Modeling Non-Maturing Deposits Using Replicating Portfolio Models

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OSKAR BRUNQVIST
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Abstract

In recent years, regulatory and legislative authorities have increased their interest in non-maturing products, more specifically modeling of non-maturing deposits. This increase stems from the ever growing portion of banks funding originating from these products. The main purpose of this thesis is to provide an overview of different replicating portfolio models available for modeling non-maturing deposits and assess their applicability and suitability. Six different models suggested in the literature and two model extensions are presented and evaluated based on three categories: goodness of fit, stability and transparency. The results indicate that static replicating portfolios provide a poor fit for modeling the interest rate behavior in current interest rate market conditions.
Sammanfattning

Tillsynsmyndigheter och lagstiftande organ har under senare år ökat sitt intresse i finansiella produkter som saknar kontrakterad förfallodag, framför allt icke tidsbunden inläning. Detta beror på att bankers finansiering i allt större utstreckning utgörs av dessa instrument. Det huvudsakliga syftet med detta arbete är att skapa en översiktlig bild av befintliga modeller som använder replikerande portföljer och utvärdera deras lämplighet. Sex olika modeller från befintlig litteratur samt två nya modeller presenteras och utvärderas baserat på tre kategorier; passform, stabilitet och transparans. Resultaten indikerar att statiska replikerande portföljer överlag har en dålig passform för att modellera räntesättningsbeteende i rådande marknadsränteläge.
Acknowledgements

I would like to extend my sincerest gratitude and give thanks to my supervisors Anders Forsgren at KTH and Mert Camlibel. Thank you for your guidance, patience and enthusiasm. Mert, thank you for the opportunity and valuable input throughout the thesis. Anders, thank you for the support and good advice.

Furthermore, I would also like to give thanks to all other people who have supported me during this project. A special thanks to my family and loved ones, without you this would not have been possible.

Stockholm, March 2018
Oskar Brunqvist
Contents

1 Introduction 1
  1.1 Background ............................................ 1
  1.2 Problematization ....................................... 2
  1.3 Research Question ..................................... 2
  1.4 Contribution ........................................... 2
  1.5 Delimitations .......................................... 3
  1.6 Structure of the Thesis ................................. 3

2 Literature and Theory 4
  2.1 Non-Maturing Deposits ................................. 4
  2.2 Replicating Portfolio Models .......................... 5
    2.2.1 Static Replicating Portfolio by Maes and Timmermans (2005) ....................... 7
    2.2.2 Static Replicating Portfolio with Moving Average by Bardenhewer (2007) .......... 9
    2.2.3 Overnight Static Replicating Portfolio by FI (2015) .......................... 12
    2.2.4 Uniform Static Replicating Portfolio by the EBA and BCBS (2016) ................. 12
    2.2.5 Dynamic Replicating Portfolio by Frauendorfer and Schürle (2007) ............... 14
  2.3 Financial Model Evaluation .............................. 19

3 Model Extension 20
  3.1 Bounded Static Replicating Portfolio with Moving Average ............................... 20

4 Methodology 21
  4.1 Data Description ....................................... 21
  4.2 Model Evaluation Methods .............................. 23
    4.2.1 Goodness of Fit ................................... 23
    4.2.2 Stability ........................................ 23
    4.2.3 Transparency ..................................... 24
  4.3 Model Selection ........................................ 24
    4.3.1 Estimation of Remaining Balance .................. 25

5 Results 26
  5.1 Overview ............................................... 26
  5.2 Performance .......................................... 27
5.2.1 Goodness of Fit .......................... 28
5.2.2 Stability ................................ 28
5.2.3 Transparency ........................... 32

6 Discussion ................................. 34
  6.1 Overview ................................ 34
  6.2 Goodness of Fit .......................... 34
  6.3 Out-of-Sample Analysis .................. 36
  6.4 Global Solution Analysis ................ 36
  6.5 Transparency ............................ 36
  6.6 A Final Note on Dynamic Replicating Portfolios ............... 37

7 Conclusion and Further Research ........ 39
List of Figures

1. Replicating portfolio example. .......................... 6
2. Replicating portfolio by FI. ............................ 12
3. Separation of NMD:s. .................................. 13
4. Deposit rates per account type ......................... 22
5. Out of sample analysis: Duration (months) ............ 29
6. Out of sample analysis per model category .......... 30
7. Out of sample analysis: Goodness of Fit. ............. 31
8. Market rates and deposit rate of $R_1$ ................. 35
List of Tables

1. Stability caps and pass-through floors by category ............ 14
2. Weights of time buckets under uniform slotting ............. 14
3. Account distinctions ........................................ 21
4. Duration (months) ........................................... 26
5. Goodness of fit ($R^2$) ....................................... 28
6. Global Solution Analysis: Standard deviation of $D_p$ ........ 31
1 Introduction

1.1 Background

Non-maturing products (NMP:s) are financial institutions’ assets and liabilities that do not have contractual defined characteristics. Their main feature is that both interest rate behavior and maturity is unknown, i.e. the customer can freely choose the maturity date and interest rates can be shifted. Typical examples of non-maturing liabilities (NML:s) are most deposit accounts such as transaction and savings accounts. Overdrafts and credit card loans are common non-maturing assets (NMA:s). This thesis will focus on NML:s, more specifically non-maturing deposits (NMD:s). However, since NMP:s share common characteristics, concepts and knowledge based on one product can easily be extended to others.

At first glance NMD:s such as savings accounts seem to be a rather uncomplicated product. However, due to the customers option to freely choose any schedule of principle cash flows and the financial institutions option to change the the deposit rate, risk management of NMD:s proves difficult.

Generally speaking, a large part of depository institutions’ funding comes from NMD:s. It is a vital part of their financial intermediation function and is used extensively as a maturity transformation instrument since the volume of NMD:s, historically, have been rather stable. According to Dzmuranova & Teply (2016), by issuing NMD:s, depository institutions such as banks harmonize the desire of consumers and business for high liquidity and security with the need for stable funding by investors partaking in diverse projects. Furthermore, Schlueter et al. (2015) highlights the issue of, self-determined behavior of customers to be challenging for banks relying extensively on NMD-funding. This further stresses the importance of how banks can and should model their NMD:s and how to influence and guide their depositors to achieve stable funding.

Regulatory and legislative authorities have in recent years increased their interest in NMD:s. In 2016, the Basel Committee on Banking Supervision (BCBS) suggested the introduction of modeling standards of core deposits and NMD-durations, effectively making it possible for banks to use self-developed models. Following BCBS suggestions, in 2017, the European Banking Authority (EBA) drafted guidelines on how these standards ought to be introduced.
1.2 Problematization

The increased interest by regulatory and legislative authorities in NMD:s have caused the European banking industry to explore various modeling methods. One such group of models is often referred to as Replicating Portfolios and is, among other European countries, commonly used by banks in Belgium (Konings & Ducuroir 2014) (Maes & Timmermans 2005). However, it is not clear which replicating portfolio model to use and if they are sufficient for modeling NMD:s. Furthermore, no real consensus exists within the industry causing different banks to utilize different replicating portfolio modeling strategies. Hence, the main purpose of this thesis is to provide an overview of the different replicating portfolio models available for NMD-modeling and assess their applicability and suitability. Furthermore, building on existing replicating portfolio models, this thesis aims to develop a new replicating portfolio model for NMD-modeling and in a similar manner assess its applicability and suitability.

1.3 Research Question

To achieve the desired purpose, this thesis will answer the following research question.

• How should NMD:s be modeled when considering replicating portfolio models?

To answer this research question the following sub-questions will be answered.

• What replicating portfolio models exists in the literature today?

• What constitutes a good NMD-model?

• What further improvements can be made to existing NMD replicating portfolio models?

1.4 Contribution

Analyzing existing replicating portfolio models for modeling NMD:s can aid decision makers and risk management in the process of deciding how to model NMD:s. Furthermore, developing on existing optimization theory for the purpose of NMD-modeling creates greater understanding of the problems regarding how these liability models should be designed and developed. Additionally, it is my hope that this thesis can be used in future replicating portfolio optimization research.
1.5 Delimitations

Since there exists a considerable amount of literature on NMD-modeling, a specific setting is vital for the work to contribute to existing knowledge instead of repeating known results. Hence, this thesis will solely focus on optimization problems of NMD replicating portfolio models. Furthermore, this thesis is conducted in collaboration with a large Swedish bank, henceforth denoted as the Bank, thus any analysis and conclusions drawn from evaluating models based on data will be subjected to the specific situation of this particular bank.

1.6 Structure of the Thesis

The structure of the thesis is as follows. In chapter 2, an introduction to the characteristics of NMD:s and financial model evaluation is given. Furthermore, a review of existing modeling methods is also presented. Chapter 3 extends on existing modeling methods by adding improvements to some of the models presented in chapter 2. Chapter 4 gives a description of the data sets and performance measures used in this thesis as well as an overview of the what models will be subjected to evaluation. Furthermore, in chapter 5, the thesis results are presented beginning with an overview of the model specific solutions followed by a description of the results from the different performance measures. Finally, in chapter 6 and 7 discussions and conclusions based on the results in chapter 5 are presented.
2 Literature and Theory

This chapter provides an overview of non-maturing deposits followed by an introduction to the basic concepts of replicating portfolios. Further, replicating portfolio modeling methods proposed in the literature are presented.

2.1 Non-Maturing Deposits

Non-maturing deposits experience stochastic cash flow patterns since the flow of capital may occur at any time depending on the depositors behavior. Similarly, banks have the option to continuously change their deposit rate. Hence, some of the uncertainty and option risk of NMD:s falls in favor of the bank and some in favor of the customer. However, Dzumuranova & Teply (2016) shows that due to the this optional nature, under severe scenarios, some banks in the EU, relying heavily on NMD-funding, might face a significant capital shortage if the market rates start to increase dramatically from recent low levels.

In spite of the uncertain nature of NMD:s, historically, deposit volumes have been relatively stable. Schlueter et al. (2015) argues that this stability to some extent comes from contractual rewards, i.e. government subsidies and qualified interest payments, effectively stabilizing savings behavior. They found that the probability of an early deposit withdrawal decreases by approximately 40% and cash flow volatility drops by 25% when contractual rewards are utilized. Additionally, Wolff (2000) states that a popular rule of thumb that has been used in the banking industry is the so called 80-20 rule. That is, to assume that 20 percent of the deposit balance is highly volatile, while the remaining 80 percent is deemed more stable. In recent years, more sophisticated methods for estimating core deposits have been developed (e.g. Basel Committee on Banking Supervision (2016); Sheehan (2013)).

Bardenhewer (2007) identifies that deposit rates set by banks are far less volatile than market rates. Adjustments are especially reluctant in an rising interest rate environment. Furthermore, he states that depositors seem to be more reluctant to withdraw their funds if interest rates are expected to increase than if they are expected to decrease. Also, depositors view savings accounts, a NMD-product, as a medium-term investment often switching to other medium-term investments rather than short-term investments. Bardenhewer (2007) also acknowledge the existence of asymmetric information within the deposit market since the knowledge of financial concepts and markets varies significantly between depositors.
An interesting aspect of the characteristics of NMD:s is the existence of formal and informal caps and floors on interest and deposit rates. Some countries have regulated thresholds on interest rates effectively acting as a form of governmental financial control (e.g. see Mounsey & Polius (2015); Maimbo et al. (2014)). Other countries utilizes informal deposit rate floors that stems from a mutual belief within the national banking industry that deposit rates below this threshold would deter depositors, effectively forcing them to withdraw their deposits. Sweden, for instance, utilizes this informal system.

2.2 Replicating Portfolio Models

The replicating portfolio approach aims to transform complex NMP:s into a portfolio of vanilla instruments that share similar characteristics. The overall goal of the portfolio is to generate cash flow streams which replicates the cash flows of the NMP:s as closely as possible. Furthermore, for a bank seeking e.g. a constant margin on their savings accounts, a replicating portfolio can be a real investment or refinancing portfolio where the bank looks for a replicating portfolio that yields the deposit rates plus a constant margin (Bardenhewer 2007).

The core mechanics of a static replicating portfolio strategy can, for the ease of exposition, be explained by the following example where a NMD (savings account) is replicated by the practical use of markets rates with moving averages. Suppose that you have a savings account with a certain volume $V$. This volume can then be invested in different time buckets, e.g. one month, six months, 12 months and two years. These buckets are then divided into monthly maturities, i.e. the six-month bucket consists of six contracts with monthly maturities, the one year bucket consists of 12 contracts with monthly maturities etc. As time progresses, each month one contract per bucket matures and is replaced by a corresponding new contract traded at par. The yield of the replicating portfolio is thus determined by the coupons of its constituents. Hence, the yield of the replicating portfolio in this example is determined by the current one-month, six-month, 12-month and two-year rates, and by historic rates from the instruments purchased in the past. All in all 43 contracts $(1 + 6 + 12 + 24)$. The yield of the portfolio is thus an average of these 43 rates. The weights, i.e. the percentage of the volume $V$, for each bucket is determined such that the yield of the replicating portfolio corresponds to that of the deposit rates payed to the depositor plus a margin over time. How these weights can and should be determined lies at the core of various replicating portfolio models and will be further examined.
Figure 1: Replicating portfolio example.

in the following sections.

One important aspect when constructing new replicating portfolios is that interest rates have changed since the inceptions of some contracts. Hence, in general, replicating portfolios does not trade at par. Furthermore, since the capital invested in a replicating portfolio must equal that of the invested capital in the saving account by the depositor, a new replicating portfolio can only be set up in one of two ways. First, the capital can be invested in a replicating portfolio constructed of existing contracts, that is in general, either traded above or below par, i.e. the nominal, is either lower or higher than the NMD:s respectively. Second, the replicating portfolio can be built over time only from newly issued contracts resulting in that the portfolio trades at par, having the same nominal as the NMD:s. Hence, e.g. the 12-month time bucket of the replicating portfolio will consist of 12 contracts not before 11 months from now. The two approaches have different advantages. The first one has the advantage of being complete from the start, whereas the second has the sought after feature that its nominal value equals that of the NMD:s.

Another aspect to consider is that the volume of NMD:s fluctuates over time. Depositors deposit and withdraw funds. There exists several different approaches to handle this fluctuation. One such approach used by Bar-デンシューエーワ (2007) is that if a constant volume is expected on average, the contract with the shortest maturity available in the replicating portfolio can function as a money market account, serving as a buffer for random fluctuations around the mean. That is, a balancing volume aligning the volume of
the NMD with that of the replicating portfolio. If the balancing volume is positive, it is invested in the shortest maturity contracts and similarly, if the balancing volume is negative, short maturity contracts equaling the volume is sold. Another approach used by Maes & Timmermans (2005) is to divide the deposit volume into three different parts; core, volatile and remaining balance and only use the remaining balance in the replicating portfolio.

In most replicating portfolio models, an optimization problem have to be solved in order to determine the proportion of the different vanilla instruments that together constitutes the portfolio. These proportions or weights are determined based on some objective function e.g. minimizing the standard deviation of the NMD margin. Depending on the actual model, these optimization problems varies greatly. They can e.g. be linear problems, non-linear problems or multistage stochastic problems etc. For instance, in the non-linear case, a reduced gradient method can be utilized to solve the optimization problem resulting in either a local or global optimal solution depending on if the problem is convex or not (Griva et al. 2009).

### 2.2.1 Static Replicating Portfolio by Maes and Timmermans (2005)

Maes & Timmermans (2005) propose a static replicating portfolio model that replicates the characteristics and dynamics of deposit balances over some historical sample period. The deposit volume is divided into three separate parts; core, volatile and remaining balance. The core part is invested in a long term asset and the volatile part is invested in a risk free short horizon asset. Only the remaining balance is replicated by the portfolio. The remaining balance \( V^b_t \) at time \( t \) is defined as the difference between the core part \( V^c_t \) and the volatile part \( V^v_t \), i.e.,

\[
V^b_t = |V^c_t - V^v_t|.
\]

(1)

The weights of the replicating portfolio are chosen after a specific objective criterion that is optimized under constraints that the portfolio replicates the NMD. Maes & Timmermans (2005) propose two objective functions for optimizing the portfolio weights. The first is to select the portfolio assets such that the standard deviation of the margin is minimized. In other words, the assets that yields the most stable margin of the deposit rate over the sample period is chosen, i.e.,

\[
\text{Min } z_1(r^p_t, d_t) = \text{std}(r^p_t - d_t).
\]

(2)
Here, \( r_t^p \) denotes the return of the replicating portfolio and \( d_t \) denotes the deposit rate, at time \( t \).

The second approach is to maximize the risk-adjusted margin, measured by its Sharpe ratio, i.e., the ratio between the average margin and the standard deviation of the margin,

\[
\text{Max } z_2(r_t^p, d_t) = \frac{(r_t^p - d_t)}{\text{std}(r_t^p - d_t)}.
\]

Here, \((r_t^p - d_t)\) denotes the average margin or the mean difference between the portfolio return and the deposit rate at time \( t \).

The objective function in either approach is subjected to three constraints.

The first constraint

\[
\sum_{i=1}^{n} w_i r_{i,t} = r_t^p \quad \forall t = 1, \ldots, T
\]

denotes the variable \( r_t^p \) as the sum of the weighed returns of the \( n \) available assets in the set \( N \), where \( T \) is the number of historical sample periods.

The second constraint

\[
\sum_{i=1}^{n} w_i = 1
\]

simply states that the portfolio weights \( w_i \) must sum up to one.

The third constraint

\[
w_i \geq 0 \quad \forall i \in N
\]

states that no short sales are allowed.

Combining the objective functions with the constraints results in the following non-linear optimization problems:
\[
\begin{align*}
\min \quad & z_1(r^p_t, d_t) = \text{std}(r^p_t - d_t) \\
\text{subject to} \quad & \sum_{i=1}^{n} w_i r_{i,t} = r^p_t \quad \forall t = 1, \ldots, T \\
& \sum_{i=1}^{n} w_i = 1 \\
& w_i \geq 0 \quad \forall i \in N
\end{align*}
\]

\[
\begin{align*}
\max \quad & z_2(r^p_t, d_t) = \frac{(r^p_t - d_t)}{\text{std}(r^p_t - d_t)} \\
\text{subject to} \quad & \sum_{i=1}^{n} w_i r_{i,t} = r^p_t \quad \forall t = 1, \ldots, T \\
& \sum_{i=1}^{n} w_i = 1 \\
& w_i \geq 0 \quad \forall i \in N
\end{align*}
\]

Here, problem (7) and (8) are convex optimization problems due to the linear constraints and the objective functions being convex functions (Hult et al. 2010).

Once the optimization problems have been solved, the duration \(D_p\) of the portfolio, and subsequently the NMD it is aiming to replicate, can be calculated as the weighted sum of the asset maturities, i.e.,

\[
D_p = \sum_{i=1}^{n} w_i m_i
\]

where \(m_i\) is the maturity of asset \(i\).

### 2.2.2 Static Replicating Portfolio with Moving Average by Bardenhewer (2007)

Bardenhewer (2007) also proposes a static replicating portfolio which similarly to Maes & Timmermans (2005) replicates the characteristics of deposit balances over some historical sample period. Furthermore, Bardenhewer (2007) also calculates the weights of the replicating portfolio by minimizing the standard deviation of the margin. However, he uses another approach
when handling deposit volume fluctuations. The volume is divided into an expected trend component and an unexpected component. The expected component follows a certain trend that can be estimated from historical data or by expert knowledge. Bardenhewer (2007) proposes three different ways to estimate trends in deposit volumes based on historical data; linear, quadratic and exponential.

Linear trend: \[ V_t = \beta_0 + \beta_1 \Delta_t + \sum_i k_i (r_{i,t} - \bar{r}_i) + \delta (ct - \bar{c}) + \epsilon_t \]

Quadratic trend: \[ V_t = \beta_0 + \beta_2 \Delta_t^2 + \sum_i k_i (r_{i,t} - \bar{r}_i) + \delta (ct - \bar{c}) + \epsilon_t \]

Exponential trend: \[ V_t = \beta_3 \exp(\beta_4 \Delta_t) + \sum_i k_i (r_{i,t} - \bar{r}_i) + \delta (ct - \bar{c}) + \epsilon_t \]

where

- \( i \in (1, \ldots, N) \) Maturity of buckets in months.
- \( V_t \) Total volume at time \( t \).
- \( r_{i,t} \) Interest rate with maturity \( i \) at time \( t \).
- \( \bar{r}_i \) Average interest rate over estimation period.
- \( cr_t \) Customer’s rate at time \( t \).
- \( \bar{c} \) Average customer rate over estimation period.
- \( \Delta_t \) Months between time 0 and \( t \).
- \( \beta_i, k_i, \delta \) Parameters to be estimated.
- \( \epsilon_t \) Residual at time \( t \).

Depending on the quality of the data, the coefficients \( \beta_i, k_i \) and \( \delta \) can be estimated using regression techniques such as ordinary least square (OLS) or robust approaches. The unexpected component is not captured by a trend function and any deviation from the trend observed in reality is put into the replicating portfolio asset with the shortest maturity date, effectively acting as a money market account, serving as a buffer for random fluctuations around the mean.

Reasoning that deposit rates adapts slowly to market rate changes, Bardenhewer (2007) adjusts the market rates by utilizing moving averages

\[ ma_{i,t} = \frac{1}{B_i} \sum_{j=0}^{B_i-1} r_{i,t-j} \]  

(10)
where \( ma_{i,t} \) is the moving average return of asset \( i \) at time \( t \). \( B_i \) is the number of periods corresponding to the maturity of asset \( i \) and \( r_{i,t} \) is the return of asset \( i \) at time \( t \).

The return of the replicating portfolio is given by

\[
    r^p_t = \frac{F_t(\cdot)}{V_t} \sum_i w_i ma_{i,t} + \frac{A_t(\cdot)}{V_t} r_{1,t} + \eta_t
\]

where \( F_t(\cdot) = F_t(\Delta_t, r_{i,t}, c_r, c_r; \beta_0, \ldots, \beta_4, k_i, \delta) \) is the trend volume at time \( t \), \( w_i \) is the portfolio weights, \( \eta_t \) is the residual at time \( t \). The balancing volume \( A_t(\cdot) = A_t(\Delta_t, r_{i,t}, c_r, c_r; \beta_0, \ldots, \beta_4, k_i, \delta) \), also known as the unexpected part of the deposit volume, at time \( t \) is given by the difference between the total volume \( V_t \) and the trend volume \( F_t(\cdot) \)

\[
    A_t(\cdot) = V_t - F_t(\cdot)
\]

The model can be described as a non-linear optimization problem

\[
    \begin{align*}
    \min & \quad z_3(r^p_t, d_t) = \text{std}(r^p_t - d_t) \\
    \text{subject to} & \quad r^p_t = \frac{F_t(\cdot)}{V_t} \sum_i w_i ma_{i,t} + \frac{A_t(\cdot)}{V_t} r_{1,t} & \forall t = 1, \ldots, T \\
    & \quad \sum_{i=1}^n w_i = 1 \\
    & \quad w_i \geq 0 & \forall i \in N.
    \end{align*}
\]

One can note that problem (13) is a convex problem due to the linear constraints and the convex objective function.

Bardenhewer (2007) also introduces liquidity constraint by a method known as market mix. This is to prevent severe liquidity crisis that can occur if the replicating portfolio is heavy with long maturing assets and a significant portion of depositors decide to withdraw their funds. The market mix methods proposed by Bardenhewer (2007) is based on historical data where the weights are adjusted if the maturing volume in the replicating portfolio have not covered withdrawals at any time in the past. The weights based on the volume of the NMD can be calculated by various methods. One such method is that the weights for each asset are set to the maximum historical volume change.
2.2.3 Overnight Static Replicating Portfolio by FI (2015)
Following the capital requirement directive, the Swedish financial supervision authority (FI) requires the calculation of IRRBB to be computed using an EVE approach that requires the duration of both equity and NMD:s to be set to zero, effectively estimating the duration of NMD:s to be overnight. Hence, one can view FI:s model of NMD:s to be that of a simple static replicating portfolio where the overnight weight is 100% and all other weights are set to zero (Paul 2017).

2.2.4 Uniform Static Replicating Portfolio by the EBA and BCBS (2016)
The European banking authority (EBA) and the Basel committee of banking supervisions (BCBS) propose a time series approach (TIA) to model NMD:s. The general approach under TIA is twofold. The first is to separate the volume of NMD:s into two categories (core and non-core). The second is to determine a cash flow slotting procedure for each category.
To separate the volume of NMD:s into core deposits and non-core deposits, one must first distinguish between stable and non-stable NMD:s using observed historical volumes changes. The stable portion of NMD:s is the portion found to remain undrawn with a high degree of likelihood. The stable portion is then further broken down into a core component and a non-core component using a pass-through rate concept. The pass-through rate refers to the proportion of a market interest rate change that the financial institution will pass onto its customers to maintain the same level of sta-
The proportion of stable NMD:s found to reprice due to a market rate change together with the non-stable part will constitute the non-core share of the NMD:s. Only the proportion of stable, non-pass through NMD:s will constitute the core part of the deposit volume.

The separation of NMD:s are made for three customer segments, Retail-transactional (TR), Retail-non-transactional (NTR) and Wholesale. Retail deposits are defined as deposits placed by individuals and are to be considered transactional when regular transactions are carried out in the corresponding account or when deposits is non-interest bearing. Other deposits by individuals that do not meet these requirements are defined as non-transactional deposits. Deposits made by legal entities, sole proprietorships or partnerships are viewed as wholesale deposits. The results of the separation of each customer segment is then aggregated to determine the overall volume of core deposits. Stability caps and pass-through floors are proposed for each customer segment to prohibit to generous calculations by financial institutions (Table 1). The segmentation and subsequently imposed stability caps and pass-through floors assume that wholesale NMD:s fluctuates more than retail NMD:s and that the stable wholesale portion is more sensitive to market rate changes than stable retail deposits. Furthermore, non-transactional deposits are assumed to be less stable and more
sensitive to market rate changes than transactional deposits. The framework also allows financial institutions to directly segment 40% of the retail deposit volume and 20% of wholesale deposit volume as core deposit under what is called the simplified TIA.

<table>
<thead>
<tr>
<th>Category</th>
<th>Stability Cap (%)</th>
<th>Pass-through floor (%)</th>
<th>Implied Cap (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Retail (TR)</td>
<td>80</td>
<td>25</td>
<td>0.80(1 – 0.25) = 60</td>
</tr>
<tr>
<td>Retail (NTR)</td>
<td>70</td>
<td>30</td>
<td>0.70(1 – 0.30) = 49</td>
</tr>
<tr>
<td>Wholesale</td>
<td>65</td>
<td>50</td>
<td>0.65(1 – 0.5) = 33</td>
</tr>
</tbody>
</table>

Table 1: Stability caps and pass-through floors by category

The non-core portion of the NMD:s are viewed to reprice immediately and is thus placed into the overnight time bucket. The core NMD:s are allocated uniformly into time buckets of up to six years.

<table>
<thead>
<tr>
<th>O/N</th>
<th>1M</th>
<th>3M</th>
<th>6M</th>
<th>9M</th>
<th>1Y</th>
<th>1.5Y</th>
<th>2Y</th>
<th>3Y</th>
<th>4Y</th>
<th>5Y</th>
<th>6Y</th>
</tr>
</thead>
</table>

Table 2: Weights of time buckets under uniform slotting

The duration of the NMDs is then estimated using the average time to maturity

\[ D_t^p = \frac{N_t}{V_t} m_1 + \frac{C_t}{V_t} \sum_{i=2}^{12} w_i m_i \]  

(14)

where \( C_t \) is the core portion of the deposit volume at time \( t \), \( N_t = 1 - C_t \) is the non-core portion at time \( t \), \( w_i \) is the weight of time bucket \( i \) and \( m_i \) is the maturity of asset \( i \).

2.2.5 Dynamic Replicating Portfolio by Frauendorfer and Schürle (2007)

To model NMD:s, Frauendorfer & Schürle (2007) propose a multistage stochastic programming model that finds an optimal replicating portfolio from future scenarios of relevant risk factors such as; volume of NMD:s, deposit rates, and market rates. Given conditional probability distributions of future risk factors, policies are determined that are feasible for all possible samples.
of the random data and achieves some optimal criterion, e.g. maximization of the margin subjected to risk limits or minimization of the tracking error. One of the main differences between static replicating and dynamic replicating portfolios is that unlike static replication, dynamic replication readjusts the portfolio weights at each stage along each scenario. Hence, the distribution of assets in the dynamic replicating portfolio changes over time. 

Frauendorfer & Schürle (2007) define their optimization model as follows:

Let \( D \) be the longest maturity of the assets that constitutes the replicating portfolio. Further, let \( D = \{1, \ldots, D\} \) be the set of dates where the assets held in the portfolio matures and let \( D^S \subseteq D \) be the set of maturities of instruments that can be used for investing purposes.

The transaction volume invested in each asset of different maturity is split into several tranches priced at different spreads. The number of tranches is given by \( I^d \) for maturity \( d \), where \( I^d := \{1, \ldots, I^d\} \) is the index set of maturity \( d \) and \( l_i^d \) is the maximum amount that can be traded in the \( i \)-tranche. This is done since on some markets, liquidity restrictions apply and the bid-ask spreads may increase if e.g. a bank places large amounts in longer maturities.

Furthermore, the stochastic process \( \omega := (\omega_t; t = 1, \ldots, T) \) in discrete time drives the joint evolution of the random data defined earlier as volume of relevant positions, deposit/client rates and market rates. It is defined on the probability space \( (\Omega, \mathcal{F}, \mathcal{P}) \) where \( \Omega = \Omega_1 \times \cdots \times \Omega_T \) is the sample space, \( \mathcal{F} \) the \( \sigma \)-field of subsets on \( \Omega \) and \( \mathcal{P} \) a probability measure. The filtration \( \mathcal{F}_t := \sigma\{\omega^t\} \) generated in \( \Omega \) by the history \( \omega^t := (\omega_1, \ldots, \omega_t) \) of the stochastic process \( \omega \) defines the information available at time \( t \) and satisfies \( \{\emptyset, \Omega\} \subset \mathcal{F}_1 \subset \cdots \subset \mathcal{F}_T \). The random vector \( \omega^t := (\eta_t, \xi_t) \in \Omega^\eta_t \times \Omega^\xi_t =: \Omega_t \subseteq \mathbb{R}^{K+L} \) can be decomposed into two components: \( \eta_t \in \Omega^\eta_t \subseteq \mathbb{R}^K \) controls volume, deposit/client rates and market rates. \( \xi_t \in \Omega^\xi_t \subseteq \mathbb{R}^L \) represents additional factors that influence only the deposit volume.

Let the relevant stochastic coefficients derived from outcomes of \( \omega^t \) at time \( t \) be defined as:

- \( r^{d,+}_{i,t}(\eta^t) \) Bid rate per period for investing in the \( i \)-th tranche \((i \in I^d)\) of maturity \( d \in D^S \).
- \( r^{d,-}_{i,t}(\eta^t) \) Ask rate per period for borrowing in the \( i \)-th tranche \((i \in I^d)\) of maturity \( d \in D^S \).
- \( c_t(\eta^t) \) Client/deposit rate paid per period for holding the deposit.
- \( v_t(\omega^t) \) NMD volume.
At $t = 0$, bid and ask rates, deposit rates and volume are all deterministic since they can be observed in the market. However, future values are unknown and hence stochastic.

The dynamic nature of the model enables, at each point in time $t = \{0, \ldots, T\}$, reallocation of maturing tranches and changes in volume. $T$ is then an upper bound on the planning horizon of the dynamic portfolio. These reallocations require state variables:

- $x^{d,+}_{i,t}$: Amount invested in the $i$-th tranche ($i \in I^d$) of maturity $d \in \mathcal{D}^S$.
- $x^{d,-}_{i,t}$: Amount financed in the $i$-th tranche ($i \in I^d$) of maturity $d \in \mathcal{D}^S$.
- $x^d_t$: Nominal amount maturing after $d \in \mathcal{D}$ periods.
- $x^S_t$: Surplus (income from replicating portfolio minus cost for deposit volume).

Frauendorfer & Schürle (2007) further define a set of constraints to ensure that the model produces feasible results. The first constraint specifies the nominal volume at time $t$ with maturity date $d \in \mathcal{D}$ by the corresponding transaction amounts

$$x^d_t = x^d_{t-1} + \sum_{i \in I^d} x^{d,+}_{i,t} - \sum_{i \in I^d} x^{d,-}_{i,t} \quad \forall d \in \mathcal{D}^S. \tag{15}$$

$$x^d_t = x^d_{t-1} \quad \forall d \in \mathcal{D} \setminus \mathcal{D}^S. \tag{16}$$

Next, the sum of all portfolio positions must equal that of the managed NMD volume at time $t$, i.e.,

$$\sum_{d \in \mathcal{D}} x^d_t = v_t. \tag{17}$$

Further, the earning surplus at time $t$ resulting from transactions is given by the constraint

$$x^S_t = \min\{t, D-1\} \sum_{\tau=0}^{\min\{t, D-1\}} \sum_{(d,\tau) \in \mathcal{D}^S} \sum_{i \in I^d} \left( r^{d,+}_{i,t-\tau} x^{d,+}_{i,t-\tau} - r^{d,-}_{i,t-\tau} x^{d,-}_{i,t-\tau} \right) + cf_{t+2} - (c_t + \alpha_0) \cdot v_t \tag{18}$$

where $cf_{t+2}$ is the corresponding cash flow received from the positions at date $t + 2$ and $\alpha_0$ is non-interest expenses for holding the deposit volume.
Frauendorfer & Schürle (2007) also define optional constraints for limits on the proportion of nominal value in certain time buckets, restriction of the amount reinvested from squared positions and shortage liquidity restrictions: Let $w^l_i$ and $w^u_i$ be the upper and lower bound for the percentage of the volume in of the $i$-th bucket defined by $D_i^w \subseteq D$; $i = \{1, \ldots, n\}$, where $n$ is the total number of time buckets where such restrictions apply. Then the constraint limiting the proportion of nominal value in certain time buckets can be formulated as

$$w^l_i \cdot v_t \leq \sum_{d \in D_i^w} x^d_{i,t} \leq w^u_i \cdot v_t \quad i = \{1, \ldots, n\}. \quad (19)$$

The constraint restricting amounts reinvested from squared positions

$$\sum_{d \in D^S} \sum_{i \in I^d} x^d_{i,t} + \sum_{d=1}^m x_{i,t-1}^d \leq v_t - v_{t-1} \quad (20)$$

may be useful if the model decides to reduce the exposure in existing instruments to reinvest the money from squared positions. These investments can be limited at time $t$ to an amount equal to the sum of the tranches maturing in $\{t, \ldots, t + m - 1\}$.

The constraint limiting short positions

$$\sum_{d \in D^S} \sum_{i \in I^d} x^d_{i,t} \leq \max\{0, -v_t + v_{t-1}\} \quad (21)$$

is useful when one wants to limit the shortage possibility to only when a volume decline in time $t$ cannot be compensated by maturing tranches.

Based on the constraints and notations formulated above, Frauendorfer & Schürle (2007) propose the following multistage stochastic optimization problem.
\[
\begin{align*}
\min & \quad \int_{\Omega} \sum_{t=0}^{T} x_t^M dP(\omega) \\
\text{subject to} & \quad x_t^d = x_{t-1}^{d+1} + \sum_{i \in I^d} x_{i,t}^{d+} - \sum_{i \in I^d} x_{i,t}^{d-} \quad \forall d \in \mathcal{D}^S, \quad t = \{0, \ldots, T\} \\
& \quad x_t^d = x_{t-1}^{d+1} \quad \forall d \in \mathcal{D} \setminus \mathcal{D}^S, \quad t = \{0, \ldots, T\} \\
& \quad \sum_{d \in \mathcal{D}} x_t^d = v_t, \quad t = \{0, \ldots, T\} \\
& \quad x_t^S = g(\cdot), \quad t = \{0, \ldots, T\} \\
& \quad x_t^M \geq -x_t^S, \quad t = \{0, \ldots, T\} \\
& \quad 0 \leq x_{i,t}^{d+} \leq l_{i,t}^{d+}, \quad \mathcal{F}_t\text{-meas}, \quad t = \{0, \ldots, T\}, \quad \forall d \in \mathcal{D}^S, \quad \forall i \in I^d \\
& \quad 0 \leq x_{i,t}^{d-} \leq l_{i,t}^{d-}, \quad \mathcal{F}_t\text{-meas}, \quad t = \{0, \ldots, T\}, \quad \forall d \in \mathcal{D}^S, \quad \forall i \in I^d \\
& \quad x_t^d \in \mathbb{R}, \quad \mathcal{F}_t\text{-meas}, \quad t = \{0, \ldots, T\}, \quad \forall d \in \mathcal{D} \\
& \quad x_t^S \in \mathbb{R}, \quad \mathcal{F}_t\text{-meas}, \quad t = \{0, \ldots, T\} \\
& \quad x_t^M \geq 0, \quad \mathcal{F}_t\text{-meas}, \quad t = \{0, \ldots, T\} \\
\text{optional} & \quad w^i \cdot v_t \leq \sum_{d \in \mathcal{D}_i^w} x_t^d \leq w^u_i \cdot v_t, \quad i = \{1, \ldots, n\}, \quad t = \{0, \ldots, T\} \\
& \quad \sum_{d \in \mathcal{D}^S} \sum_{i \in I^d} x_{i,t}^{d+} - \sum_{d \in \mathcal{D}^S} \sum_{i \in I^d} x_{i,t-1}^{d-} \leq v_t - v_{t-1}, \quad t = \{0, \ldots, T\} \\
& \quad \sum_{d \in \mathcal{D}^S} \sum_{i \in I^d} x_{i,t}^{d-} \leq \max\{0, \neg v_t + v_{t-1}\}, \quad t = \{0, \ldots, T\} \\
\end{align*}
\]

where \(x_t^M\) is a non-negative variable to ensure that only a negative surplus at time \(t\) will enter the objective function, thus, earnings with a positive sign will not be minimized. Further \(g(.)\) is just a short handed notation of constraint (18), i.e. \(g(.) = \sum_{\tau=0}^{\min\{t,D_t-1\}} \sum_{(d,r) \in \mathcal{D}^S} \sum_{i \in I^d} \left( r_{i,t-\tau}^{d+} x_{i,t-\tau}^{d+} - r_{i,t-\tau}^{d-} x_{i,t-\tau}^{d-} \right) + cf_{t-1} \neg (c_t + a_0) \cdot v_t.\)

Depending on the convexity of the objective function, it is not clear whether or not the solution produced by a reduced gradient solver is globally optimal.
2.3 Financial Model Evaluation

In their paper, Supervisory Guidance for Assessing Bank’s Financial Instrument Fair Value Practices from 2009, the Basel Committee on Banking Supervision states that models used for valuation of financial instruments should be evaluated based on:

- theoretical soundness and mathematical integrity;
- the appropriateness of model assumptions, including consistency with market practices and consistency with relevant contractual terms of transactions;
- sensitivity analyses to assess the impact of variations in model parameters on fair value, including under stressed conditions; and
- benchmarking of model results with observed market conditions at the time of valuation or independent benchmark model.

Furthermore, Bardenhewer (2007) states that financial models should be assessed based on three categories; flexibility, complexity and implementation.

**Flexibility**

By flexibility Bardenhewer means that a good model should adequately incorporate changes in underlaying historical data as well as being applicable to modeling extensions.

**Complexity**

According to Bardenhewer a good model should also be transparent and communicable to senior managements as they lay the foundation for funding programs and hedging strategies. Furthermore, the probability of operating failures rises with the model complexity hence a simple model that can adequately simulate reality is to prefer.

**Implementation**

Closely linked to complexity, Bardenhewer argues that a good model should be easy to implement into existing risk management, funding and pricing processes. Furthermore, falling under the category of implementation, calculation costs in terms of storage demand and calculation time as well as maintainability are also decisive factors when assessing models.
3 Model Extension

This chapter presents an extension of Bardenhewer’s two models presented in section 2.2.2.

3.1 Bounded Static Replicating Portfolio with Moving Average

The different trend functions proposed by Bardenhewer (2007) might yield negative trend volumes $F_t(\Delta_t, r_{i,t}, r_0, \ldots, \beta_4, k_i, \delta)$ depending on the historical data. Hence, a bound can be introduced on the trend volume to floor it at zero to prevent unrealistic deposit balances

$$F_t(.) = \begin{cases} F_t(.), & \text{if } F_t(.) > 0. \\ 0, & \text{otherwise.} \end{cases} \quad (23)$$

This will result in the following non-linear optimization problem.

$$\begin{array}{ll}
\min & z_4(r_t^p, d_t) = \text{std}(r_t^p - d_t) \\
\text{subject to} & r_t^p = \frac{\hat{F}_t(.)}{V_t} \sum_i w_i m_{a_i,t} + \frac{\hat{A}_t(.)}{V_t} r_{1,t} \quad \forall t = 1, \ldots, T \\
& \sum_{i=1}^n w_i = 1 \\
& w_i \geq 0 \quad \forall i \in N
\end{array} \quad (24)$$

where $\hat{A}_t(.) = V_t - \hat{F}_t(.)$.

Furthermore, the same liquidity constraints proposed in the original model can be extended to the bounded version as well.

Problem 24 is a non-convex optimization problem due to the bounded trend function $\hat{F}_t(.)$ causing $r_t^p = \frac{\hat{F}_t(.)}{V_t} \sum_i w_i m_{a_i,t} + \frac{\hat{A}_t(.)}{V_t} r_{1,t}$ to become a non convex function. Hence, a global optimal solution to this problem is not guaranteed when using a reduced gradient solver.
4 Methodology

This chapter presents the methodology used in the thesis. Beginning with section 4.1, a description of the data sets used to evaluate the models is given. Secondly, the different evaluation methods are presented in section 4.2. Finally, the different models subjected to evaluation are described in section 4.3.

4.1 Data Description

All data used for evaluation of the proposed models is provided by the Bank consisting of deposit volumes, daily historical market rates and deposit rates. No significant deposit volumes are observed before October 2007 and thus the data ranges over a sample period between this date and January 2018. Furthermore, the market rates data set is comprised of the Stockholm Interbank Offer Rate (STIBOR), Swedish Government Bond rates (SEGVB) and swap rates. The STIBOR rates are; overnight, one week, one month, two months, three months, six months, nine months and 12 months. The SEGVB rates are two years and five years. The swap rate data set are exclusively used to construct the replicating portfolio proposed by EBA and BCBS and consist of the 18 months, three years, four years and six years swap rates.

The deposit rates and volume data sets are composed by 11 different account types. The different groups of account types, A-BP, consists of different levels separated by monetary restrictions on the accounts. Here, $V_t$ is the account balance at time $t$. These restrictions are connected to the

<table>
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<th>Name</th>
<th>Segment</th>
<th>Monetary Restriction (mSEK)</th>
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<tr>
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Table 3: Account distinctions

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<td>$V_t \leq 25$</td>
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</table>
interest rate set by the Bank where smaller deposits are premiered with a higher interest rate as is evident by Figure 4.

The retail deposit segment of the Bank consists of three account types, A_1, A_2 and R_1 and are available for individual persons and sole proprietorships. The main difference between the groups is that group A is exclusively for customers with a mortgage in the bank, and is thus given a higher deposit rate than R. The wholesale segment of the Bank consists of account types F_1, F_2 and F_3 and are exclusively used by legal entities other than financial clients. These accounts were not introduced until June of 2009 and did not attract higher tier level customers until September of 2011. The condominium cooperative segment of the Banks consists of account types B_1, B_2, B_3, BP_1 and BP_2. These accounts are used by cooperative owned housing associations and are separated from the wholesale segment due to the Banks belief that these clients differ greatly in terms of deposit and withdraw behavior. The main difference between group B and BP is that group BP is exclusively for cooperative owned housing associations with a mortgage in the bank and is thus given a higher deposit rate than group B.
4.2 Model Evaluation Methods

All models subjected to assessment will be evaluated based on three categories: goodness of fit, stability and transparency. These categories are chosen based on the supervisory guidance given by Basel Committee on Banking Supervision (2009) for assessing bank’s financial instrument fair value practices and suggestions made by Bardenhewer (2007).

4.2.1 Goodness of Fit

The models capability to accurately depicting reality will be evaluated based on a goodness of fit measure. The coefficient of determination $R^2$ which measures the proportion of the variance in the dependent variable that is predicted by the independent variables will be used as this measure. The definition of $R^2$ is as follows:

Let a data set $N$ have $n$ values given by $(y_1, \ldots, y_n)$ each associated with a predicted value $(f_1, \ldots, f_n)$. Then the mean of the observed data is given by

$$
\bar{y} = \frac{1}{n} \sum_{i=1}^{n} y_i
$$

(25)

and the variability of the data set can be measured by the total sum of squares and the residual sum of squares

$$
SS_{tot} = \sum_{i=1}^{n} (y_i - \bar{y})^2
$$

(26)

$$
SS_{res} = \sum_{i=1}^{n} (y_i - f_i)^2
$$

(27)

which gives the coefficient of determination $R^2$

$$
R^2 = 1 - \frac{SS_{res}}{SS_{tot}}.
$$

(28)

4.2.2 Stability

To measure stability of the models an Out-of-Sample analysis will be conducted. Here, model results will be based on a historical data period of 5 years which are continually moved one month at a time, beginning in October 2007 and ending in January 2018.
Furthermore, to measure the stability of the model solutions that utilizes non-linear optimization problems, a global solution analysis will be conducted. Here, model results will be generated 50 times using different starting points for the non-linear solver to measure variations in the solutions. For this analysis the entire historical data set will be used.

4.2.3 Transparency

Model transparency is a subjective measure and thus hard to quantify. The measure will inevitable be affected by the subjective views of the author. However, it is included into the overall evaluation of the models since it represents an important practical aspect when deciding which model to implement.

4.3 Model Selection

The following models will be evaluated and given abbreviation notations used in sections 5, 6 and 7.

- Standard Deviation of Margin Minimization (MT\textsubscript{1}) - Static Replicating Portfolio by Maes and Timmermans presented in section 2.2.1.
- Sharpe Ratio Maximization (MT\textsubscript{2}) - Static Replicating Portfolio by Maes and Timmermans presented in section 2.2.1.
- Static Replicating Portfolio (BhW\textsubscript{1}) by Bardenhewer presented in section 2.2.2.
- Liquidity Adjusted Static Replicating Portfolio (BhW\textsubscript{2}) by Bardenhewer presented in section 2.2.2.
- Overnight Static Replicating Portfolio (FI) by FI presented in section 2.2.3.
- Time Series Approach with Uniform Slotting Procedure (BCBS) by EBA & BCBS presented in section 2.2.4.
- Bounded Static Replicating Portfolio with Moving Average (X\textsubscript{1}) presented in section 3.1.
- Liquidity Adjusted - Bounded Static Replicating Portfolio with Moving Average (X\textsubscript{2}) presented in section 3.1.
4.3.1 Estimation of Remaining Balance

Maes & Timmermans (2005) does not state how to estimate the core and volatile part of the deposit volume and in extension the remaining balance. Thus, the core part of the deposit volume is estimated using the bounds provided by the Basel Committee on Banking Supervision (2016) in their Time Series Approach for wholesale and retail segments. The volatile part of the deposit volume is estimated using the maximum deviation from a quadratic trend function over the historical sample period.
5 Results

This chapter presents the thesis findings. First, an overview of the model results regarding duration is presented. Secondly, the performance results are presented beginning with the goodness of fit measure followed by the stability and transparency analysis.

5.1 Overview

The duration of the replicating portfolios varies greatly between the different models and for the different account types. Overall, the retail segment accounts; A₁, A₂ and R₁ have longer duration periods than the wholesale segment of accounts, apart from FI’s baseline model. This is most likely due to a more stable deposit and withdraw behavior in the retail accounts. This is also in accordance with EBA’s and BCBS’s views reflected in their Time Series Approach.

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</tr>
<tr>
<td>BP₁</td>
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<td>0.05</td>
<td>0.05</td>
<td>8.00</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Table 4: Duration (months)

Both models by Maes & Timmermans produce the largest duration periods due the segmentation of deposit volumes into three categories; volatile (short duration), core (long duration) and remaining balance which is distributed according to the solution of the actual optimization problem. The core part is put into the 5 year bucket and is estimated to be 49% for the retail segment and 33% for the wholesale segment, thus extending the duration period. The volatile part of the deposit volume is put into the overnight bucket and is estimated to be only 19% for the retail segment and 13% for the wholesale segment. Hence, the overall effect on the duration period is less than that of the core deposit volume. The remaining balance is cal-
culated to be 32% and 55% for retail and wholesale segments respectively. Furthermore, in both MT₁ and MT₂ the retail accounts; A₁, A₂ and R₁ have the same duration periods. Hence, the distribution of the remaining balance is the same for these three account types. It is also worth noting that the minimization of the standard deviation of the margin (MT₁) has a shorter duration period than the maximization of the Sharpe ratio (MT₂).

The two models by Bardenhewer produces short duration periods for all account types. Further, the Market Mix method used in BhW₂ does not yield different results than in BhW₁. This is due to the already high portion of short term market assets in the replicating portfolio BhW₁. Hence, the maturing volume in the replicating portfolio covers all withdraws made in the past, i.e. the liquidity constraints have no effect.

The Bounded Static Replicating Portfolio with Moving Average, X₁, yields, for most accounts, longer portfolio durations than that of BhW₁ and BhW₂. This is due to the bounds introduced on the trend volume to handle unrealistic trend movements caused by low volumes when some accounts where first introduced to the public. Furthermore, as is also the case with BhW₁ and BhW₂, the liquidity adjusted model, X₂, yields the same results as X₁ due to the already high portion of short term maturing assets.

FI’s baseline model and the uniform distribution under the Time Series Approach by EBA and BCBS yields, unsurprisingly, the intended duration periods for all accounts. The core deposit balance of the Time Series Approach is fixed at 40% and 20% for retail and wholesale accounts respectively provided by the simplified TIA approach.

5.2 Performance

The performances of the analyzed models varies greatly between the different performance measurements. For instance, MT₁ by Maes & Timmermans tend to be more stable in terms of duration than X₁ and X₂. However, X₁ and X₂ tend to have a better average goodness of fit. In general, models with a higher duration stability tend to have a lower degree of explanation when utilizing the entire historical sample period. However, the model proposed by the Basel Committee on Banking Supervision, BCBS, have a rather high degree of explanation when compared to the model enforced by FI, both being models not effected by historical data and thus completely stable models.
### 5.2.1 Goodness of Fit

In Table 5, the overall goodness of fit measure for all models and accounts is rather low with 68% being the highest degree of explanation. This is caused by the models' inability to replicate the interest rate behavior of the Bank using the financial instruments available. $X_1$ and $X_2$ produces the highest average degree of explanation of all models and unsurprisingly the model enforced by FI yields the lowest average degree of explanation.

Some accounts like $F_3$, $B_2$, $B_3$ and $BP_2$ have negative coefficients of determination, meaning that the mean of the market data set provides a better fit to the deposit rate behavior of the Bank rather than the models provide. Account $B_1$ have had the same deposit rate since it was first introduced causing the total sum of squares to be zero. Hence, the coefficient of determination cannot be calculated for this account.

<table>
<thead>
<tr>
<th></th>
<th>MT1</th>
<th>MT2</th>
<th>BhW1</th>
<th>BhW2</th>
<th>X1</th>
<th>X2</th>
<th>BCBS</th>
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</tr>
<tr>
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<td>0.54</td>
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</tr>
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</tr>
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<td>-1.64</td>
<td>-0.41</td>
<td>-3.15</td>
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</table>

*Table 5: Goodness of fit ($R^2$)*

### 5.2.2 Stability

#### Out-of-Sample Analysis
For the sake of stability comparison between the different models that utilizes historical data, the Out-of-Sample analysis is conducted on the $R_1$ accounts. This group have the largest amount of depositors and the largest total deposit volume over time for all account groups. The model proposed by EBA and BCBS does use historical data to estimate core deposits, if one so choses, however this thesis uses the deposit segmentation provides by the simplified TIA. Hence, the EBA and BCBS model is left out of the stability analysis.

28
In Figure 5 the variation of the duration is displayed for each historically calibrated model when the data set is incrementally changed. It is evident that the MT\textsubscript{1} model proposed by Maes & Timmermans, have a more stable duration than MT\textsubscript{2}, BhW\textsubscript{1}, BhW\textsubscript{2}, X\textsubscript{1} and X\textsubscript{2}. This is due to the rather large portion of deposit volumes put into the overnight and 5 year time buckets, thus limiting the overall fluctuations in duration. MT\textsubscript{2} does experience a jump in duration when the data set starts approximately 10 months from October 2007. This is due to a shift in portfolio weights from the one year bucket to the five year bucket. Apart from this jump, the model generates stable results.

Figure 6 gives a more detailed view on the variations of the durations per model category. MT\textsubscript{1} and MT\textsubscript{2} have rather different stability characteristics where MT\textsubscript{2} experience a large change in duration over the different sample periods. The increase in duration in MT\textsubscript{1}, caused by the 5 year data set beginning approximately 45 months after October 2007, is most likely due to that the Banks interest rate behavior is more aligned with longer markets rates following the more stable period after the financial crises of 2008/2009. Using the same logic, the sub-sequential drop in duration at 50 months from October 2007 is most likely caused by the Greek government-debt crisis. Where the Bank is more aligned with the shorter market rates due to market instability.

BhW\textsubscript{1} and BhW\textsubscript{2} have identical stability characteristics. This is due to the Market Mix method not yielding different results caused by the al-
ready high portion of short term market assets in the replicating portfolio. This effect is also seen in the Bounded Static Replicating Portfolio with Moving Average models, $X_1$, $X_2$. Furthermore, $X_1$ and $X_2$ and the models proposed by Bardenhewer have similar stability characteristics where BhW$_1$ and BhW$_2$ is somewhat more stable due to the lower duration values in the first 10 increments. One can also note the increase and sub-sequential drop in duration between increments 30 and 50 months from October 2007. This is most likely caused by the same phenomenon seen affecting MT$_1$. However, the smoother peaks seen in Figure 6b and Figure 6c is caused by the utilization of moving averages which reduces the effect of large market movements.

![Graphs showing duration trends over time](image)

(a) Maes & Timmermans  
(b) Bardenhewer

(c) Bounded Static Replicating Portfolio with Moving Average

**Figure 6: Out of sample analysis per model category**

Figure 7 gives an overview of how the goodness of fit measure varies during the out of sample analysis. It is clear that when more recent data is incorporated into the data set the degree of explanation decreases over all models. Initially, both models by Bardenhewer and $X_1$, $X_2$ have a high
degree of explanation, in the range of 80%-90%. However, shifting the interval 30 months ahead results in a negative coefficient of determination. The models proposed by Maes & Timmermans have an overall lower degree of explanation compared to the other models utilizing historical data. Furthermore, in terms of stability, the high variation in the goodness of fit measure indicates that these models are very susceptible to changes in the underlaying data.

![Figure 7: Out of sample analysis: Goodness of Fit.](image)

**Global Solution Analysis** To further analyze the stability of the evaluated non-linear optimization models, in particular the stability of the solutions, a global solution analysis is conducted on the $R_1$ accounts.

<table>
<thead>
<tr>
<th></th>
<th>MT$_1$</th>
<th>MT$_2$</th>
<th>BhW$_1$</th>
<th>BhW$_2$</th>
<th>X$_1$</th>
<th>X$_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>R$_1$</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Table 6: Global Solution Analysis: Standard deviation of $D_p$.

Table 6 shows the standard deviation of the duration $D_p$ for 50 iterations per non-linear optimization model. As is evident by the table, all models generates stable solutions. MT$_1$ and MT$_2$ as well as BhW$_1$ and BhW$_2$ are convex optimization problems and thus one would expect global optimal results. Given a standard deviation of 0.00 in duration, one can conclude that this is indeed the case. More surprisingly, X$_1$ and X$_2$ also produces
zero standard deviation in duration despite being non-convex optimization problems.

5.2.3 Transparency

The transparency of the models, or rather how easy model structure, parameters, calibrations and results are to communicate to non-quantitative risk analysts such as CEO and board members, is rather high for all models. This stems from the general method employed by replicating portfolios. That is, to utilize well know market instruments to replicate behavior of more complicated financial products. Furthermore, static replicating portfolios in particular are more transparent than their dynamic counterparts due to the rather uncomplicated model structure.

Of the models analyzed in this thesis, the model enforced by FI can be seen as the most transparent. This model utilizes only the overnight time bucket and the results are not dependent on any data. Thus, both the model structure, parameters and results becomes almost trivial and easy to explain to a non-quantitative risk analyst.

The second most transparent model is that of the European banking authority and the Basel committee of banking supervision, BCBS. This model utilizes a uniform slotting procedure and a two-phase separation procedure of core deposits and non-core deposits under imposed caps. Thus, the model is clearly more advanced than the one enforced by FI. However, the uniform slotting procedure is still easy to communicate since it involves a basic distribution of core deposits into different time buckets. Furthermore, the two-phase separation procedure can easily be visualized and broken down into a step by step instruction thus facilitating communications to non-quantitative risk analysts.

The static replicating portfolios proposed by Maes & Timmermans, MT\textsubscript{1} and MT\textsubscript{2}, is less transparent than the models enforced by FI, EBA and the Basel committee of banking supervisions. MT\textsubscript{1} and MT\textsubscript{2} share similarities with BCBS in terms of separating deposit volumes into different portions based on deposit characteristics. However, Maes & Timmermans models solves for the optimal distribution of weights across different time buckets under one of two objective functions. This will inevitably make the models less transparent since the structure, parameters and results are all connected to a non-linear optimization problem.

BhW\textsubscript{1} and BhW\textsubscript{2} proposed by Bardenhewer builds on the non-linear optimization problem in model MT\textsubscript{1}. Bardenhewer incorporates a trend function into the optimization problem to separate the portion of deposit ex-
plained by a trend and the portion that cannot be explained. Using a more sophisticated method to separate deposit balances will reduce the transparency of the model since it will be harder to communicate. Furthermore, utilizing liquidity adjustments with the market mix method, as is the case with model BhW₂, will also reduce overall transparency.

The bounded static replicating portfolio with moving average models, X₁ and X₂, builds on BhW₁ and BhW₂ only with the small addition that the trend functions are floored at 0 to prevent unrealistic deposit balances. Hence, the transparency of X₁ and X₂ is deemed to be similar if not identical to that of BhW₁ and BhW₂.
6 Discussion

This chapter analyzes and discuss the results presented in chapter 5. The discussion stems from the same three performance measures; goodness of fit, stability and transparency as presented in the previous chapter. In addition, a brief exposition regarding the dynamic replicating portfolio proposed by Frauendorfer & Schürle (2007) is made.

6.1 Overview

In general, the models evaluated in this thesis produce vastly different results. Although all models share similar structures that stems from the theory of static replicating portfolios, they also differ, mainly in the partitioning of deposit volume but also in objective function. Furthermore, it is important to remember that all models that utilizes historical data are subjected to the quality and specific situation of the institution where it is gathered. In other words, the results presented in this thesis are all dependent on the data provided by the Bank and in extension limited to the specific situation of this financial institution. Hence, the same models presented in this thesis would most likely yield different results when evaluated on data provided by other financial institutions. However, some conclusions can still be drawn which are applicable in a more general setting. These conclusions will be presented in chapter 7.

6.2 Goodness of Fit

The low goodness of fit measure for all models utilizing historical data is caused by the models inability to replicate the deposit rate behavior of the Bank. This means that the overall interest rate behavior of the vanilla market instruments used in the replicating portfolios cannot replicate the deposit rate behavior of the Bank accurately. Since 2009, the Bank has adopted a rather aggressive pricing strategy to attract larger deposit volumes in order to increase diversification in the funding portfolio. As is evident by Figure 8, due to this strategy the Bank has been reluctant to decrease the deposit rates when the market rates decreases. This, at least to some extent, is a contributing factor to the overall low goodness of fit measures of the models. This effect can also be seen in Figure 7, where the coefficients of determination decrease as the data set is incrementally shifted from 2007 towards 2018.

FI:s model produces a negative coefficient of determination for all eval-
uated accounts. Compared to the other models, this result is rather poor. Effectively, the mean of the market data set provides a better fit for the deposit rate behavior of the Bank than the model enforced by FI. Thus, one can conclude that FI’s model is a poor fit for the Bank, inaccurately depicting deposit rate behavior and in extension deposit duration. The uniform static replicating portfolio proposed by EBA and BCBS manages to produce a fairly high degree of explanation compared to FI:s model, both being models not utilizing historical data. This is caused by the uniform approach allowing weights to be slotted across longer market instruments which are more aligned with the deposit rates behavior of the Bank. Furthermore, $X_1$ and $X_2$ produces the highest average degree of explanation most likely caused by the utilization of moving averages and bounds on the trend volume smoothening market movements and unrealistic deposit balances.
6.3 Out-of-Sample Analysis

The Out-of-Sample Analysis gives an indication of model stability in terms of how results vary when the historical data set used to calibrate the models changes. Since the model enforced by FI does not use historical data to calibrate model parameters, from an Out-of-Sample perspective, this model is completely stable with constant results. Further, the model proposed by EBA and BCBS utilizes historical data to calibrate the portion of stable and non-stable deposits. However, due to imposed caps on the deposit portions the results are found to remain constant over the Out-of-Sample Analysis. Similar to FI, this model is thus also completely stable.

The models proposed by Maes & Timmermans, Bardenhewer and the new models presented in this thesis all change when the data set is shifted. One can note that the models tend to produce longer portfolio durations when the market has undergone a volatile period, meaning that the longer market rates, at this time, are more aligned with the Banks deposit rate behavior. An important exception is MT2 which experience a jump in duration when the data set interval is shifted 10 months a head from October 2007. This is caused by a sudden drop in the STIBOR 12M rate from approximately 5.5% to 1.5% surpassing the five year Swedish government bond rate. Hence, the model opts for the longer five year market rate.

6.4 Global Solution Analysis

The global solution analysis gives an indication of the solution stability of the non-linear optimization models. Of particular interest is the non-convex optimization problems where global solutions are not guaranteed since a reduced gradient solver only fulfills first order necessary conditions for optimality. Hence, solutions to these models can change depending on if the solver finds another local optimal solution. However, the results of the analysis indicates that the non-convex models X1 and X2 produces stable results. To no surprise, the analysis also indicates that the convex optimization problems have global optimal solutions.

6.5 Transparency

Model transparency is an important measure reflecting the practical aspects of implementation, verification and communication of model results. However, due to the subjective nature of this measurement, the results presented in this thesis are therefore the product of the authors opinion and cannot be verified by quantitative means.
In general, the static replicating portfolios have a rather high degree of transparency due to the simple model structure and static nature. The model presented by EBA and BCBS as well as FI gives an indication that regulatory agencies favors simple transparent models over complicated ones. This is most likely due to that the verification and validation processes are less resource demanding. However, in most cases, increased transparency comes at the cost of decreased model accuracy. This is evident, for instance, by the model enforced by FI which produces negative goodness of fit measures for all accounts. Thus, in general, the selection process for choosing a model to measure the duration of NMDs involves a trade-off problem between transparency and model accuracy. Most financial institutions search for simple transparent models that are sufficiently good at depicting reality to save resources in implementation and maintenance processes. However, if there are benefits surpassing the overall costs of utilizing a less transparent model, a financial institution might decide to choose this option. E.g. for most Swedish banks, cost benefits can be achieved if the NMD volume is estimated to have a duration closer to the banks assets since the capital requirement to cover interest rate risk will decrease. This is one of the reasons why the banking industry in Sweden have pushed for the right to use other models than the simple model enforced by FI.

6.6 A Final Note on Dynamic Replicating Portfolios

Although not subjected to the performance analysis of this thesis, the dynamic replicating portfolio proposed by Frauendorfer & Schürle (2007) is indeed a more advanced model for replicating interest rate behavior of NMD:s. There are several clear advantages of using this model. Perhaps the most obvious one is the utilization of numerous future scenarios whereas the static replicating portfolio models only takes historical scenarios as input. Furthermore, the dynamic replicating portfolio also accounts for the possibility of future changes in the reinvestment strategy. Another advantage is the guarantee of no investment rule violations, meaning that any output from the dynamic replicating portfolio by Frauendorfer & Schürle (2007) is per definition funded from the current maturing amounts. Since static replicating models optimizes a new composition of the whole replicating portfolio independent from the previous periods’ solutions or current maturing amounts, theoretically, the solution of the model might lead to that the current optimal distribution cannot be achieved by reinvesting solely maturing amounts. Hence, for real investments some assets might need to be sold before maturity, adding primarily interest rate risk to the portfolio (Straßer 2014).
All the different advantages given by the dynamic replicating portfolio by Frauendorfer & Schürle (2007) comes at the cost of transparency. In most cases, a more advanced model becomes more complex increasing the gaps in communication of model results, limitations and conditions to non-quantitative risk analysts. Also, the model becomes more resource demanding in both implementation and maintenance procedures. Furthermore, the complex nature of the model also increases the operational risk.

Given current trends in regulation, promoting transparent internal models within a clearly defined regulatory structure, it proves difficult to make an informed decision regarding the utilization of more advanced models in this specific setting. On one hand, analysts strive to produce results similar to reality. On the other hand, one has to trade transparency and increased utilization of resources to achieving these results. Hence, it is up to the banks to make the decision regarding accuracy or increased transparency.
7 Conclusion and Further Research

Due to the extensive use of NMD funding by most large banks, there is an growing interest in NMD modeling research. Also, the increased interest from regulatory agencies in recent years further highlights the banking industry’s desire to implement good models for modeling of NMD duration. When considering replicating portfolio models, some important realization can be made. Given the current market conditions, replicating portfolio models provides a poor fit for replicating the interest rate behavior under the specific setting of the Bank. There is a clear mismatch between market rates movements and deposit rates most likely caused by the Banks desire to attract larger deposit volumes. Although the dynamic replicating portfolio prosed by Frauendorfer & Schürle (2007) have not been subjected to the same analysis as the static replicating portfolios, one would likely find that the result would have a rather poor coefficient of determination as well. This is due to the underlaying structure of all replicating portfolios, they are in essence limited by the available assets on the market. However, further performance analysis is needed to make a more thorough analysis.

The results of this thesis also highlights the high variability in duration and goodness of fit when the data set used to calibrate the models is changed. Hence, when implementing replicating portfolio models relaying extensively or solely on historical data, it is important to perform a comprehensive analysis of the data set. Furthermore, an initial analysis will probably give a good indication regarding the portfolios ability to replicate the interest rate behavior of the NMD subjected for analysis.

The performance evaluation of the models have been performed based on three different categories; goodness of fit, stability and transparency. These categories stem from the suggestions made by the Basel Committee of Banking Supervisions and have proven to be sufficient for analyzing the performances of the different models. In contrast to the quantitative performance measurements; goodness of fit and stability, the transparency measurement is utilized to include a practical aspect in the analysis. The goal of the transparency measurement is to provide decision makers with a sens of how resource demanding a model will be both in terms of implementation and maintenance but also in communication of model results. Overall, the analysis indicates that less transparent replicating portfolios provides more accurate results. However, the analysis is performed on a small set of models and further research is required for the findings to be validated.

Of the models subjected to analysis, the thesis shows that the bounded
replicating portfolio with moving averages produces the overall best performance results. However, due to the generally low goodness of fit for all models and the low stability measure of some, it is questionable if the model result is acceptable for implementation at the Bank. Further research into other modeling techniques based on the specific setting of the Bank is required to put the replicating portfolio results into a more comprehensive context.
References


