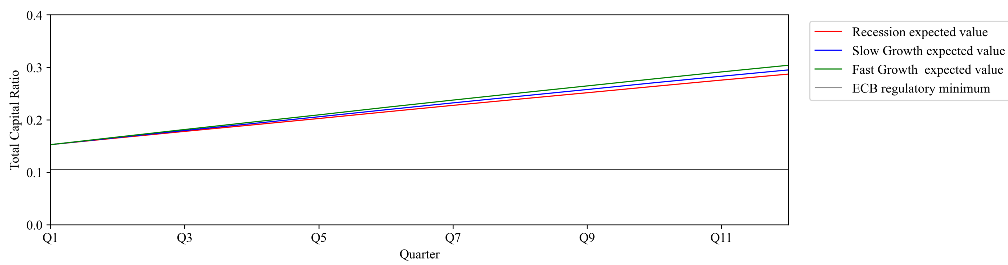
*Note: Note: The table shows the results of the expected Return on Assets in three macroeconomic states (Recession, Slow Growth and Fast Growth states), for twelve quarters ahead. For each state, upper and lower bounds for the confidence interval are given, which is constructed by taking the 2.5th and 97.5th percentile expected values of the risk variables.*

## A.2 Figures

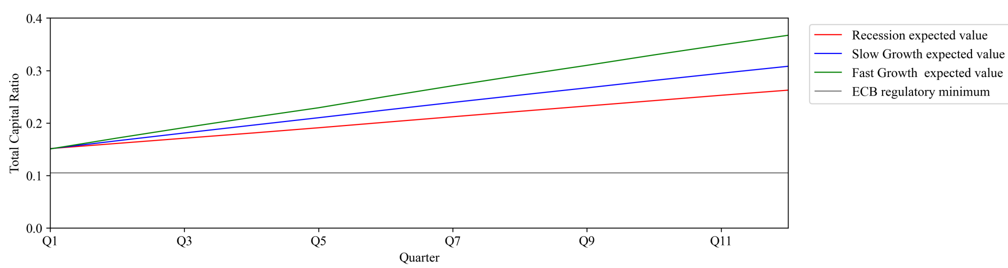
This Appendix shows figures containing the results of the performance measures.




(a) With conditional market risk and conditional credit risk



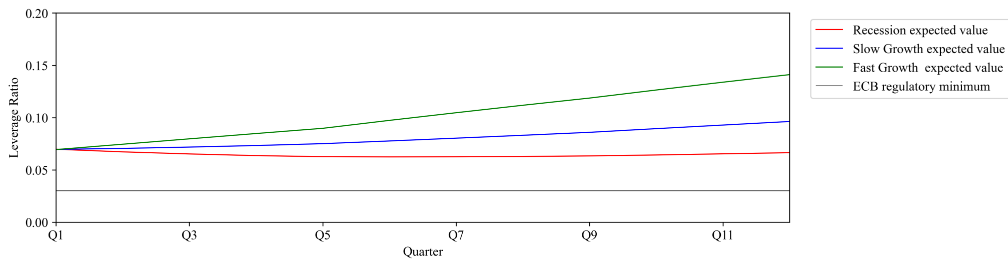

(b) With conditional market risk only



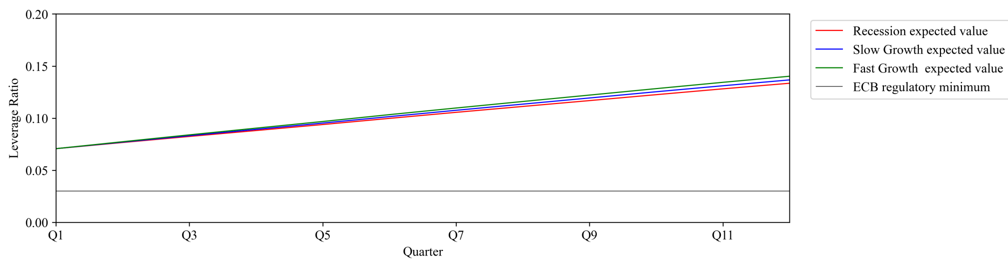

(c) With conditional credit risk only

Figure 18: Total Capital Ratio of a retail bank

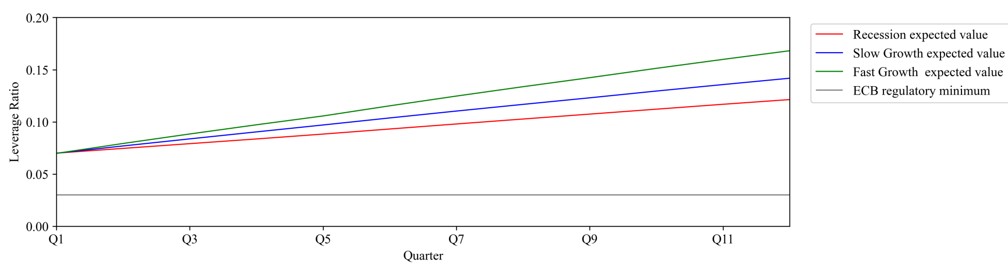
*Note: The Total Capital Ratio is given for three macroeconomic states (Recession, Slow Growth and Fast Growth state) when both market risk and credit risk (a), only market risk (b) and only credit risk (c) are modelled conditional on the macroeconomic state.*




(a) With conditional market risk and conditional credit risk



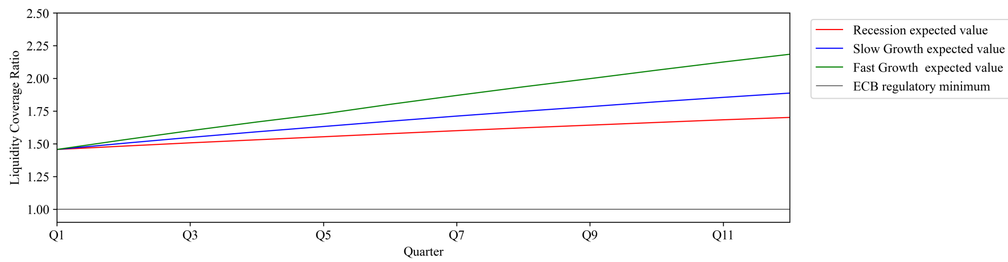

(b) With conditional market risk only



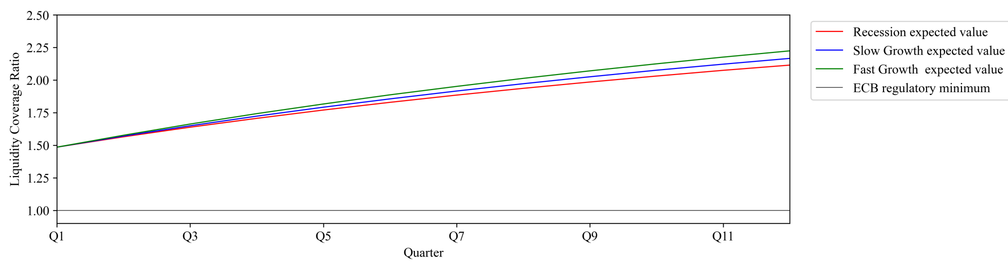

(c) With conditional credit risk only

Figure 19: Leverage Ratio of a retail bank

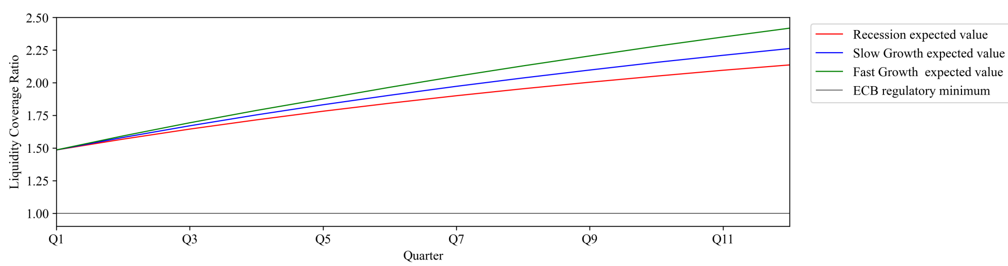
*Note: The Leverage Ratio is given for three macroeconomic states (Recession, Slow Growth and Fast Growth state) when both market risk and credit risk (a), only market risk (b) and only credit risk (c) are modelled conditional on the macroeconomic state.*




(a) With conditional market risk and conditional credit risk



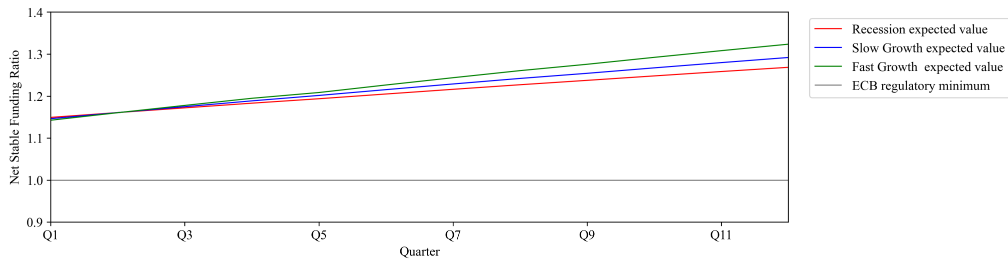

(b) With conditional market risk only



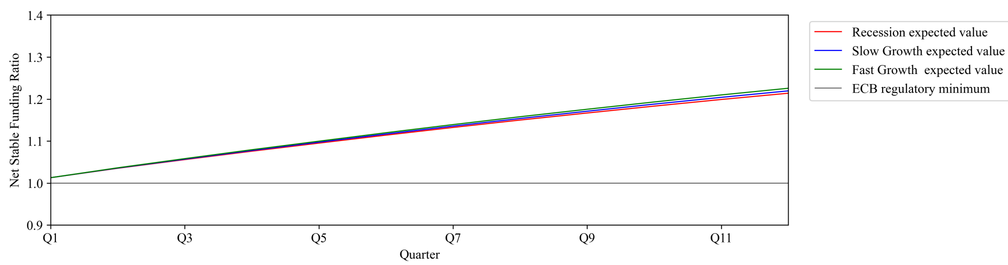

(c) With conditional credit risk only

Figure 20: Liquidity Coverage Ratio of a retail bank

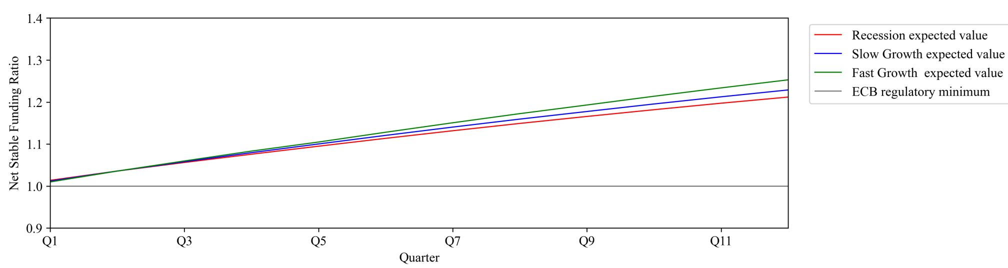
*Note: The Liquidity Coverage Ratio is given for three macroeconomic states (Recession, Slow Growth and Fast Growth state) when both market risk and credit risk (a), only market risk (b) and only credit risk (c) are modelled conditional on the macroeconomic state.*




(a) With conditional market risk and conditional credit risk




(b) With conditional market risk only




(c) With conditional credit risk only

Figure 21: Net Stable Funding Ratio of a retail bank

*Note: The Net Stable Funding Ratio is given for three macroeconomic states (Recession, Slow Growth and Fast Growth state) when both market risk and credit risk (a), only market risk (b) and only credit risk (c) are modelled conditional on the macroeconomic state.*