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SCHOOL OF ECONOMICS AND BUSINESS

UNDERGRADUATE THESIS

FORECASTING INFLATION IN SLOVENIA USING AUTOREGRESSIVE MOVING AVERAGE PROCESSES

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LIST OF ABBREVIATIONS

ACF – autocorrelation function

ADF test – augmented Dicky-Fuller test

AIC – Akaike criterion

AR – autoregressive

ARIMA – autoregressive integrated moving-average

ARMA – autoregressive moving-average

BS – Bank of Slovenia

DSGE – dynamic stochastic general equilibrium

ECB – European Central Bank

EU – European Union

HICP – harmonized index of consumer prices

KPSS test – Kwiatkowski–Phillips–Schmidt–Shin test

MA – moving average

NCBs – national central banks

NN model – neural network model

PACF – partial autocorrelation function

SQ – Schwartz criterion

SURS – Republic of Slovenia Statistical Office

VAR – vector autoregressive

VECM – vector error correction models

INTRODUCTION

Inflation and its forecasting have important implications not only for the monetary policies of a certain country but, as Meyler, Kenny and Quinn (1998) explain, also for the general stability of the economy as they affect real economic indicators, such as wages and consumers' real purchasing power. In this thesis, we, therefore, wish to explore, as Chatfield (2001) states, one of the most basic approaches for forecasting time series data, as well as the autoregressive and moving-average processes. More specifically, we are interested in constructing an autoregressive integrated moving-average (hereinafter: ARIMA) model for Slovenian inflation based on the data from January 2012 to December 2021. The ARIMA is a statistical model that makes forecasts based on the past values of the variable we wish to forecast. With the before-mentioned array of data for Slovenian inflation, we wish to model forecasts for the monthly inflation indices from January 2022 to June 2022 and compare these to the already existing forecasts made by the Bank of Slovenia (hereinafter: BS), as well as the actual inflation numbers for that period. We use the methodology presented in Box, Jenkins, Reinsel and Ljung (2016).

Similar analyses were done for other countries. For example, Fritzer, Moser and Scharler (2002). construct the ARIMA model on data from Austria's inflation. Junttila (2001) does the same for Finnish inflation. Pufnik and Kunovac (2006) construct the seasonal ARIMA model for inflation data of Croatia and Thabani (2019) constructs ARIMA forecasts for Tanzania. Junttila (2001) and Fritzer et al. (2002), especially, show that ARIMA models are good at predicting short-term inflation, that is inflation up to 6 months in the future, chiefly in times of the stable economy, and are proved to perform better than more complicated models in this short term horizon. Fritzer et al. (2002) even find an almost perfect one-month ahead performance of ARIMA models for headline harmonized index of consumer prices (hereinafter: HICP). This indicates that our goal of predicting inflation for the 6-month horizon using the ARIMA model should yield relatively accurate results. Further, we can also compare the forecasts with the actual values of inflation and determine the accuracy of our forecasts, as was similarly done by, for example, Baciu (2015). Even though Krušec (2007) constructs forecasts for inflation in Slovenia based on the autoregressive process. The added value of this thesis is the use of these processes for the newer data range. While Krušec (2007) uses data from 1997 to 2001, we use data from January 2012 to December 2021. Thus, we use a newer as well as longer data range.

Thus this thesis contributes to the empirical literature on the inflation ARIMA modeling and aims to prove the comparable accuracy of ARIMA model forecasts against other models' forecasts, such as the vector autoregressive (hereinafter: VAR) models that construct predictions based on the time series data of several variables that, according to economic theory, affect the variable we predict (Dhakal, Kandil, Sharma & Trescott, 1994). Specifically, we do this analysis with the goal of answering two research questions:

1) What is the forecasted inflation rate in Slovenia based on the ARIMA model for the period from January 2022 to June 2022?
2) Does the constructed model provide comparable results to the models used by the BS and European Central Bank (hereinafter: ECB)?

The thesis is structured as follows. The first chapter develops the methodological framework of ARIMA models and the practical application of forecasting models, as well as data that are used in the autoregressive and moving-average processes. In chapter two, we explain inflation as a phenomenon and why its measurement and forecasting are an important part of the central bank's tasks. Further, in the third chapter, we present the forecasting methods used by official monetary institutions and present the advantages and disadvantages of ARIMA modeling as compared to other methods. Finally, in the fourth chapter, our empirical analysis of Slovenian inflation data is presented. Specifically, we build an ARIMA model and produce forecasts for the months between January 2022 and June 2022 and compare these results with the actual values for Slovenian inflation in the analyzed period, as well as with the BS's official forecast. We continue with the discussion of our findings and finish the thesis with the conclusion.

1 ARIMA MODELS

The statistical analysis offers a great number of different forecasting approaches. One of the simpler ones, as Chatfield (2001) explains it, is the ARIMA used in this thesis. We call it simple in part because it does not require any underlying economic theory for its empirical application. For example, if we look at the VAR models, they require multiple economic variables to construct the movement in inflation. Thus, there needs to be some economic theory supporting the choice of these explanatory variables. Dhakal et al. (1994), for example, use a VAR model to model the inflation for the United States with the producer price index, narrowly defined money stock M1, the interest rate on Moody's AAA corporate bonds, and the gross national product in constant 1982 American dollars. However, ARIMA models construct their forecasts solely on the past values and past error terms of the observed variable (Chatfield, 2001).

ARIMA models use time series data. Time series data is a type of data where the observed values are sequentially observed through time. Essentially, this data – which has been collected at equally spaced points in time – presents specific challenges in statistical analysis and modeling. One of the differing factors of time series analysis, and specifically ARIMA modeling, in comparison to other statistical tools is that the time series observed is going to be the only realization of this series of data. In our case of inflation data that means that inflation in July of 2021, for example, can only be observed once, since July 2021 will never happen in the future again. That means we only have one possible value for the particular variable of the July 2021 inflation rate. Nevertheless, time series analysis tools can detect the properties of the underlying model. ARIMA models are, thus, one of the base components of this part of the time statistical theory (Shumway & Stoffer, 2006).

In the following subchapters, we build up the theory behind the construction of ARIMA models. ARIMA models consist of three parts: the AR – autoregressive, I – integrated, and MA – moving average process. We explain each part separately.

1.1 Autoregressive process

The autoregressive (hereinafter: AR) process is a valid statistical model for the construction of forecasted values of the variable X when the predicted values of the series, X_t, can be explained by a weighted average function of p numbers of its past values, with p being the number of past lags, needed to sufficiently explain the value of X_t. Mathematically, an autoregressive process of order p, AR(p), is presented in equation (1).

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + Z_t \quad (1)$$

The predicted value, X_t, is thus a linear combination of its past p values, as well as some white noise error term or random shock Z_t. φ_1, φ_2,…,φ_p are model coefficients that indicate the effect of a specific lagged value on our predicted model solution X_t Chatfield (2001).

1.2 Moving average process

While the AR model assumes a linear combination of past lagged values of the observed variable X_t, the moving average (hereinafter: MA) process assumes a linear combination of the lagged white noise error terms that explain the current value of X_t. The mathematical notation of a MA process of order q, MA(q), is written in equation (2).

$$X_t = Z_t + \theta_1 Z_{t-1} + \cdots + \theta_q Z_{t-q} \quad (2)$$

A time series is a moving average process if the values of the time series can be expressed as a linear sum of the white noise error terms Z, or alternatively called random shocks. The Z time series has an assumption of being a purely random process, with a mean of zero and a constant variance. θ_1,…,θ_q represent model coefficients that can be explained as weights representing the effect of a particular Z factor on the predicted X_t value (Chatfield, 2001).

1.3 ARMA models

The current values of time series, X_t, can often be dependent both on past values of itself and the past white noise error terms Z_t. In this case, both the AR and MA processes can be used when constructing a model that explains the movement of the time series data. Such models are called autoregressive moving-average (hereinafter: ARMA) models. ARMA models' mathematical notation is represented in equation (3).

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + Z_t + \theta_1 Z_{t-1} + \cdots + \theta_q Z_{t-q} \tag{3}$$

1.4 Degree of integration

After explaining the specifics of ARIMA modeling, it is important to define what type of data is eligible for this type of statistical analysis. ARIMA models, as we have mentioned before, work on time series data. However, not all time series data can be used to model usable forecasts. Before we start with the model construction, it is crucial to determine whether the time series data we are working with is stationary or not (Chatfield, 2001).

Box et al. (2016) define stationarity as a state when the conditions are in a state of statistical equilibrium, which means the statistical properties of the model do not change with time. In other words, the mean $E(X_t)$ and the covariance between X_t and its *k*-th lag X_{t+k} are constant and finite. The covariance argument also includes the lag where k equals zero, which represents the variance of X_t. Stationarity implies that shifting from a selected time period of the sample data to another period of the same sample data should not affect the joint distribution of this set of observations. This condition is necessary to construct an ARIMA model that produces viable forecasts.

The roughest check of stationarity is simply looking at a plotted graph of the time series data. Big changes in the mean level of observations, indicated usually by a noticeable trend, or differences in variability of data can be easily recognized from the graph. This indicates the non-stationarity of the data. However, to formally confirm the presence of stationarity in the data, there are several statistical tests. One of the most widely used is the augmented Dicky-Fuller (hereinafter: ADF) test. The ADF test checks for the presence of a unit root in the data, or in other words, the presence of non-stationarity in the data. If we can statistically reject the null hypothesis of the existence of a unit root, this implies that our data is in fact stationary. Similarly, the Kwiatkowski–Phillips–Schmidt–Shin (hereinafter: KPSS) test checks for non-stationarity due to the presence of a unit root. The null hypothesis rejects the presence of a unit root, thus proving that the data is stationary (Lütkepohl & Krätzig, 2006).

In general, however, many time series data sets are non-stationary and hence cannot be applied to the AR, MA, and ARMA processes. One solution to the non-stationarity problem is differencing. The simplest form is the first difference. However, some time series data requires differencing up to the d-th order to achieve stationarity. When the original data is differentiated d-times before fitting it into the ARMA process, the final model is denoted as ARIMA(p,d,q) model. The "I" in the ARIMA notation comes from the word "integrated" and represents the process of differentiation among data points which we alternatively call the degree of integration (Chatfield, 2001).

Even with a stationary process, the time series data can exhibit another characteristic that can inhibit the efficacy of further modeling. This phenomenon is called seasonality. Economic time series data, like inflation data, often include regular annually occurring patterns and fluctuations which are called the seasonal component of the dataset. Importantly, however, seasonality is not the only phenomenon that affects the efficiency of the data. We also need to check for phenomena, such as autocorrelations and heteroscedasticity which will be done in later chapters. However, the explanation of seasonality states here because (while we construct our ARIMA model) we check for seasonality and stationarity of our data before even constructing the ARIMA model.

As Chatfield (2001) explains, seasonality is not always detrimental to the models since we are sometimes interested in the patterns that evolve because of this seasonal component. However, the problem occurs when seasonality is changing over time. This means that as we move from one period in our data to another, the size of the seasonal component also changes. That is why often, to make data stationary and ready for the ARIMA modeling, some sort of data adjustment is necessary to reduce the effect of the seasonal component. According to Chatfield (2001), two of the methods of getting rid of seasonality are seasonal differencing and the inclusion of seasonal dummy variables in the forecasting model. Seasonal differencing is a very simple approach that takes the difference between the variables belonging to the same season. For monthly data, for example, we would differentiate the value of a certain month from the value of the same month a year ago. The other method is the inclusion of the seasonal dummy variables in the regression model. In that way we can add the specific effect characteristic of that time period to the point in the future we are forecasting for. For example, accounting for the seasonality in the 6^{th} month of every year by adding a seasonal dummy that adds that seasonal effect when we construct a forecast for the 6^{th} month of the year. If the inflation tends to be higher in the 6^{th} month of the year compared to the rest of the months, on average, we can account for that when making projections by adding the seasonal dummy for the 6^{th} month. This approach is especially useful when we have a seasonal effect that is constant through time.

Particularly in inflation data, seasonality is often present (Lis & Porqueddu, 2018). According to Lis and Porqueddu (2018), part of the reason lies in the seasonal sales of goods and services like clothes (as in winter and summer clothes) and tourism (summer and winter tourism highs). Additionally, the problem identified by Lis and Porqueddu (2018) is that the seasonal factor present in the inflation has been getting bigger over time for the Eurozone. For example, an earlier or later start in winter clothes sales and the duration of their sales period can affect the intensity of clothing price changes, thus affecting the intensity of the change in inflation and the year-on-year seasonal factor. The same is true for the sales of tourism products and services. The size of the seasonality factor for the Eurozone inflation after 2001 has greatly increased, especially in the non-energy industrial goods inflation. Thus, we might have to keep that in mind when constructing our model. It might be wise to use seasonal differencing and seasonal dummies to account for this change in seasonality in the data.

2 INFLATION

The primary objective of monetary policy in the Eurozone has generally been the maintenance of a low and stable rate of aggregate price inflation. Thus, inflation is a central topic of monetary policy (Meyler et al., 1998). Laidler and Parkin (1975) explain inflation as a process of continuously rising prices. When we talk about inflation, we generally discuss the overall price movements, not the price movements of a specific good, since inflation is calculated as a weighted index of prices of a bundle of goods in the economy. Zlobec (2018) states that the Republic of Slovenia Statistical Office (hereinafter: SURS) abides by the commonly accepted methodology for calculating inflation indices for countries inside the European Union (hereinafter: EU) determined by the Regulation (EU) 2016/792 (2016). This means the SURS calculates the HICP as an annually chain-linked Laspeyres-type index.

Frisch (1990) explains inflation as a phenomenon that has accompanied economic development throughout human history. However, with the development of the more sophisticated monetary regulators in the past centuries, the science of explaining the causes and movements in inflation has become an increasingly complicated and debated-over topic. As Meyler et al. (1998) expound, the central and arguably the most important job of most countries' monetary policy is the maintenance of stable and relatively low inflation. Most developed countries set their inflation targets to account for around 2-3%. The reasoning for this is the general consensus, supported by numerous economic studies, that inflation is damaging to the economy when it undermines real economic activity.

From the adoption of the euro onwards, the Slovenian monetary authority, the BS, has relinquished its monetary authority to the ECB. This means that the monetary policy of the Eurozone, such as inflation targeting or control over the monetary aggregates, is shaped by the ECB based on the state of the economy of the Eurozone as a whole. Together with the national central banks (hereinafter: NCBs), the ECB also closely monitors the inflation forecasts since these can help it formulate the best course of action for the future of its economy (ECB, 2021a).

Slovenia, as a relatively small economy, represents only a small fraction of the common weighted price index of the Eurozone. However, as BS (2022a) states, the BS still closely monitors the movement of domestic price levels. Karanasos, Koutroumpis, Karavias, Kartsaklas and Arakelian (2016) find that even after the adoption of the euro, there are still sustained regional differences in inflation movements. Therefore, the strict monitoring of domestic inflation can be crucial for understanding the subsequent impact of the inflation differentials on competitiveness. Thus, the BS continually makes an effort in monitoring

Slovenian inflation and analyses Slovenian inflation as a separate entity from the composite inflation index for all Eurozone countries (BS, 2021).

Hartmann and Smets (2018) discuss how inflation in the euro area has been a well-controlled economic indicator ever since the euro's inception in 1999, averaging 1.7%. It has persisted around the target 2% levels, in contrast to many other economic indicators, such as national debt that led to the sovereign debt crisis and overall euro area unemployment that at times exceeded double digits after 2012 (Eurostat, 2022a) presented much bigger issues for the ECB in the first 20 years since the start of the Eurozone. Since the beginning of 2022 however, Slovenia as well as the other Eurozone countries have begun experiencing higher levels of inflation. Approximately one year ago, in June of 2021, the year-on-year inflation was 0.7%. One year later, in June of 2022, that figure rose all the way up to 7.3% (SURS, 2022a). That is the highest value of year-on-year inflation in Slovenia since the adoption of the euro in 2007. In ECB (2022a), April 14th, 2022 press conference, therefore, almost all of the questions posed by the press included concerning remarks about the persistence of high inflation levels seen at the beginning of 2022.

However, measuring inflation as it appears can only explain the effect of past and, to some extent, present economic conditions. To shape economic policies for the future better, we need to analyze this past data and from it, employing statistical theories, derive the future forecasts of the inflation movement. Thus, monetary and fiscal authorities can actively shape the future of inflation in the country they govern. Since taking control of inflation is one of the pillars of a well-functioning economy, inflation forecasting is likewise one of the pillars of the central bank's economic analysis (Meyler et al., 1998).

In the absence of an autonomous monetary policy, the Slovenian economy is even more reliant on its fiscal policy. Thus, domestic inflation forecasts should be considered, perhaps in an even bigger part, when constructing fiscal policy decisions, as well as when conducting the yearly wage negotiations (Meyler et al., 1998). Forecasting inflation is thus a worthwhile endeavor for the national economy, as well as to measure international competitiveness.

3 INFLATION FORECASTING

There are various statistical models used for forecasting inflation. ARIMA models are useful tools for monetary institutions because they provide a base prediction that can help in the interpretations of the other models' results (ECB, 2021b).

3.1 Inflation forecasting methodologies in practice

Even though their simplicity does not necessarily indicate a lower utility, ARIMA models are not the main methodology used by most monetary authorities for forecasting inflation or other monetary indicators. As Alessi, Ghysel, Onorante, Peach, and Potter (2014) state, a combination of other models is usually used, especially since ARIMA models are not good predictors in times of shifts in the general fluctuations of the monetary variable and general economic instability. However, the ARIMA is used in connection with other forecasting techniques according to ECB (2016).

Ever since its formation, the ECB has been publishing macroeconomic projections for the Eurozone. Over the years, the projection techniques and practices developed to accommodate the changes in the economic environment in the euro area countries. Therefore, the models used in the projections of macroeconomic indicators are continuously evolving. The results of these models' projections are published four times a year. They are used by the Governing Council to help with forming the monetary policy for the euro area. Among the projections included in these reports, there are the inflation projections in the form of HICP forecasts. The projection horizon is the current year, as well as the following two years (ECB, 2021b).

When constructing the inflation projections, the NCBs, such as the BS, play a crucial role since they provide the national data and forecasts as well as expert opinions. In the process of constructing the quarterly reports, NCBs provide the short-term projections for overall inflation projections as well components of inflation (such as food, energy, etc.) in the country they oversee. The ECB then aggregates this data to create the overall euro area inflation path. The ECB calls this process the Narrow Inflation Projection Exercise (ECB, 2021b).

Alessi et al. (2014) and Kontogeorgos and Lambrias (2019) list that ECB forecasts are conditional on a set of assumptions like the international environment, financial conditions, and fiscal variables. VAR models and Beynesian VAR models, which differ from VAR models in that the parameters of the model are treated as random variables with certain probabilities and not as fixed variables are generally used by NCBs and ECB for forecasting the general price index and some especially important components of the price index. These are often accompanied by ARIMA time series techniques for specific components of prices to provide the initial baseline projection jointly (ECB, 2021a). Alessi et al. (2014) also claim a frequent use of Dynamic Stochastic General Equilibrium (hereinafter: DSGE) models, which – as explained in Del Negro and Schorfheide (2012) – derive forecasts by modeling various assumptions about preferences, technologies, and monetary and fiscal policy regimes. The DSGE models are used for a structural interpretation of the forecasts.

One such NCB that aids in the ECB forecasting is the BS that biannually publishes its macroeconomic projections for the Slovenia report. In addition to other economic indicators, such as the economic activity and labor market, they also include their projections for inflation in Slovenia. The methods they use for forecasting are analogous to the ones used by the ECB (BS, 2021).

The aggregation of the national inflation data is carried out by the method used by the statistical office of the European Union, Eurostat. It is the annual chain index with specific country weights. The weights reflect the country's share of private final domestic consumption expenditure to the euro area's total private final domestic consumption expenditure. Naturally, the weights change over time with changes happening in the before-mentioned expenditure shares (Eurostat, 2022b).

The models (VAR, DSGE, etc.) by themselves, however, do not give a sufficient explanation of the possible future movements in economic indicators, including inflation. Therefore, an important part of the ECB projections includes the expert opinion and judgment of the calculated results. In addition to that, the projections are subject to forecasting errors. No one model perfectly sums up the nature of economic and financial agents. Therefore, the models cannot predict the future with 100% certainty. In fact, the models can sometimes be quite inaccurate. There are multiple sources of forecasting errors. An obvious one is the unpredictability of certain world events. Another factor that gives rise to forecasting errors is the data. Data on the current situation is often incomplete and needs to be thoroughly processed before being made viable for use in the forecasting models. For example, a large array of economic indicators that are collected in different ways and periods has to be combined in the correct way to be able to construct an accurate VAR or DSGE inflation forecasting model.

To measure the quality of the ECB forecasts, these forecasts and the forecasting errors are regularly compared to the forecasts of other institutions, such as the International Monetary Fund, Organisation for Economic Co-operation and Development, European Commission, and some private institutions like the Survey of Professional Forecasters and Consensus Economics. The qualitative part of the projections that include the possible key risk factors that could skew the actual values of inflation away from the projected values and expert opinions on the calculated projection results are, thus, as important in the overall forecasting path for Eurozone inflation as the quantitative model calculations part (ECB, 2016).

3.2 Advantages and disadvantages of using ARIMA models

Now, when we explained what models the official authorities use to forecast inflation, it is sensible to explain why ARIMA would be a valid choice for inflation forecasting. A big advantage of ARIMA is that it requires only the data of the time series we are interested in, which means it works with univariate time series data. That, in some ways, has the advantage over multivariate time series data. When dealing with multivariate time series data, the pool of appropriate data is usually smaller, since we can only take the intersection of the time series variables. Taken from our previous example of Dhakal et al. (1994), the VAR model, which works with multivariate time series data, can only be constructed for the period for which all the variables listed before have reliable data. For example, a VAR model can use past values of inflation and past GDP values to model inflation. Since GDP data is more widely offered on a quarterly or yearly basis and not monthly like inflation, we can lose a lot of data points by adding GDP as a variable in our model. Thus, the simplicity of ARIMA models gives them an advantage (Chatfield, 2001).

On the other hand, ARIMA models also have certain disadvantages. One disadvantage is the fact that a specific ARIMA model is not based upon a theoretical economic model and, therefore, the economic importance of such a model is not clear whereas VAR and vector error correction models (hereinafter: VECM), these being cointegrated VAR models, do derive their meaning from economic theory. Similarly, as for VAR and VECM, perhaps, the biggest downside of the ARIMA model is the fact that all these models are entirely backward-looking. Because of that, they are generally very bad at predicting turning points unless the turning point in question is a step back to the long-run equilibrium. One of the disadvantages that applies to other modeling techniques as well is the fact that the determination of the model form can often depend greatly on the skill and experience of the person constructing a model (Meyler et al., 1998).

Nevertheless, according to Stockton and Glassman (1987), ARIMA models have been proven as quite useful or at least on par with other more complicated models, such as the VAR, that are based on economic theory. Similarly, Bokhari and Feridun (2006) found that ARIMA models perform better than VAR models while Espasa, Poncela and Senra (2002) found that ARIMA models perform better than VECM. These studies, as well as Junttila (2001), Fritzer et al. (2002), and Pufnik and Kunovac (2006) prove that ARIMA models are either on par with other models or better at predicting short-term inflation. As was previously stated, Fritzer et al. (2002) show nearly perfect forecasts for a month ahead with ARIMA models. Olaoluwa (2019) additionally proves that univariate ARIMA models perform on par or even better than more complicated multivariate alternative models in situations with steady and low inflation.

ARIMA model's drawbacks lie in the situation when inflation is high and less stable. i.e. when more complicated models of predicting inflation are sometimes preferred. For example, Hubrich (2003) claims that AR models do not perform better than VAR models when predicting inflation. However, this claim is refuted by the short-term forecasts by before mentioned Bokhari and Feridun (2006). Additionally, Binner, Bissoondeeal, Elger, Gazely and Mullineux (2005) explore the comparison of linear and nonlinear forecasting methods. They find that linear forecasting methods, such as ARIMA models, perform worse than the nonlinear forecasting methods like the neural network (hereinafter: NN) model which is based on the idea of a network resembling the human nervous system with various layers of interconnected processing units. As the authors admit, however, this superiority is not always true because the nonlinearity in the data is often hard to model. Therefore, NN models can, in fact, perform worse due to the complexity of their setup. Based on that we claim that using ARIMA models for short-term forecasting in relatively stable environments can be a suitable choice, at least in the times when this analysis was performed.

4 EMPIRICAL STUDY

Following Box et al. (2016), the whole process of constructing an ARIMA model starts with collecting data which is then checked for stationarity and seasonality in the next step. If the data is found to be stationary, we can start to estimate the best fitting model for our data. The model is then statistically tested. If the model satisfies the statistical model testing, predictions are made and interpreted.

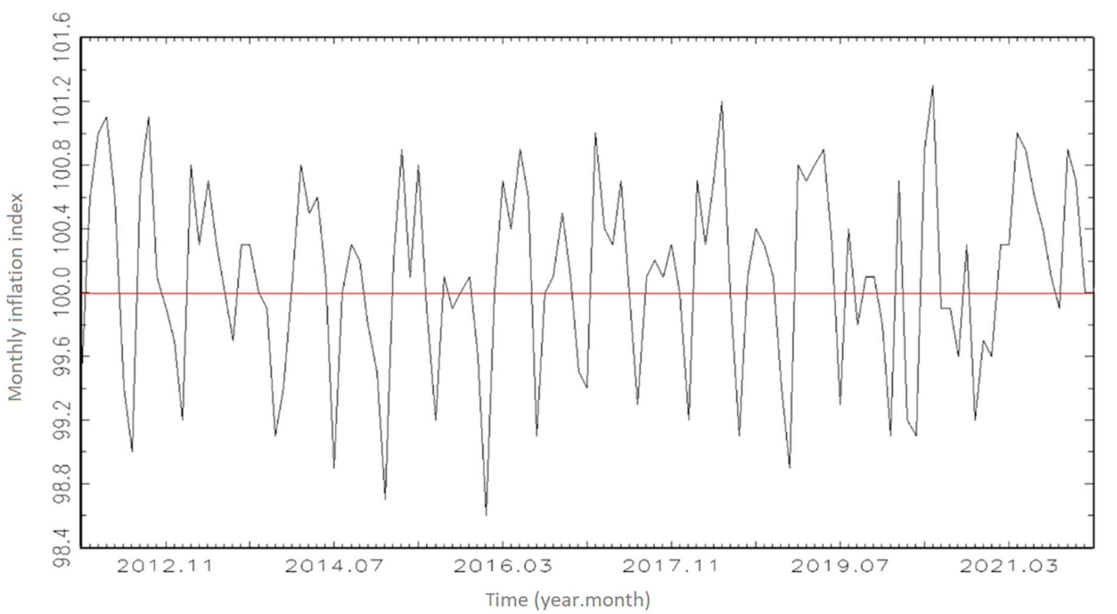
4.1 The data

We use the inflation data for Slovenia from the SURS (2022b). The monthly inflation data is shaped as a month-on-month index (i.e. relatively upon the previous month's data) from January 2012, a period when the global economic crisis began to wane, to December 2021. In total, the data consists of 120 observations. To analyze the data, construct the model, and predict monthly inflation from January 2022 to June 2022, we use the JMulti statistical software.

4.2 Checking for stationarity

To check for stationarity, we can look at the plot of all the data as seen in Figure 1. The red line is an informative indicator of rising or falling price indices with the numbers above the line indicating rising month-on-month price index, while the numbers under indicate falling month-on-month price index. Figure 1 shows that the data, at a first glance, looks stationary. There is no clear trend since the mean of the dataset looks constant through time. The variability of data also does not have a significant change over time. However, we could potentially see some seasonality, since the dips and rises in inflation seem to happen around similar times of the year. Looking solely at the graphical presentation reveals that our data seems to be stationary. However, for a more precise conclusion, statistical tests are necessary. In particular, ADF and KPSS tests were performed.

Figure 1: Slovenian monthly HICP from January 2012 to December 2021



Source: SURS (2022b).

The ADF test does confirm our prediction that the data series is stationary. The test is significant even at a 1% level, as can be seen in Figure 2 in the appendices. This shows strong evidence that the null hypothesis of the ADF test – that the series is not stationary – can be rejected. To be sure, we perform another stationarity test, the KPSS test. In contrast to the ADF test, the null hypothesis of the KPSS test is that the series is stationary. Again, the test confirms the stationarity of the data as we can see in Figure 3 in the appendices since we cannot reject the null hypothesis of the KPSS test. This goes in line with our ADF test results. We can conclude that our data is stationary. This means, as explained in Chatfield (2001), that there is no need for the "integrated" part of our ARIMA model. We do not need to difference the data to achieve stationarity because the data is already stationary.

4.3 Determining the shape of the model

4.3.1 Autocorrelation and partial autocorrelation function

As Box et al. (2016) define, the autocorrelation (hereinafter: ACF) and partial autocorrelation (hereinafter: PACF) function can be useful when looking at a univariate time series. The ACF shows us the correlations of a time series with a lagged version of itself. It can indicate whether the time series is random (no correlation between past and current values). If the process is proved not to be random, the ACF can indicate which past observations (up to what number of lags) have a statistically significant effect on the current observation. On the other hand, the PACF shows a correlation between the current time series observation X_t and a specific lag X_{t-p} without the effect of all the past values among these two-time points. That is where the name "partial" comes from since PACF measures the correlation with a "part" of the past lagged values.

Further, Box et al. (2016) explain that the ACF and PACF can be useful for checking which models seem to be appropriate for a specific time series analysis. Just looking at the ACF and PACF graphs is usually not an adequate method of determining the appropriate model. However, it can give us a good insight into what the model could look like. The first useful indicator of the shape of the model is thus the ACF and PACF functions. We can look at the ACF and PACF graphs to see whether specific time series data could be modeled under the AR process. To be able to imagine what the ACF and PACF functions are supposed to look like for us to be able to assume the AR, MA, or ARMA form of the model, we add Figure 4 in the appendices. If, as in Figure 4 in the appendices, the ACF shows signs of geometric decay where the values of correlation decrease exponentially or in a sinusoidal fashion, and the PACF shows significant correlations up to lag p and after that cuts off, an AR model could be an appropriate way to explain the movement of our time series. The PACF can give us a hint about the order of the AR model. The lag p where the graph values suddenly cut off could be the order of the model AR(p) (Chatfield, 2001).

As with the AR process, we can again look at the ACF and PACF to make sense of the time series data and applicability of the MA process. However, the roles of the ACF and PACF are reversed when we try to determine a MA process. If the PACF shows signs of a geometric decay and the ACF shows a significant correlation up to the q-th lag and cuts off after that, an MA model could be appropriate for this specific time series data. Essentially, the situation is a reversed picture of Figure 4 in the appendices. The ACF can give us a hint about the order of the MA model. The lag q where the graph values suddenly cut off could be the order of the model MA(q) (Chatfield, 2001).

The applicability of an ARMA model can be deduced from the ACF and PACF graphs as well. In the case of ARMA being the best model option for specific time series data, both the ACF and PACF graphs will show geometrically decaying correlation values (Meyler et al., 1998). It means both ACF and PACF graphs will have a shape similar to that of the ACF graph in Figure 4 in the appendices.

However, as Meyler et al. (1998) state, sometimes the ACF and PACF graphs show a strong correlation at specific lags. This could be a sign of a seasonal component in the data. In this case, the model we can use is the seasonal ARMA model. Keeping all this in mind, we construct and interpret the ACF and PACF graphs for our inflation data.

Figure 5 in the appendices shows the ACF and PACF graphs for our set of data. The dark columns indicate the intensity of the correlation at a certain lag, while the dotted line indicates the point of statistical significance, which means that the certain lags that reach above or below the dotted line are statistically significant. There is no clear indicator in the graphs of the optimal autoregressive moving average form. There is no significant cut-off in either of the graphs. Therefore, we cannot say with certainty that specific order of p or q is the appropriate one. Both graphs present a sinusoidal pattern which could hint at an ARMA shape of the final prediction model. However, the problem is that there is no significant decaying of the sinusoidal amplitudes. Therefore, we cannot say with certainty that this will produce an ARMA model. Nevertheless, an interesting feature of the data reveals in these graphs. We can see significant lags in both graphs at the 6^{th} and 12^{th} lags. This could suggest some sort of seasonality because we have suspected from looking at the plotted time series. To account for this seasonality, we later include seasonal dummies when constructing the final model. Since the ACF and PACF functions do not give us definitive answers as to what the shape of the model should be, we turn to other indicators.

4.3.2 Akaike, Schwartz, and Hannan-Quinn criterion and Hannan-Rissanen procedure

We have already described the standard method of looking at ACF and PACF graphs. However, that method is very subjective and requires a lot of experience in ARIMA modeling (Chatfield, 2001). More objective tests check for the best order of p and q. The main test we use in this thesis's modeling is the Hannan-Rissanen procedure developed by Hannan and Rissanen (1982) because this procedure is specifically used when constructing an AR and MA model. However, following the Box et al. (2016) methodology, checking the Akaike (hereinafter: AIC), Schwartz (hereinafter: SQ) also known as Bayesian information criterion and Hannan-Quinn criterion of different possible model specifications is also standard practice. Since these tests are general tests for model specification and are not specifically used just in ARIMA modeling, they do not give specific results in order of p and q. They only offer the optimal number of lags or, analogously, the value of p.

The tests require an input of the maximum number of lags of the ARIMA model which we set to 4 since, according to Figure 5 in the appendices, that is the number of lags in which we could somewhat reasonably say if we do not include the seasonally affected 6^{th} and 12^{th} lag where the ACF and PACF cut off (when the columns do not reach the significance dotted line anymore).

The results show that AIC and Hannan-Quinn criteria suggest 3 lags to be best. Therefore, the last 3 past values of inflation best predict the next period's inflation. Meanwhile, SQ shows the 1 lag model to be the best. Therefore, taking only the previous period's inflation value is best when predicting inflation according to SQ. However, Weiß and Feld (2019) find that for datasets of around 100 observations AIC performs better than the Schwarz criterion. Therefore, we take the 3-lag model as more accurate, because we have 120 data observations.

Before estimating the model, we do another test for determining the optimal number of p and q, the Hannan-Rissanen procedure. This procedure gives us the ARMA model with optimal *p* of 2 and *q* of 0. With that, we get the optimal model for the data in the form of ARIMA(2,0,0). The best model to forecast inflation data from our time series is the model that relies on the values of the past two observations. We decide to follow the Hannan-Rissanen criteria results because of their relation to the ARMA forecasting processes as we mentioned previously.

4.4 Estimating the model and diagnostic checking

We define our model as having 2 AR lags (*p=2*), 0 MA lags (*q=0*), and 0 order of differencing (*d=0*) and we also include seasonal dummies as we follow the findings of Lis and Porqueddu (2018) about the presence of a seasonal component in inflation data for the Eurozone countries and our own findings from the ACF and PACF graphs in Figure 5 in the appendices. In conclusion, this means that we determine an AR(2) model as the best predictor of inflation based on our dataset. As can be seen in Figure 6 in the appendices, the model coefficients, as well as the constant, are all significant with just one insignificant seasonal dummy for the seventh month of the year, *S7*, which we nevertheless keep in the model to be able to interpret the model as a whole.

We still need to check the validity of the model as was modeled in Baciu (2015). We need to check the residuals of the model. They should be:

- white noise (the residuals of the model are not correlated among themselves),
- normally distributed (residuals of the model must follow the distribution where a specific percentage falls inside 1, 2, or 3 deviations from the mean),
- homoscedastic (have a constant variance).

Firstly, we plot the graphs of autocorrelation and partial autocorrelation of the residuals of the model. This can be found in Figure 7 in the appendices. Autocorrelations are all very small since they do not reach the significance dotted line. The 6^{th} lag autocorrelation is the only one showing small signs of significance, which is explained by the seasonality of the data. To show the improvement of the model because of the addition of the seasonal dummies we plot the autocorrelation of the same ARIMA(2,0,0) model forecasts' residuals but without the added seasonal dummy variables. The correlations among the model residuals of the model without seasonal dummy variables can be seen in Figure 8 in the appendices. We can see that this form of the model would not pass the white noise requirement since a lot of the residuals have statistically significant correlations among themselves. Choosing to account for the seasonality in the data when constructing the model is thus clearly validated. At the same time, we can say that the residuals in our model are indeed white noise because, as we can see in Figure 7 in the appendices, their correlations among each other are, in general, not statistically significant.

To prove that the residuals are in fact white noise in an even more objective way, we construct the Ljung-Box test for autocorrelation among the model's residuals. Our p-value is 0.63. Because the p-value is bigger than 0.05, we can be sure that our model is sound with the residuals being white noise.

Lastly, we test the model for the normality of residual distribution. We construct a Jarque-Bera test. We reject the null hypothesis of normally distributed residuals with a p-value of 0.0002. The test also gives us the values of the kurtosis and skewness indicating a left skew with heavier tails. However, this again is not an important problem since nonnormality only causes inefficiency in our estimated parameters and not inconsistency.

To test for heteroscedasticity, we use the ARCH-LM test. We reject the null hypothesis of homoscedasticity with a 0.0247 p-value. However, we do not consider this to be an important problem since conditional heteroscedasticity present in our model merely makes the parameters inefficient and not inconsistent.

4.5 Forecasting results

We forecast values for our inflation indicator 6 periods after our last data point from December 2021. We chose to only present forecasts for 6 periods in the future since we are working with ARIMA models that tend to give suitable predictions in the short run. Our monthly predictions, therefore, start from January 2022 (denoted as 2022 M1) and go until June 2022 (denoted as 2022 M6). The predictions are presented in Table 1.

Table 1: Model forecasts (month-on-month indices)

Time	Forecasted month-on-month index
M1	98.99
M2	100.36
M3	100.45
M4	100.52
M5	100.80
M6	100.21

Source: Own work

The final results show a series of monthly inflation indices. The indices for all months except for January show a rise in monthly inflation indices. In January, the model predicts a slight deflation compared to the previous month. In the following months, however, our model predicts rising price indices that peak in May with 0.7984% monthly inflation and then slow down but remain positive in June.

5 DISCUSSION

Next, we compare our model's results to the actual values of inflation in the predicted period. Since we now have actual values for all the periods our model predicted, we can comment on the forecasts' actual accuracy. We transform our indices that show the change in inflation of a specific month compared to the previous month (month-on-month) into indexes showing the change in inflation of a specific month compared to the same month in the previous year (year-on-year). We do this transformation because BS (2021) publishes its inflation forecasts in a year-on-year format. This is necessary as after comparing our predictions with the actual values of inflation we also wish to compare our predictions to the BS predictions for this period. These new indices are shown in Table 2. Our predicted year-on-year indices show that inflation will be positive throughout the whole forecasted period and will peak in March and fall to its lowest levels in June. In Table 2, we compare our model's projected inflation with the actual inflation, sourced from SURS (2022a) and SURS (2022b), up until the most recent available data. We also calculate the relative difference (i.e. error) in prediction between our predicted value and the actual one. The relative error is calculated as the absolute difference between the predicted and actual value, relative to the actual value.

Table 2: Actual and forecasted indices of Slovenian inflation

		Jan 2022	Feb 2022	March 2022	April 2022	May 2022	June 2022
Year-on-year index	Actual values	105.8	106.9	105.4	106.9	108.1	110.4
	Predicted values	104.15	104.21	104.37	103.87	103.76	103.36
	The relative error in prediction (in %)	-1.56	-2.52	-0.98	-2.83	-4.01	-6.38

Adapted from SURS (2022a) and own work.

We can see that our model has underpredicted inflation levels in most months. However, our forecasts and the actual data both show the same direction of movement, that is, they both show mainly rising inflation. Nevertheless, the degree of increase in inflation has proven to be much higher than predicted by our model. The first three forecasted periods show a lesser percentage point difference between actual and predicted values than the last three periods. This shows the possibility of ARIMA having somewhat accurate predictions that were later deteriorated because of the unexpected rise in prices. For example, the relative errors in year-on-year predictions for the first three predicted months are inside the 0-3% range while the relative errors in prediction for the last three predicted periods are in the 1-6% range.

We wished to compare our predictions to that of the official government institutions. Similar projections were made in the BS's December 2021 Macroeconomic projections for Slovenia publication. They forecasted that inflation is going to keep steady at high levels, around 3.8% year-on-year, until the end of 2022 and then fall to normal 2% year-on-year levels (BS, 2021). This looks similar to our own predictions of around 4% throughout the first half of

2022 as shown in Table 2. The official prediction and our own ARIMA predictions are therefore similarly accurate.

The ECB (2021b) forecasters also ran into some miscalculations. They projected a sharp decline in year-on-year inflation at the beginning of 2022. However, as we mentioned in the literature review, inflation is very unpredictable when it comes to uncertain periods in politics or the economy. As BS (2022b) states, in the months after December 2021, the world has experienced many shocking events that greatly affected the economy and as a result the inflationary situation. The year-on-year inflation reached values as high as 10.4% in Slovenia in June 2022 (SURS, 2022b), which is much higher than the values anticipated by the BS. At the same time, Eurozone annual inflation reached 8.6% in the same month (Eurostat, 2022c). Clearly, the statistical models did not anticipate such a great increase. The ECB even issued a formal apology article by Chahad, Hofmann-Drahonsky, Meunier, Page and Tirpák (2022) regarding their inflation forecasting errors. The understatement of the first quarter inflation rate for 2022 has been the biggest forecasting error since the start of the ECB staff projections publication in 1998. The projection accuracy has been declining throughout the pandemic period. Nevertheless, up until the middle of 2021, it has stayed above the accuracy levels achieved during the last turbulent period, the 2008 financial crisis, even though the economic activity in the pandemic period has been much more turbulent than during the 2008 financial crisis. After the third quarter of 2021, however, the accuracy has steadily declined (Chahad et al., 2022).

Even though inflation forecasting has been one of the main activities under the ECB and BS's role as the monetary authorities of their assigned territories, it has become more and more evident how complicated the practice actually is. As Chahad et al. (2022) explain, the accuracy of the complicated models used to predict inflation has also come into question. There is no perfect model for predicting inflation, especially in situations like today when social catastrophes, such as the war in Ukraine or the global pandemic, present a totally unpredictable effect on the world price levels. The models have proven quite inefficient in this turbulent period. The ECB lists two main reasons for the unprecedented error in their predictions. Firstly, the already rising commodity and energy prices have experienced an even higher boom in prices since the start of the war in Ukraine in February of 2022. Secondly, the mismatch between the unexpectedly fast recovery in global demand and persisting supply constraints is putting additional upward pressure on prices. The supply bottlenecks, partially due to new lockdowns caused by the Omicron variant, have insisted longer than previously expected (Chahad et al., 2022). Celasun, Mineshima, Hansen, Zhou and Spector (2022) claim that the shortages in supply could last up to 2023, which presents further uncertainty for the movement of prices. Thus, this casts doubt on the BS's 3.8% year-on-year 2022 forecast as well as a 2% year-on-year inflation forecast for 2023.

The combination of models BS and ECB use did not fare much better than our ARIMA model with ECB (2021b) facing great difficulties, especially in the first month of 2022. This can be taken as proof that ARIMA indeed is comparable to technically more complicated models.

CONCLUSION

Predicting inflation is a crucial part of the work carried out by the ECB, which oversees the euro countries' monetary policy. That means it also oversees Slovenia's monetary policy. Even though Slovenia's inflation is only a small part of the whole inflation index for the Eurozone, its prediction is still crucial for the performance of the Slovenian economy. That is why the BS still carries out biannual forecast publications.

This thesis has attempted to form forecasts for Slovenian monthly inflation for the first half of 2022. We followed the Box et al. (2016) methodology for time series analysis and ARIMA modeling. First, we had to examine whether our time series inflation data is stationary. Through ADF and KPSS tests, we determined that our month-on-month index data is in fact stationary and thus can be used in the modeling process. The next step was to determine the form of the model by determining the AR and MA lags. We firstly looked at a graph of ACF and PACF. However, their shape did not strongly indicate any specific form of AR or MA since, as we assume, the seasonality present in the data distorted the sizes of correlation between certain period lags, especially the 6^{th} and 12^{th} lags. We examined the Hannan-Rissanen procedure and determined that ARIMA (2,0,0) would be the best fitting model for forecasting our data. We also added dummy variables to account for the seasonality detected both in the general plot of the data and ACF and PACF graphs. We were able to predict the inflation in the chosen period and compare the predictions with the actual values of inflation in those periods obtained from SURS (2022a) and SURS (2022b). In doing so, we answered the first question of our thesis: "What is the forecasted inflation rate in Slovenia based on the ARIMA model for the period from January 2022 to June 2022?" We forecasted monthly inflation indices and predicted deflation in January 2022 and then rising prices in the following months. The highest inflation is predicted for May at 0.8%. From the comparison with the actual values of inflation, we can conclude that our model predicted the right general direction of movement in inflation, namely a rise in inflation indices. However, it underestimated the intensity of the rise. Additionally, following our second question in this thesis: "Does the constructed model provide comparable results to the models used by the BS and ECB?" we found that the official institutions produced results for inflation in this period that were similarly underestimating the intensity of the rise in inflation, both for Slovenian inflation, as well as Eurozone inflation. Thus, we concluded that not all fault for the errors in our model's prediction can be attributed to the model. Some of the faults lie in the difficulty of predicting inflation in today's volatile environment. Thus, we cannot say with certainty that this study would be exponentially improved by constructing more complicated multivariate or nonlinear models to forecast Slovenian inflation.

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APPENDICES

Appendix 1: Povzetek (Summary in Slovene Language)

V diplomski nalogi z naslovom "Napovedovanje inflacije v Sloveniji z uporabo avtoregresijskih procesov premikajoče sredine" smo poskušali napovedati inflacijo za obdobje med januarjem 2022 in junijem 2022. Napoved je bila narejena s pomočjo integriranega avtoregresijskega procesa premikajoče sredine (angl. *autoregressive integrated moving average model – ARIMA*), kjer smo uporabili podatke o mesečnih indeksih cen življenjskih potrebščin za Slovenijo, v obdobju med januarjem 2012 in decembrom 2021. Oblikovali smo dve raziskovalni vprašanji:

1) Kakšna je napovedana inflacija za Slovenijo na podlagi ARIMA modela za obdobje med januarjem 2022 in junijem 2022?
2) Ali naš model poda rezultate, ki so primerljivi z rezultati modelov, uporabljenimi s strani Banke Slovenije in Evropske centralne banke?

Rezultati so pokazali rastoče letne indekse cen življenjskih potrebščin v vseh mesecih napovedi. Letni indeks cen življenjskih potrebščin za naše napovedano obdobje naj bi dosegel vrh v marcu 2022, ko je le ta znašal 104.37, in se nato v mesecu aprilu začel nižati. V zadnjih treh analiziranih mesecih, t. j. od aprila do junija, smo napovedali med 3,4 in 3,9 % inflacijo. Banka Slovenije je na drugi strani do konca leta 2022 napovedala letno inflacijo v vrednosti okoli 3,8 %. Iz tega lahko sklepamo, da so naše napovedi precej podobne napovedim Banke Slovenije. Naše rezultate smo primerjali tudi z dejanskimi vrednostmi indeksov cen življenjskih potrebščin v napovedanem obdobju, saj so bile le-te že dostopne ob zaključevanju naše raziskave. Ta primerjava je pokazala precejšnje razlike med napovedanimi in dejanskimi vrednostmi. Inflacijske napovedi so precej podcenile višino inflacije v napovedanem obdobju. Enako velja tudi za napovedi Banke Slovenije in Evropske centralne banke. Naš zaključek je torej, da je naš model podal primerljive napovedi z modeli Banke Slovenije in Evropske centralne banke, vendar je turbulentno politično in ekonomsko okolje v začetku leta 2022 naredilo napovedovanje inflacije precej zapleteno in nepredvidljivo.

Appendix 2: Figures

Figure 2: ADF test results

```
ADF Test for series:       covid20122021
sample range:              [2012 M4, 2021 M12], T = 117
lagged differences:        2
intercept, no time trend
asymptotic critical values
reference: Davidson, R. and MacKinnon, J. (1993),
"Estimation and Inference in Econometrics" p 708, table 20.1,
Oxford University Press, London
 1%         5%         10%
-3.43      -2.86      -2.57
value of test statistic: -7.6006
regression results:
---------------------------------------
variable      coefficient   t-statistic
---------------------------------------
 x(-1)        -1.0935       -7.6006
dx(-1)         0.3535        3.1787
dx(-2)         0.1127        1.2104
constant       109.4568      7.6003
RSS            35.7231
```

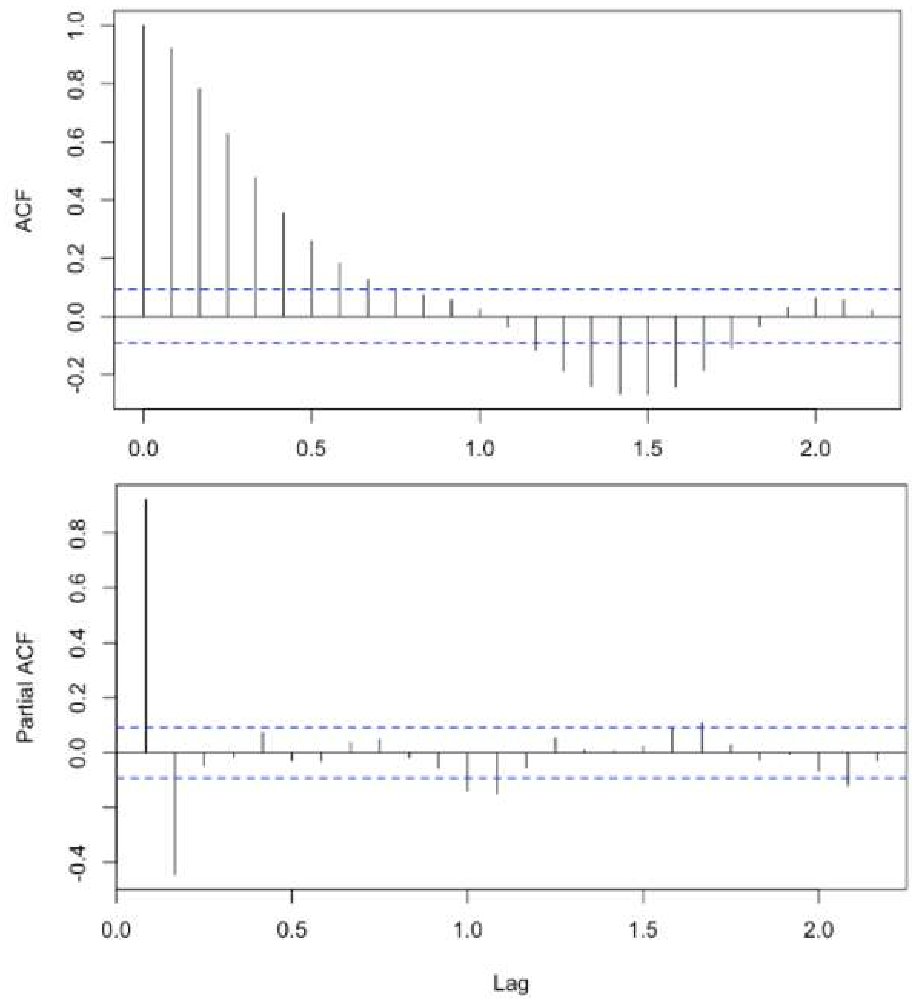
Source: Own work

Figure 3: KPSS test results

```
KPSS test for series:  covid20122021
sample range:          [2012 M1, 2021 M12], T = 120
number of lags:        2
KPSS test based on y(t)=a+e(t) (level stationarity)
asymptotic critical values:
 10%        5%         1%
0.347      0.463      0.739
value of test statistic: 0.0702
reference: reprinted from JOURNAL OF ECONOMETRICS,
Vol 54, No 1, 1992, pp 159-178, Kwiatkowski et al:
"Testing the null hypothesis of stationarity ...",
with permission from Elsevier Science
```

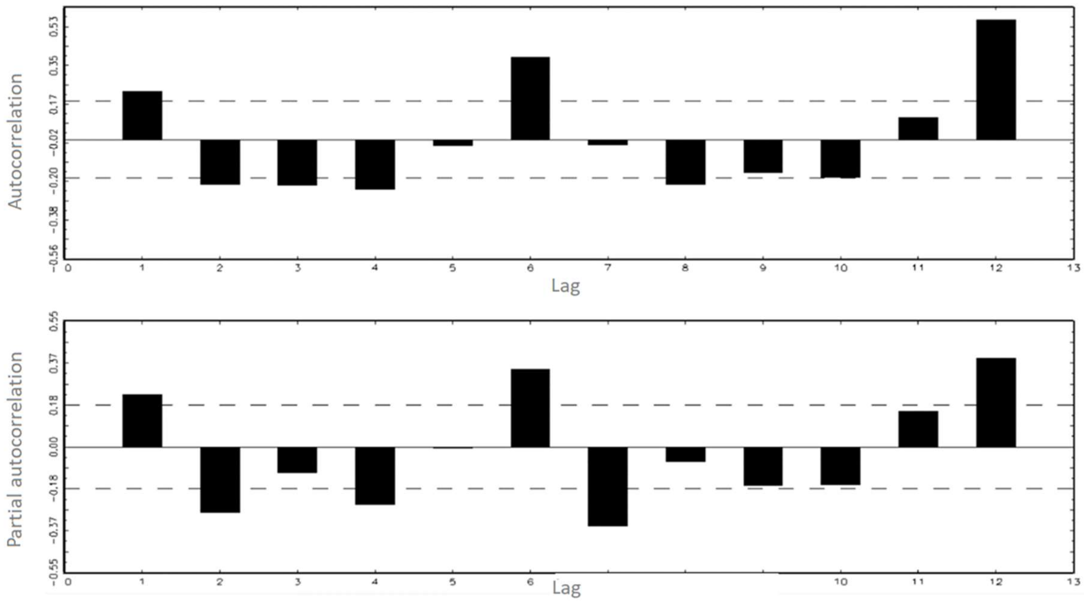
Source: Own work

Figure 4: Example of ACF and PACF



Source: Medium (2021)

Figure 5: ACF and PACF graphs of our data



Source: Own work

Figure 6: Model specification

Log Likelihood: -43.724613 Number of Residuals: 119
AIC : 115.449225 Error Variance : 0.138065309
SBC : 154.356954 Standard Error : 0.371571405

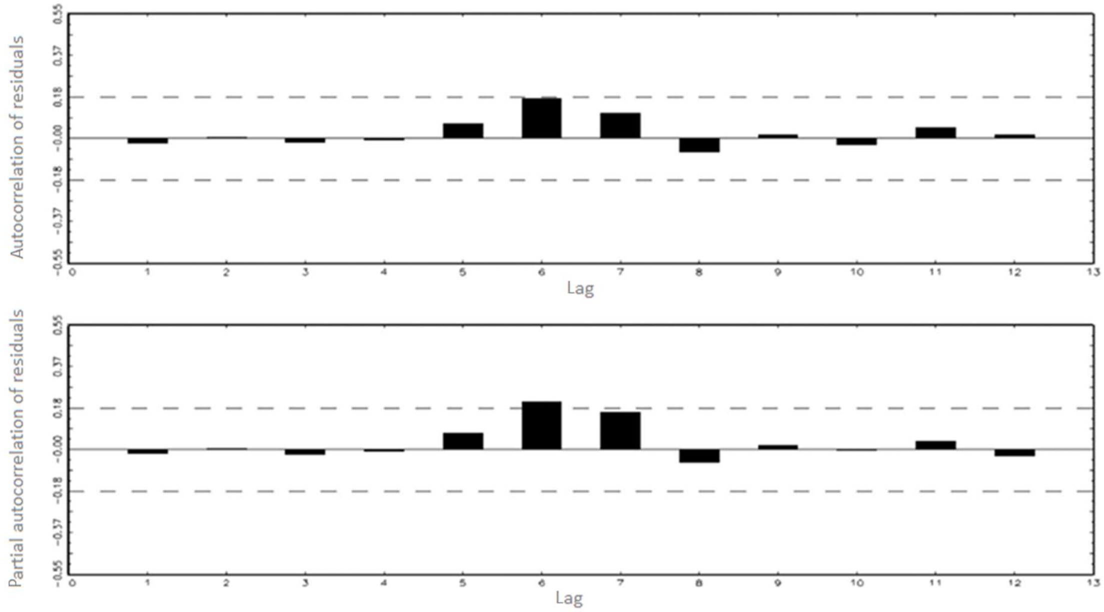
DF: 105 Adj. SSE: 14.528523635 SSE: 14.496857420

Dependent Variable: covid201

	Coefficients	Std. Errors	T-Ratio	Approx. Prob.
AR1	0.29696089	0.09281878	3.19936	0.00182
AR2	-0.31371411	0.09415298	-3.33196	0.00119
CONST	99.62278862	0.12639640	788.17742	0.00000
S1	-0.52746060	0.16125320	-3.27101	0.00145
S2	0.88239287	0.19757816	4.46604	0.00002
S3	0.83591671	0.19000989	4.39933	0.00003
S4	0.85147448	0.17681216	4.81570	0.00000
S5	1.15902238	0.17591050	6.58870	0.00000
S6	0.59654701	0.17807595	3.34996	0.00112
S7	-0.23386867	0.17531203	-1.33401	0.18509
S8	0.54637059	0.17642810	3.09685	0.00251
S9	0.53761252	0.19120782	2.81167	0.00588
S10	0.63021151	0.19964937	3.15659	0.00208
S11	0.39946017	0.15757320	2.53508	0.01272

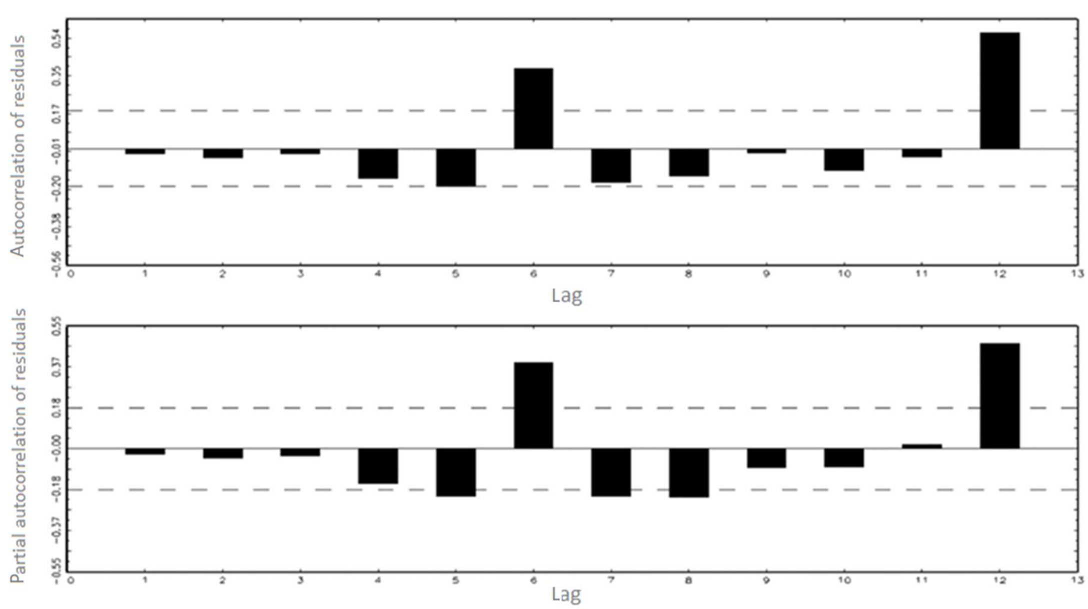
Source: Own work

Figure 7: ACF and PACF of residuals of the model



Source: Own work

Figure 8: ACF and PACF of residuals of the model without seasonal dummy variables



Source: Own work