FORECASTING FINLAND-KOREA BILATERAL TRADE WITH THE BOX-JENKINS METHOD

Lappeenranta–Lahti University of Technology LUT

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Examiner: Professor Azzurra Morreale

ABSTRACT

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This thesis aims to investigate the trade relationship between Finland and South Korea, and forecast future progress by building time-series models with the Box-Jenkins methods. The source of the research data is the database of the Finnish Custom that is called “Uljas” (uljas.tulli.fi). Two time-series data, monthly Finnish export to South Korea and monthly Finnish import from South Korea, have been acquired for further analysis and model building. The period of the original data is from January 1996 to December 2021 and the total number of observations is 312 for each data.

The model building process follows the steps of the Box-Jenkins method. After a brief exploratory analysis, import and export data are checked for stationarity. Then, following the identification, estimation, and diagnosis checking stages, two time-series models are built. In the conclusion part, 10-year future monthly imports and exports are forecasted. According to the forecasts, the bilateral trade between Finland and South Korea is anticipated to show steady growth in the long term.

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Lappeenranta, 17.6.2022

Sangwoo Dan

Abbreviations

AR	Autoregressive
MA	Moving Average
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
SARIMA	Seasonal Autoregressive Integrated Moving Average
RSS	Residual Sum of Squares
AIC	Akaike Information Criterion
SBIC	Bayesian Information Criterion of Schwarz
HQIC	Hannan-Quinn Criterion
ADF	Augmented Dickey-Fuller
PP	Phillips-Perron
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
ACF	Autocorrelation Function
PACF	Partial Autocorrelation Function
ARCH	Auto-Regressive Conditional Heteroskedasticity
GARCH	Generalized Auto-Regressive Conditional Heteroskedasticity
EGARCH	Exponential Generalized Auto-Regressive Conditional Heteroskedasticity
GJR	Glosten, Jagannathan, and Runkle model

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1 Introduction

1.1 Background

At first look, Finland and South Korea can seem to be quite different nations with no links or similarities between them at all. Nevertheless, in many other aspects, there exist linkages and parallels. Even after hundreds of years of influence from their countries' immediate neighbors, for instance, the people of both nations have managed to preserve their distinct identities and successfully fend off foreign incursions on their territory throughout the course of their respective national histories. Both Finns and South Koreans worked hard during the 20th century to transform their homelands into one of the most successful nations in the world, complete with a high-tech manufacturing economy.

The Miracle on the Han River refers to South Korea's economic boom. On a worldwide scale, the rate of economic development has reached previously unheard-of levels. South Korea is an affluent nation now, having the world's 10th highest nominal GDP in 2021. Finland, in the eyes of many Koreans, is a fascinating mix of modern technology and pristine nature. Young South Koreans, in particular, are drawn to Finland because of its well-known work-life balance, which is still difficult to come by in South Korea, where individuals typically work the highest hours among OECD nations.

Both nations are free-market democracies reliant on international commerce in terms of political and economic systems. Indeed, international commerce with other nations accounts for over 80% of the total GDP of South Korea. The main trading partners of South Korea are now the United States, Japan and China. South Korea is Finland's 17th largest trade partner internationally and Asia's third largest export market after China and Japan. South Korea wants to strengthen its ties with ASEAN and the European Union member nations. The Free Trade Agreement between EU and South Korea has been in place since 2015, and it has helped to promote trade between the two countries by decreasing tariffs for companies.

The economy of South Korea has been growing slowly recently, compared to its previous strong expansion. The annual GDP growth rate has decreased to roughly 2%. The traditional marine sector and heavy equipment production remain the most notable in terms of trade commodities. Services exports have also been steadily increasing in recent years. The entire sum is not exactly equal to goods exports, but it is quite close, coming in at roughly 800 million euros.

Food and tourism have been two of the fastest expanding trade industries between the two nations in recent years. In South Korea, Finnish food has earned a reputation for great quality and is regarded as premium product. Korean customers have a strong need for high-quality, organic, and ecologically friendly food. In South Korea, a new demand for organically farmed food and alternative protein sources is getting popular. In recent years, visitor traffic between Finland and South Korea has continuously increased. Increasing number of South Koreans are visiting or traveling through Finland. Not only Finland is luring Korean tourists with its unique atmosphere with pristine nature, but the Helsinki Vantaa airport is also functioning as the hub airport for many Korean tourist who wish to travel to other cities in Europe.

In 2020s and forward, the market in South Korea will offer new possibilities for Finland to develop its innovation across a range of different industries. In particular, the bioeconomy and circular economy are two areas in which Finland is in the position to benefit on the current momentum. The industrial and consumer sectors in South Korea are both in the process of receiving more sustainable solution information that will be distributed according to a plan that is now being implemented. Finland is in a position to make the most of this momentum and capitalize on its opportunities. Also, the innovative companies based in Finland may take advantage of a diverse range of possibilities thanks to the country's well-established reputation in the field of information and communications technology.

At the beginning of 2020s, it is a good moment to discover and promote opportunities for Finland and South Korea to work together on projects that are both profitable and implementable. In 2019, South Korean President Moon Jae-in visited and had a summit with

Finnish President Sauli Niinistö in Finland, where the fundamental groundwork for further economic cooperation on both the political and business levels was established. The collaboration has already started in some areas, for instance in the field of medicine as well as the manufacturing of foods and drinks. In addition, the governments of the two nations have reached an agreement to work together in order to promote the development of new startup businesses. Since the spring of 2020, the Korean government has been selecting and sending Korean entrepreneurs to Finland for the purpose of gaining knowledge from the flourishing startup ecosystem in Finland. Despite the fact that Finland and Korea are increasingly competing with one another in the technological sphere, there is a significant opportunity for the two countries to deepen their ties to one another. These exchanges have the potential to boost both nation's economic competitiveness as well as high-tech innovation in the years to come, which would be advantageous for both nations.

1.2 Brief history

The statistical data on the trade amount between Finland and South Korea has been started to be recorded only since 1960s. Fibers and mechanical pulp were among the modestly valued Finnish exports to South Korea in 1964. There were only a few sporadic trade movements until the late 1970s, largely chemical exports from Finland. Finland imported wigs from South Korea in the 1960s. In the 1960s, wigs, wood boards, and shoes were the three South Korean products that dominated their respective worldwide marketplaces. This was due to the Korean government's backing for these labor-intensive sectors via the expansion of the industrial base and promotion of exports. (Korhonen et al, 2005)

The Finnish Embassy in Seoul was created in 1977 and began promoting Finnish goods to Korea immediately. The introduction of Finnish fur products to Koreans, for example, resulted in increase of fur import to South Korea. In 1977, Finland exported almost 5 million euros to Korea, which comprised machine components, motors, wheat flour and cigarette papers. In addition to conventional exports, other kinds of commerce have become crucial, such as the provision of entire projects, knowledge transfers, and third-country collaboration. Particularly full projects in the domains of ore concentration, pulp manufacture, and dock construction were exported by Finland. (Korhonen et al, 2005) In the 1970s and 1980s, Finnish imports from Korea were mostly textiles and clothing, but by the latter of the decade, the structure of trade began to shift as the percentage of Korean electronics and electric items began to rise. Nokia, for example, purchased components from Korea at a reasonable price. (Karjalainen, 1986)

The level of economic cooperation became increasingly intense in the 1980s. Traditionally, Japan and China have been the most significant Asian export destinations for Finnish goods, and South Korea also started to take important position at the start of the 1980s. Furs were a prominent feature of Finnish exports to South Korea during that period and once accounted for more than 50% of all Finnish exports to South Korea in the 1980s. Fur exports from Finland to Korea reached a high of 4 million euros in 1981, climbing to 16 million euros in 1982, representing 61 percent of the total amount of Finnish goods sent to Korea (2002, Finnish Customs)

The recession brought on by the sudden end of the Soviet Union regime damaged the Finnish economy in the early 1990s. Meanwhile, the South Korean economy was expanding rapidly, requiring the purchase of foreign technology. As a consequence, Finnish exports could expand to include additional high-tech commodities such as equipment. In 1994, Valmet won the contract to provide five new paper machines to Hankuk Paper and Shin Ho Paper in Korea. POSCO, a South Korean steel company, purchased a measurement system from Rautaruukki in 1994 (HS, 1994). Traditionally popular items such as furs were still exported to South Korea in large quantities. In 1994, around 70% of all Finnish fox furs were exported at the record high level of prices. As South Korea's living standards improved, there was a rise in demand for fur accessories. Imports of Korean autos from companies such as Hyundai and KIA began in the 1990s. While electronic product imports grew rapidly during this period, consumer electronic products such as color televisions started to take over in the mid-1990s and eventually accounted for majority of imports from South Korea. (OECD, 2022)

1.3 Literature review

In this section, the current state of academic literature on the methodology and research topic are examined and presented. First, we look at the academic works that apply ARIMA models to predict real-world exports or imports. Second, we attempt to find the previous research regarding Finland and South Korea in business and economic fields.

It should come as no surprise that academic studies have attempted to forecast import and export using time series models like ARIMA in the past. Khan (2011) sought to develop a model for projecting Bangladesh's total imports over time. Seasonal ARIMA, Holt-Winters' trend, and VAR model are the three methodologies employed. For each of the three models, several forecasting accuracy measures were obtained. The result of the research shows that the evaluated performance of the VAR model is superior than those of the other 2 models.

Upadhyay (2013) used Box-Jenkins approach to develop a suitable ARIMA model for forecasting India’s wood panel trade during a 16-year period from 1996-97 to 2011-12. To forecast the export and import of wood-based panels, this research identified ARIMA (0,1,0) with R2 of 0.83 for the export and ARIMA (0,1,1) with R2 of 0.87 for the import. In comparison to 2012, the predicted export and import of wood-based panels in 2020 would grow by 170 percent and 127 percent, respectively.

Farooqi (2014) used the Box and Jenkins method to forecast the annual total trade of Pakistan from 1947 until 2013. ARIMA (2, 2, 2) was chosen for the best model for the annual imports, and ARIMA (1, 2, 2) model for the annual exports.. After that, Pakistan’s future import and export amounts were forecasted with the selected models. As the result of the research, it was identified the increasing patterns for both exports and imports.

Baser et al. (2018) utilized the ARIMA model to forecast chestnut production and exports in Turkey. The United Nations' Food and Agriculture Organization provides time series figures on Turkey's chestnut output and export. Annual data from 1961 to 2016 was used in the study. ARIMA (1, 1, 1) was chosen for predicting the total chestnut production, and ARIMA (1, 2, 1) was found to be the most appropriate for forecasting the export amount.. Turkey's chestnut production and exports are expected to increase in the coming years, according to the research. .

Unfortunately, there is not much earlier literature closely related to the research topic of this paper. In Scopus, the keywords "Korea" and "Finland" were typed and then filtered out the articles that belonged to the two categories "Business, Management and Accounting" and "Economics, Econometrics, and Finance". From these, 4 academic documents that are found most relevant to the chosen topic have been selected.

Ahmed, Chung, and Eichenseher (2003) study how business students' views and attitudes toward the ethical component of business differ among nations, as well as whether socio-cultural variables impact business ethics perspectives. Business students in six nations participated in the study including Finland and South Korea.

Piekut (2013) analyzes the level of innovation spending and sources of R&D funding in selected countries, including South Korea and Finland, from 2000 to 2010, showing that there is considerable diversification in both the level of R&D spending across countries and the sources of funding. Finland is one of the top countries, with R&D spending similar to the United States and Japan. South Korea has seen a rapid increase in R&D spending and a growing number of patent applications, placing this country among the world leaders.

Kabaklarli, Duran & Ucler (2018) tried to identify the factors that contributed to high-tech exports in 14 OECD member states, including Finland and South Korea, between the years 1989 and 2015. The main finding is that foreign direct investment and patent applications have a positive correlation with the successful exports of high-tech products.

Ambrocio and Jang (2021) investigated the effect that the financial crisis has caused on the South Korean and Finnish investment. First, it was discovered that following the crisis, Finnish investment and production dropped dramatically, but the crisis in South Korea was significantly milder. External demand and financial issues were the key reasons that initially impacted investment after the crisis, according to the findings. Furthermore, unfavorable internal variables slowed investment in Finland in later years, whereas negative international demand and financial concerns slowed investment in South Korea.

Even though there has been significant amount of previous research that build ARIMA models for the purpose of forecasting real-life export and import, there has never been any attempt to develop ARIMA models to forecast the bilateral trade relationship between Finland and South Korea. Considering the increasing size and importance of the trade relationship, the lack of previous literature suggests that there is a significant gap in the quantitative research regarding the economic relationship between the two countries. As a result, this study aims to address and fill the research gap that has been identified.

Filling this research gap is especially important for policy makers. Finland and South Korea are becoming more important as trade partners. Therefore, in order to create effective policies that would encourage the trade relationship, policymakers must have a clear grasp of how the trade will change over time. In addition, the CEO of a multinational corporation with operations in both countries, for example, may be among the parties with an interest in the expansion of economic relations between the two countries who might also gain from the study of this research.

1.4 Objective and scope

There has been an increase in demand for forecasts of key economic parameters both domestically and internationally in an increasingly globalized world that has been characterized in recent decades by increasing interdependence among nations and involves intense political, social, and economic interaction. Considering the significance of trade in the era of globalization, it is not surprising that estimating the total trade amount of important trading countries and regional blocs such as EU have become a crucial component of economic forecast providers. (WTO, 2008)

In that regard, investigating the trade relationship of Finland and South Korea is the goal of this study., with a particular focus on the trade between the two nations. Given South Korea's geographical proximity to Japan and China, it is often easy to assume similarities between these countries. Furthermore, due to South Korea's economy is smaller than those of China and Japan, it's easy to overlook the country's value as a trading partner. South Korea, on the other hand, is a unique nation in East Asia that demands special attention.

The commercial ties between the two countries are substantial. Even though South Korea is one of the most significant economic partners for Finland in the Asian region. (Korhonen et al, 2005) Even so, relatively little study has been conducted on the topic. This research aims to fill this research gap and contribute to improving the friendship and economic relationship between the two countries. Therefore, the development of the economic relationship will be investigated by analyzing the trend of bilateral trade. In addition, there will be an attempt to forecast the future development of the bilateral trade between South Korea and Finland by adopting a quantitative method called the Box-Jenkins method.

1.5 Research questions

The research aims to have a better understanding of the development in the trade relationship between Finland and South Korea and try to forecast the trend in the future. It seems that academic literature that has direct connections to the research topic is limited as of now. Therefore, there is a significant research gap to cover in the hopes of offering valuable insights to various parties such as students, investors, policymakers, and further researchers.

Based on the aim of the research stated above, the main research question has been formulated as follows: **"How will the bilateral trade between Finland and South Korea develop in the next 10 years from 2022 to 2031?"**

2 Data and research methodology

2.1 Finnish export data

The time series data on the bilateral trade between South Korea and Finland was acquired from the database of Finnish Customs (tulli.fi). It is time-series data of the monthly Finnish imports and exports. The period of the data is between January 1996 and December 2021, which is the most recent 25 years available. The size of the original data consists of 312 observations and 3 columns. Each observation contains the corresponding date, export, and import for each month. The first column, date, is written in such a format that year and month are written together, for example, 199601 means January of 1996. In the second and third columns, the amount of monthly exports and imports are written in the unit of thousand euros. In this research, the second column and the third column of the data are saved separately for further analysis and model buildings. For the first step of the exploratory analysis, the second column is saved as the new vector called “export” and plotted as below.

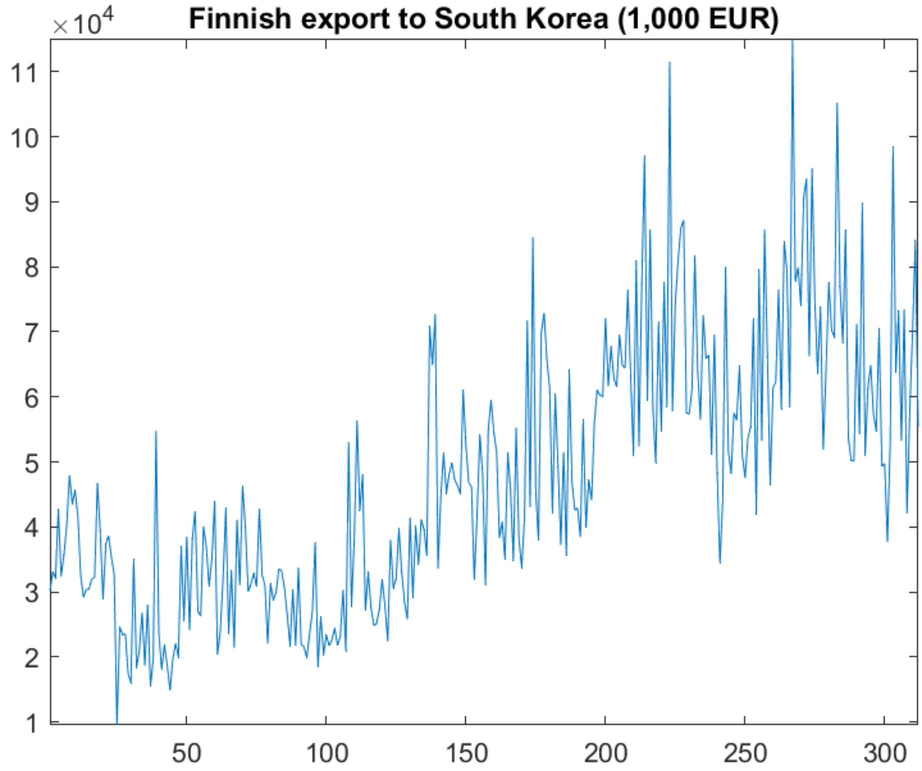

Figure 1. Monthly Finnish export to South Korea from 1996 to 2021

During the research period that spans from 1996 to 2021, there is an overall increase trend seen in the monthly export figures for Finland. Nevertheless, it seems that the trend has been staying the same or even going in the opposite direction during the past few years. It all begins with 30,170,000 euros in January 1996 and progresses all the way up to 55,433,000 euros by December 2021. The lowest amount of goods exported during the time period was 9,566,000 euros in January 1998, and the highest amount that was exported was 114,865,000 euros in March 2018. Because there is a clear increasing trend, it is to be anticipated that the data will needs differencing in order to construct a time-series model.

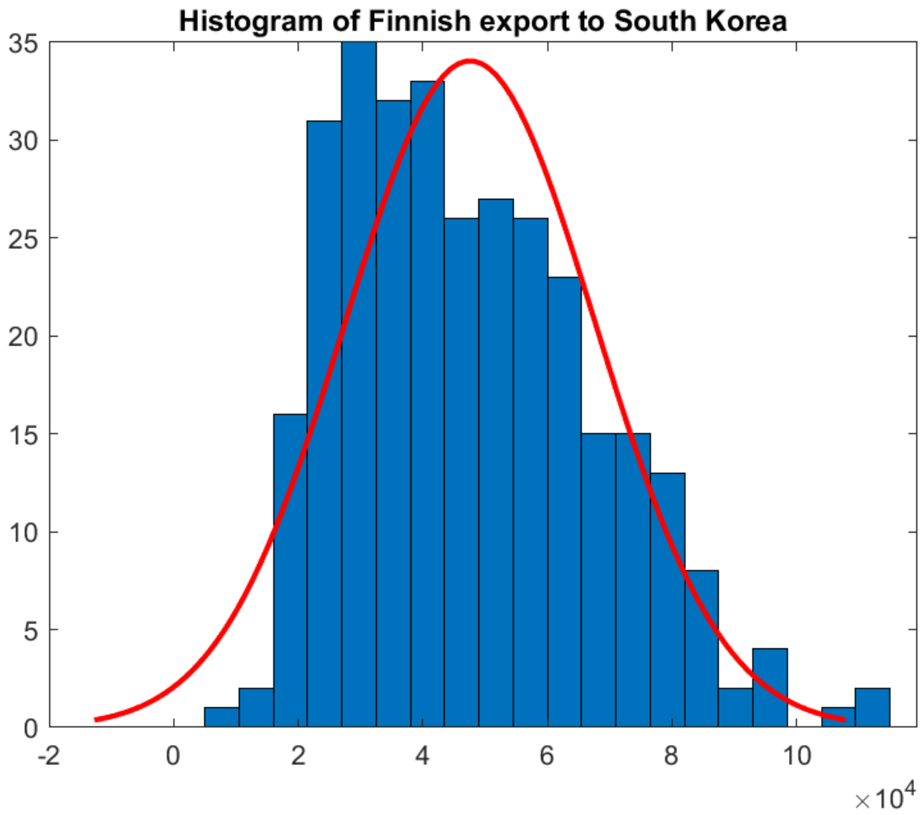

Figure 2. Histogram of Finnish export to South Korea

In the histogram, it can be observed that the shape of the distribution is not exactly normally distributed but skewed on the right side. When the histogram is compared with the normal distribution described with the red line in the figure, the skewness can be more obviously observed. Jarque-Bera test confirms this observation with Jarque-Bera statistics of 18.9377, the critical value of 5.7805, and the p-value of 0.0023. The result leads to the conclusion that it is possible that we can reject the null hypothesis of normal distribution in the original export data.

2.2 Finnish import data

In this part, the third column of the original raw data is saved as the new vector called "import" and plotted as below. Again, the period of the data is between January 1996 and December 2021, which is the most recent 26 years available. There are 312 observations in the data.

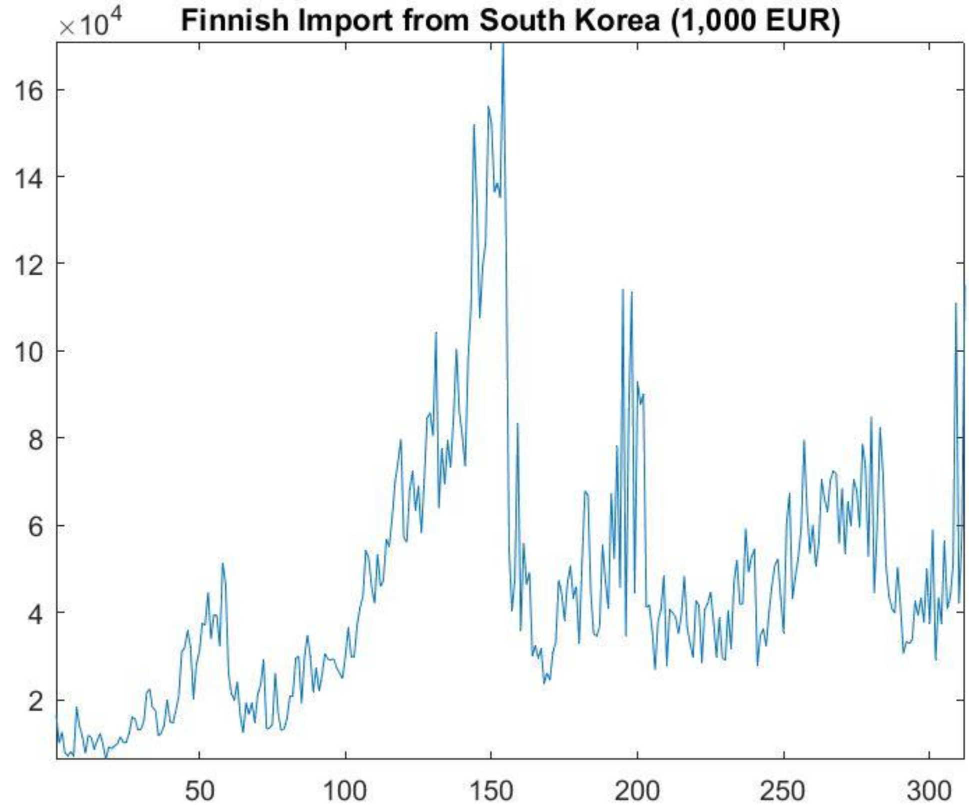

Figure 3. Monthly Finnish imports from South Korea from 1996 to 2021

The most notable characteristic of the monthly Finnish import from South Korea is that there are a couple of huge peaks during the period, which makes the plot a shape of a wave. The tallest import peak happened in October 2008. Korea's exports to Finland, which had increased due to the supply of mobile device parts to Nokia until 2008, declined in a short amount of time. The size of total imports reached EUR 1,594,125 in 2008, which declined to 550,095 EUR in 2009. In percentage, it was a 76% decrease from the previous year. It was mainly due to Nokia's poor performance in the mobile phone business and the prolonged economic crisis in the Eurozone. After the huge drop, the increase in the export of wired communication device parts in 2011 and the temporary energy export following the Finnish energy crisis in 2012 compensated for the decline in mobile device parts and lead to the second peak. Since 2014, exports of automobiles, pharmaceuticals, and rubber products have been increasing.

The plot shows a rather rough but long-term upward trend during the period from 1996 to 2021. It starts with EUR 16,679,000 in January 1996 and ends with EUR 115,121,000 in December 2021. The maximum amount of export during the period is EUR 170,907,000 in October 2008, and the minimum amount is EUR 6,317,000 in June 1997. The average amount is EUR 46,034,000 throughout the period. Due to the observable upward trend in the data, it is expected that the import data also needs to be differenced before building a time-series model with the Box-Jenkins method.

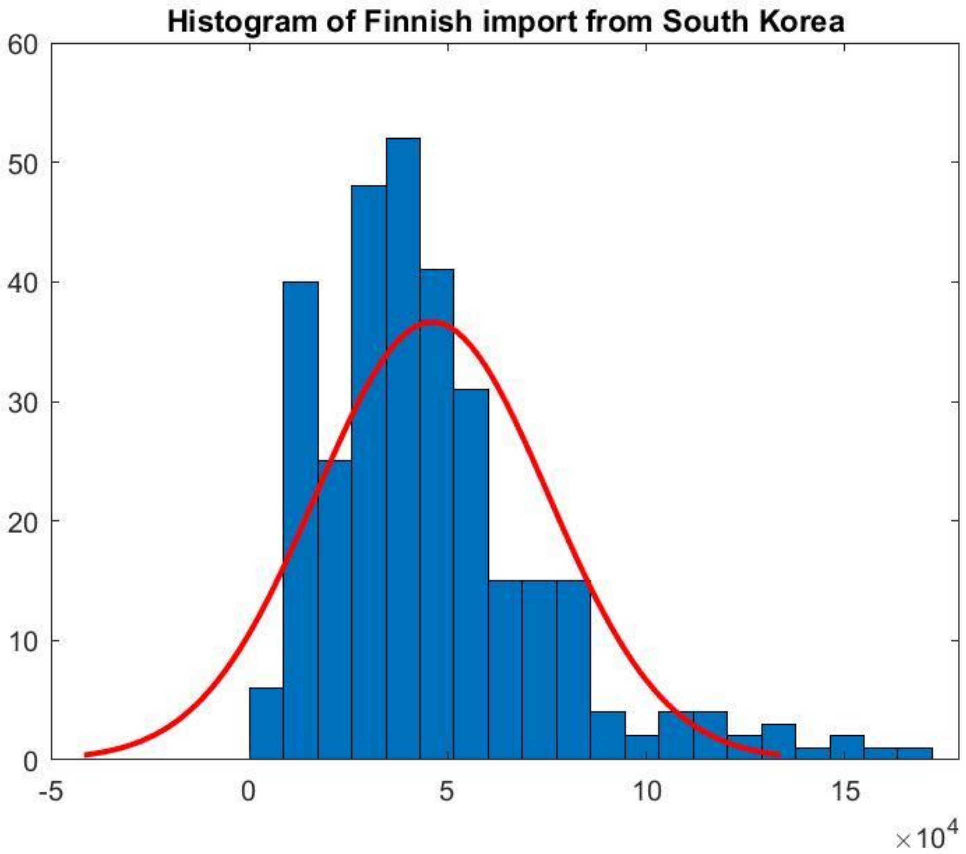

Figure 4. Histogram of Finnish imports from South Korea

In the histogram, it can be observed that the distribution is right skewed. When the histogram is compared with the normal distribution described with the red line in the figure, the skewness can be more obviously observed. Jarque-Bera test confirms this observation with Jarque-Bera statistics of 199.3105 the critical value of 5.7805, and the p-value of 0.001. We reject the null hypothesis of normal distribution in the original import data and reconfirm what is seen from the histogram.

2.3 Univariate time-series forecasting method

To answer the research question **"How will the bilateral trade between Finland and South Korea develop in the next 10 years from 2022 to 2031?"**, time-series models will be built based on the statistics data explained in the previous sections. ARIMA models are built with the Box-Jenkins method and tested for the fitness of the model. The models that pass diagnostic checking will be chosen and the future trend will be forecasted based on the models.

A family of specifications known as univariate time series models aims to model and predict financial variables just using data from their own historical values, potentially together with the past and present values of an error term. This contrasts with multidimensional structural models, which try to explain the changes in one variable in regard to changes in other explanatory variables. A time series model is not usually built on a specific theory, and thus often called a-theoretical. It means that building the model is not predicated on a theoretical model of a variable's behavior. One of the most well-known time series models could be mentioned as the autoregressive integrated moving average (ARIMA) model, which can be traced back to Box and Jenkins (Brooks, 2019).

The ARIMA model is a variant of ARMA model. Either a better comprehension of the data or future series points' predictions are the two objectives of fitting both models to time-series data. The non-stationarity of the mean function may be eliminated in cases where the data are non-stationary with respect to the mean by performing one or more initial differencing steps. We must first treat non-stationary in the time series, for example by differencing, before using the ARMA model. (Wang et al., 2019)

The AR component of ARIMA denotes that the relevant variable has been regressed against its own lagged values. The MA part of the equation suggests that the regression error is a linear combination of error components whose values occurred simultaneously and at diverse points in the past. The letter "I," which stands for "integrated," shows that the data values are replaced with the difference between those values and those of the previous values. The goal is to improve the model's fit to the data. (Box & Jenkins, 2015)

A non-seasonal ARIMA model is typically referred to as ARIMA (p, i, q). In that expression, “p” is the order of the AR component, “I” is the degree of differentiation, and “q” is the order of the MA component. A seasonal ARIMA model is often denoted as ARIMA(p, i, q)(P, I, Q)m, where the capital letters “P”, “I”, and “Q” represent the AR component, differentiating, and MA component respectively, and “m” represents the number of periods in each season. (Hyndman & Athanasopoulos, 2021) If two of the three components are zero, the model may be denoted by eliminating the name of the components with zero value. For instance, ARIMA (1, 0, 0) might alternatively be expressed as AR (1), ARIMA (0, 1, 0), and ARIMA (0, 0, 1) could be expressed as MA (1).

Box and Jenkins propose a systematic way to estimate an ARIMA model. The method can be broken down as three steps: identification, estimate, and diagnostic checking.

The first step, identification, is finding the model order required to reflect the dynamic characteristics of the data. Initial research might be conducted using graphical tools; however plots seldom yield clear findings. Utilizing so-called information criteria is a second method for removing some subjectivity from interpretation. Two elements make up information criteria: a term that depends on the sum of residual squares and a penalty for sacrificing degrees of freedom caused by adding more parameters. As a result, the information criterion is affected in two opposed ways by adding more variables to the model: While the value of the penalty factor increases, the sum of the squares of residuals decreases. The objective of the identification stage is deciding the number of parameters that minimize the value of information criterion. Only when the reduction in the sum of the squares of the residuals is enough to more than make up for the higher value of the penalty term does the addition of an additional term reduce the value of the criterion. Depending on how severe the penalty is, a number of variables change. The three most well-known information criteria are the Akaike Information Criterion (AIC), Bayesian Information Criterion of Schwarz (SBIC), and Hannan-Quinn Criterion (HQIC).

The second step estimation is numerically approximating the solutions of nonlinear equations for estimating the parameters. Since almost all current statistical programs have this functionality, it is normal practice to utilize statistical software designed to handle the method. Nonlinear least squares and maximum likelihood estimation are the two basic methods for fitting Box–Jenkins models. In most cases, maximum likelihood estimation is the recommended method. (Parag et al, 2017)

The final step, diagnostic checking refers to assessing if the estimated model is acceptable or not at the end of the model development process. Overfitting and residual diagnosis are two strategies suggested by Box and Jenkins. Overfitting means that unnecessarily large model is fitted to describe the characteristics of the data. If the model determined is already satisfactory, any additional terms would be unnecessary. Residual diagnostics is the process where the residuals are examined for indications of linear dependency. In case linear dependency is found, it indicates that the previously constructed model is not appropriate. It's possible to employ the ACF, PACF, or Ljung-Box tests. (Brooks, 2019) Overfitting is far less common than residual diagnosis. (Brooks, 2019)

3 Finnish exports to South Korea

3.1 Stationarity tests

The time series is assumed to be stationary in ARMA models. The characteristics of a stationary time series is that its average, variance, and autocovariance are all constant. A non-stationary time series violates some of those assumptions. The persistence of a shock in a non-stationary series is unlimited, but the impact of a shock is less in a stationary time series.

Before a non-stationary series may become stationary, it must be differenced. When a time series must be differenced "t" times, it could be said as an integrated of order "t" series, or simply I (t) series. The I (0) series, for example, is stationary and does not need any differencing. An I (1) series has a single unit root and requires just one differencing to achieve stationarity. Because an I (2) series has two unit roots, it must be differentiated twice before it reaches stationarity.

Stationarity and the unit roots in the data could be checked by using three distinct methods. First, Augmented Dickey-Fuller (ADF) tests the null hypothesis that a unit root exists in a time series. The alternative hypothesis is that the time series is stationarity. Second, the Phillips-Perron (PP) test is more thorough. It's similar with the ADF test, except it includes an automated Dickey-Fuller method adjustment to account for autocorrelated residuals. The test often yields the same results as the ADF test. Third, Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests are employed to verify the null hypothesis that an observable time series is stationary. This is how KPSS test is different from ADF and PP tests since the alternative hypothesis is that unit roots exist in the time-series data. A KPSS test result may be compared to those of the comparable ADF and PP tests to make the results of the test more robust.

ADF, PP, and KPSS tests have been conducted to check the stationarity and the existence of unit roots in the original monthly Finnish export to South Korea. The summary of the test results is as follows.

Table 1. Summary of stationarity tests (export)

	ADF	PP	KPSS
H_0	yt ~ I (1)	yt ~ I (1)	yt ~ I (0)
H_1	yt ~ I (0)	yt ~ I (0)	yt ~ I (1)
Result	Do not reject H_0	Do not reject H_0	Reject H_0
Interpretation	Non-stationary	Non-stationary	Non-Stationary

The ADF and PP test results are identical and do not reject the null hypothesis that the export data is non-stationarity. In addition, the KPSS test rejects the null hypothesis that the export data is stationary, reaffirming the non-stationarity of the export data and making the results of first two tests more robust. According to the findings, the original time series data of monthly Finnish exports to South Korea is non-stationary.

To conduct further analysis and build time-series models, the non-stationarity should be treated properly. As mentioned earlier, differencing is one of the methods to transform non-stationarity data into stationary data. Differencing is a method that can remove the trend that exists in a time series data. It is done by subtracting the lagged value of the original time series from the original time series. The monthly Finnish export data has been differenced once and plotted as below.

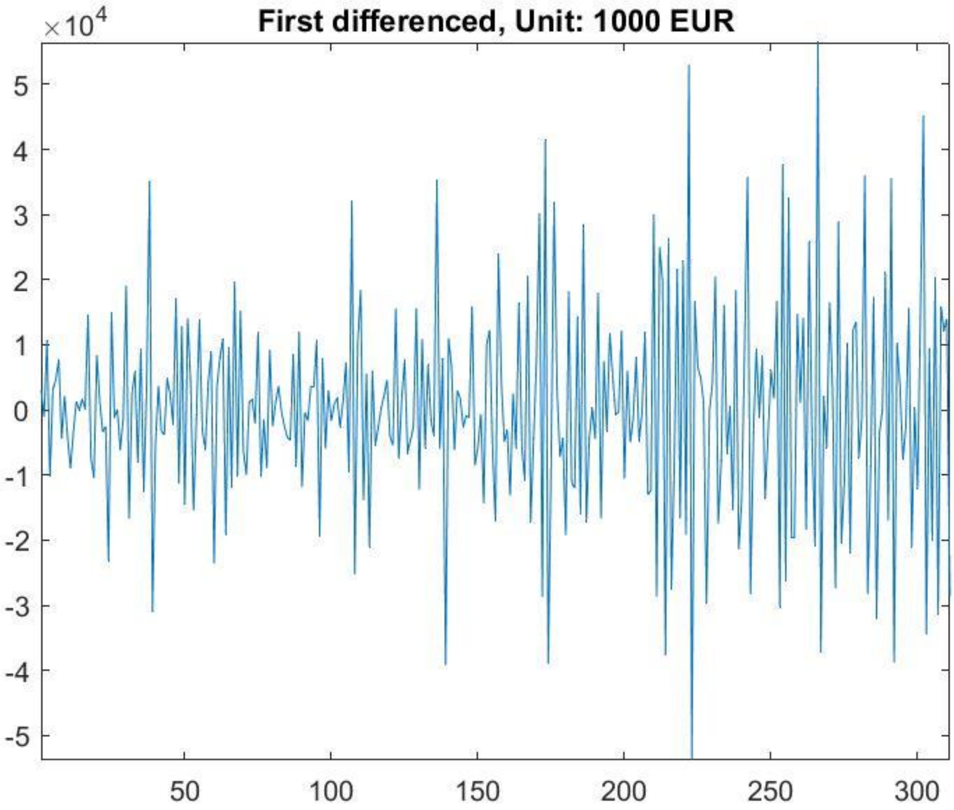

Figure 5. First differenced export data

The differenced data seem weakly stationary based on the plotted values, even though it is often inaccurate to gauge stationarity by eye. Again, ADF, PP, and KPSS tests have been conducted to check the stationarity with more subjective standards and the existence of unit roots in the differenced data. The test results are summarized as follows.

Table 2. Stationary tests of first differenced export

	ADF	PP	KPSS
H_0	$yt \sim I(1)$	$yt \sim I(1)$	$yt \sim I(0)$
H_1	$yt \sim I(0)$	$yt \sim I(0)$	$yt \sim I(1)$
First differenced	Reject H_0	Reject H_0	Do not reject H_0

The tests results say that the first differenced data is stationary and thus do not require further treatment. That means that the first differenced data can be a good candidate for building time-series models.

3.2 Model Building with Box-Jenkins method

The Box-Jenkins method uses autoregressive moving average (ARMA) or autoregressive integrated moving average (ARIMA) models to determine the most appropriate model for a time-series data. Although ARMA models had existed before, it was George Box and Gwilym Jenkins that suggested the systematical way of estimating an ARMA model for the first time. Their strategy consisted of three steps: Identification, estimation, and diagnostic testing are the three steps in the process.

3.2.1 Identification

In the identification stage, the appropriate order of the model is “identified”. One of the ways to identify the appropriate order of the model is a “graphical method”. For this method, the autocorrelation (ACF) and partial autocorrelation (PACF) functions of the time series are are plotted and analyzed together. By looking at the shape and the number of lags in the plots, it is possible to guess the correct order of the model intuitively.

First, an autoregressive process (AR) shows a geometrically decaying ACF and several points outside of significance levels in PACF, which is the correct AR order. Second, A moving average process (MA) has a geometrically decaying PACF and several non-zero points in ACF, which is the correct MA order. Finally, a autoregressive moving average process (ARMA) shows geometrically decaying ACF and PACF. How to recognize the patterns in the ACF and PACF and find the correct order of the model is summarized in the table below.

Table 3. Patterns of ACF and PACF

Autocorrelation (ACF)	Parcial Autocorrelation (PACF)	Model
Geometrically decaying	p significant lags	AR(p)
q significant lags	Geometrically decaying	MA(q)
Geometrically decaying after q lags	Geometrically decaying after p lags	ARMA(p,q)

The plots for ACF and PACF have been made for the first differenced series as below. The blue lines are the confidence boundary. If any lag is located between the blue lines, it is considered statistically insignificant.

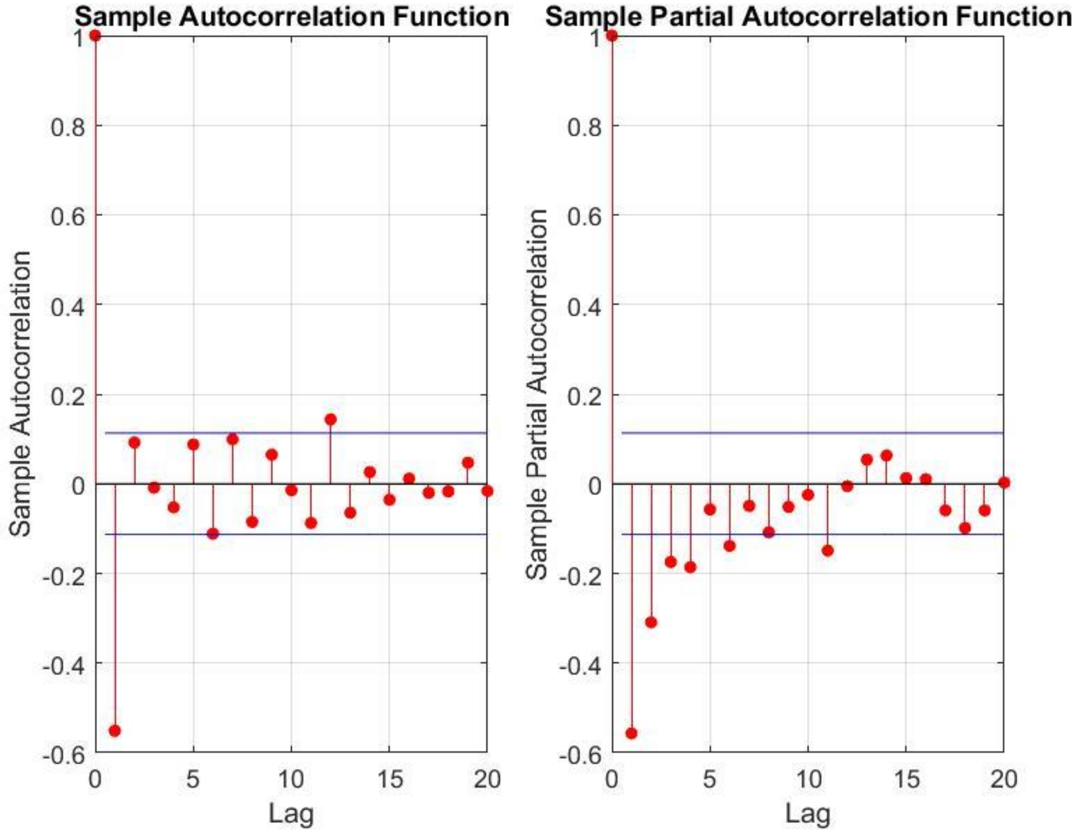

Figure 6. ACF and PACF of first differenced export

The most notable characteristic of ACF of the first differenced series is that it has only one significant lag and cuts off after the second lag. The PACF seems to decay and geometrically cuts off after lag 4. According to the plots above, this behavior suggests a first-degree moving average model or MA (1) model. Even though the graphical method is intuitively easy to interpret, it might not be the best identification method. In many cases, the real data of interest could be messy and unfortunately rarely shows simple patterns. Identification of the model would typically not be done using the sample and partial sample autocorrelation functions. The modern development in the process has brought up the so-called "information criteria", which consists of 2 parts: the first part is a function of the Residual Sum of Squares (RSS)and the second part is the penalty for making the model more complex. This technique removes some of the subjectivity of interpretation and gives algebraically calculated scores or "criteria" that enables more objective decision on the order of a model.

The objective is to minimize this information criterion. We have three popular information criteria: AIC, BIC, and HQIC. AIC is inconsistent and will choose larger models owing to the lighter penalty whereas BIC is highly consistent yet inefficient. BIC has a bigger penalty term than AIC. The testing for the correct orders is usually done by comparing the size of the information criteria between different models.

To check the AIC and BIC values of possible candidate models, lines of codes have been built in MATLAB. A for-loop function is used to calculate the AIC and BIC values of every possible combination of ARMA (i, j) where i represents the AR order and j represents the MA order. By looking at the plots of ACF and PACF above, it is expected that the maximum order of any model cannot be larger than 5 because ACF is cutting off after the 1^{st}. lag and PACF is cutting off after the 4^{th} lag. Therefore, the possible maximum orders for i and j are both set as 5. AIC and BIC matrices are shown as the results of the calculation below.

Table 4. AIC matrix of export

AIC (Unit: 1,000)

ARMA (i, j)	j = 0	j = 1	j = 2	j = 3	j = 4	j = 5
i = 0	6.9101	6.7801	6.7419	6.7421	6.7841	6.7449
i = 1	6.7981	6.7410	6.7429	6.7425	6.7853	6.7459
i = 2	6.7692	6.7420	6.7422	6.7432	6.7864	6.7458
i = 3	6.7617	6.8263	6.7446	6.7447	6.7870	6.7450
i = 4	6.7530	6.7440	6.7466	6.7464	6.7887	6.7412
i = 5	6.7540	6.7861	6.7443	6.7463	6.7453	6.7485

Table 5. BIC matrix of export

BIC (Unit: 1,000)

ARMA (i, j)	j = 0	j = 1	j = 2	j = 3	j = 4	j = 5
i = 0	6.9176	6.7913	6.7569	6.7608	6.8066	6.7711
i = 1	6.8093	6.7560	6.7616	6.7649	6.8115	6.7758
i = 2	6.7842	6.7607	6.7647	6.7693	6.8164	6.7794
i = 3	6.7804	6.8487	6.7707	6.7746	6.8206	6.7824
i = 4	6.7755	6.7702	6.7765	6.7800	6.8261	6.7824
i = 5	6.7802	6.8160	6.7780	6.7837	6.7864	6.7934

In both AIC and BIC matrices, ARMA (1,1) has the smallest criteria values. In conclusion, the graphical method suggests MA (1), and the information criteria method suggests ARMA (1,1) for the best possible models. Moving on to the next step, two models will be built based on the suggestions from the graphical identification and information criteria identification.

3.2.2 Estimation

From the stationarity tests, it has been clarified that the original monthly data series has one unit root, I (1) and it has been differenced once for further analysis including identification of the correct order of the model. In addition to that information, the possible orders of the model, MA (1) and ARMA (1, 1), have been identified from the graphical identification method and information criteria method.

Estimating parameters utilizing computer techniques to get the coefficients that best suit the specified ARIMA models is part of the estimation stage. Maximum likelihood and non-linear least-squares are the most often utilized approaches. Given the observed univariate time series, the "estimate" function in MATLAB utilizes the maximum likelihood technique to estimate the parameters of the ARIMA (p, i, q) model. As a consequence, by incorporating all of the information obtained so far, two alternative ARIMA models, ARIMA (0, 1, 1) and

ARIMA (1, 1, 1), can be constructed. The command window summaries of ARIMA (0, 1, 1) and ARIMA (1, 1, 1) are displayed below.

Table 6. Summary of ARIMA (0,1,1)

ARIMA(0,1,1) Model (Gaussian Distribution):

	Value	StandardError	TStatistic	PValue
Constant	97.478	231.33	0.42138	0.67348
MA{1}	-0.80777	0.05166	-15.636	4.1281e-55
Variance	2.5797e+08	0.00086587	2.9793e+11	0

Therefore, the estimated ARIMA (0, 1,1) model's equation can be written as

$$yt = 97.478 + yt_{-1} + \varepsilon t - 0.80777\varepsilon t_{-1},$$

$$\varepsilon t \sim N\,(0,\, 2.5797 * 10^{\wedge 8})$$

Table 7. Summary of ARIMA (1,1,1)

ARIMA(1,1,1) Model (Gaussian Distribution):

	Value	StandardError	TStatistic	PValue
Constant	117.39	171.8	0.68329	0.49442
AR{1}	-0.09783	0.073464	-1.3317	0.18297
MA{1}	-0.7648	0.041165	-18.579	4.7607e-77
Variance	1.5537e+08	0.0012581	1.2349e+11	0

Therefore, the estimated ARIMA (1,1,1) model's equation can be written as

$$\Delta y_t = 117.39 - 0.09783\Delta y_{t-1} + \varepsilon_t - 0.7648\varepsilon_{t-1},$$

$$\varepsilon_t \sim N\,(0,\ 1.5537 * 10^{\wedge 8})$$

To check the fitness of the predicted models graphically, fitted values of the models and the actual values are plotted against each other as below.

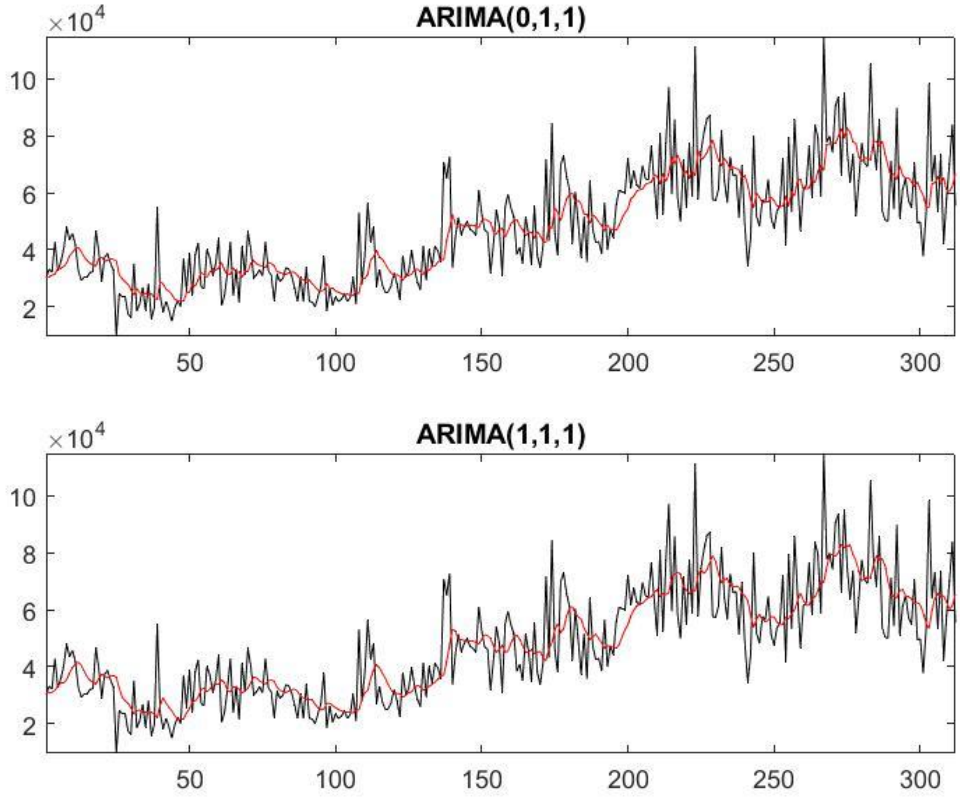

Figure 7. Fitted vs Actual (export)

In the plots, the fitted values are shown as the red lines, while the actual values are described as the black lines. It would appear that the fitted models are doing a good job of following the long-term patterns of the actual values. But the red lines in the two plots don't seem to indicate any clear distinctions between them.

3.2.3 Diagnostic checking

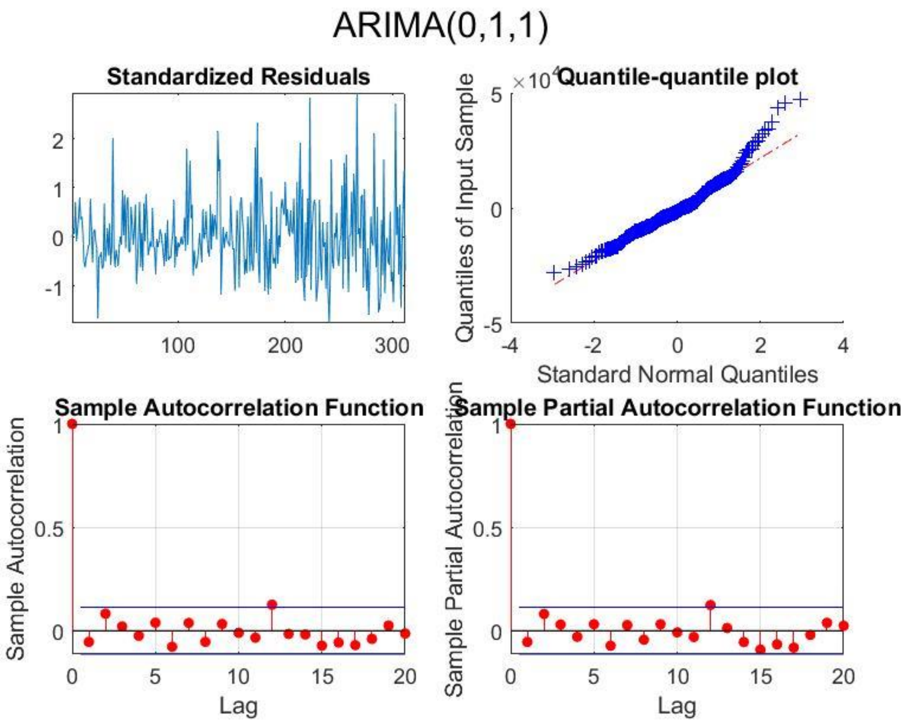

Figure 8. ARIMA (0,1,1) diagnostic checking

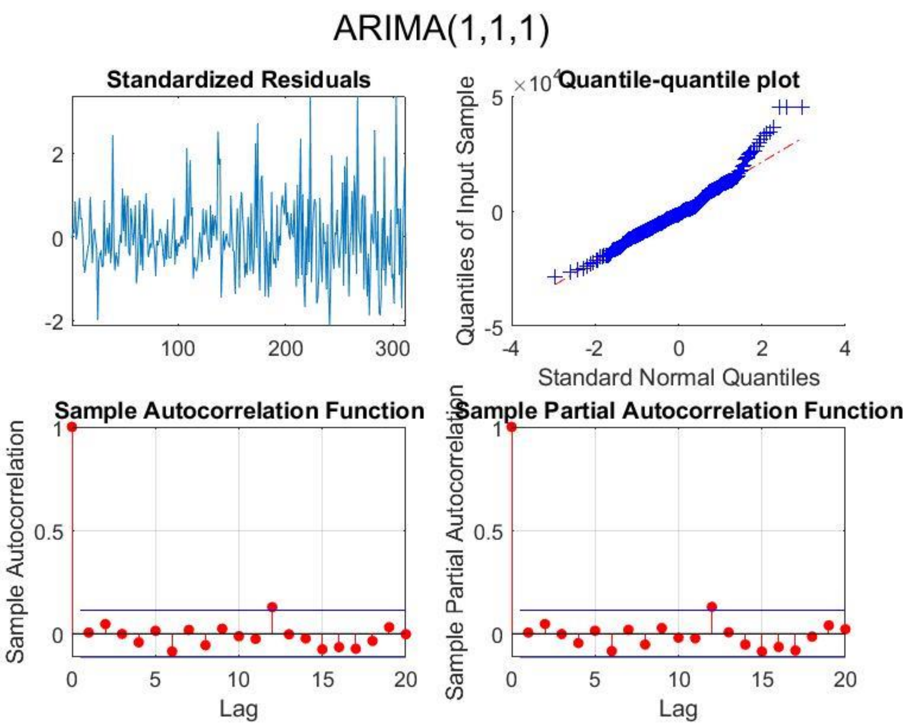

Figure 9. ARIMA (1,1,1) diagnostic checking

Several charts have been made for the residual diagnosis of the models. In both ARIMA (0, 1, 1) model and ARIMA (1, 1, 1) model, the residuals seem reasonably normally distributed when standardized residuals and quantile-quantile plots are checked. However, we can observe that there are still some existing correlations in the residuals from ACF and PACF plots, which should not be present in an appropriate model. Especially, the 12th lags in ACF and PACF of both models are outside of the significant level. This suggests that there might be existing seasonality in the model, which opens the possibility of using Seasonal Autoregressive Integrated Moving Average (SARIMA) models.

3.2.4 SARIMA Models

The two previous models ARIMA (0, 1, 1) and ARIMA (1, 1, 1) did not pass the diagnostic checking. The 12th lags in the ACF and PACF of the residuals were outside of the significant level. Therefore, two additional models have been built to reflect the seasonality of the time series data. The first model is SARIMA (0, 1, 1) x (0, 1, 1)12 and the second model is SARIMA (1, 1, 1) x (1, 1, 1)12. The command window's summaries of the two models are shown below.

Table 8. Summary of SARIMA (0,1,1) x (0,1,1) 12

ARIMA(0,1,1) Model Seasonally Integrated with Seasonal MA(12) (Gaussian Distribution):

	Value	StandardError	TStatistic	PValue
Constant	0	0	NaN	NaN
MA{1}	-0.78842	0.093913	-8.3953	4.6488e-17
SMA{12}	-0.87625	0.082795	-10.583	3.5572e-26
Variance	4.3488e+08	1.3833e-11	3.1439e+19	0

Therefore, the equation form of the estimated SARIMA (0, 1, 1) x (0, 1, 1)12 model can be described as

$$(1 - L)\,(1 - L^{12})\,y_t = (1 - 0.78842L)\,(1 - 0.87625L^{12})\,\varepsilon_t,$$

$$\varepsilon_t \sim N\,(0,\ 4.3488 * 10^{\wedge 8})$$

Table 9. Summary of SARIMA (1,1,1) x (1,1,1) 12

ARIMA(1,1,1) Model Seasonally Integrated with Seasonal AR(12) and MA(12) (Gaussian Distribution):

	Value	StandardError	TStatistic	PValue
Constant	0	0	NaN	NaN
AR{1}	-0.10733	0.10901	-0.98459	0.32482
SAR{12}	0.019449	0.0869	0.22381	0.8229
MA{1}	-0.73366	0.06669	-11.001	3.7755e-28
SMA{12}	-0.8754	0.049084	-17.834	3.8158e-71
Variance	2.2462e+08	1.8072e-11	1.243e+19	0

Therefore, the equation form of the estimated SARIMA (1, 1, 1) x (1, 1, 1)12 model can be described as

$$(1 + 0.10733L)\,(1 - 0.019449L^{12})\,(1 - L)\,(1 - L^{12})\,y_t$$

$$= (1 - 0.73366L)\,(1 - 0.8754L^{12})\,\varepsilon_t,$$

$$\varepsilon_t \sim N\,(0,\ 2.2462 * 10^{\wedge 8})$$

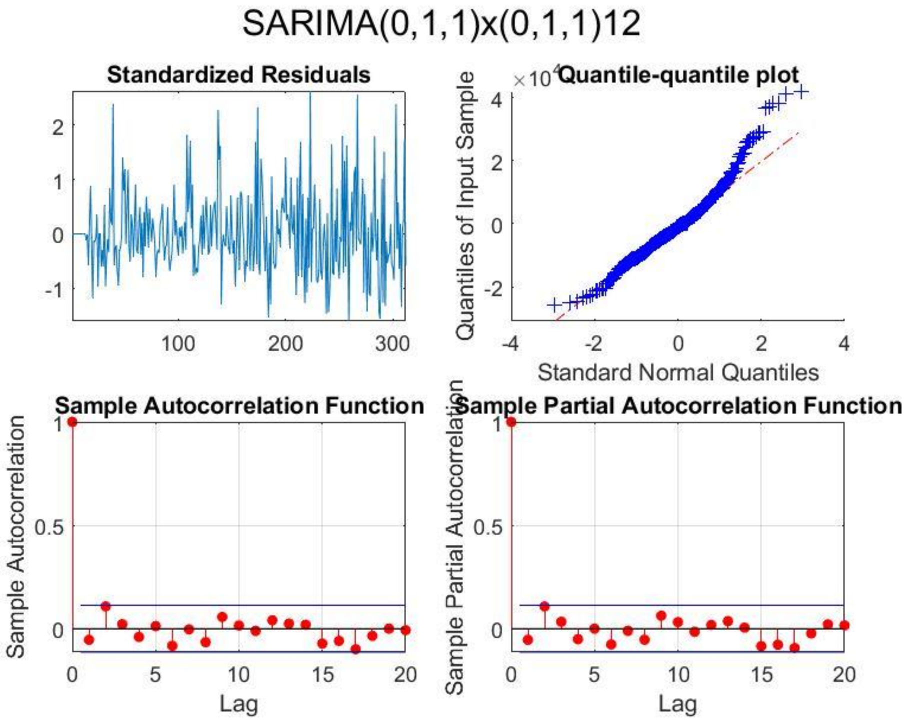

Figure 10. Diagnostic checking of SARIMA (0,1,1) x (0,1,1) 12

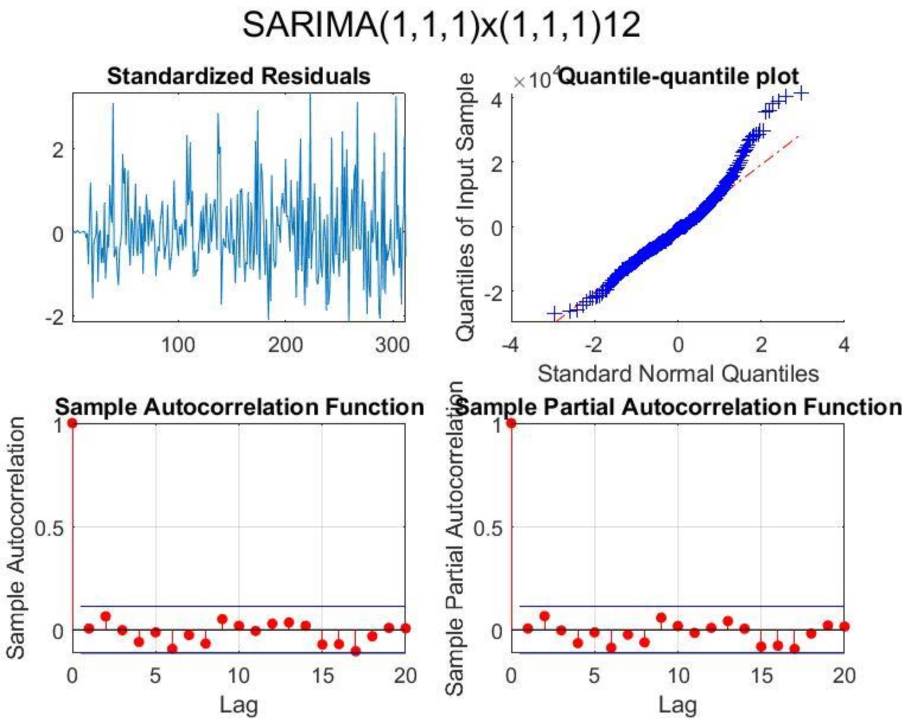

Figure 11. Diagnostic checking of SARIMA (1,1,1) x (1,1,1) 12

Finally, several residual diagnostic charts have been made for the two SARIMA models. The residuals seem reasonably normally distributed when the plot of standardized residuals and the plot of quantile-quantile are checked. However, it is observed from ACF and PACF plots of the residuals of SARIMA (0, 1, 1) x $(0, 1, 1)_{12}$ model that the 2nd lags still tough the significant level, which should not be present in an appropriate model. On the contrary, all the lags in ACF and PACF of SARIMA (1, 1, 1) x $(1, 1, 1)_{12}$ model stay between the blue lines. Therefore, SARIMA (1, 1, 1) x $(1, 1, 1)_{12}$ model is selected as the most appropriate model among the two candidates.

The Ljung-Box Q-test is another way to check for a diagnosis. The Ljung-Box Q-test is a somewhat more quantitative and objective method of simultaneously testing for autocorrelation that might exist in multiple lags. This test is often used to determine autocorrelation in each series with a constant mean. This contains residual series that may be used in model diagnostics to check for autocorrelation. For this test, the null hypothesis is that the n autocorrelations are all 0. (1978, Ljung & Box) The tests have been coded for SARIMA (1, 1, 1) x $(1, 1, 1)_{12}$ model, and the result is reported in the table below.

Table 10. Summary of Ljung-Box Q-test

	SARIMA (1, 1, 1) x $(1, 1, 1)_{12}$
H_0	No autocorrelation
Test statistics	15.9196
Critical value	31.4104
h	0
Result	Do not reject H_0

The result of the Ljung-Box Q-test does not reject the null hypothesis that there is no autocorrelation in the residuals of the SARIMA model. This indicates that the model has successfully passed the diagnostic testing and could be utilized to make projections for exports from Finland to South Korea.

4 Finnish imports from South Korea

4.1 Stationarity tests

Same with the Finnish export, ADF, PP - and KPSS tests were performed to check stationarity and the presence of unit roots in the original monthly Finnish imports from South Korea. The summary of the test results is as follows.

Table 11. Summary of stationary tests of import data

	ADF	PP	KPSS
H_0	$y_t \sim I(1)$	$y_t \sim I(1)$	$y_t \sim I(0)$
H_1	$y_t \sim I(0)$	$y_t \sim I(0)$	$y_t \sim I(1)$
Result	Do not reject H_0	Reject H_0	Reject H_0
Interpretation	Non-stationary	Stationary	Non-Stationary

The test result of ADF and PP match do not match. The ADF test does not reject the null hypothesis that import time-series data is non-stationary, but the PP test rejects the null hypothesis. However, the test result of KPSS rejects the null hypothesis of stationarity and supports the result of the ADF test. Overall, we assume that the original time series data of monthly Finnish imports to South Korea is non-stationary considering the plot in the previous part, and the ADF and KPSS test results altogether.

To conduct further analysis and build time-series models, the non-stationarity should be treated properly. As mentioned earlier, differencing is one of the methods to transform non-stationarity data into stationary data. Differencing is a method of removing a trend in a time series data, which subtracts the lagged values from the original values. The monthly Finnish import data has been again differenced once.

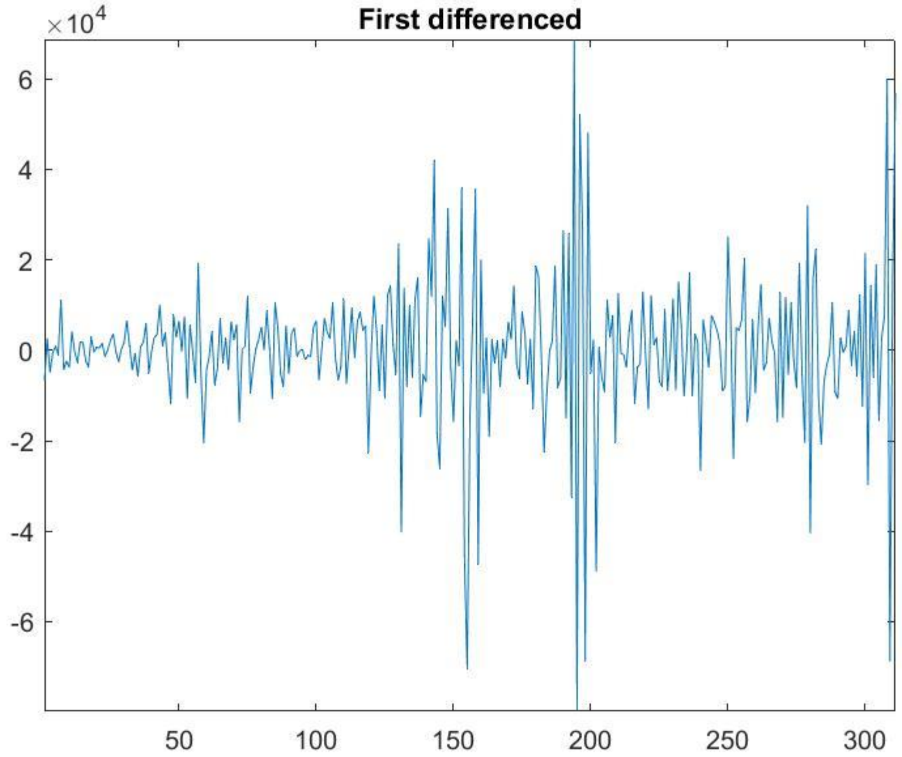

Figure 12. First differenced import data

Both differenced data seem weakly stationary based on the plotted values, even though it is often inaccurate to gauge stationarity by eye. Again, ADF, PP, and KPSS tests have been conducted to check the stationarity with more subjective standards and the existence of unit roots in the differenced data. The test results are summarized as follows.

Table 12. Stationarity tests of first differenced import

	ADF	PP	KPSS
H_0	$y_t \sim I(1)$	$y_t \sim I(1)$	$y_t \sim I(0)$
H_1	$y_t \sim I(0)$	$y_t \sim I(0)$	$y_t \sim I(1)$
First differenced	Reject H_0	Reject H_0	Do not reject H_0

Now all the test results give the same results. The first differenced data is stationary and thus does not require further treatment. That means the first differenced import data can be a good candidate for building a time-series model for the monthly Finnish import from South Korea.

4.2 Model Building with Box-Jenkins method

4.2.1 Identification

The plots for ACF and PACF have been made for the first differenced series as below. The blue band represents the bounds for the upper and lower confidence. If any lag is located between the blue lines, it is considered statistically insignificant.

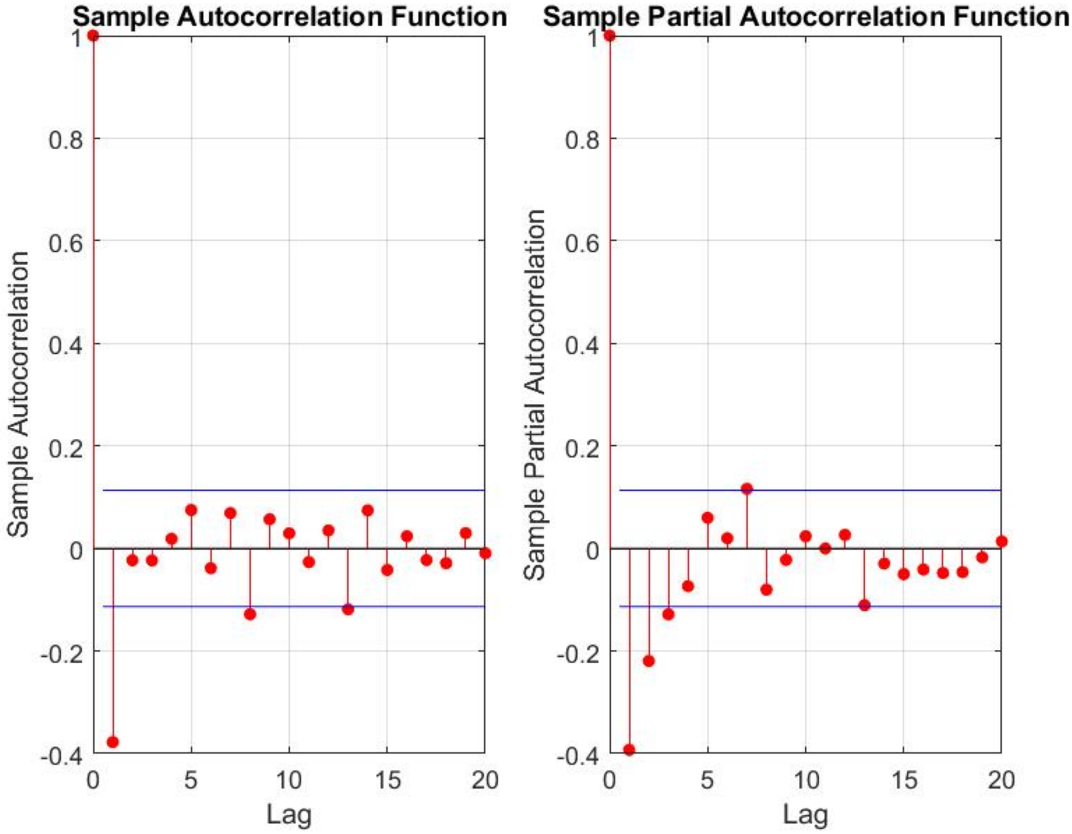

Figure 13. ACF and PACF of first differenced import

The ACF has only one significant lag and cuts off after the second lag. The PACF seems to decay and geometrically cuts off after lag 3. According to the plots above, this behavior is consistent with a first-degree autoregressive model or MA (1) model.

In addition, the AIC and BIC values of possible candidate models have been checked. By looking at the plots of ACF and PACF above, it is expected that the maximum order of any model cannot be larger than 4 because ACF is cutting off after the 1st lag and PACF is cutting off after the 3rd lag. Therefore, the possible maximum orders for i and j are both set as 4. AIC and BIC matrices are shown as the results of the calculation below.

Table 13. Summary of AIC (import)

AIC (Unit: 1,000)

ARMA (i, j)	j = 0	j = 1	j = 2	j = 3	j = 4
i = 0	6.9198	6.8536	6.8555	6.8564	6.8570
i = 1	6.8718	6.8555	6.8568	6.8588	6.8586
i = 2	6.8594	6.8570	6.8567	6.8593	6.8595
i = 3	6.8567	6.8581	6.8581	6.8595	6.8547
i = 4	6.8572	6.8578	6.8586	6.8598	6.8618

Table 14. Summary of BIC (import)

BIC (Unit: 1,000)

ARMA (i, j)	j = 0	j = 1	j = 2	j = 3	j = 4
i = 0	6.9273	6.8648	6.8704	6.8751	6.8795
i = 1	6.8830	6.8704	6.8755	6.8813	6.8848
i = 2	6.8743	6.8757	6.8791	6.8854	6.8894
i = 3	6.8754	6.8805	6.8843	6.8894	6.8883
i = 4	6.8797	6.8839	6.8885	6.8934	6.8992

In both AIC and BIC matrices, ARMA (0, 1) or MA (1) has the smallest criteria values. In conclusion, both the graphical method and the information criteria suggest that the best order of model for the import time series data is MA (1).

4.2.2 Estimation

From the stationarity tests, it has been clarified that the original monthly data series has one unit root, I (1) and it has been differenced once for further analysis including identification of the correct order of the model. In addition to that information, the possible order of the model, MA (1) has been identified from the graphical identification method and information criteria method. Therefore, ARIMA (0, 1, 1) has been built by combining all the results that have been conducted so far. The summary of ARIMA (0, 1, 1) from the command window is shown below.

Table 15. Summary of ARIMA (0, 1, 1)

ARIMA(0,1,1) Model (Gaussian Distribution):

	Value	StandardError	TStatistic	PValue
Constant	225.05	422.72	0.53239	0.59445
MA{1}	-0.50847	0.026526	-19.169	6.7725e-82
Variance	2.2163e+08	0.0027099	8.1785e+10	0

Therefore, the equation form of the estimated ARIMA (0, 1, 1) model can be written as

$$y_t = 225.05 + y_{t-1} + \varepsilon_t - 0.50847\varepsilon_{t-1},$$

$$\varepsilon_t \sim N(0, 2.2163 * 10^{8})$$

To check the fitness of the predicted models graphically, fitted values of the model are plotted against the actual values.

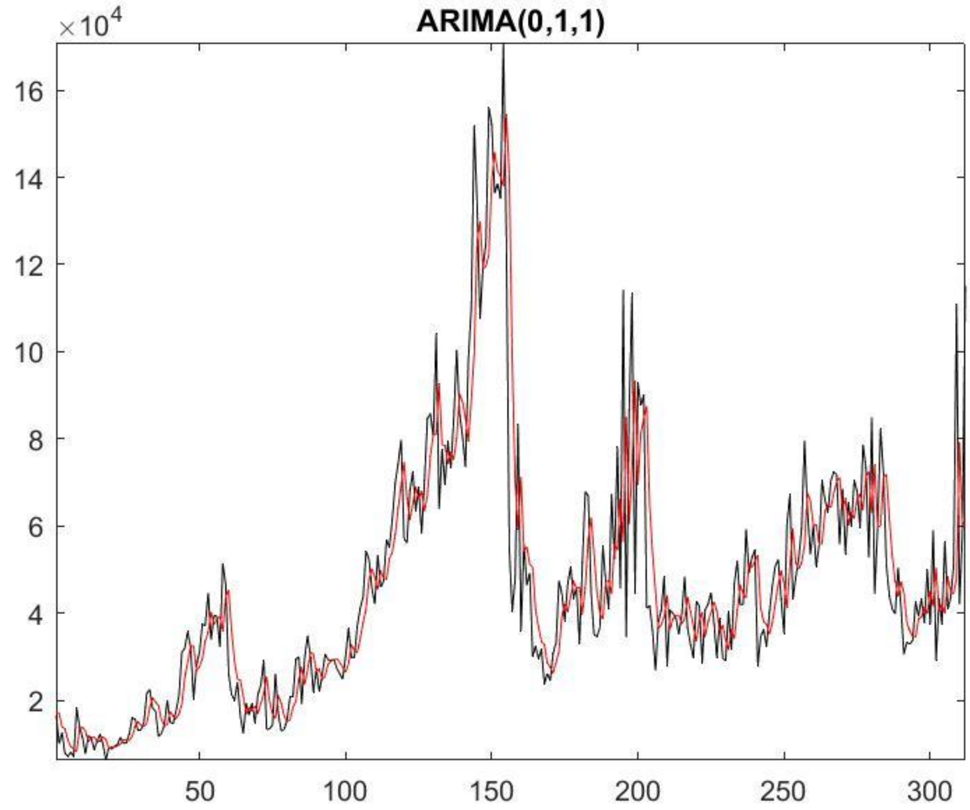

Figure 14. Fitted vs Actual (import)

The fitted values are expressed as the red lines against the actual values expressed as the black lines in the plots. The model seems to perform reasonably well.

4.2.3 Diagnostic checking

The charts for the residual diagnosis checking of the ARIMA (0, 1, 1) have been made as below.

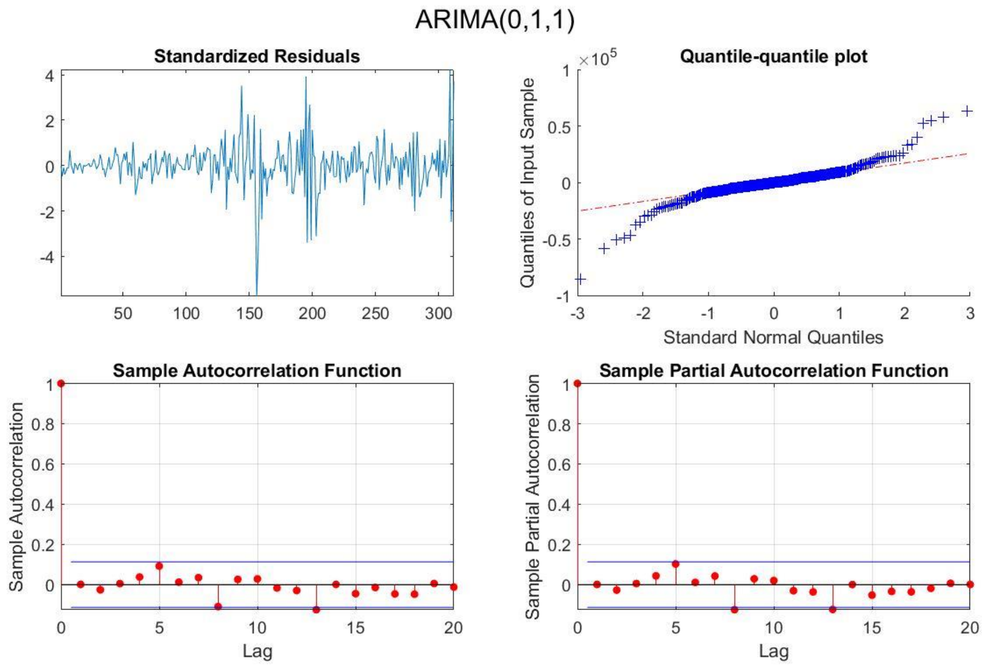

Figure 15. Diagnostic checking of ARIMA (0,1,1)

From the plot of standardized residuals and the plot of quantile-quantile, the residuals seem reasonably normally distributed. In addition, all lags in the ACF and PACF fall between the blue lines, which represent a significant level. Therefore, we can assume that the residuals are also uncorrelated. For more objective diagnostic checking, Ljung-Box Q-test has been conducted, and the summary of the test result is shown below.

Table 16. Summary of Ljung-Box Q-test

	ARIMA (0,1,1)
H_0	No autocorrelation
Test statistics	15.8641
Critical value	31.4104
h	0
Result	Do not reject H_0

The results of the Ljung-Box Q-test also support that we should not reject the null hypothesis of no autocorrelation in the residuals of the ARIMA (0,1,1) model. This reconfirms the interpretation of the ACF and PACF plots. In conclusion, the ARIMA (0,1,1) model is the most appropriate time-series model selected by the Box-Jenkins method for the monthly Finnish import from South Korea.

5 Research findings and implications

Based on the time-series models for Finnish export and import, forecasts for the next 10 years from 2022 to 2031, or 120 months, have been simulated. And then, the simulated forecasts for export and import have been plotted as below. In each plot, the blue line represents the forecasts, and the red dotted lines represent the 95% confidence interval.

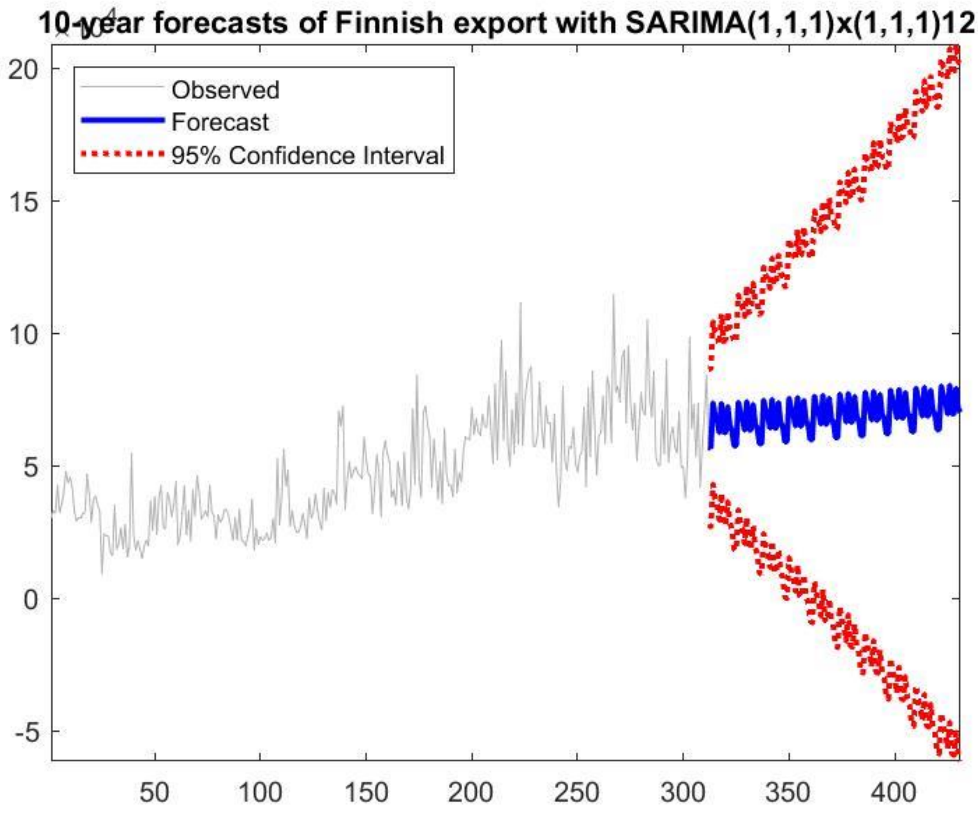

Figure 16. Forecasts of Finnish export to South Korea

The first plot represents the forecasts of the Finnish export to South Korea that is obtained by applying the first model SARIMA (1,1,1) x $(1,1,1)_{12}$ for the next 120 months from January 2022 to December 2031. The forecast for January 2022 is EUR 57,223,000 and the last forecast for December 2031 is EUR 70,197,000. The forecasted average export during the next 10 years is EUR 68,908,000. Overall, the forecast shows a clear upward trend in the forecasted period. According to the result, Finnish export to Korea is expected to increase in the next 10 years.

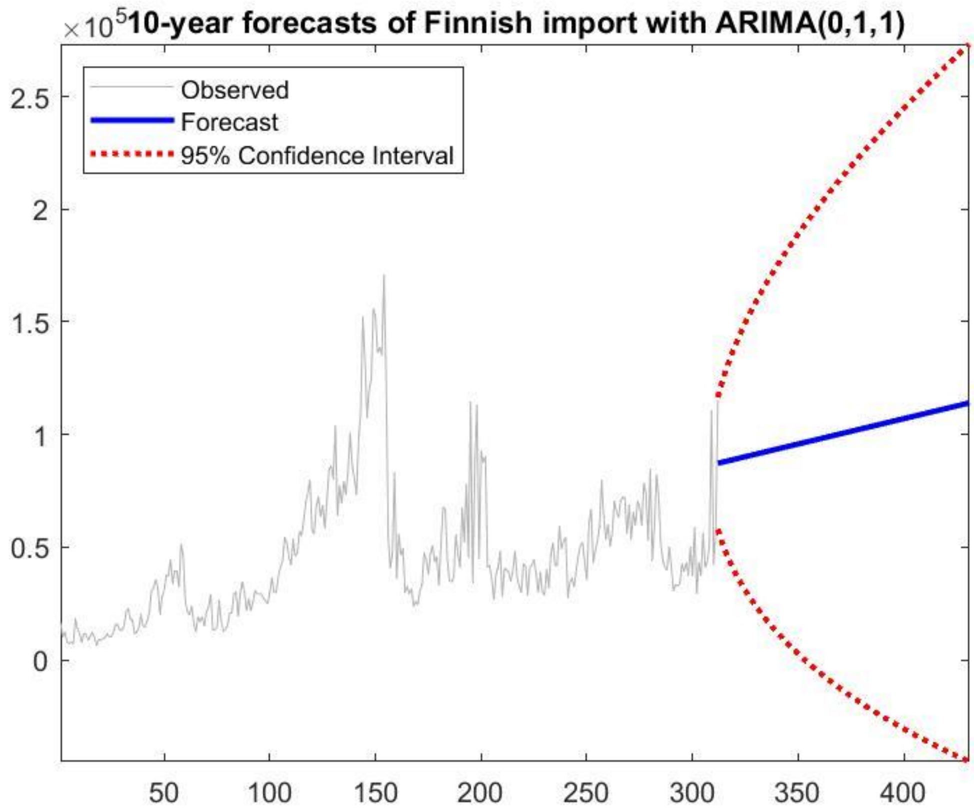

Figure 3. Forecasts of Finnish import from South Korea

The second plot represents the forecasts of the Finnish import to South Korea that is obtained by applying the first model ARIMA (0,1,1) for the next 120 months from January 2022 to December 2031. The forecast for January 2022 is EUR 87,295,000 and the last forecast for December 2031 is EUR 114,080,000. The forecasted average export during the next 10 years is EUR 100,690,000. According to the result, Finnish import to Korea is expected to increase in the next 10 years as well.

6 Conclusions

The ability to accurately forecast macroeconomic factors, such as a country's imports and exports, is essential for an economically sound nation. In addition, conducting research on and making projections regarding the bilateral trade relationship between two countries is a great way to get a better understanding of the relationship that exists between the two countries of interest. As a result of this, the focus of this thesis was to perform an analysis of the historical data pertaining to the bilateral trade and to construct time-series models in order to make a trend prediction for the next ten years.

By adhering to both the historical research method and the Box-Jenkins method, the research has successfully accomplished the objectives. A cursory investigation into the history of the trade that occurred prior to the period for which there is data (prior to 1996) has been carried out. After that, export and import data from the past, spanning the years 1996 to 2020, have been used to develop models. After running a series of statistical comparisons, we have chosen the ones that are the most applicable. Both SARIMA (1, 1, 1) x (1, 1, 1) 12 and ARIMA (0, 1, 1) have been chosen as the appropriate models for calculating monthly exports from Finland to South Korea and imports into Finland from South Korea, respectively. The findings from the diagnostic checking demonstrate that the models have the potential to be utilized for the purpose of forecasting the future trend of bilateral trade.

The forecasts show that the volume of imports and exports carried out by Finland will, collectively, demonstrate a rising trend between the years 2022 and 2031. In the time period under consideration, it is anticipated that Finland's annual imports will amount to approximately 101 million euros, while the country's exports will total 69 million euros. As a result, it is anticipated that Finland will run a trade deficit throughout the period equal to 32 million euros on an annual average basis. This implication may provide individuals who are interested in the economic relationship between Finland and South Korea, such as policy makers, economists, or students, with valuable insights into the nature of that relationship.

This study does not make use of a wide variety of models, which is one of the things that holds it back. It can be seen in Figures 5 and 11 that heteroskedasticity exists in both the first differenced export data and the first differenced import data. In this particular scenario, an alternative to the process of building ARIMA models would be to actively implement the heteroscedasticity into the errors by way of the construction of autoregressive conditional heteroskedasticity (ARCH) models. Generalized autoregressive conditional heteroskedasticity (GARCH) models, exponential autoregressive conditional heteroskedasticity (EGARCH) models, and Glosten, Jagannathan, and Runkle (GJR) models are all members of the ARCH model family. These models do not make the presumption that the variance of the errors is homoscedastic.

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