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Modelling the Swedish Krona Short Term Rate

SWESTR: An ARIMA Approach

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Abstract

This thesis investigates the feasibility of forecasting the SWESTR using an ARIMA model, in addition to evaluating the potential benefits of incorporating international interest rates as exogenous variables. More specifically the €STR that represents the short-term rate in the eurozone, which the Swedish market is expected to follow due to macro-economic factors. Despite the inherent challenges in outperforming a random walk model, the results indicate that ARIMA models augmented with €STR capture some variations in SWESTR, and manage to beat the random walk. This thesis applies known methods of forecasting interest rates by using ARIMA models on the SWESTR.

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1 Introduction

In the interconnected and complex world of finance, interest rates play a crucial role in the financial system both as an enabler and a regulating entity, with the goal of overall stability of the financial system. One particular type of interest rate that has been gathering more attention in the past few years is the overnight rate. After the London Interbank Offered Rate (LIBOR) scandals in 2012, there has been a global financial reform aimed at replacing the existing reference rates around the world with transaction-based rates. As a part of that reform, the Swedish central bank introduced the Swedish Krona short-term rate (SWESTR) in September 2021 to adhere to international recommendations. The SWESTR is a transaction-based reference representing the average rate for overnight unsecured lending for financial institutions (Sveriges Riksbank, 2021).

There are many reference rates around the world tied to their specific market and market segment, in this thesis however one rate in particular is examined, the SWESTR. Reference rates play an integral role in the financial system as they act as a benchmark rate for a plethora of financial contracts and products, especially those with floating rates (Sveriges Riksbank, 2021). This linkage means that fluctuations in the short-term rates can affect everything from homeowners' mortgage payments to large institutions' investment returns. For businesses and banks being able to predict these short-term rates accurately can help significantly in managing liquidity risk and cash flow. Therefore, to be able to forecast these short-term rates, even just one period out can be seen as highly desirable.

Despite Sweden maintaining financial independence by not being part of the eurozone or any other currency cooperation, allowing greater control over monetary policies. There is evidence to suggest that the Swedish interest rates are not determined autonomously. Instead, it is in large part determined by the international market, and fluctuations in major economies' interest rates, like the United States and the eurozone, have been shown to impact other markets' interest rates (Holmes, 2005; Cumby and Mishkin, 1984; Fujihara and Mougue, 1996).

Given the high value of accurately forecasting SWESTR and the potential influence of other major rates, this thesis aims to assess the plausibility of making one-period-ahead forecasts for SWESTR and to explore whether incorporating the Euro short-term rate (€STR) could improve this forecasting accuracy.

1.1 Background

An overnight rate, such as the SWESTR, is a reference rate published daily by central banks, based on the average interest rates at which banks lend to one another overnight without collateral. It is calculated from actual transactions of the previous day, and these rates are not set by the central banks but by the market, although heavily influenced by the policy rate. And unlike market rates that can fluctuate throughout the day, overnight rates are fixed for the entire day.

As alluded to previously, there has been a global financial reform aimed at replacing existing benchmark rates with alternative, transaction-based rates. The shift towards transaction-based reference rates is largely a result of the LIBOR scandal uncovered in 2012, which exposed vulnerabilities in self-reported and estimate-based benchmark rates. Since LIBOR was composed of self-reported estimates from banks rather than actual transactions, it allowed banks to manipulate it to their benefit. The objective of the new rates is to provide a more robust interest rate against market stress and manipulation and to offer a rate that truly reflects the unsecured overnight borrowing cost based on actual transactions, thereby increasing transparency and reliability (Sveriges Riksbank, 2021).

As part of the global shift towards transaction-based rates, the SWESTR was introduced in September 2021 by the Swedish Central Bank to align with international standards (Sveriges Riksbank, 2021). However, unlike many other financial markets such as the Eurozone, which has replaced the Euro Overnight Index Average (EONIA) with the transaction-based €STR as their primary reference rate for overnight unsecured lending between banks (Deutsche Bundesbank, 2020), SWESTR has not yet replaced the traditional Stockholm Interbank Offered Rate (STIBOR) as the reference rate, or the STIBOR Tomorrow-Next for overnight rates. The traditional STIBOR still plays a significant role in the Swedish financial system. Nonetheless, the Swedish central bank has urged market participants to transition from STIBOR to SWESTR as the reference rate for overnight lending by all market participants, with the long-term goal of replacing STIBOR altogether across all maturities (Sveriges Riksbank, 2024). Despite STIBOR's historical prominence, the push from Riksbanken towards SWESTR suggests its growing relevance as the primary reference rate in Sweden.

Despite not being part of the Eurozone or engaged in similar currency cooperation, Sweden's financial system remains thoroughly integrated with and influenced by the Eurozone (Lindé and Reslow, 2017). This interconnectedness means that Sweden's interest rates, including

SWESTR, are often impacted by fluctuations in major markets rather than being entirely autonomous. Historical data supports this, with studies like Holmes (2005) demonstrating interest rate parity across EU countries, implying that changes in Eurozone rates could predict similar movements in SWESTR. Additionally, the research by Cumby and Mishkin (1984) indicates that United States interest rate movements also influence rates in other nations. These findings underscore the potential benefits of incorporating major external interest rates, such as those from the Eurozone, into forecasting models to enhance the accuracy of predictions for SWESTR.

As the SWESTR was officially introduced in 2021, it is a relatively new rate. Consequently, there is little to no research specifically focusing on the SWESTR. However, research on interest rate forecasting is a well-established field. Beating the random walk has proven to be difficult, but Butter and Jansen's (2013) research demonstrated the legitimacy of forecasting interest rates. The question then becomes which models are best suited for forecasting a rate like the SWESTR. Traditionally, the Autoregressive Integrated Moving Average (ARIMA) model, or variations thereof, has been widely used to model time series data. The development of machine learning algorithms has also shown potential in quantitative finance and in predicting time series data (Rundo et al., 2019). However, no single method has been proven to consistently outperform others, and ARIMA models still perform the best in many scenarios (Babu and Reddy, 2015).

Benchmark rates, also known as reference rates, such as the €STR and SWESTR, play a crucial role in the financial system. They aim to represent the general cost of borrowing within their market segment. As previously noted, these reference rates are foundational in the pricing of numerous financial contracts and products, thereby influencing a wide range of economic activities. Consequently, the ability to forecast these short-term reference rates accurately, even if not with absolute certainty, can be hugely beneficial for a myriad of reasons and parties. For financial institutions and banks, accurately forecasting the short-term rate helps in managing their liquidity and funds, mitigating liquidity and interest rate risks. Short-term rates also directly affect the pricing of a range of financial products, including loans, bonds, and derivatives. Investors use interest rate forecasts to make informed strategic decisions about investments in interest-bearing assets, and therefore making correct predictions of interest rate trends essential. For policymakers, understanding future interest levels is crucial for implementing effective measures. Thus, short-term rate forecasts can be decisive for many aspects of the financial markets and overall economic stability, as well as significantly enhancing financial decision-making for banks, businesses, and individuals.

1.2 Problematization and Research Question

Despite SWESTR´s introduction as the new intended primary overnight reference rate and its integral role in the financial system, there is little to no designated previous research on the specific topic of SWESTR. Even though machine-learning methods have made some strides in time series forecasting, their black box nature coupled with SWESTR´s limited historical data due to its recent introduction makes an ARIMA approach more suitable. Traditional models, such as ARIMA, are still widely recognized for their effectiveness in forecasting time series data. However, the integration of the global financial market suggests that domestic interest rates like SWESTR are not entirely autonomous, instead they are influenced by international financial movements. This raises the question of whether the inclusion of indicators from major economies such as the lagged interest rates of the Eurozone (€STR), could enhance the predictive ability of SWESTR when using an ARIMA model.

To include such external factors as the €STR is theoretically supported by the principle of interest rate parity, which states that interest rates between countries should converge, and reflect the interconnectedness of global finance. Excluding these factors when modelling the SWESTR might mean a miss of predictive power derived from global financial dynamics and macroeconomic factors. Furthermore, previous research such as Holmes (2005) and Cumby and Mishkin (1984) suggests that fluctuations in major economies' interest rates have a profound effect on other markets' interest rates, which further supports the notion that rates from other markets could provide information for forecasting SWESTR.

Given the above, the research objective and purpose of this thesis is to explore the feasibility of accurately making one-step-ahead forecasts for SWESTR using an ARIMA approach. In addition to evaluating the effectiveness of using other lagged interest rates, such as €STR, as exogenous variables for forecasting the SWESTR. This does not only fill the gap in the current research, where specific studies on SWESTR are scarce but also test the applicability of integrating international economics indicators in forecasting short-term rates. Therefore the research questions are as follows:

1. Can a precise one-step prediction of SWESTR be achieved using an ARIMA model?

2. Does the inclusion of lagged values of €STR enhance the predictive accuracy of the ARIMA model for SWESTR?

The outline of the thesis is as follows. Section 2 starts with a general discussion and literature review of time series modelling followed by a discussion of the suitability of an ARIMA model for forecasting interest rates. Section 2 ends with the economic theory behind using other markets' interest rates as indicators for the SWESTR is presented. Section 3 introduces the theoretical base, which aims to give an overview of the statistical theory for time series analysis. In section 4 the specific models are introduced accompanied by the evaluation criteria for the models. In section 5 the results of the thesis are presented. Lastly, sections 6 and 7 contain discussion followed by the conclusions.

2 Theoretical Background

This section begins with a literature review of time series modeling in general, followed by a more specific discussion on modeling and forecasting financial data. Finally, the economic motivation for using other interest rates to forecast SWESTR is presented.

2.1 Time Series Modelling

A time series is a sequence of data points measured at equally spaced intervals. Time series modelling is a statistical technique used to analyse these data points over time. The main idea of time series modelling is to use previously observed values to make future forecasts. Interest rates are not randomly generated data points, rather, they are a prime example of time series data due to their sequential nature, making time series modelling particularly applicable for analyzing them. There are many methods for modelling and forecasting time series data, classically one of the most widely used is the ARIMA, or a version thereof. This method was first introduced by George Box and Gwilym Jenkins in the 1970s (Box et al., 2008).

Even though ARIMA models are still the most widely used method for forecasting time series, other methods have gained popularity in recent years. In their 2019 evaluation, Rundo et al. (2019) argued that machine learning methods, such as neural networks, can outperform classical time series models in terms of forecast accuracy due to their ability to model more complex and non-linear relationships. Masini et al. (2021) reviewed the most recent developments in machine learning for time series modelling and forecasting. They highlighted how machine learning techniques could result in superior performance in certain complex forecasting scenarios compared to more traditional methods. This emphasizes a theme in recent research, that more advanced machine-learning models tend to outperform traditional models like ARIMA in certain circumstances, especially those involving non-linear relationships and complex data.

Despite machine learning models having some advantages in certain scenarios, ARIMA models remain reliable for forecasting time series such as interest rates due to several benefits, model transparency, interpretability, statistical testing, effectiveness in smaller data sets, and robustness to noise. ARIMA models are more transparent than other machine learning models, meaning that the different parts of the model have clear mathematical definitions. This transparency allows for clarity of how the inputs are used to make forecasts. Additionally, each component of the ARIMA model has a clear interpretation, making it favorable for understanding the rationale behind model predictions. Being able to interpret the effects of different parts of the model can be crucial, especially in fields such as economics, where understanding the cause-and-effect relationship is often essential. This contrasts with the black-box nature of many advanced machine-learning models, where it can be difficult, if not impossible, to know how input features are transformed into forecasts. This makes it challenging to explain the rationale behind specific forecasts or the influence of the variables. Another drawback of the black-box nature of machine learning models, particularly deep learning models, is that they are ill-suited for statistical testing. Their complexity and non-linearity make it hard to attribute specific effects in the output to specific input features or parameters in the model. In contrast, ARIMA models support rigorous statistical hypothesis testing, useful both for validating the model's assumptions and for testing the significance of predictions. Furthermore, many machine learning models require large data sets to perform well, and considering that SWESTR was introduced in late 2021, the sample size may be more suitable for an ARIMA model, which is not as sensitive to sample size.

As stated earlier, there has been significant development and research into other methods of time series modelling and forecasting, with promising results. However, the preference for ARIMA-based methods extends beyond their straightforward interpretability and capacity for statistical testing. ARIMA models have still managed superior performance in various forecasting scenarios, demonstrating their continued relevance and effectiveness. Yamak et al. (2019) compare the performance of different time series methods in forecasting Bitcoin prices. They found that the ARIMA model performed the best, outperforming deep-learning methods such as Gated Recurrent Unit and Long Short-Term Memory networks. In an extensive literature review on the topic of ARIMA versus machine learning approaches to time series modelling, Kontopoulou et al. (2023) conclude that despite recent developments in machine learning methods, no single forecasting method consistently outperforms the other. Furthermore, they show that the ARIMA method still outperforms machine learning techniques in several cases.

2.2 Financial Time Series Modelling

The SWESTR is a relatively new rate, and as such, there is no previous research specifically focused on forecasting this rate. However, the modelling and forecasting of interest rates is a well-established field. Beating the random walk has however proven to be a difficult task (Butter and Jansen, 2013).

There is much research that, although addressing different rates, employs a variety of methods that may be applicable to forecasting the SWESTR. Benito et al. (2007) study models the EONIA, a predecessor to €STR, by introducing jump components into single-regime ARCH-Poisson–Gaussian models, which are augmented with either a piece-wise function or an autoregressive conditional specification. This approach is based on the premise that the policy rate has a significant impact on the short-term rate, and they conclude that the policy rate plays a crucial role in the mean reversion behavior of the euro short-term rate. Audrino and Medeiros (2011) model 1-month US Treasury bill rates using combined regression trees and GARCH models, concluding, among other things, that these can be modeled quite accurately. Pesando (1979) adopts an efficient market perspective for forecasting interest rates and argues that, from a theoretical standpoint, long-term interest rates should follow a random walk. However, the author also suggests that this is not true for the short-term rate and concludes that, unlike long-term rates, short-term rate forecasts outperformed the no-change prediction.

The discussion of more classical econometric time series models versus machine learning approaches mirrors, not surprisingly, the general debate on time series modelling. Hsu et al. (2016) discuss the superior performance of machine learning methods over classical econometric methods such as ARIMA. However, just as with time series modelling in general, there is no unified view on which models to use. In their research, Babu and Reddy (2015) concluded that ARIMA was still able to outperform some more advanced machine learning methods in some cases. This, coupled with the fact that ARIMA models are still frequently used in financial time series modelling, shows how ARIMA methods remain highly relevant. Radha and Thenmozhi (2006) researched the Indian short-term rate, with ARIMA constituting one of the models tested. Jilhajj (2023) investigates the Interest Rate and Deposit Interest Rate of Bangladesh using a Box-Jenkins approach. Yıldıran and Fettahoğlu (2017) use an ARIMA model to predict the exchange rate, which is highly connected to interest rates, between the Turkish lira and the US dollar. Kobiela et al. (2022) also concluded that the ARIMA model outperformed deep learning methods for forecasting the NASDAQ stock exchange.

To summarize everything stated regarding the appropriateness of using an ARIMA model to forecast interest rates, such as SWESTR. Despite the increased popularity of machine learning models, ARIMA models remain a cornerstone in time series modelling, and in particular financial forecasting. This is likely attributed to its robustness and ability for statistical testing and interpretation. These benefits make ARIMA not only a reliable method but often preferred in scenarios where transparency and interpretability are essential. While machine learning models have shown promising signs in terms of performance, especially in handling complex, nonlinear relationships, no model has been shown to consistently outperform ARIMA. Furthermore, the continued prevalence of ARIMA models in the financial time series modelling literature emphasizes their utility and effectiveness.

2.3 Economic Theory

Interest rate parity is a macroeconomic theory that explains how interest rates between countries tend to converge over time. The theory is part of the law of one price, which states that any identical asset or commodity will have the same price globally, assuming a strict free market and no friction. This occurs because if price differences exist, they would quickly disappear under these conditions due to arbitrage opportunities. Interest rate parity is based on the notion that in international capital markets, capital will flow to the market where it can achieve the highest return. If one market offers higher interest rates than others, capital will flow into that market to take advantage of the higher rate, which will lower the interest rate in that market while pushing up rates in other markets. Under free movement of capital, the same arbitrage possibilities, as described by the law of one price, will lead to interest rates converging across different markets until an equilibrium is reached. The impact of smaller countries tends to be minimal or nonexistent on the international market rate as a result, their rates are largely determined externally (Fegert and Jonung, 2018).

However, in practice, interest rates between countries do not always achieve parity due to a myriad of factors, with depreciation and risk premiums being the primary reasons discussed within the framework of interest rate parity. If an investor seeks to place capital in another market with a higher rate, they must also consider the potential depreciation or appreciation of the currency. Effectively, the real interest rate in this scenario combines the market interest rate with the expected currency value change. Even if investors anticipate higher returns in a different market, they might still require a risk premium to compensate for additional risks associated with investing in foreign currencies. These risks include volatility in exchange rates and country-specific risks such as political instability or economic mismanagement. Market imperfections, namely transaction costs and regulatory barriers, also contribute to deviations from interest rate parity by preventing the free movement of capital and hindering the equalization of interest rates across markets (Fegert and Jonung, 2018).

Despite some frictions preventing the full application of interest rate parity in reality, Holmes (2005) researched the extent of economic and financial integration in the European Union by investigating real interest rates from 1979 to 2003. The author found strong evidence of real interest rate parity between EU countries, suggesting a substantial level of economic integration. Cumby and Mishkin (1984) explored the relationship between real interest rates in Europe and the United States. Their study provides evidence of interest rate parity, demonstrating a strong positive relationship between the real interest rates in the United States and Europe. Their findings suggest that movements in the real interest rate in the United States are transmitted to other industrialized countries. Fujihara and Mougue (1996) researched the relationship between short-term rates across countries, focusing on whether changes in the real interest rates in the United States have a significant impact on other countries' real interest rates. Their findings suggest a linkage between the United States and other countries' short-term rates, indicating that United States rates can provide information on trends in other countries' real interest rates. Modjtahedi (1987) also investigates the dynamic of real interest rates across countries and concludes that lagged effects of the United States real interest rates can be utilized.

While much of the existing literature primarily focuses on the influence of United States interest rates on global financial markets, it is reasonable to assert that large economies have significant effects on other financial markets. Although the United States may have a broader global reach, given Sweden's geographic and economic ties to the Eurozone, coupled with substantial trade relationships, the Eurozone's influence on Sweden might be more pronounced. Therefore, incorporating the lagged interest rates of the €STR into models forecasting Swedish interest rates is not only justified by economic theories such as interest rate parity but also supported by empirical evidence of financial integration within the EU and the effects of large economies.

3 Statistical Theory

In this section, the main statistical methods used in this thesis are outlined to give an understanding of the models being formulated in the following section and later tested.

3.1 Stationarity

To make robust inference from time series data some assumptions have to be fulfilled, such as no correlated errors. The most important assumption however is that of stationarity. For a stochastic process to be stationary its statistical properties need to be constant over time. There are two main types of stationarity: strong stationarity, also called strict stationarity, and weak stationarity, also called Covariance Stationarity. A time series is said to be strictly stationary if the joint distribution for any subset of the process does not change. That is the joint distribution of $Y_{t1}, Y_{t2} \dots Y_{tn}$ must equal $Y_{t1+k}, Y_{t2+k} \dots Y_{n1+k}$ at any time point t and any time shift k. For the less stringent assumptions of covariance stationarity, the following conditions need to be fulfilled (Cryer and Chan, 2008),

$$\mathrm{E}[Y_t] = \mathrm{E}[Y_{t-k}] = \mu \quad \forall\ t, k \tag{1}$$

$$\mathrm{COV}(Y_t, Y_{t-k}) = \gamma_k \quad \forall\ t, k \tag{2}$$

that is, the mean, denoted μ, is constant over time. γ_k is the autocovariance at lag k, which implies that the autocovariance between Y_t and Y_{t-k} is independent of t, and only a function of lag-length k. Note that Equation 2 also implies that the variance is constant and not dependent on t. Henceforward, the term stationary refers to covariance stationarity.

3.2 Autoregressive Integrated Moving Average

The Autoregressive Integrated Moving Average predicts future values in a series based on its own past values. This subsection explores the three components of the ARIMA model, Autoregressive (AR), Integrated (I), and Moving Average (MA). Each of which captures different aspects within the data.

3.2.1 Autoregressive Process

The AutoRegressive (AR) part of the model describes the relationship any given value has to the previous lagged version of the same variable. That is, it utilizes regressions on past values of itself to predict future levels (Cryer and Chan, 2008). This is done through a linear combination

$$\begin{aligned} Y_t &= c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \epsilon_t, \\ \text{or} \quad \Phi(L) Y_t &= c + \epsilon_t, \\ \text{where} \quad \Phi(L) &= 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p. \end{aligned} \tag{3}$$

ϕ_1, $\phi_2 \ldots \phi_p$ are the coefficients that measure the influence of the first, second, and all the way through to the p-th lags of Y_t respectively, with p representing the highest lag considered in the model. ϵ_t is the error at time t, representing unpredicted changes in Y_t and assumed to be white noise, that is normally distributed with mean zero and constant variance.

3.2.2 Moving Average Process

The Moving Average (MA) part of the model describes the relationship between the current value of the series and the past white noise error terms. Specifically, the MA model assumes that the current value is a linear combination of its own past forecast errors (Cryer and Chan, 2008). Mathematically, the MA model is expressed as

$$\begin{aligned} Y_t &= c + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q}, \\ \text{or} \quad Y_t &= c + \Theta(L) \epsilon_t, \\ \text{where} \quad \Theta(L) &= 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q. \end{aligned} \tag{4}$$

Y_t is the current value of the series, and $\theta_1, \theta_2 \ldots \theta_q$ are the coefficients for the MA model which represent the impact of the q previous error terms on the current value. With q representing the maximum lag considered in the model. ϵ_t is the white noise error term at time t, assumed to be normally distributed with a mean of zero and constant variance.

3.2.3 ARIMA Process

As mentioned above, one of the key assumptions for time series analysis is that the data is stationary. The ARIMA model has the advantage of being able to transform non-stationary data to make it stationary. The Integrated (I) part describes how the data is transformed by taking the difference between each data point, to achieve stationarity. If a time series has a stochastic trend, taking the first difference of the data helps stabilize the mean and thereby aid in obtaining stationarity. The amount of times this transformation is done is denoted as order d

$$\Delta^d(Y_t) = (1 - L)^d Y_t. \tag{5}$$

When the autoregressive (AR), integrated (I), and moving average (MA) are combined it results in the ARIMA model often denoted ARIMA(p, d, q). p represents the order of the AR part, d represents the order of integration, and q the order of MA. A general ARIMA(p, d, q) can be expressed as

$$\Phi(L)\Delta^d Y_t = c + \Theta(L)\epsilon_t. \tag{6}$$

Note that an ARIMA(p,0,0) would make an AR(p) model, and an ARIMA(0,0,q) would make an MA(q) model, where p and q being at least one.

3.3 ARIMAX

An ARIMAX model is the same as an ARIMA with the addition of exogenous variables as linear regressors. These are added onto the ARIMA equation as a linear combination, just like in a linear regression

$$\Phi(L)\Delta^d Y_t = c + \Theta(L)\epsilon_t + \sum_{i=1}^{m} \beta_i(L)\Delta^d X_{i,t}, \tag{7}$$

$$\text{where}\quad \Phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p,$$
$$\Theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q,$$
$$\beta_i(L) = \beta_{i1} L + \beta_{i2} L^2 + \cdots + \beta_{ik} L^m.$$

Equation 7 is an extension of the standard ARIMA model, with the addition of exogenous variables $X_{i,t}$, these exogenous variables, denoted as $X_{i,t}$, can include multiple different variables or the same variable with different lags, allowing for the ability to account for external factors that could influence the dependent variable.

3.4 Granger Causality

Granger causality is a statistical hypothesis test to determine if one time series can be used to predict another. The Granger causality test does not imply a causal relationship in the strict sense. But it indicates whether adding lagged values of another time series contains information that improves the prediction of future values. This is done by performing an F-test between a restricted model that only includes lags of the dependent variable Y_t, and the unrestricted model that contains lags of both the dependent variable Y_t and lags of the potential causal variable X_t (Granger, 1969).

$$\text{Restricted model: } Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \epsilon_t$$
$$\text{Unrestricted model: } Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \beta_j X_{t-j} + \epsilon_t$$

By comparing models with and without the lagged variable and testing if the coefficient associated with the lagged variable significantly deviates from zero, it can indicate whether past values of the variable in question can indeed explain some variation in the variable of interest. The null Hypothesis is that $\beta_1 = \beta_2 = \cdots = \beta_j = 0$, and the alternative is that at least one $\beta_j \neq 0$. Rejecting the null hypothesis suggests that the lagged variable contains valuable information for predicting the behavior of the variable of interest. The F-statistic can be mathematically expressed as

$$F = \frac{(SSR_R - SSR_U)/q}{SSR_U/(n-k-1)} \,,$$

it follows a F-distribution and where SSR_R is the sum of squared residuals of the restricted model, SSR_U is the sum of squared residuals of the unrestricted model, q is the number of lagged X_t terms in the unrestricted model, n is the number of observations and k the number of parameters in the unrestricted model. Note that the Granger causality test is performed only on in-sample data. A significant result does not guarantee improved forecasting ability, although it is a good indication of the viability of including lags of the predictor time series for forecasting.

4 Method

This section follows the process of fitting the ARIMA models to the data. Each step is described, from gathering and processing data, to justifying the use of additional variables, as well as the thought process when fitting models.

4.1 Data

The data has been processed in Rstudio, it comes from the European Central Bank (2024) and the Swedish Riksbank (2024). The SWESTR is published at 9:00 CET each day and the €STR at 8:00 CET each day. The data spans from September 1, 2021, all the way to March 28, 2024, when the cut off for this thesis was set.

The €STR for any specific day is calculated as a function of the central 50 percent quantile of trades on the previous day, which are then weighted by the trade volume. The selected trades relate to the unsecured overnight loans and deposits. (European Central Bank, 2024)

The SWESTR is similar to the €STR, however, it reflects the changes in interest rate for the Swedish Krona market as opposed to the Euro market. (Sveriges Riksbank, 2021)

To process the data, the SWESTR was used as the reference when merging the data sets, since it is the SWESTR that is being modeled. Data points are available for bank days only, leaving out weekends and holidays. The dates available for SWESTR were used as a reference to trim the other variables since these have different dates available in their respective datasets. The only real outliers in the SWESTR data were three values, occurring each year on the 29th of December, where Sweden has special requirements for banks and their currency reserves, making SWESTR dip down to anywhere between -5 and -9 percent. These observations were removed, due to not having to do with capturing information in the time series, since these are influenced by external laws and not a true representation.

When using the lagged version of these external variables, to avoid error, these were lagged with respect to their own available dates, before being trimmed according to SWESTR's available dates. This makes the lagged external variables use the most up-to-date value, while still being lagged with respect to SWESTR.

4.2 Additional Variables

The main focus is on the €STR, but seeing that the Swedish policy rate has a large impact on the SWESTR, it is also included. To determine the number of lags used, the Granger causality test is conducted to determine if the lagged version of the exogenous variable €STR captures significant information in the SWESTR, after which the significant variables are added to the ARIMAX model. Testing the Granger causality is most important for €STR, since the variable is exogenous to SWESTR. Given that SWESTR follows the policy rate, due to both of these having to do with the Swedish krona, it is motivated to use the policy rate as an additional variable when modelling SWESTR.

4.3 Fitting Models

4.3.1 Stationarity First Approach

Fitting ARIMA models are done by firstly checking for stationarity of the data. This is a necessary requirement for fitting AR terms. When non-stationary, the data can be transformed by taking the first difference. After which autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals can be analysed to fit MA and AR terms respectively, with external regressors being added once the ARIMA model captures all the information it can. This is the process that was initially followed when fitting the model. This process ends up creating an ARIMA(0,1,0). Then the Swedish policy rate as well as €STR as external variables, making Model 1.

The first step to determine the ARIMAX model is determining the orders of the ARIMA part. These are based only on the time series itself, that being the SWESTR. Here follows an overview of the data.

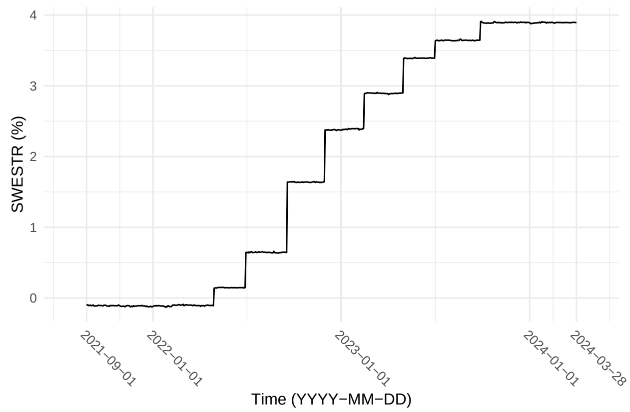
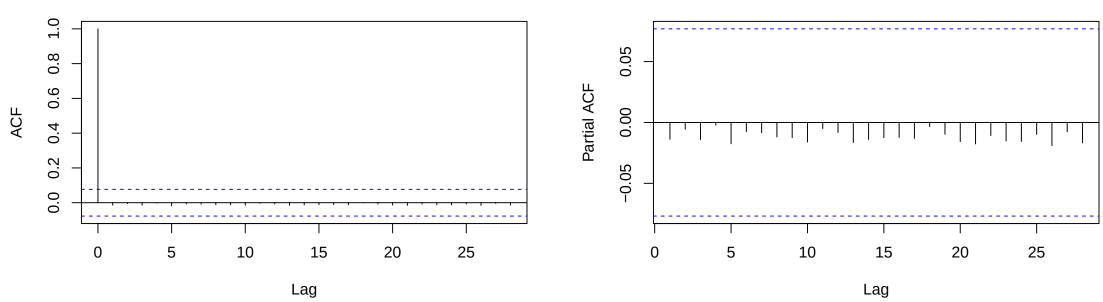


Figure 1: Plot of SWESTR

The data must be tested whether it is stationary before fitting the orders. To test for stationarity an Augmented Dickey-Fuller(ADF) test was performed. With the alternative hypothesis of the data being stationary, the p-value acquired was 0.7136.

To reach stationarity, the data is transformed by taking the first difference, meaning an order of d = 1 for the model. After the ADF test is conducted on the residuals of the differenced model, the p-value is less than 0.01, meaning order d = 1 is appropriate.

To further analyse the data and determine the amount of AR and MA orders needed, the ACF and PACF plots of the residuals are investigated. Once the data is integrated, any further information that can be captured by the model are seen as spikes in the residuals' ACF and PACF.



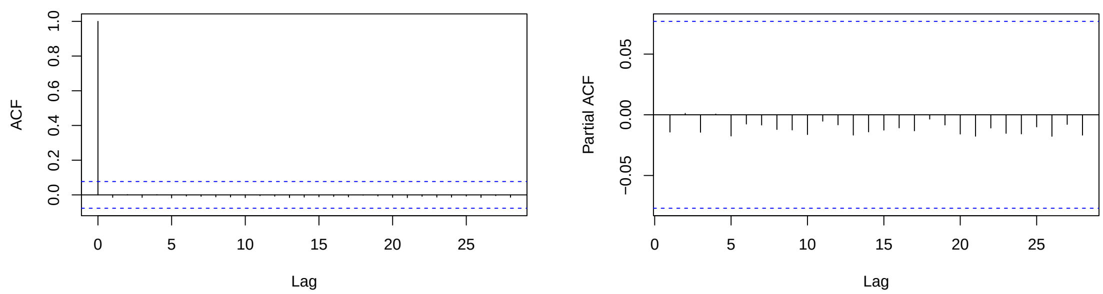
(a) ACF after first difference

(b) PACF after first difference

Figure 2: Autocorrelation functions of residuals

As seen in Figure 2, the ACF and PACF for the first-difference data of the SWESTR do not contain any significant spikes at any lag, indicating that there is no information from previous values, which suggests an ARIMA(0,1,0) model. An ARIMA(0, 1, 0) is also known as a random walk. Leading to the next step of creating the model, fitting the regressors. In this case both the Swedish policy rate and the €STR were used.

Since the first-difference of the data is being modeled, the first difference is also taken on any other variable used. Then the ARIMA(0, 1, 0) is fit with the regressors, and again, look at the residuals' ACF and PACF.



(a) ACF after first difference and regressors (b) PACF after first difference and regressors

Figure 3: Autocorrelation functions of residuals

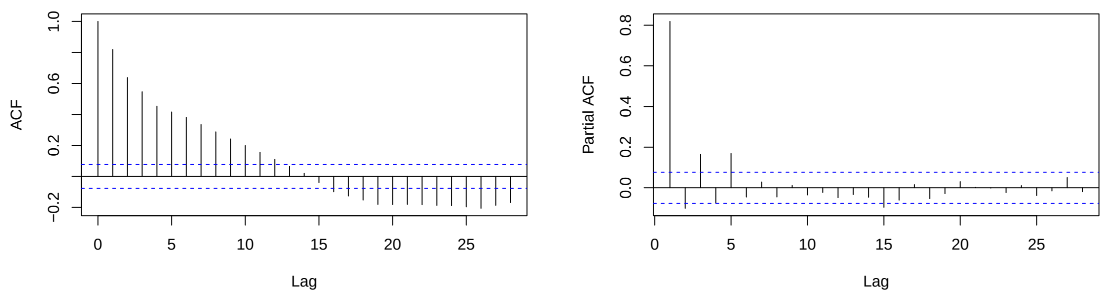
From Figure 3, the ACF and PACF of the residuals has no significant spikes for any of the lags. Meaning there is no need for more AR or MA terms to capture further information within the data. Since there are no ARMA terms, this model is a random walk, with added regressors.

4.3.2 Regressors First Approach

Another approach is to fit the model with regressors first instead of starting by fulfilling the stationary requirement. When inspecting the SWESTR as a time series on its own, it has an upward trend for the selected time period and therefore is not stationary. Since it is known that the Swedish policy rate (Appendix: Fig. 13) dictates the major increases in SWESTR, the policy rate can be added as an exogenous variable to the model. Once the regressor is added, the information in the jumps will be captured, leaving the day-to-day variations to be captured by the ARIMA model. The variation left in the model after applying the regressors has to be tested for stationarity before fitting the rest of the model, due to stationarity being a requirement for AR terms. First the regressors are set, after which ARMA orders are set based on the residuals' ACF and PACF. The process describes how Model 3 is created, it being an ARIMA(3,0,1) with the Swedish policy rate and €STR as regressors.

Starting by fitting the ARIMAX model with regressors, these being the Swedish policy rate and €STR. The residuals are then tested for stationarity with the ADF test, and gives a p-value of less than 0.01, indicating stationarity, and no need for taking the first difference of the data.

Then to fit the AR and MA, the residuals' are analysed with regards to their ACF and PACF.



(a) ACF after regressors (b) PACF after regressors

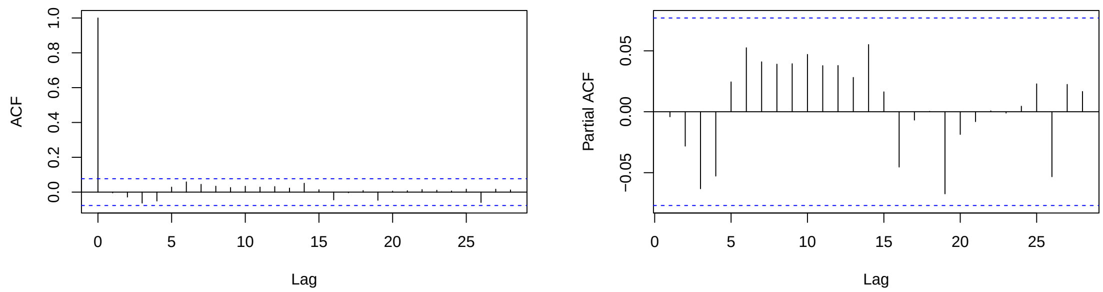
Figure 4: Autocorrelation functions of residuals

Due to the varied information given by the ACF and PACF plots in Figure 4, it is hard to say directly which MA and AR orders would capture this information. The steady decrease in autocorrelation in the peaks on the ACF plot could call for an AR term, which is confirmed by the significant peak at lag 1 in the PACF plot. The best way to be sure is to fit the AR MA terms and analyse the autocorrelation plots of the residuals.

After iterating the process of adding AR and MA terms, and analysing the residuals, three autoregressive terms and one moving average term was found to capture the information in the data well. After which the residuals are checked to make sure all information left is captured within the AR-MA framework as seen by the lack of significant peaks in Figure 5.

4.4 Evaluation criteria

As an evaluation criteria, expanding window forecasting is used to predict one value out of sample, which is then compared with the true value of the short-term interest rate. The prediction are done one step out, based on AR MA terms and the lagged values of external



(a) ACF after regressors and ARMA orders (b) PACF after regressors and ARMA orders

Figure 5: Autocorrelation functions of residuals

variables.

Instead of comparing models to each other directly, to have a more intuitive understanding they are compared to a baseline model. This is achieved by setting the baseline, for ARIMA models a random walk is most fitting, and using its error measure as a reference point. The root mean square error (RMSE) is used and is calculated as follows,

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

by taking a ratio of the RMSE of the models compared to the baseline, the ratios are easily comparable to each other.

5 Results

In this section, the results are presented. First by showing each individual model's prediction plot, as well as a comparison of all models to a baseline.

5.1 Granger Causality Result

The Granger Causality test was applied to test the predictive capability of €STR on SWESTR.

€STR				
Lag 1	**Lag 1-2**	**Lag 1-3**	**Lag 1-4**	**Lag 1-5**
0.8583	0.934	0.980	0.982	0.000

Table 1: P-values for Granger causality tests

An assumption of the Granger causality test is data stationarity, as seen in in the method section, SWESTR is stationary when taking the first difference of the data. This is also applicable to €STR. Interestingly, up to 4 lags is not significant, with very high p-values. Only when adding lags 1 through 5 does the Granger causality test indicate significant predictive ability of €STR on SWESTR. A theory as to why 5 lags of €STR is significant could be due to there being 5 days in a bank week. There is also the possibility of the significant result of the test being an error.

The Swedish policy rate is also tested, with no amount of lags being significant. This doesn't make the variable unusable, with it being the logical cause of the jumps of SWESTR, meaning it is relevant for modelling SWESTR.

5.2 First Difference Data Models

5.2.1 First Difference Data Baseline Model

To evaluate the predictive performance of more complex models in time series analysis, having a baseline model is crucial. The most common baseline model is the random walk, which assumes that the value at time t is just the previous value plus a random error term. The random walk with first-difference data can be expressed as $\Delta Y_t = \epsilon_t$, and its simplicity makes it useful because if any model cannot outperform the random walk, it is likely not of practical use. Following the first method of fitting a model as described in the method section, these are the predictions obtained from the baseline model:

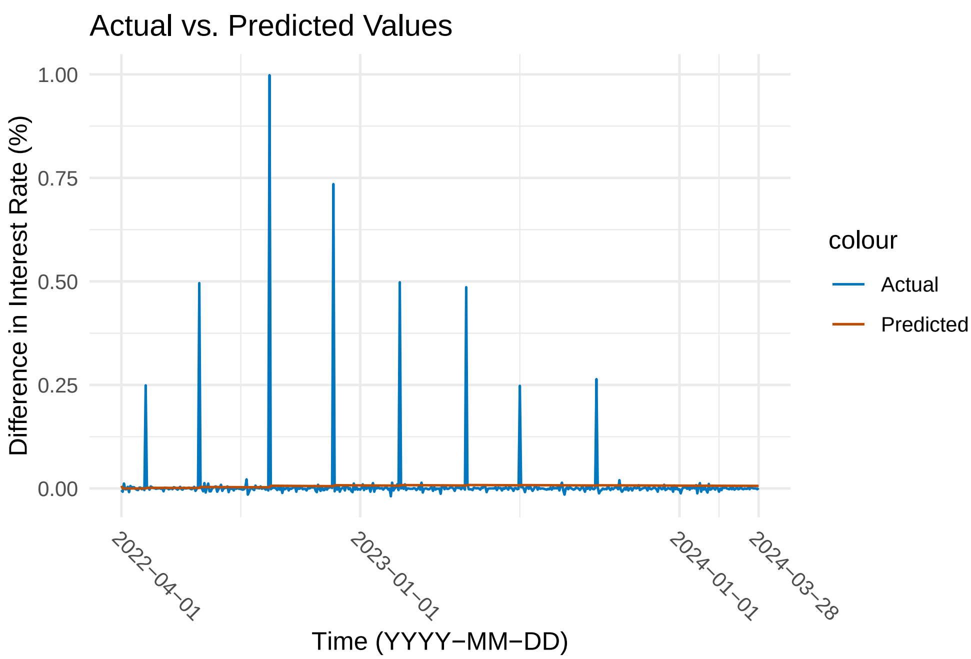


Figure 6: Expanding window predictions of random walk model

The RMSE of the predicted values compared to the actual values is: 0.07005 Which is used as the reference point to compare other similar models with first-difference data.

5.2.2 Model 1

Model 1 is an ARIMAX(0,1,0) with five lags of €STR as regressors. For this model, the general ARIMAX Equation 7 is used, where $X_{1,t-1}$ represents the €STR lagged by one period, $X_{1,t-2}$ represents the €STR lagged by two periods, all the way through to $X_{1,t-5}$ representing the €STR lagged by five periods. This model was described in the first part of the method section, by first fulfilling the stationarity requirement and subsequently fitting the ARMA terms as well as the regressors. Note that there are no AR and MA terms that this model, due to the lack of significant peaks in the ACF and PACF, which makes the model a random walk with regressors. As seen in the equation above this model is a random walk with the 5 regressors being 5 lags of €STR, corresponding to the significant findings of the Granger causality test.

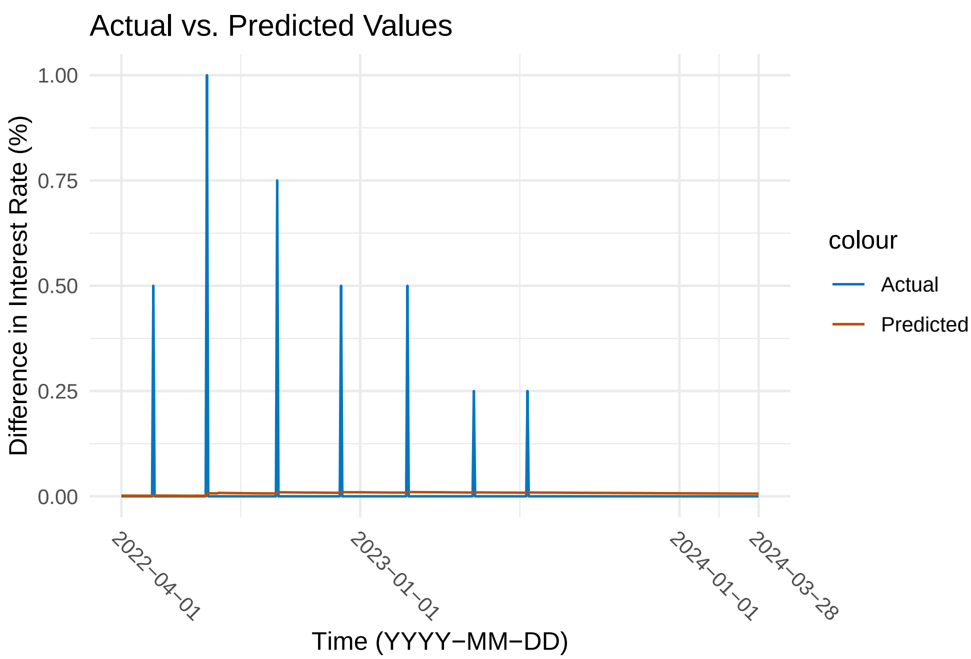


Figure 7: Expanding window predictions of model 1

The RMSE is 0.06940 which is comparable to the baseline. This model lacks AR and MA terms, which are present in the second method of fitting the models. Having AR MA terms is wanted to capture more day-to-day variation The first-difference data models are random walks with regressors. By introducing ARMA terms to the model, more detailed results may be achieved.

5.3 Non-modified-data Models

5.3.1 Baseline Model

Since the models being tested in this section are on non-differenced data, a new baseline random walk model on non-differenced data is needed to make a better comparison for these models. The random walk can be expressed as $Y_t = Y_{t-1} + \epsilon_t$. As before, any time t is modeled by the preceding term $t-1$ with an added random error. This error is assumed to be normally distributed with the mean being the last value $t-1$. When taking a prediction the expected value is the best choice. Therefore the prediction for any given t is the same value as $t-1$ and the predictions can be seen in Figure 8.

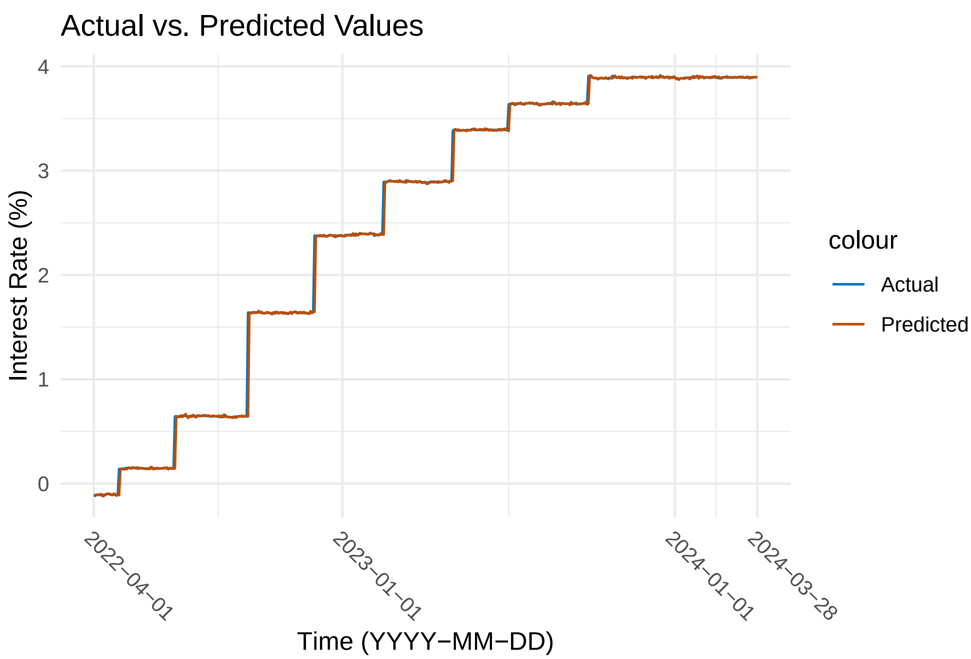


Figure 8: Random Walk predictions

The prediction RMSE amounts to 0.07059. This value sets the reference to compare the other models to. Since the unmodified data was used in this baseline, it will only be used to compare models where the first difference of the data was not applied.

5.3.2 Model 2

Model 2 is an ARIMAX(3,0,1) with the lagged regressors Swedish policy rate and €STR. It is based on the second part described in the method section. Since the jumps in the SWESTR are likely determined by the Swedish policy rate, the external regressors should be considered. The general ARIMAX Equation 7 is used, where $X_{1,t-1}$ represents the Swedish policy rate lagged by one period, and $X_{2,t-1}$ represents the €STR lagged by one period. The following plot shows the 1 step-out forecasting of this model:

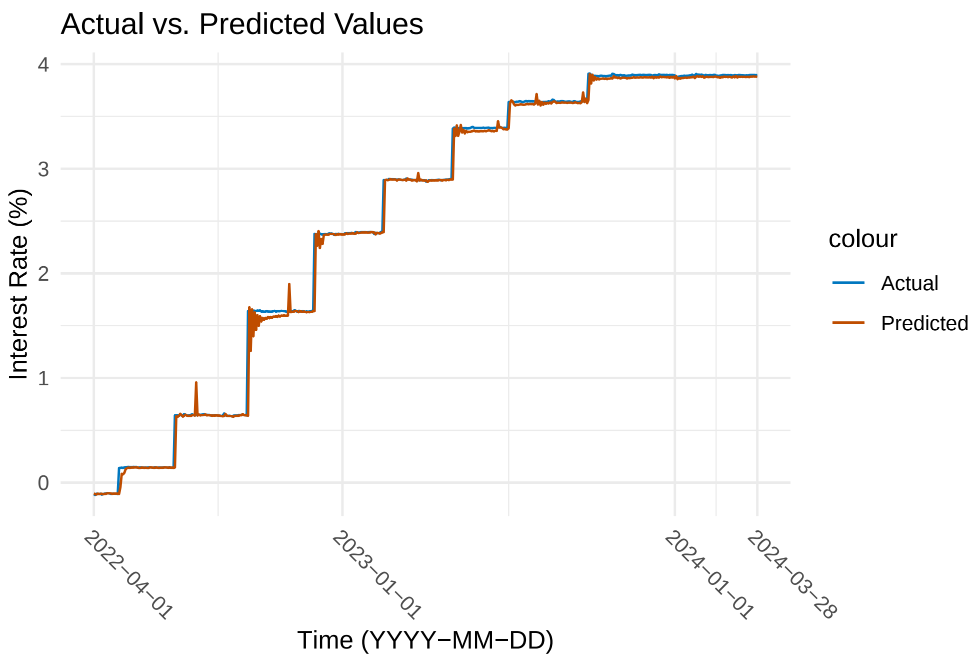


Figure 9: Expanding window predictions of model 2

The RMSE is 0.08018, which is worse than the random walk model. Looking at Figure 9, there are some jumps in predictions, leading to worse error metrics. This is due to the external variables not varying together, leading to more randomness in forecast values.

5.3.3 Model 3

Model 3 is an ARIMAX(3,0,1) with the only regressors being the one-step lagged Swedish policy rate. Model 3 is a special case of Model 2 without €STR as a regressor. The objective is to compare the two models, where the only change is the presence of €STR, and see if there is any change in predictive performance. For Model 3 the ARIMAX Equation 7 is used, where $X_{1,t-1}$ represents the Swedish policy rate lagged by one period. Just like in the method section, by looking at ACF and PACF plots (Appendix: Fig. 16) it confirms that despite removing the €STR as a regressor, there is no further information uncovered that could be captured by AR or MA terms.

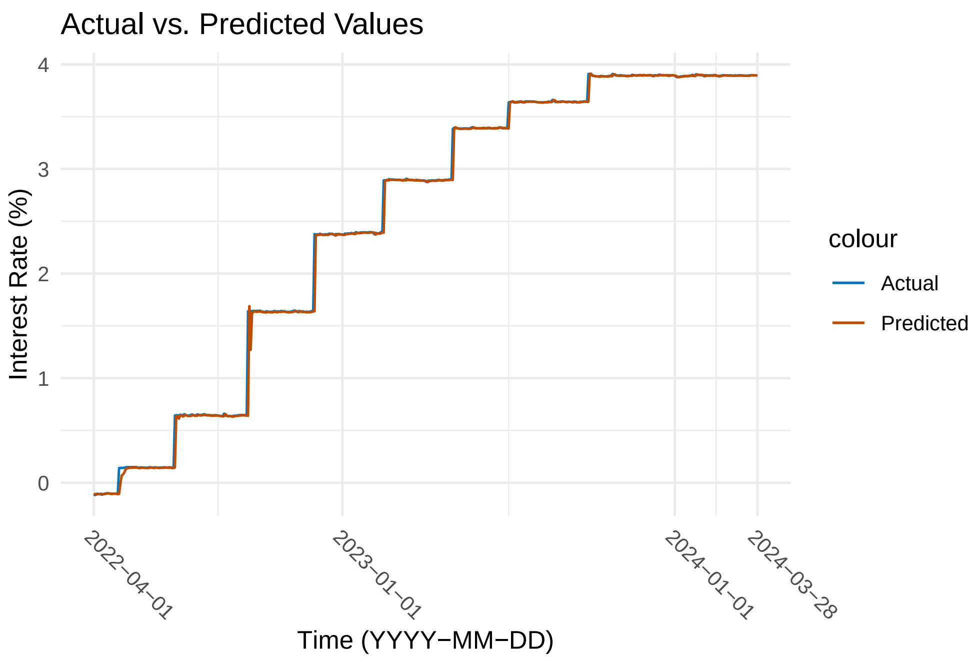


Figure 10: Expanding window predictions of model 3

With an RMSE of 0.07306, this models performs similarly to the baseline. Indicating that the Swedish policy rate did not help the model's predictions. Theoretically the policy rate changes proceed those of the SWESTR. The predictions are skewed due the accuracy in predictions of the Policy rate on the SWESTR, which could be caused by the difference between these two rates changing over time (Appendix: Fig. 14).

5.3.4 Model 4

Model 4 is an ARIMAX(1,0,0) with the sole regressor being one-step lagged €STR. This means it is an AR(1) model with exogenous variables, making it a special case of an ARIMAX model. Like the previous models, Equation 7 is also used for Model 4, where $X_{1,t-1}$ represents the €STR lagged by one period. Fitting this model with only the €STR was done the same way as previous models, with regressor first, then looking at the ACF and PACF (Appendix: Fig. 17), the combination of many significant ACF peaks, and only one major significant PACF peak at lag 1 leads to an AR(1) model. It is normal to see many significant peaks on the ACF since theoretically an AR(1) is the same as a MA(∞) (Cryer, 2008). Only AR(1) is needed, which was confirmed by looking at the ACF and PACF of the residuals of the model (Appendix: Fig. 18).

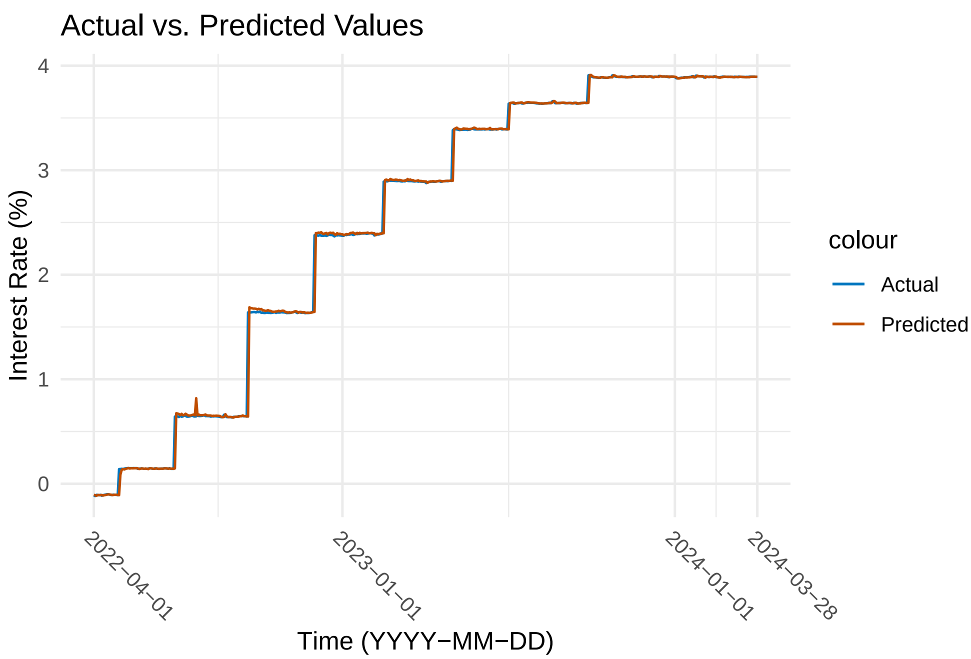


Figure 11: Expanding window predictions of model 4

The model performs similarly to Model 3 as well as the random walk, with an RMSE of 0.07118. Due to the models with one regressor not performing better than the random walk, this could indicate the need for a different approach to implement the lagged variables that contain information on SWESTR.

5.4 Model Comparison

	First Difference Data		Non-modified Data			
	Δ Random Walk	**Model 1 (0,1,0) EU 5 Lags**	**Random Walk**	**Model 2 (3,0,1) SE + €STR**	**Model 3 (3,0,1) SE Policy**	**Model 4 (1,0,0) €STR**
RMSE	0.07005	0.06940	0.07059	0.08018	0.07306	0.07118
Ratio	1	0.991	1	1.14	1.03	1.01

Table 2: RMSE ratios compared to respective baseline models

To determine the effects of the regressors on modelling the SWESTR, Models 2 - 4 are relevant. It has been determined that regressors are needed for modelling the SWESTR. Both the Swedish policy rate and EU short-term rate were tested first in Model 2. To then see if the €STR has any effect, it is removed, leading to Model 3. Finally to be able to cross validate, Model 4 has only the €STR as regressor.

These 3 models are compared to the baseline random walk Model. As described in the Method section, a ratio of the RMSE of the different models to the RMSE of the random walk model is taken to compare, and more intuitively be able to draw conclusions.

6 Discussion

The purpose of this thesis was to investigate if SWESTR could be modeled accurately using ARIMA models, in addition to exploring if the forecast accuracy could be improved when incorporating the €STR. The inclusion of €STR where justified by economic theory, previous research, and a Granger causality test, which suggested that the €STR significantly capture variations in SWESTR. The Swedish policy was also included as a regressor on the basis that it captured the jumps in the SWESTR. Analysing models containing €STR, and comparing these to models without, the goal is to see if €STR could actually help predict variation in SWESTR. The result of this study suggests that incorporating the €STR had an improved effect on forecasting accuracy.

The results from the previous sections reveal that the SWESTR is best modeled as a random walk, indicated by both the ACF and PACF plots. This indicates that past values of

SWESTR alone do not provide useful information for forecasting future values, other than the previous value. Contrary to this, the Granger causality test suggests that the €STR can significantly predict SWESTR when considering using 5 lags. This would suggest that while SWESTR might follow a random walk on its own, external economic factors, such the €STR, has predictive power over SWESTR. This implies that the movements in €STR contain valuable information that can enhance the forecasting of SWESTR beyond what is possible with its own past values alone.

The incorporation of the €STR as an exogenous variable in Model 1 leads to a slight improvement in forecasting accuracy compared to the baseline random walk, and as such the forecasting accuracy can be improved with the inclusion of lagged values of the €STR. This improvement, although marginal, has significant implications. The improved performance of the Model 1 suggests that the random walk nature of SWESTR can be supplemented with exogenous information to better capture the some underlying dynamic.

The performance of Model 2 having both the Swedish policy rate and €STR as regressors is worse. Model 2 with both regressors has a risk for multicollinearity since the regressors have a correlation of 0.957. This makes estimation of the model harder by not being able to distinguish the effects of each regressor individually. When compared to model 3 and 4 with only one of these regressors each, these two have better predictive power, despite neither being able to beat the random walk model.

SWESTR has a lot of randomness in its day-to-day variation. The increases in the Swedish policy rate cause a sharp increase in the short-term rate, adding the Swedish policy rate to the model would ideally have helped the model by avoiding the large errors at time points where the interest rate increases. These large errors can not be forecast in the random walk model since there is no external variable adding this information to the model. Therefore Model 3 should have performed better in theory, this was not the case however. The difference between the Interest rate and the short-term rate is not constant over time (Appendix: Fig. 14). This can be intuitively seen as the profit the banks take through arbitrage. If this profit is constant, the interest rate may be more precise in modelling the jumps in the short-term rate. The changes in the spread between the rates have to do with macroeconomic factors which dictated how much profit the Swedish Central Bank is inclined to take. These factors are outside the scope of this thesis.

Model 4 with only €STR as a regressor has performance on par with the random walk, meaning it doesn't harm the model to add the regressor, but in this case it doesn't capture any more useful information, only adding the potential for more error. As seen is the slightly higher error as compared to the random walk.

When compared to the other approach of models, with more ARMA terms, these do not perform any better than the random walk baseline. Models 3 and 4 have similar performance, meaning that these models with regressors do not hinder predictive capability.

Reflecting on Models 2 through 4, these do not outperform the random walk. Despite there being autocorrelation terms when fitting the models, these AR and MA terms do not significantly capture information in the model leading to better predictions. If SWESTR is assumed to be random, it is expected that any ARMA model would not beat the random walk, which is the case. It can not be concluded that SWESTR is fully random, however ARMA models may not be fit to significantly capture information about how the data varies.

7 Conclusion

The purpose of this thesis was to investigate the feasibility of forecasting the SWESTR using an ARIMA method and the applicability of integrating international rates, specifically the €STR, to improve forecasting accuracy. As suggested by previous research, beating the random walk has proven to be difficult in interest rate forecasting. This study's results are consistent with that sentiment, as the baseline random walk model proved difficult to outperform. However, one model manage to beat the random walk by including five lagged terms from the €STR. This indicates that the forecast accuracy was improved by incorporating the €STR. Despite the model only outperforming the random walk by a small margin, it suggests that the inclusion of the €STR captures some variations in the SWESTR. Overall, these findings imply that external rates can be incorporated to create better forecasting models, and this research contributes to the understanding of international interest rate dynamics.

Based on these results, further research should consider incorporating other international interest rates to evaluate their potential to improve forecast performance. Additionally, exploring other time series methods that may capture more complex patterns than the ARIMA could be an appropriate approach. Longer forecasting horizons should also be assessed to determine if the benefits of including the other international rates persist over time. By exploring these suggestions, future research can build on the findings of this thesis for a more comprehensive understanding of interest rate dynamics and forecasting.

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Appendix

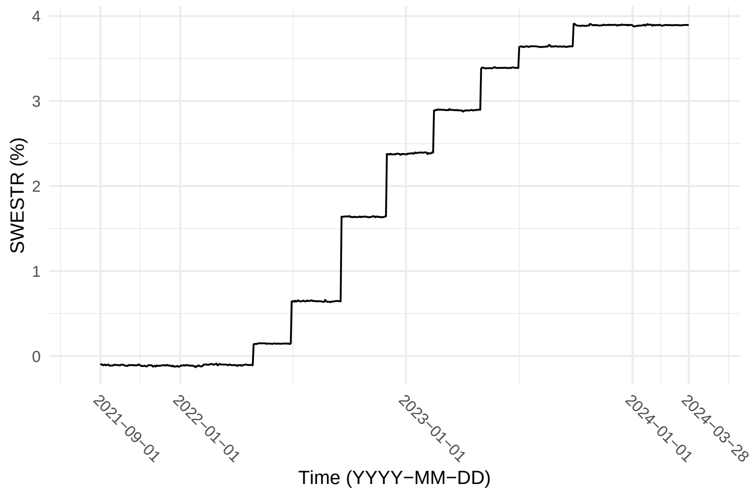


Figure 12: Plot of SWESTR

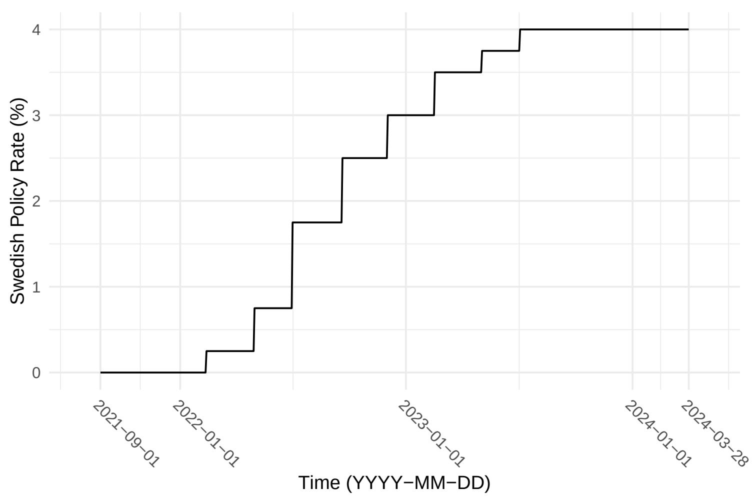


Figure 13: Plot of Swedish policy Rate

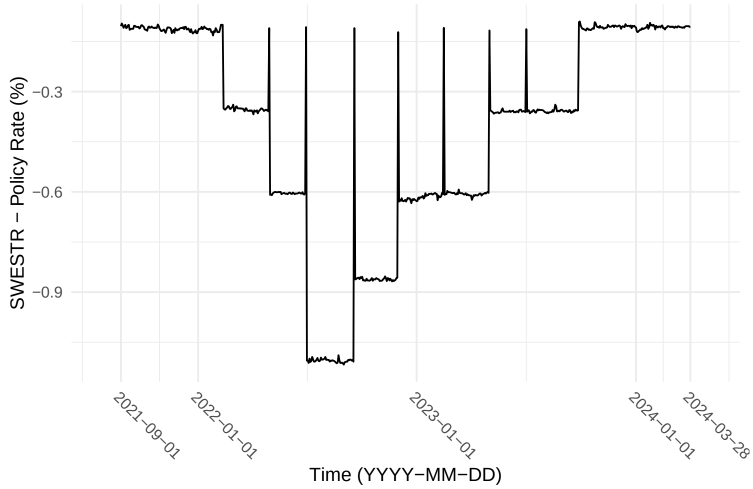


Figure 14: Plot of SWESTR - Swedish policy rate

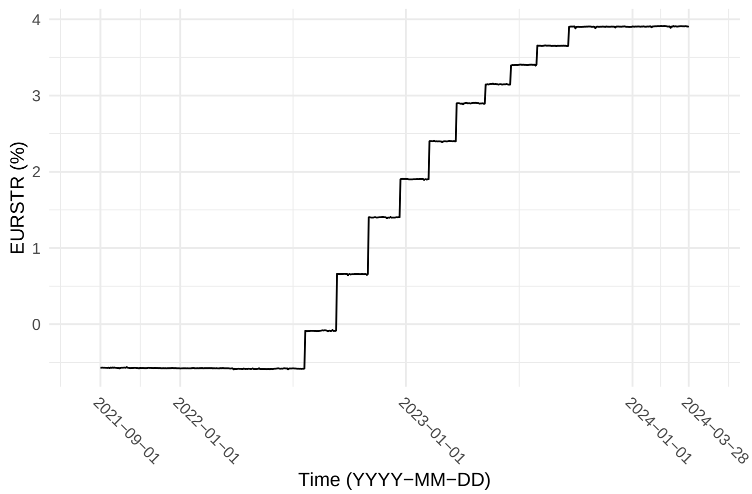
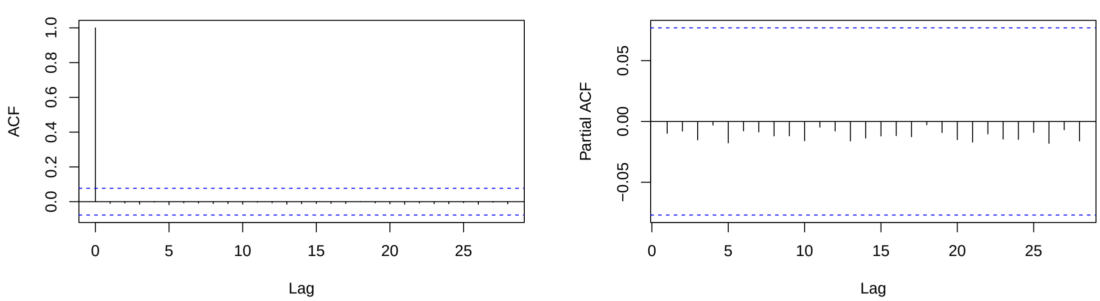


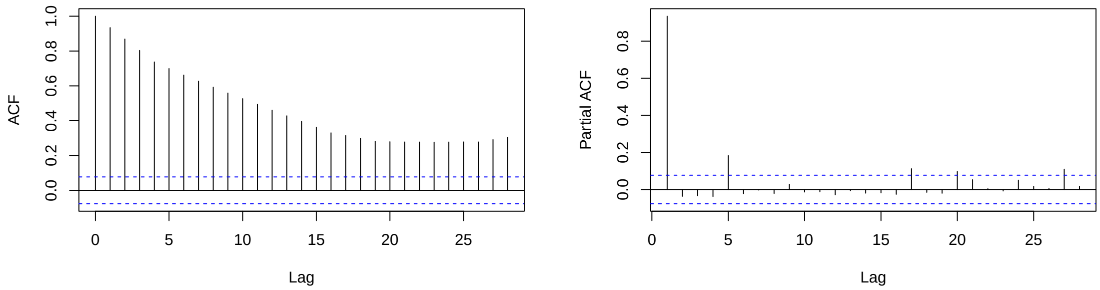
Figure 15: Plot of €STR



(a) ACF

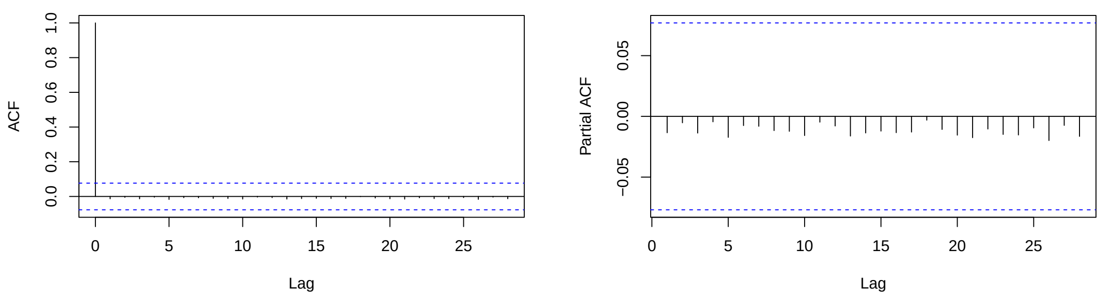
(b) PACF

Figure 16: Autocorrelation functions of residuals



(a) ACF (b) PACF

Figure 17: Model 4 autocorrelation functions



(a) ACF (b) PACF

Figure 18: Model 4 autocorrelation functions of residuals